Design and Analysis of Automotive Supply Chain Enablers to Reduce the Bullwhip Effect Using Soft Systems Methodology, FCM, and ISM

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Abstract

The supply chain inherently possesses a high degree of complexity, which has become increasingly exacerbated due to globalization, market expansion, and the continuous evolution of customer preferences. This growing complexity may lead to asset invisibility, inefficient inventory management, or logistical mismanagement. These complications often culminate in the well-known phenomenon of the "Bullwhip Effect" (BE) within supply chains. The aim of this study is to identify the key enablers that effectively reduce the Bullwhip Effect in the automotive supply chain sector. This research is descriptive in methodology and applied in purpose. To determine the importance of critical enablers influencing the mitigation of the Bullwhip Effect, a thorough review of the literature was first conducted to identify a preliminary list of significant enablers. Subsequently, using the Fuzzy Delphi Method, the final set of influential enablers for minimizing the Bullwhip Effect in the automotive supply chain was identified. To analyze the interrelationships among the 13 foundational enablers—based on literature and data collected through questionnaires—the study employed Fuzzy Cognitive Mapping (FCM) and Interpretive Structural Modeling (ISM) to determine the most impactful enablers. FCMapper software was used for the FCM method, while Excel software facilitated the ISM approach. Based on centrality metrics within the Fuzzy Cognitive Mapping approach, five enablers were found to be critically important: information quality in the supply chain, big data, supply chain flexibility, customer relationship management, and trust in the supply chain. Additionally, business intelligence, visibility capability, supply chain agility, order volume, information sharing capability, coordination and collaboration in the supply chain, supply chain integration and transparency, and delivery time were ranked sixth to thirteenth, respectively. According to the ISM results, the following enablers were identified in order of significance as the primary factors in reducing the Bullwhip Effect in the automotive supply chain: big data, business intelligence, information sharing capability, integration and transparency, trust in the supply chain, delivery time, coordination and collaboration, visibility capability, information quality, customer relationship management, order volume, supply chain agility, and flexibility.

Keywords: *Supply Chain, Bullwhip Effect, Enablers, Fuzzy Cognitive Mapping, Interpretive Structural Modeling (ISM)*

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1. Introduction

The globalization of business markets and intensifying global competition have created an increasingly uncertain environment for manufacturing organizations. As a result, managers of such organizations must exert greater effort and engage in more strategic planning to ensure organizational survival. The supply chain is a complex structure characterized by numerous and diverse inputs and outputs as well as a wide range of stakeholders, making its management highly challenging (Bozarth et al., 2009). Consequently, it faces numerous issues, the most common of which include a lack of transparency, low traceability, smuggling, product and document counterfeiting, excessive bureaucracy, the bullwhip effect, high rates of human error, and difficulties in tracking financial transactions. Modern technologies offer potential solutions to many of these problems [1, 2].

All of these complexities negatively affect supply chain performance and heighten supply chain threats, including the Bullwhip Effect (BE). Transactional delays, increased costs, and the erosion of trust among stakeholders are among the most significant risks. The Bullwhip Effect, first identified by Forrester (1958) through a case study in supply chain management, can be effectively mitigated through the use of modern technologies [3]. According to Forrester's theory, this amplification arises due to non-zero lead times and inaccurate demand forecasts—largely driven by the absence of timely information feedback across supply chain tiers [1]. In addition, Lee et al. (1997) examined the propagation of demand variability and its triggers, coining the term "Bullwhip Effect" to describe this phenomenon. Overall, the BE fosters instability within production and distribution systems, significantly impairing their operational and financial performance [4, 5].

The Bullwhip Effect is widely prevalent in supply chains and is one of the most critical areas in supply chain management research [6]. Moreover, market demand is becoming increasingly random due to intensifying market competition and the unpredictability of consumer preferences [7].

Today, the development of advanced technologies has opened new avenues for scientific study in supply chain coordination (SCC) [3, 8]. In practice, many well-known companies such as Apple, IBM, and Walmart have actively begun integrating modern technologies into their operational management processes [1, 2, 9-13].

Big data plays a pivotal role in demand forecasting and the reduction of the BE [11, 14]. Through real-time information sharing across the supply chain, cloud computing can reduce information inconsistencies and time delays, thus minimizing the BE [15-17].

