Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/BA08.20250087
Published: December 20, 2025

Barriers to Digital Supply Chain Transformation: Identification and Prioritization through Fuzzy Best–Worst Method

Md. Tanjid Hossen Irfan, Shahriar Hasan Ratul, Jahid Hasan Ashik and Md. Saiful Islam Seam
Department of Industrial Engineering and Management
Khulna University of Engineering and Technology
Khulna 9203, Bangladesh
irfan@iem.kuet.ac.bd, shahriar@iem.kuet.ac.bd, jhashik@iem.kuet.ac.bd, itssiam25@gmail.com

Abstract

The transition from conventional supply chains to digitally enabled supply chains has been sped up by the emergence of digital technology, but many businesses still struggle with adoption because of a number of interconnected barriers. A thorough literature analysis led to the original identification of 25 barriers, which were then narrowed down to 17 major barriers in four categories: technological, organizational, operational, and economic. The Fuzzy Best–Worst Method (FBWM), which successfully controls uncertainty and lessens inconsistency in expert opinion, is used in this study to rank these barriers. According to expert assessments, the biggest challenges are lack of support from top management and a lack of digital skills and talent, which are followed by large investment in digital infrastructure. The stability of the rankings was validated through comparative analysis with other fuzzy multi-criteria decision-making techniques. The results highlight that, although important, personnel and budgetary concerns become secondary if leadership commitment and technology preparedness are met as requirements for a successful digital supply chain implementation. By providing a structured framework that directs managers especially in situations with limited resources to prioritize efforts for digital transformation.

Keywords
Digital Supply Chain, Adoption Barriers, Fuzzy Best–Worst Method (FBWM), Multi-Criteria Decision Making (MCDM), Industry 4.0 Transformation

1. Introduction
Digital technology has expanded very quickly, and this has put an immense impact on how businesses come up with new ideas, especially when it comes to managing their supply chains. In this area, digitization is now necessary to incorporate more features (Lee et al., 2024). Cloud and edge computing, the Internet of Things (IoT), cyber-physical systems, Artificial Intelligence (AI), advanced analytics, and blockchain are all part of the Digital Supply Chain (DSC). It connects all components of the supply chain, from planning to sourcing to production to logistics to after-sales. This facilitates collaborative efforts across organizations through data utilization (Büyüközkan & Göçer, 2018). They have also changed the way people communicate with each other and interact with the world around them in a big way. The digital transformation is moving forward because of new digital technologies that are useful. These technologies including lean tools are meant to ensure and decide flexibility, profitability, productivity and stability (Irfan et al., 2025) by using new business models, making and selling competitive products, and having good effects on complicated and intelligent digital networks (Minculete et al., 2022).

Previously, supply chains used to rely heavily on manual processes and separate company systems, which made it hard to respond quickly and see what was going on (Mubarik & Khan, 2024). A well-implemented DSC gives managers near-real-time access to all the information they need to keep an eye on resources, capacity, and shipments focusing customers satisfaction (Ratul & Hossain, 2024). It does this by combining data from IoT devices, enterprise systems, and partner platforms. This level of visibility helps with improved collaboration between different departments and helps with reporting on sustainability and compliance (Attaran, 2020; Rahman et al., 2024). DSC solutions make workflows easier, automate common decisions, and cut down on waste in procurement, production, and logistics. This leads to measurable improvements in quality and efficiency. In small and medium-sized businesses (SMEs), evidence demonstrates that when complementary capabilities are in place, adopting digital technology leads to increases in flexibility, cost, and competitiveness. These benefits grow as companies get older (Masood & Sonntag, 2020).

Despite this assurance, implementation remains inequitable due to numerous interdependent impediments. Large investment in digital infrastructure, coupled with an ambiguous return on investment (ROI), weaken the business case. Lack of support from top management, fragmented decision-making, and Lack of digital skills and talent impede progress. Employee resistance and tenuous partner trust complicate data sharing and the collaborative redesign of procedures (Kache & Seuring, 2017). Technology-related challenges, including erroneous or inconsistent data, underdeveloped analytics, cybersecurity, privacy threats, and unstable connectivity, diminish the likelihood of interoperability and value realization (Shupti et al., 2024). The limits are intensified for SMEs and firms in underdeveloped countries, where cash, skills, and digital infrastructure are relatively scarce, hence widening the adoption gap (Ivanov et al., 2019). Addressing adoption challenges, including inadequate management support and poor data governance, enhances scalability, especially for small and medium-sized enterprises that need targeted capabilities development. DSCs provide enduring strategic benefits only when technologies like IoT, analytics, blockchain, and cloud computing are integrated with corresponding organizational capabilities. The reduction of operational barriers enables efficient data and process transfer between nodes, thereby lessening disruptive ripple effects and improving risk analytics.

Even though more and more people are realizing how revolutionary DSCs could be, there isn't enough research that looks at all the problems and how important they are. Most empirical research is either context-specific, e.g., sectoral or regional, or descriptive, with few initiatives to emphasize the challenges faced by firms. This dispersion makes it harder for managers, policymakers, and practitioners to come up with good plans for putting DSCs into action. Because of the information gap described above, this study aims to answer the following questions (RQ).

RQ1: What barriers prevent firms from embracing and employing DSC?
RQ2: How significant are these barriers to widespread adoption of DSC?

The present study seeks to respond to research question RQ1 by pinpointing barriers through a detailed literature review and RQ2 by prioritizing these barriers using the Fuzzy Best–Worst Method (FBWM), which has not been widely applied in this context. FBWM is a well-recognized approach to handle complex system behaviors and make decisions under uncertainty. One of the main advantages of FBWM is that it requires fewer pairwise comparisons compared to traditional methods, reduces inconsistency in judgments, and can effectively incorporate both qualitative and quantitative data (Nasrollahi et al., 2020). This study provides a validated ranking framework by cross-checking results with other fuzzy MCDM methods (TOPSIS, VIKOR, WASPAS, COPRAS), strengthening reliability. Integrating divergent findings into a unified framework improves theoretical understanding, while the utilization of FBWM strengthens scientific rigor by reducing ambiguity in expert assessments.

2. Literature Review

2.1 Initial survey

Using the keywords ‘Supply Chain Management’, ‘Digital Supply Chain’, ‘Barriers of Digital Supply Chain’, ‘Industry 4.0’, ‘Adoption of Digitization’, an exploratory survey was performed to identify initial barriers. Google Scholar database is preferred in this survey because it is less methodical. Initially, 25 relevant barriers were identified.