Recent literature has increasingly emphasized the role of advanced digital technologies—such as blockchain, big data, artificial intelligence, business intelligence, and supply chain agility—in mitigating the Bullwhip Effect (BE) and enhancing supply chain performance. Coordination and transparency have emerged as central themes, with studies such as Ran et al. (2020) highlighting the resistance of supply chain actors to adopting digital tools, even under collaborative contract frameworks. Sarfaraz et al. (2021, 2023) and Al-Sukhni & Migdalas (2021) proposed blockchain-based architectures to improve trust, visibility, and data sharing, thereby reducing BE in multi-tiered supply chains [18]. Hsu et al. (2021), Nyamukoroso (2022), and Zeng et al. (2022) demonstrated that big data analytics and supply chain agility significantly contribute to dampening demand variability and fostering sustainability [7, 11, 15]. Similarly, Sundarakani et al. (2021) examined blockchain's utility in Industry 4.0 and visibility enhancement, noting that appropriate data-sharing frequencies are vital [19]. Rossi (2022) compared traditional and technology-enabled approaches, concluding that collaborative strategies, although complex, outperform pure technological reliance [5]. Ghode et al. (2022) and Sarkar et al. (2023) emphasized the benefits of information symmetry through blockchain and demand data sharing [10, 20]. Papanagnou (2022) explored the IoT's role in reducing inventory variance and BE in closed-loop supply chains. Moreover, studies by Jafari et al. (2023) and Raj et al. (2023) explored the influence of business intelligence and artificial intelligence, respectively, with the latter offering a structured framework grounded in digital skills, leadership, and collaboration to combat BE [14, 21]. Collectively, this body of work highlights a paradigm shift from isolated technology adoption to integrated, agility-driven, and trust-based digital ecosystems aimed at improving supply chain resilience and minimizing the Bullwhip Effect.

The presence of multiple enablers that influence supply chain performance and the Bullwhip Effect—as well as the interconnectedness of most of these events—motivated the current research. This study aims to examine, define, and analyze various enabling factors and to develop a model representing the enabling events in supply chains that contribute to reducing the BE. This model can be used by researchers and practitioners alike to assess their impact on supply chains and systems designed to mitigate the BE. To define and analyze the enabling factors affecting supply chain performance, the study relies on expert knowledge in supply chain processes. For modeling and quantifying these factors, Fuzzy Cognitive Mapping (FCM) and Interpretive Structural Modeling (ISM) are employed.

FCM is a problem-structuring method regarded as a suitable and established tool for designing interpretive and knowledge-based systems. Fuzzy Cognitive Mapping is a hybrid soft-computational approach that integrates characteristics of fuzzy logic, nonlinear models, system dynamics, and neural network techniques. FCMs are used to represent expert knowledge through interconnected causal nodes that simulate scenario-specific models. Owing to their simplicity and flexibility in modeling and designing complex systems, FCMs have gained widespread application in various domains [22]. Moreover, FCMs are well-suited for decision-making and event-based analysis in complex and dynamic systems such as supply chains, as they facilitate the execution of "what-if" scenarios, enabling decision-makers to understand the impact of supply chain changes based on causal relationships among supply chain factors.

ISM is an exploratory method grounded in the interpretive paradigm, designed to identify and hierarchically structure relationships among indicators. This method helps uncover causal and complex relational patterns within a set of factors. ISM illustrates the interrelationships between elements in a complex system and can be used to analyze the influence of one variable on others. In general, the ISM algorithm is an iterative process in which a set of interconnected elements is structured into a comprehensive and systematic model. This method also enables prioritization and hierarchical classification of system elements [23].

In this study, given that a hybrid approach combining FCM and ISM is employed to analyze enablers in the automotive industry, and since these techniques establish a feedback network among identified enablers, they allow for a more in-depth analysis of interactions and relationships within the system. Consequently, fundamental enablers in mitigating the BE are more precisely studied and can be effectively reduced through appropriate interventions. The central research question of this study is: What are the key enablers for reducing the Bullwhip Effect in the automotive supply chain, and what role do they play in its mitigation?

2. Methodology

This study is applied in terms of purpose and involves both quantitative and qualitative variables, thus employing a mixed-methods approach. It is categorized as a descriptive study and is conducted using a survey method. For conducting the research, based on a review of the literature and scientific articles related to the Bullwhip Effect in supply chains, the relevant enablers were identified and compiled into a questionnaire, which was then distributed to experts. These experts included academic professionals in the field of supply chain management and managers from Iran's automotive industry, all of whom were familiar with supply chain enablers and the concept of the Bullwhip Effect.