2.2 Digitization of SCs

Businesses are increasingly being forced to digitize in order to improve performance and maintain their existence in the competitive market. Supply chain digitization is the process of transforming manual, paper-based, and traditional operations into digital representations using cutting-edge technologies like the Internet of Things (IoT), cloud computing, blockchain, big data analytics, and artificial intelligence (Ellis et al., 2019). Industry 4.0, the fourth industrial revolution, uses digital platforms to link all corporate verticals and horizontals and make all business processes intelligent (Bag et al., 2018).

2.3. Adoption of DSC

Though the transformation to DSC using technologies like blockchain, IoT, cloud computing, and advanced analytics but a number of barriers prevent their widespread adoption. Armengaud et al. (2020) explored the impact of organizational barriers in digitization of automotive sector. Buyukozkan & Gocer (2018) emphasized how crucial it is for SCs to use digital technology in order to obtain a competitive edge. Although Industry 4.0's information and digital technologies are thought to be driving the SC digital transformation, it is still necessary to look into the major drivers and hurdles as well as the best practices for SC digitization (Oliveira-Dias et al., 2022). Prior studies have identified economic challenges such as high infrastructure investment and uncertain return on investment (Ding, 2018; Arunachalam et al., 2018), organizational issues including lack of top management support and political instability (Bughin et al., 2015; Ye et al., 2022), operational barriers such as fear of job loss and inefficient information flows (Kumar et al., 2021; Khan et al., 2021), and technological constraints like data inaccuracy, cybersecurity risks, and shortage of digital skills (Müller et al., 2018; Liboni et al., 2019). However, they identify and rank barriers from Triple Bottom Line (TBL) perspective, ignoring either organizational or technological barriers. This study not only focused on those barriers but also performed cross-checking results with other fuzzy MCDM methods.

3. Methodology

To identify and rank the barriers to the adoption of digital supply chains, this study used a 5-step methodological approach shown in Figure 1.

3.1 Step 1: Barriers Identification

To investigate the barriers preventing the implementation of digital supply chains, a thorough literature review was carried out. To compile a thorough list of probable barriers, pertinent research, industry publications, and scholarly journals were examined. The Google Scholar database was used mainly for barrier identification. Search keywords such as 'Digital Supply Chain', 'Digitization', 'Supply Chain Barriers', etc. were used. A total of 25 barriers were identified initially.

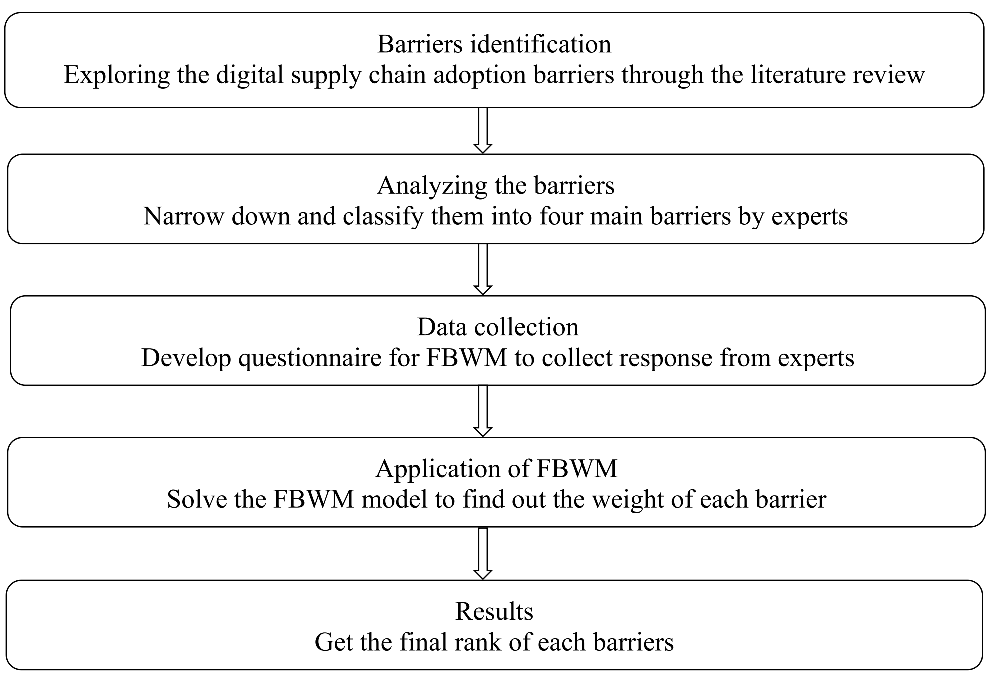

Figure 1. Research framework

3.2 Step 2: Analyzing the barriers

With the help of domain experts, the identified 25 barriers were further refined and divided into four primary categories: technological, organizational, operational, and economic. The 17 most important barriers, shown in Table 1, were chosen for further study after being reviewed with five experts active in different supply chain phases. By taking this approach, the framework was guaranteed to include both general and detailed viewpoints on adoption barriers.

Table 1. Final selected barriers

Main Barriers	Sub-barriers	Description	References
Economical capabilities	C1: Large investment in digital infrastructure	Building the necessary digital infrastructure is a capital-intensive activity, and the large investment required acts as a significant barrier for companies.	(Ding, 2018)
	C2: Uncertainty about ROI	Large sums of money are required for digitization, and since these investments are not immediately linked to observable results, their returns are unpredictable.	(Arunachalam et al., 2018)
	C3: Inefficient budget allocation	It means that even if a company has the funds, they are not being used effectively to support digital transformation projects, often because of a lack of a clear strategy or a failure to prioritize necessary investments.	(Deepu & Ravi, 2022)
	C4: Lesser investments in R & D	Businesses that don't spend in research and development (R&D) aren't allocating resources to investigate and create novel technologies or procedures.	Dalenogare, et al., 2018)
Organizational capabilities	C5: Lack of support from top management	The adoption of digitization is impacted by a lack of top management support and motivation (recognition, reward, and incentive).	(Bughin, et al., 2015)
	C6: Lack of motivation and support from the government	Government attention and assistance, such as steps to prevent tax evasion, can help companies in their digitization efforts by creating a more stable and attractive economic environment for investments in digital infrastructure and technology.	(Ghadimi et al., 2022)
	C7: Small companies face barriers in digital transformation	Small companies face barriers to digital transformation because of financial constraints, a lack of skilled employees, and limited resources to invest in new technologies and the necessary strategic planning.	(Arunachalam et al., 2018)
	C8: Political uncertainty/instability	Changes in the government have a direct effect on the profitability of a business operator or the value that investors place on a certain economic move.	(Ye et al., 2022)
Operational capabilities	C9: Fear of losing the job	Automation has made individuals fearful of losing their employment.	(Kumar, et al., 2021)
	C10: Ineffective approach for identifying and managing waste	It is necessary to improve waste identification and management, which can be accomplished by implementing technology.	(Fatimah et al., 2020)
	C11: Insufficient trust between partners	Effective management is required for data and information misuse and leakage among partners.	(Han & Trimi, 2022)
	C12: Lack of efficient information flows and its management	Controlling the information flow and timely updates within organization	(Khan et al., 2021)
Technological capabilities	C13: Data accuracy	Errors, inconsistencies, or incompleteness in data can seriously impair analytics' dependability and make it challenging to obtain a clear view of the supply chain and make wise decisions.	(Müller et al., 2018)
	C14: Lack of digital skills and talent	Companies lack employees with the necessary expertise to manage new digital systems, and they have difficulty finding or training new talent to fill this gap	(Liboni et al., 2019)
	C15: Cyber security & privacy issues	Technologies that offer intelligence and connectivity are necessary for SCs to embrace digitization, which leads to a massive data flow with multiple layers of protection.	(Balaji et al., 2019)
	C16: Unstable internet connectivity	Internet access has emerged as one of the primary obstacles to digitization as a result of climate change, natural disasters, and political unrest.	(Ganesh & Kalpana, 2022)
	C17: Data analysis issues	Because it is challenging to ensure data quality, integrate information from various sources, and possess the requisite skills to evaluate it for valuable insights, data analysis problems pose a serious obstacle in digital supply chains.	(Oesterreich & Teuteberg, 2016)