Sampling was conducted using the Fuzzy Delphi Method. Since the goal of the research is not to generalize the results, purposive sampling was applied. The criteria for selecting experts included theoretical proficiency, practical experience, willingness and ability to participate in the study, and accessibility.

To achieve the objectives of the study, the relevant literature was synthesized, and the enablers identified as effective in reducing the Bullwhip Effect were extracted and categorized. Subsequently, using the fuzzy cognitive mapping (FCM) methodology, the enabler components were structured and analyzed. A hybrid approach combining FCM and Interpretive Structural Modeling (ISM) was used for analysis in the automotive industry. These techniques facilitate better analysis of system interactions and relationships by creating a feedback network among the identified elements. As a result, the fundamental problems related to the Bullwhip Effect are studied with greater precision and can be mitigated through appropriate actions.

The software used to implement the fuzzy cognitive mapping technique was FC-Mapper; diagram visualization was performed using Visio 2019; and ISM was executed using Excel 2019.

Table 1. Demographic Characteristics of the Sample Participants

Classification	Frequency	Percentage
Managerial Experience		
More than 5 years	5	50%
More than 10 years	8	50%
Total	13	100%
Educational Qualification		
Master's Degree	8	80%
Doctorate	5	20%
Total	13	100%
Total Years of Experience		
10 to 20 years	7	70%
More than 20 years	6	30%
Total	13	100%

Number of Employees in Organization		
Fewer than 15,000	3	10%
15,000–30,000	3	30%
More than 30,000	7	60%
Total	13	100%
Organizational Turnover *(in thousand billion IRR)*		
Less than 30	2	10%
30–45	4	30%
45–60	7	60%
Total	13	100%

The primary objective of this study is to design and analyze enablers within the automotive supply chain to reduce the Bullwhip Effect and examine the interactions among influencing factors based on Fuzzy Cognitive Mapping (FCM) and Interpretive Structural Modeling (ISM). Therefore, based on a hybrid approach, the factors contributing to reducing the Bullwhip Effect in the supply chain are first identified through big data and business intelligence. Then, by designing FCM and ISM models, the quality and interrelationships of the core supply chain enablers in mitigating the Bullwhip Effect are analyzed, as detailed in the following sections.

3. Findings and Results

In the first stage of the research, the Fuzzy Delphi Method was used to screen the enablers identified from the literature review. In this study, the distributed questionnaire among the experts employed a five-point Likert scale, where the significance of each factor was evaluated using linguistic variables (Table 2). In various studies, a Delphi expert group may consist of 10 to 20 members, provided that consensus exists among the group. In this research, the sample size was determined to be 13 individuals. After the initial round of questionnaire collection, the results of the first round were sent back to the experts to allow them to revise their judgments, if necessary, based on the preliminary outcomes.

After collecting and analyzing the experts' responses in the second round, the mean difference was examined. If the difference was less than 0.2, consensus was considered to have been achieved, and the Fuzzy Delphi process was concluded. Otherwise, the questionnaire would be sent to the experts once again. This iterative data collection process would continue until consensus was reached.

In the final step, to confirm the variables and key operators for reducing the Bullwhip Effect (BE) in the supply chain (SC) through Big Data (BD) and Business Intelligence (BI), the average score of each factor was compared to a threshold value (0.7). For this purpose, the linguistic terms used in expert evaluations were first converted into triangular fuzzy numbers, and then their fuzzy mean values were calculated to determine the average of the *n* expert responses. Table 2 presents the scale used to convert linguistic values into their equivalent triangular fuzzy numbers.

Table 2. Linguistic Terms and Their Equivalent Triangular Fuzzy Numbers

Linguistic Term	Triangular Fuzzy Number
Very High	(7, 9, 9)
High	(5, 7, 9)
Medium	(3, 5, 7)
Low	(1, 3, 5)
Very Low	(1, 1, 3)

Based on the above discussion, the statistical analysis results reviewed and interpreted at each stage by automotive domain experts and the authors are presented in Table 4. The 13 factors with the highest mean values and lowest standard deviations compared to others were identified as the key variables and operators for reducing the performance of the Bullwhip Effect in the automotive supply chain through the application of BD and BI.

In the first round of the Fuzzy Delphi Method, experts primarily assessed Bullwhip Effect enablers based on Big Data and Business Intelligence, extracted from the literature. In that stage, 30 enablers were identified as relatively more important. Next, to calculate the importance of these enablers, a questionnaire was distributed in the first round of the Delphi process asking experts to rate their significance. After analyzing the results, a second-round Delphi questionnaire was sent out, including the mean scores of each enabler from round one for expert reconsideration.