3.3 Step 3: Data Collection

A structured questionnaire was designed following the Fuzzy Best–Worst Method (FBWM). Questionnaires were sent through email to 10 experts, out of which 4 responded. Cronbach's alpha value is 0.7, which is a measure of internal consistency of the data collected.

3.4 Step 4: Application of FBWM

The detailed procedure of FBWM is available in (Afrasiabi et al., 2022). A brief overview of the key steps is presented below.

3.4.1 Determine the Best and Worst Barriers

Following the identification of pertinent barriers of digital supply chains, the participating experts were asked to rank main barriers as Best and Worst. The barrier that is thought to be most significant or crucial in influencing the adoption of digital supply chains is known as the Best (C_B) barrier. On the other hand, the barrier with the least relative importance among the others is represented by the Worst (C_W) barrier. Experts were asked to follow a similar procedure for sub-barriers under the main barriers.

3.4.2 Fuzzy Best-To-Others and Others-To-Worst Comparisons

After identifying the best and worst barrier, Experts were required to use two sets of comparisons to explain their preferences. The chosen best barrier was first compared with each of the other barriers in the Best-to-Others (BO) comparisons to ascertain its relative relevance. Second, in the Others-to-Worst (OW) comparisons, all barriers were compared against the selected Worst barrier. Linguistic preference scales shown in Table 2 were used for the comparisons in order to account for the ambiguity and uncertainty that are inherent in human judgment. Experts were asked to follow a similar procedure for sub-barriers under the main barriers. This step produced a BO and OW vector as follows:

$A_B = (a_{B1}, a_{B2, \ldots,} a_{Bn})$
$A_W = (a_{W1}, a_{W1, \ldots,} a_{Wn})$

Table 2. Triangular Fuzzy Number (TFN) and Consistency Index (CI)

Linguistic terms	Equally important (EI)	Weakly important (WI)	Fairly important (FI)	Very important (VI)	Absolutely important (AI)
TFNs	(1,1,1)	(2/3,1,3/2)	(3/2,2,5/2)	(5/2,3,7/2)	(7/2,4,9/2)
CI	3.00	3.80	5.29	6.69	8.04

3.4.3 Solve the FBWM Optimization Model

Linguistic terms are transformed into triangular fuzzy numbers (TFNs) to solve FBWM model. The model minimizes the maximum deviation to obtain fuzzy weights for each barrier, while checking the consistency ratio (CR). A nonlinear programming model, is derived from the elements of the BO and OW vectors.

Min ξ^*
Subject to,

$$\left| \frac{(l_B^w, m_B^w, u_B^w)}{(l_j^w, m_j^w, u_j^w)} - l_{Bj}, m_{Bj}, u_{Bj} \right| \leq (k^*, k^*, k^*)$$

$$\left| \frac{(l_j^w, m_j^w, u_j^w)}{(l_W^w, m_W^w, u_W^w)} - l_{jW}, m_{jW}, u_{jW} \right| \leq (k^*, k^*, k^*)$$

$\sum_{J=1}^{N} R(W_J) = 1$
$l_j^w \leq m_j^w \leq u_j^w$
$l_j^w \geq 0$
$j = 1, 2, \ldots, n$

where $a_{Bj} = (l_{Bj}, m_{Bj}, u_{Bj})$ and $a_{jW} = (l_{jW}, m_{jW}, u_{jW})$ symbolize, respectively, the j-th component of the BO and OW vectors. $W_J = (l_j^w, m_j^w, u_j^w)$, $W_B = (l_B^w, m_B^w, u_B^w)$, $W_W = (l_W^w, l_W^w, l_W^w)$ are the fuzzy weights of the j-th criterion c_J, best criterion c_B, and worst criterion c_W, respectively. $\xi = (l^\xi, m^\xi, u^\xi)$, with $l^\xi \leq m^\xi \leq u^\xi$, and $\xi^* = (k^*, k^*, k^*)$, with $k^* \leq l^\xi$. To make the sum of weight 1 the fuzzy weights should be defuzzified using following equation $R(A) = 1/6*(a_1 + 4a_2 + a_3)$ where (a_1, a_2, a_3) be a TNF. The formula $CR=\xi^*/CI$ is used to calculate the consistency ratio (CR) values. LINGO 15.0 was used to solve this optimization model.

3.4.4 Aggregate the Results

The results must be combined into a single representative set of weights because expert opinions can differ. To guarantee a collective evaluation, the fuzzy weights obtained from each decision maker (DM) in this investigation were first combined. The geometric mean strategy, which is frequently used in multi-criteria decision-making techniques incorporating fuzzy data, was used to complete the aggregation.

4. Results

The fuzzy Best-Worst Method (FBWM) analysis resulted in the stable hierarchy of obstacles to implementation of digital supply chains, which was confirmed by using several comparison techniques. It was examined by four professionals (DM1-DM4) on the basis of 17 refined barriers which were judged on the four broad categories of Economical, Organizational, Operational, and Technological using linguistic judging number which were transformed into triangular fuzzy numbers (TFNs). Table 6 all consistency ratios (CR) were under 0.1, which proved the trustworthy input of experts.