Analysis of the second-round responses revealed that, for five enablers, the average difference in expert judgments between rounds one and two exceeded 0.2. Therefore, a third-round Delphi questionnaire containing the second-round average scores for each enabler was sent to the experts. Since the differences in expert judgments between the second and third rounds for all enablers were less than 0.2, consensus was achieved. Thirteen enablers had average scores greater than 0.7 and were thus identified as the core variables and operators for mitigating the Bullwhip Effect in the automotive supply chain using BD and BI. The final results of the third round of the Fuzzy Delphi Method are presented in Table 3.

The results of the third round of the Fuzzy Delphi method are presented in Table 3.

Table 3. Results of the Fuzzy Delphi Method

Linguistic Terms	Very Low	Low	Medium	High	Very High	Mean	Difference	Approved / Rejected
Fuzzy Values	(1,1,3)	(1,3,5)	(3,5,7)	(5,7,9)	(7,9,9)			
Use of blockchain in the supply chain	1	3	6	3	0	4.743	0.122	Rejected
Use of AI in the supply chain	0	4	2	4	3	5.769	0.133	Rejected
Supply chain flexibility	0	0	2	4	7	7.410	0.133	Approved
Information quality in the supply chain	0	0	3	5	5	7.051	0.000	Approved
Demand uncertainty in the supply chain	3	2	4	4	0	4.538	0.133	Rejected
Environmental uncertainty and risk in the supply chain	2	1	4	4	2	5.461	0.133	Rejected
Supply chain agility	0	0	2	5	6	7.307	0.000	Approved
Customer relationship management	1	0	1	5	6	7.051	0.011	Approved
Supply chain optimization	1	3	6	3	0	4.743	0.133	Rejected
Use of IoT in the supply chain	2	5	4	2	0	4.025	0.133	Rejected
Organizational commitment to new technologies	1	2	3	5	2	5.717	0.133	Rejected
Delivery time in the supply chain	0	1	1	6	5	7.051	0.110	Approved
Supply chain speed capability	2	1	5	3	2	5.307	0.122	Rejected
Supply chain variety capability	3	1	5	3	1	4.794	0.122	Rejected
Value and accuracy of supply chain data	1	5	5	2	0	4.282	0.133	Rejected
Supply chain integration and transparency	0	1	2	3	7	7.102	0.133	Approved
Coordination and collaboration in the supply chain	0	1	2	4	6	7.000	0.000	Approved
Customer service management	2	0	3	5	3	6.025	0.133	Rejected
Trust in the supply chain	0	0	2	7	4	7.102	0.011	Approved
Digital transformation and social media	2	2	3	6	0	5.102	0.122	Rejected
Availability and predictive analytics	0	2	5	4	2	5.820	0.122	Rejected
Order volume in the supply chain	0	0	1	5	7	7.564	0.000	Approved
Behavioral roles in the supply chain	2	1	6	3	1	5.051	0.133	Rejected
Information sharing capability	0	0	0	2	11	8.128	0.133	Approved
Visibility capability	0	2	5	6	–	7.307	0.133	Approved
Management team skills	1	1	8	1	2	5.256	0.122	Rejected
Increased connectivity via cloud computing	1	2	5	3	2	5.410	0.133	Rejected
Innovation capability in the supply chain	0	0	7	3	3	6.230	0.133	Rejected
Business intelligence (BI)	0	0	1	6	6	7.461	0.133	Approved
Big data (BD)	0	0	1	7	5	7.358	0.000	Approved

According to the results, the following indicators were selected as the core enablers for implementing the second phase of the study: supply chain flexibility, trust in the supply chain, information quality, supply chain agility, customer relationship management, delivery time, integration and transparency, coordination and collaboration, order volume, information sharing capability, visibility, business intelligence, and big data (Table 4).

Table 4. Core Variables and Operators for the Second Phase of the Study to Reduce the Bullwhip Effect (BE) in the Supply Chain through Big Data (BD) and Business Intelligence (BI)

No.	Factor	References

H1	Supply Chain Flexibility (FSC)+	[14, 16, 17]
H2	Trust in the Supply Chain (TSC)+	[24, 25]
H3	Information Quality in the Supply Chain (IQSC)+	[26-28]
H4	Supply Chain Agility (ACSC)+	[11, 15, 21, 29]
H5	Customer Relationship Management (CRM)+	[1, 30]
H6	Delivery Time in the Supply Chain (LTSC)+	[9, 31]
H7	Integration and Transparency in the Supply Chain (ITSC)+	[32, 33]
H8	Coordination and Collaboration in the Supply Chain (CCSC)+	[32]
H9	Order Volume in the Supply Chain (OVSC)+	[20, 34, 35]
H10	Information Sharing Capability (ISC)+	[20, 34-36]
H11	Visibility Capability (VC)+	[16]
H12	Business Intelligence (BI)+	[3, 37]
H13	Big Data (BD)+	[1, 38]

In this study, after identifying the key variables and operators for reducing the performance of the Bullwhip Effect (BE), the initial matrix was constructed based on expert questionnaires and the scores they assigned to thirteen selected factors. All thirteen identified factors are positively associated with reducing the Bullwhip Effect. The scores given by the experts to the questionnaire items — with rows representing key enablers of BE mitigation in the supply chain (SC) through Big Data (BD) and Business Intelligence (BI), and columns representing the experts — indicate the impact level of each factor on the supply chain. The Likert scale used in the questionnaire includes five degrees, represented by the values 1, 3, 5, 7, and 9. A score of 1 indicates very low impact, 3 indicates low impact, 5 indicates moderate impact, 7 indicates high impact, and 9 indicates very high impact.

After analyzing the questionnaire data, the Initial Success Matrix (IMS) was constructed, shown in Table 5.

Table 5. Initial Success Matrix (IMS)

Xi(Oij)	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12	Expert 13
C1	5	5	7	7	9	9	9	9	9	9	9	9	9
C2	5	7	7	7	9	9	9	9	9	9	9	9	9
C3	7	7	7	7	7	9	9	9	9	9	9	9	9
C4	7	7	7	7	7	9	9	9	9	9	9	9	9
C5	3	5	5	7	7	7	9	9	9	9	9	9	9
C6	5	5	5	9	9	9	9	7	7	7	9	9	9
C7	5	5	9	9	9	9	9	9	9	9	7	7	7
C8	5	9	9	9	9	7	7	7	9	9	9	9	9
C9	9	9	9	5	5	5	7	7	9	9	9	9	9
C10	9	9	9	9	9	9	7	7	9	9	9	9	9
C11	9	9	9	9	9	9	7	7	9	9	9	9	9
C12	9	9	9	9	9	9	7	7	9	9	9	9	7
C13	9	9	9	9	9	9	9	9	9	9	9	9	9

It should be noted that the rows of this matrix correspond to the 13 enablers identified as influential in reducing the Bullwhip Effect, while the columns represent the responses of each of the 13 experts.

Not all key success factors in the matrix are interrelated, nor do they always exhibit causal relationships. To analyze the data and convert the influence matrix into the final matrix, it must be understood that only fuzzy elements indicating causal relations between factors are included in the Fuzzified Matrix (FZMS).

Table 6. Fuzzified Matrix of Factors (FZMS)

Xi(Oij)	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12	Expert 13
C1	0.33	0.33	0.67	0.67	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
C2	0.33	0.67	0.67	0.67	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
C3	0.67	0.67	0.67	0.67	0.67	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

C4	0.67	0.67	0.67	0.67	0.67	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
C5	0.00	0.33	0.33	0.67	0.67	0.67	1.00	1.00	1.00	1.00	1.00	1.00	1.00
C6	0.33	0.33	0.33	1.00	1.00	1.00	1.00	0.67	0.67	0.67	1.00	1.00	1.00
C7	0.33	0.33	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.67	0.67	0.67
C8	0.33	1.00	1.00	1.00	1.00	0.67	0.67	0.67	1.00	1.00	1.00	1.00	1.00
C9	1.00	1.00	1.00	0.33	0.33	0.33	0.67	0.67	1.00	1.00	1.00	1.00	1.00
C10	1.00	1.00	1.00	1.00	1.00	1.00	0.67	0.67	1.00	1.00	1.00	1.00	1.00
C11	1.00	1.00	1.00	1.00	1.00	1.00	0.67	0.67	1.00	1.00	1.00	1.00	1.00
C12	1.00	1.00	1.00	1.00	1.00	1.00	0.67	0.67	1.00	1.00	1.00	1.00	0.67
C13	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

The Success Relationship Matrix (SRMS) is an $N \times N$ matrix where both the rows and columns represent the main enablers of performance reduction in the Bullwhip Effect through BD and BI, and each element *(Wij)* represents the relationship strength between factors *i* and *j*, with values ranging from –1 to 1.