Tables 3 and 4 show the expert preference pattern in best to others (BtO) and others to worst barriers (OtW). Three of the four decision-makers (DM1, DM2, and DM4) categorized Technological barriers as the most serious category whereas the most significant among the four is DM3 which classifies as Organizational barriers. The linguistic assessments in these tables were successfully transformed to triangular fuzzy numbers demonstrated in Table 5 which effectively represented uncertainty and subjectivity of the expert judging. Fuzzy local weights of main barriers and sub-barriers in Tables 6 and 7 were determined by averaging optimal fuzzy weights from all DMs. To calculate global optimal fuzzy weights for sub-barriers, the components of fuzzy local weights were weighted by the main barriers.

Table 3. Best to other barriers comparison

DM	**BtO of main barriers**				
	Best	Economical	Organizational	Operational	Technological
DM1	Technological	VI	WI	AI	EI
DM2	Technological	AI	FI	WI	EI
DM3	Organizational	FI	EI	AI	WI
DM4	Technological	AI	FI	WI	EI

Table 4. Others to worst barriers comparison

DM	**OtW of main barriers**				
	Worst	Economical	Organizational	Operational	Technological
DM1	Operational	FI	WI	EI	AI
DM2	Economical	EI	VI	FI	AI
DM3	Operational	WI	AI	EI	FI
DM4	Economical	EI	WI	FI	AI

Table 5. TFN of Fuzzy Linguistic value

DM	**BtO of main barriers**				
	Best	Economical	Organizational	Operational	Technological
DM1	Technological	5/2,3,7/2	2/3,1,3/2	7/2,4,9/2	1,1,1
DM2	Technological	7/2,4,9/2	3/2,2,5/2	2/3,1,3/2	1,1,1
DM3	Organizational	3/2,2,5/2	1,1,1	7/2,4,9/2	2/3,1,3/2
DM4	Technological	7/2,4,9/2	3/2,2,5/2	2/3,1,3/2	1,1,1
DM	**WtO of main barriers**				
	Worst	Economical	Organizational	Operational	Technological
DM1	Operational	3/2,2,5/2	2/3,1,3/2	1,1,1	7/2,4,9/2
DM2	Economical	1,1,1	5/2,3,7/2	3/2,2,5/2	7/2,4,9/2
DM3	Operational	2/3,1,3/2	7/2,4,9/2	1,1,1	3/2,2,5/2
DM4	Economical	1,1,1	2/3,1,3/2	3/2,2,5/2	7/2,4,9/2

As seen in Table 6, the Technological barriers had the highest fuzzy weight (0.325, 0.390, 0.405), in that order, followed by the Organizational (0.231, 0.274, 0.294), Operational (0.172, 0.201, 0.223), and Economical barriers (0.130, 0.152, 0.162). Under these, the C5: Lack of support from top management had the highest weight (global 0.111) with the C14: Lack of digital skills and talent in Table 8 having the second highest weight (0.108). This prioritization highlights that leadership determination and technological preparedness is the main key to effective execution of digital supply chain adoption. The global crisp weights presented in Table 8 sheds further light on the fact that, economical sub-barrier C1: Large investment in digital infrastructure (0.082) and operational sub-barrier C9: Fear of losing the job (0.073) placed same in the third and the fourth place respectively. The rest of the barriers - between 0.071 and 0.023 - had a lower priority in turn meaning that when the top-management support and digital skills are resolved, the winning will be the financial and operational issues, although they also exist and will be the next problem.

Table 6. Relative and local fuzzy weights of the main barriers

Main Barriers	**DM1**	**DM2**	**DM3**	**DM4**	**Fuzzy local weights**
Economical	(0.167, 0.198, 0.208)	(0.104, 0.103, 0.105)	(0.141, 0.180, 0.210)	(0.108, 0.125, 0.124)	(0.130, 0.152, 0.162)
Organizational	(0.199, 0.245, 0.254)	(0.211, 0.259, 0.311)	(0.367, 0.422, 0.422)	(0.145, 0.172, 0.187)	(0.231, 0.274, 0.294)
Operational	(0.122, 0.137, 0.137)	(0.211, 0.259, 0.311)	(0.106, 0.121, 0.122)	(0.247, 0.288, 0.323)	(0.172, 0.201, 0.223)
Technological	(0.371, 0.441, 0.452)	(0.316, 0.389, 0.422)	(0.241, 0.300, 0.315)	(0.373, 0.431, 0.432)	(0.325, 0.390, 0.405)
CR	0.098	0.062	0.061	0.061	

Table 7. Relative and local fuzzy weights of the sub-barriers

Sub-barriers	**DM1**	**DM2**	**DM3**	**DM4**	**Fuzzy local weights**
C1	(0.512, 0.628, 0.745)	(0.387, 0.475, 0.563)	(0.378, 0.464, 0.551)	(0.524, 0.642, 0.762)	(0.445, 0.546, 0.648)
C2	(0.166, 0.187, 0.202)	(0.125, 0.142, 0.153)	(0.122, 0.139, 0.15)	(0.169, 0.192, 0.207)	(0.144, 0.163, 0.176)
C3	(0.174, 0.199, 0.229)	(0.131, 0.15, 0.173)	(0.128, 0.147, 0.169)	(0.178, 0.204, 0.234)	(0.151, 0.173, 0.199)
C4	(0.329, 0.375, 0.401)	(0.249, 0.283, 0.303)	(0.243, 0.277, 0.297)	(0.336, 0.384, 0.411)	(0.286, 0.326, 0.349)
CR	0.061	0.052	0.083	0.06	

C5	(0.42, 0.481, 0.521)	(0.317, 0.363, 0.394)	(0.31, 0.355, 0.385)	(0.429, 0.492, 0.533)	(0.365, 0.418, 0.453)
C6	(0.144, 0.162, 0.185)	(0.109, 0.123, 0.14)	(0.106, 0.12, 0.137)	(0.147, 0.166, 0.189)	(0.125, 0.141, 0.161)
C7	(0.25, 0.304, 0.354)	(0.189, 0.23, 0.268)	(0.184, 0.224, 0.262)	(0.255, 0.311, 0.362)	(0.217, 0.264, 0.308)
C8	(0.235, 0.26, 0.291)	(0.177, 0.197, 0.22)	(0.173, 0.192, 0.215)	(0.24, 0.266, 0.298)	(0.204, 0.226, 0.253)
CR	0.028	0.081	0.057	0.07	
C9	(0.369, 0.42, 0.474)	(0.279, 0.317, 0.358)	(0.273, 0.31, 0.35)	(0.378, 0.429, 0.485)	(0.321, 0.365, 0.412)
C10	(0.263, 0.308, 0.345)	(0.199, 0.233, 0.261)	(0.195, 0.228, 0.255)	(0.269, 0.315, 0.353)	(0.229, 0.268, 0.300)
C11	(0.291, 0.342, 0.374)	(0.22, 0.258, 0.283)	(0.215, 0.252, 0.276)	(0.298, 0.349, 0.382)	(0.253, 0.297, 0.325)
C12	(0.12, 0.131, 0.138)	(0.09, 0.099, 0.104)	(0.088, 0.097, 0.102)	(0.122, 0.134, 0.141)	(0.104, 0.114, 0.120)
CR	0.054	0.069	0.056	0.065	
C13	(0.171, 0.215, 0.255)	(0.13, 0.163, 0.193)	(0.127, 0.159, 0.189)	(0.175, 0.22, 0.261)	(0.149, 0.187, 0.222)
C14	(0.307, 0.315, 0.37)	(0.232, 0.238, 0.28)	(0.227, 0.233, 0.274)	(0.314, 0.322, 0.379)	(0.267, 0.274, 0.322)
C15	(0.176, 0.205, 0.237)	(0.133, 0.155, 0.179)	(0.13, 0.151, 0.175)	(0.18, 0.209, 0.242)	(0.153, 0.178, 0.206)
C16	(0.162, 0.213, 0.254)	(0.123, 0.161, 0.192)	(0.12, 0.157, 0.188)	(0.166, 0.218, 0.26)	(0.141, 0.185, 0.221)
C17	(0.132, 0.177, 0.256)	(0.1, 0.134, 0.194)	(0.098, 0.131, 0.19)	(0.135, 0.181, 0.262)	(0.115, 0.154, 0.223)
CR	0.082	0.056	0.057	0.058	

Table 8. Global weights and rank of digital supply chain adoption barriers

Main barriers	Weights	Sub-barriers	Weights	Global weight	Crisp value	Rank
Economical	(0.130, 0.152, 0.162)	C1	(0.445, 0.546, 0.648)	(0.058, 0.083, 0.105)	0.082	3
		C2	(0.144, 0.163, 0.176)	(0.019, 0.025, 0.028)	0.024	16
		C3	(0.151, 0.173, 0.199)	(0.020, 0.026, 0.032)	0.026	15
		C4	(0.286, 0.326, 0.349)	(0.037, 0.049, 0.056)	0.048	13
Organizational	(0.231, 0.274, 0.294)	C5	(0.365, 0.418, 0.453)	(0.084, 0.115, 0.133)	0.111	1
		C6	(0.125, 0.141, 0.161)	(0.029, 0.039, 0.047)	0.038	14
		C7	(0.217, 0.264, 0.308)	(0.050, 0.072, 0.090)	0.071	5
		C8	(0.204, 0.226, 0.253)	(0.047, 0.062, 0.074)	0.061	10
Operational	(0.172, 0.201, 0.223)	C9	(0.321, 0.365, 0.412)	(0.055, 0.073, 0.092)	0.073	4
		C10	(0.229, 0.268, 0.300)	(0.039, 0.054, 0.067)	0.053	12
		C11	(0.253, 0.297, 0.325)	(0.043, 0.060, 0.073)	0.059	11
		C12	(0.104, 0.114, 0.120)	(0.018, 0.023, 0.027)	0.023	17
Technological	(0.325, 0.390, 0.405)	C13	(0.149, 0.187, 0.222)	(0.048, 0.073, 0.090)	0.070	6
		C14	(0.267, 0.274, 0.322)	(0.087, 0.107, 0.130)	0.108	2
		C15	(0.153, 0.178, 0.206)	(0.050, 0.069, 0.083)	0.068	8
		C16	(0.141, 0.185, 0.221)	(0.046, 0.072, 0.090)	0.069	7
		C17	(0.115, 0.154, 0.223)	(0.037, 0.060, 0.090)	0.063	9

4.1 Comparative Validation via Other Fuzzy MCDM Methods

Table 9 presents the rankings compared with FBWM results concerning stability to test the fuzzy TOPSIS, VIKOR, WASPAS, and COPRAS. C5 and C14 were the two dominant barriers that consistently appeared in the first and second ranks, although their positions were switched in COPRAS. Table 10 shows that the rank correlations of FBWM with each of the methods were greater than 0.85, indicating a very strong agreement. Figure 2 further corroborates these findings through a heatmap comparison, where the brightest cells at C5 and C14 across all five methods highlight their unanimous significance.

Table 9. Comparative analysis showed the top 10 barrier rankings across different MCDM methods

Rank	Fuzzy BWM	Fuzzy TOPSIS	Fuzzy VIKOR	Fuzzy WASPAS	Fuzzy COPRAS
1	C5	C5	C5	C5	C14
2	C14	C14	C14	C14	C5
3	C1	C1	C1	C9	C1
4	C9	C9	C9	C1	C9
5	C7	C7	C7	C7	C7
6	C13	C13	C16	C13	C13
7	C16	C16	C13	C16	C16
8	C15	C15	C15	C15	C15
9	C17	C8	C8	C17	C17
10	C8	C17	C17	C8	C8

Table 10. Degree of agreement between the methods, (Spearman's rank correlation coefficients)

Method Comparison	Spearman's ρ	Significance
Fuzzy BWM vs Fuzzy TOPSIS	0.916	$p < 0.01$
Fuzzy BWM vs Fuzzy VIKOR	0.883	$p < 0.01$
Fuzzy BWM vs Fuzzy WASPAS	0.897	$p < 0.01$
Fuzzy BWM vs Fuzzy COPRAS	0.851	$p < 0.01$

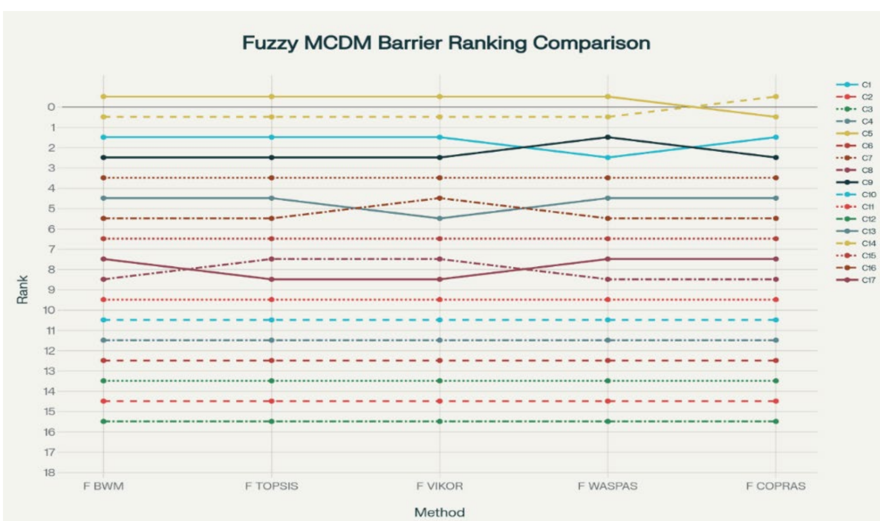

Figure 2. Comparison of the ranking results with those of other fuzzy MCDM methods

5. Discussion and Implications

The FBWM analysis clearly shows that the lack of support from top management (C5) and lack of digital skills and talent (C14) are the most important barriers to digital supply chain transformation. These two factors were consistently among the top in prioritization and prove the significance of strong leadership commitment and a skilled workforce as fundamental prerequisites for successful digitization. Of particular relevance, both C5 and C14 emerged across all the comparative analyses based on different fuzzy MCDM methods as potential top barriers, which highlights a broad consensus on primacy. This finding is consistent with the larger body of literature that points to leadership involvement and technological capability as important prerequisites for successful digital transformation. Organizations must therefore pro-actively secure executive sponsorship and nurture digital competencies before they embark on extensive digital investment programs.

While economic and operational barriers such as the need for relatively high infrastructure investment (C1), and the fear of job loss among the employees (C9), also emerged from the analysis, the moderate rankings imply that these challenges are comparatively secondary ones. C1: Large investment in digital infrastructure was found to be the third ranked barrier. However, its position after leadership and talent problems suggests financial barriers are considered overcomeable once top management buy-in and a digitally adept workforce are in position. In actuality, experts view that budgetary problems can be checked by cautious planning and budgeting plan of action when strong administration drives the activity. Similarly, C9: Fear of job loss (staff resistance) was ranked lower suggesting the workforce fears, while important, can be overcome with open communication and systematic reskilling efforts. In essence, the analysis underlines an important interdependency: while investment and employee concerns raise very real barriers, they become much easier to manage once the commitment and technological readiness of leadership is established. This strengthens the argument that strengthening organizational leadership and digital capacity first will create conditions under which economic and operational issues can be addressed better. Furthermore, the robustness of the FBWM results was verified by comparing the results to other fuzzy MCDM techniques (including Fuzzy TOPSIS, VIKOR, WASPAS, and COPRAS). Very similar rankings of the barriers were generated by all methods (Spearman's rank correlation coefficients between the FBWM-derived ranking and each of the alternative techniques all greater than 0.85 (and statistically significant at p less than 0.01)). This high level of agreement in ranking results across multiple methods does give more confidence in the priority order revealed by FBWM. The heatmap in Figure 2 provides a visual verification of this alignment, as the highest priority barriers are consistent regardless of the analytical method used. Such cross-method convergence seems to indicate that the prioritization obtained is not an artifact of a single approach, but rather is a reliable reflection of the underlying expert judgements. For decision-makers, this consistency between different evaluation techniques enhances the credibility of findings and the focus on the top-ranking issues recommended.

From a practical standpoint, these findings deliver a clear roadmap for managers planning digital supply chain transformation initiatives. The prioritized list of barriers can be translated into a phased implementation strategy. In the first phase, managers should concentrate on securing executive support and involvement (addressing C5) and on developing the necessary digital skills and talent within the organization (addressing C14). By tackling these highest-priority issues up front, firms build a strong foundation for change. In the second phase, with leadership and skills in place, managers can focus on mobilizing and allocating financial resources for digital infrastructure (addressing C1). At this stage, ensuring a reasonable budget and incorporating cost-contingency plans will help overcome the economic constraints identified. Finally, the third phase can address operational and workforce-related concerns, such as employee resistance and retraining needs (mitigating C9). Clear communication about the transformation's benefits, along with training and reskilling programs, will alleviate fear of job loss and foster employee buy-in. Especially in resource-constrained environments like small and medium-sized enterprises (SMEs), this stepwise approach allows managers to prioritize limited resources on the most impactful areas first. By following the priority order – leadership commitment and digital talent first, then infrastructure investment, then change management for staff – managers can systematically dismantle the key barriers and improve the chances of a successful digital supply chain implementation. In summary, the study's results act as a practical guide, helping practitioners direct attention and resources to where they will make the greatest difference in the transformation process. Beyond the firm level, the findings carry important implications for policymakers and authorities aiming to foster digital transformation across industries. The dominance of leadership and skill-related barriers suggests that public policy and support programs should first and foremost enhance the digital readiness of organizations and their workforce. Policymakers can play a facilitative role by promoting education and training initiatives that build digital skills and talent (addressing C14) on a broad scale. For example, government-funded training programs, partnerships with educational institutions for upskilling, and certification courses in digital supply chain management can help create a talent pool capable of driving and sustaining digital initiatives. Likewise, given the pivotal role of executive support, industry forums and government agencies might develop awareness campaigns or leadership development programs to encourage top management engagement in digital transformation efforts.

In addition, to reduce economic barriers such as high costs of infrastructure investments (C1), financial incentives and infrastructure support for digital adoption by policymakers should be considered. This may involve subsidies or tax breaks to companies (in particular SMEs) investing in approved digital technologies, grants or loans with low interest rates to digital infrastructure projects and the development of shared digital infrastructure or platforms to reduce the burden on individual companies. Such measures would reduce the cost of entry for firms suffering from tight access to capital, which is a direct address of one of the main economic factors noted by the experts. Policymakers are also encouraged to develop facilitating legislations and develop collaborative eco-systems that support digital innovation. This may involve making some changes to regulations to adapt to the new digital processes, data security and privacy laws that provide trust in digital systems, and encouraging collaboration among large enterprises, SMEs, and technology providers. By concentrating on workforce development and offering targeted economic support, government and industry bodies can go a long way to making businesses more digitally prepared, especially smaller businesses that operate in resource-constrained settings. In turn this supportive environment will complement the internal managerial efforts to accelerate the overall transition to digitally enabled supply chains at a regional and national level.

6. Research Directions, and Limitations

This study's primary drawback is its dependence on a small group of four experts, which may not adequately represent the range of viewpoints from various sectors and geographical areas even though it guarantees in-depth understanding. Furthermore, the investigation was limited to a specific industrial sector, which limits how broadly the results may be applied. To improve robustness, future studies should broaden the professional and demographic backgrounds of the experts who participate, bringing in perspectives from other sectors, regions, and organizational sizes. It is also advised to do longitudinal research to monitor the changes in the relative significance of barriers over time, especially as market dynamics and digital technologies develop. Furthermore, the reliability of prioritization results may be increased by implementing more complex fuzzy generalization techniques, such as interval type-2 fuzzy sets, which may provide a deeper representation of subjectivity and uncertainty in expert assessment.

References

Afrasiabi, A., Tavana, M., and Di Caprio, D., "An Extended Hybrid Fuzzy Multi-Criteria Decision Model for Sustainable and Resilient Supplier Selection," *Environmental Science and Pollution Research*, Vol. 29, No. 25, pp. 37291–37314, **2022**, https://doi.org/10.1007/s11356-022-19329-3.

Armengaud, E., Fruhwirth, M., Rothbart, M., Weinzerl, M., and Zembacher, G., "Digitalization as an Opportunity to Remove Silo-Thinking and Enable Holistic Value Creation," in Hick, H., Kupper, € K., and Sorger, H. (Eds.), *Systems Engineering for Automotive Powertrain Development. Powertrain*, Springer, Cham, **2020**, https://doi.org/10.1007/978-3-319-68847-3_24-1.

Arunachalam, D., Kumar, N., and Kawalek, J. P., "Understanding Big Data Analytics Capabilities in Supply Chain Management: Unravelling the Issues, Challenges and Implications for Practice," *Transportation Research Part E: Logistics and Transportation Review*, Vol. 114, pp. 416–436, **2018**, https://doi.org/10.1016/j.tre.2017.04.001.

Attaran, M., "Digital Technology Enablers and Their Implications for Supply Chain Management," *Supply Chain Forum*, Vol. 21, No. 3, **2020**, https://doi.org/10.1080/16258312.2020.1751568.

Bag, S., Telukdarie, A., Pretorius, J. H. C., and Gupta, S., "Industry 4.0 and Supply Chain Sustainability: Framework and Future Research Directions," *Benchmarking: An International Journal*, Vol. 28, No. 5, pp. 1463–5771, **2018**, https://doi.org/10.1108/BIJ-03-2018-0056.

Balaji, S., Nathani, K., and Santhakumar, R., "IoT Technology, Applications and Challenges: A Contemporary Survey," *Wireless Personal Communications*, Vol. 108, No. 1, pp. 363–388, **2019**, https://doi.org/10.1007/s11277-019-06407-w.

Bughin, J., Holley, A., and Mellbye, A., *Cracking the Digital Code: McKinsey Global Survey Results*, McKinsey & Company, **2015**, https://www.mckinsey.com/business-functions/business-technology/our-insights/cracking-the-digital-code.

Büyüközkan, G., and Göçer, F., "Digital Supply Chain: Literature Review and a Proposed Framework for Future Research," *Computers in Industry*, Vol. 97, **2018**, https://doi.org/10.1016/j.compind.2018.02.010.

Dalenogare, L. S., Benitez, G. B., Ayala, N. F., and Frank, A. G., "The Expected Contribution of Industry 4.0 Technologies for Industrial Performance," *International Journal of Production Economics*, Vol. 204, pp. 383–394, **2018**, https://doi.org/10.1016/j.ijpe.2018.08.019.

Deepu, T. S., and Ravi, V., "Modelling of Interrelationships Amongst Enterprise and Inter-Enterprise Information System Barriers Affecting Digitalization in Electronics Supply Chain," *Business Process Management Journal*, Vol. 28, No. 1, pp. 178–207, **2022**, https://doi.org/10.1108/BPMJ-12-2020-0554.

Ding, B., "Pharma Industry 4.0: Literature Review and Research Opportunities in Sustainable Pharmaceutical Supply Chains," *Process Safety and Environmental Protection*, Vol. 119, pp. 115–130, **2018**, https://doi.org/10.1016/j.psep.2018.06.031.

Ellis, S., Knickle, K., Veronesi, L., and Brown, V., "Digital Transformation Drives Supply Chain Restructuring Imperative," *International Data Corporation*, **2017**.

Fatimah, Y. A., Govindan, K., Murniningsih, R., and Setiawan, A., "Industry 4.0 Based Sustainable Circular Economy Approach for Smart Waste Management System to Achieve Sustainable Development Goals: A Case Study of Indonesia," *Journal of Cleaner Production*, Vol. 269, Article 122263, **2020**, https://doi.org/10.1016/j.jclepro.2020.122263.

Ganesh, A. D., and Kalpana, P., "Future of Artificial Intelligence and Its Influence on Supply Chain Risk Management—A Systematic Review," *Computers & Industrial Engineering*, Vol. 169, Article 108206, **2022**, https://doi.org/10.1016/j.cie.2022.108206.

Ghadimi, P., Donnelly, O., Sar, K., Wang, C., and Azadnia, A. H., "The Successful Implementation of Industry 4.0 in Manufacturing: An Analysis and Prioritization of Risks in Irish Industry," *Technological Forecasting and Social Change*, Vol. 175, Article 121394, **2022**, https://doi.org/10.1016/j.techfore.2021.121394.

Han, H., and Trimi, S., "Towards a Data Science Platform for Improving SME Collaboration Through Industry 4.0 Technologies," *Technological Forecasting and Social Change*, Vol. 174, Article 121242, **2022**, https://doi.org/10.1016/j.techfore.2021.121242.

Irfan, M. T. H., Rafiquzzaman, M., and Manik, Y. A., "Productivity Improvement Through Lean Tools in Cement Industry – A Case Study," *Heliyon*, Vol. 11, No. 3, **2025**.

Ivanov, D., Dolgui, A., and Sokolov, B., "The Impact of Digital Technology and Industry 4.0 on the Ripple Effect and Supply Chain Risk Analytics," *International Journal of Production Research*, Vol. 57, No. 3, **2019**, https://doi.org/10.1080/00207543.2018.1488086.

Kache, F., and Seuring, S., "Challenges and Opportunities of Digital Information at the Intersection of Big Data Analytics and Supply Chain Management," *International Journal of Operations and Production Management*, Vol. 37, No. 1, **2017**, https://doi.org/10.1108/IJOPM-02-2015-0078.

Khan, S. A., Naim, I., Kusi-Sarpong, S., Gupta, H., and Idrisi, A. R., "A Knowledge-Based Experts' System for Evaluation of Digital Supply Chain Readiness," *Knowledge-Based Systems*, Vol. 228, Article 107262, **2021**, https://doi.org/10.1016/j.knosys.2021.107262.

Kumar, P., Bhamu, J., and Sangwan, K. S., "Analysis of Barriers to Industry 4.0 Adoption in Manufacturing Organizations: An ISM Approach," *Procedia CIRP*, Vol. 98, pp. 85–90, **2021**, https://doi.org/10.1016/j.procir.2021.01.010.

Lee, K. L., Teong, C. X., Alzoubi, H. M., Alshurideh, M. T., Khatib, M. El, and Al-Gharaibeh, S. M., "Digital Supply Chain Transformation: The Role of Smart Technologies on Operational Performance in Manufacturing Industry," *International Journal of Engineering Business Management*, Vol. 16, **2024**, https://doi.org/10.1177/18479790241234986.

Liboni, L. B., Cezarino, L. O., Jabbour, C. J. C., Oliveira, B. G., and Stefanelli, N. O., "Smart Industry and the Pathways to HRM 4.0: Implications for SCM," *Supply Chain Management: An International Journal*, Vol. 24, No. 1, pp. 124–146, **2019**, https://doi.org/10.1108/SCM-03-2018-0150.

Masood, T., and Sonntag, P., "Industry 4.0: Adoption Challenges and Benefits for SMEs," *Computers in Industry*, Vol. 121, **2020**, https://doi.org/10.1016/j.compind.2020.103261.

Müller, J. M., Kiel, D., and Voigt, K.-I., "What Drives the Implementation of Industry 4.0? The Role of Opportunities and Challenges in the Context of Sustainability," *Sustainability*, Vol. 10, No. 1, **2018**, https://doi.org/10.3390/su10010247.

Minculete, G., Stan, S. E., Ispas, L., Virca, I., Stanciu, L., Milandru, M., Mănescu, G., and Bădilă, M. I., "Relational Approaches Related to Digital Supply Chain Management Consolidation," *Sustainability (Switzerland)*, Vol. 14, No. 17, **2022**, https://doi.org/10.3390/su141710727.

Mubarik, M. S., and Khan, S. A., "Digital Supply Chain Management: Evolution, Definitions, and Dimensions," in *The Theory, Methods and Application of Managing Digital Supply Chains*, Emerald Publishing Limited, pp. 1–14, **2024**.

Nasrollahi, M., Ramezani, J., and Sadraei, M., "A FBWM-PROMETHEE Approach for Industrial Robot Selection," *Heliyon*, Vol. 6, No. 5, Article e03963, **2020**, https://doi.org/10.1016/j.heliyon.2020.e03963.

Oesterreich, T. D., and Teuteberg, F., "Understanding the Implications of Digitisation and Automation in the Context of Industry 4.0: A Triangulation Approach and Elements of a Research Agenda for the Construction Industry," *Computers in Industry*, Vol. 83, pp. 121–139, **2016**, https://doi.org/10.1016/j.compind.2016.09.006.

Oliveira-Dias, D. E., Maqueira-Marın Juan, M., and Moyano-Fuentes, J., "The Link Between Information and Digital Technologies of Industry 4.0 and Agile Supply Chain: Mapping Current Research and Establishing New Research Avenues," *Computers and Industrial Engineering*, Vol. 167, Article 108000, **2022**, https://doi.org/10.1016/j.cie.2022.108000.

Rahman, M. A., Saha, P., Belal, H. M., Hasan Ratul, S., and Graham, G., "Big Data Analytics Capability and Supply Chain Sustainability: Analyzing the Moderating Role of Green Supply Chain Management Practices," *Benchmarking: An International Journal*, **2024**.

Ratul, S., and Hossain, M., "From Click to Cart: A Conjoint Analysis View of the Road to Customer Satisfaction and Willingness to Pay in Online Shopping," in *7th IEOM Bangladesh International Conference on Industrial Engineering and Operations Management*, December 2024, https://doi.org/10.46254/BA07.20240165.

Shupti, M. N., Hossain, N. U. I., Fazio, S. A., and Ashik, J. H., "Leveraging Graph Theory Approach for Managing Design Principles for Sustainable Manufacturing of Industry 4.0: A Case Study of Electrical Equipment Manufacturing Industry," *Sustainable Manufacturing and Service Economics*, Vol. 3, Article 100027, **2024**, https://doi.org/10.1016/j.smse.2024.100027.

Ye, F., Liu, K., Li, L., Lai, K. H., Zhan, Y., and Kumar, A., "Digital Supply Chain Management in the COVID-19 Crisis: An Asset Orchestration Perspective," *International Journal of Production Economics*, Vol. 245, Article 108396, **2022**, https://doi.org/10.1016/j.ijpe.2021.108396

Biographies

Md. Tanjid Hossen Irfan completed his BSc Engineering degree in Industrial and Production Engineering from Khulna University of Engineering & Technology (KUET). His research interests include Optimization, Operations Research, and Supply Chain Management. Currently, he is serving as a Lecturer in the Department of Industrial Engineering and Management at KUET, Khulna, Bangladesh. He has been actively involved in academic teaching, research supervision, and departmental activities. His recent works focus on data-driven decision-making and improving operational efficiency in manufacturing and service industries. He aims to pursue advanced research that integrates analytical modeling with real-world industrial applications.

Shahriar Hasan Ratul is currently a Lecturer in the Department of Industrial Engineering and Management at Khulna University of Engineering and Technology (KUET), Bangladesh. He holds a Bachelor of Science in Industrial and Production Engineering (IPE) from KUET, where he graduated as the top student in his department, in 2024. He is currently pursuing a Master's degree in Industrial Engineering and Management at the same institution. Shahriar's research interests lie in Supply Chain Management, Structural Equation Modeling, Reverse Logistics, Sustainability, and Conjoint Analysis. He is developing skills in Machine Learning and Artificial Intelligence. His future research focuses on integrating these technologies into supply chain management, especially in strategic fit and supply chain resilience. He has publications in Benchmarking: An International Journal and IEOM conference.

Jahid Hasan Ashik received BSc Engineering degree in Industrial and Production Engineering from Khulna University of Engineering & Technology. His research interests include Operations Research, System Dynamics, Human Factors, Supply Chain Management, and Operations Management. He is currently pursuing his MSc Engineering in the Department of Industrial Engineering and Management at Khulna University of Engineering & Technology, Khulna, Bangladesh.

Md. Saiful Islam Seam is a postgraduate student in the Department of Industrial Engineering and Management at Khulna University of Engineering & Technology (KUET), Khulna, Bangladesh. Alongside his academic pursuits, Seam is a multidisciplinary researcher whose work spans Supply Chain Management, Artificial Intelligence, Machine Learning, Operations Research, and Lean Manufacturing. His research interests extend across diverse and impactful domains, including sustainability, environmental monitoring, cellular manufacturing, worker safety, value stream mapping, standard operating procedures (SOPs), and the circular economy. Driven by a commitment to innovation and practical problem-solving, Seam focuses on integrating data-driven methodologies with industrial systems to enhance efficiency, safety, and environmental responsibility.