Table 7. Success Relationship Matrix (SRMS)

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
C1	0.00	0.97	0.92	0.92	0.90	0.87	0.87	0.92	0.70	0.80	0.70	0.80	0.84
C2	0.97	0.00	0.89	0.86	0.87	0.89	0.89	0.89	0.84	0.92	0.84	0.92	0.80
C3	0.92	0.89	0.00	0.96	0.92	0.70	0.70	0.70	0.77	0.92	0.84	0.77	0.89
C4	0.92	0.86	0.96	0.00	0.84	0.75	0.75	0.75	0.74	0.84	0.77	0.74	0.86
C5	0.90	0.87	0.92	0.84	0.00	0.92	0.92	0.92	0.70	0.75	0.72	0.75	0.74
C6	0.87	0.89	0.70	0.75	0.92	0.00	0.86	0.86	0.74	0.84	0.77	0.84	0.75
C7	0.87	0.89	0.70	0.75	0.92	0.86	0.00	0.86	0.74	0.84	0.77	0.92	0.70
C8	0.92	0.89	0.70	0.75	0.92	0.86	0.86	0.00	0.92	0.87	0.92	0.87	0.80
C9	0.70	0.84	0.77	0.74	0.70	0.74	0.74	0.92	0.00	0.86	0.80	0.86	0.77
C10	0.80	0.92	0.92	0.84	0.75	0.84	0.84	0.87	0.86	0.00	0.96	0.90	0.87
C11	0.70	0.84	0.84	0.77	0.72	0.77	0.77	0.92	0.80	0.96	0.00	0.89	0.92
C12	0.80	0.92	0.77	0.74	0.75	0.84	0.92	0.87	0.86	0.90	0.89	0.00	0.92
C13	0.84	0.80	0.89	0.86	0.74	0.75	0.70	0.80					

In this study, a focus group comprising six members was formed to develop the final matrix. The focus group consisted of six automotive industry experts in Iran with experience in supply chain management. Based on their opinions, meaningless connections between the factors were eliminated, and the causal directions of relationships were determined. This matrix represents a refined portion of the Success Relationship Matrix (SRMS) tailored by the automotive supply chain expert group. Not all key success factors in the matrix are interrelated, and causal relationships do not always exist among them. For data analysis and the conversion of the SRMS into the Final Matrix of Success (FMS), only fuzzy elements indicating valid causal relationships were retained, and those without meaningful causal links were excluded. The results of this review are presented in Table 8.

Table 8. Final Matrix of Success (FMS)

	FSC	TSC	IQSC	ACSC	CRM	LTSC	ITSC	CCSC	OVSC	ISC	VC	BI	BD
FSC	0.00	0.97	0.92	0.00	0.90	0.87	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TSC	0.97	0.00	0.89	0.00	0.87	0.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IQSC	0.92	0.89	0.00	0.96	0.92	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ACSC	0.92	0.00	0.96	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CRM	0.90	0.87	0.92	0.00	0.00	0.92	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LTSC	0.87	0.89	0.00	0.00	0.92	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ITSC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CCSC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.92	0.00	0.00	0.00	0.00
OVSC	0.00	0.00	0.77	0.00	0.00	0.00	0.00	0.92	0.00	0.00	0.00	0.00	0.00
ISC	0.00	0.00	0.92	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.00
VC	0.00	0.00	0.84	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.00	0.00
BI	0.00	0.00	0.77	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BD	0.00	0.00	0.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

In the graphical representation of this model, each node corresponds to one of the key enablers for mitigating the Bullwhip Effect in the supply chain using BD and BI. Each edge between nodes *i* and *j*—assigned a specific weight—reflects the strength and direction (direct or inverse) of the causal relationship between these factors. The causal direction vector was established based on input from a focus group of three supply chain managers from the automotive sector.

Based on the fuzzy cognitive mapping model, the core enablers were classified into two groups according to their proximity in relationship structure:

- **Group 1 – BI-related enablers**:
  - Supply Chain Flexibility (FSC)
  - Trust in the Supply Chain (TSC)
  - Information Quality (IQSC)
  - Agility in the Supply Chain (ACSC)
  - Customer Relationship Management (CRM)
- **Group 2 – BD-related enablers**:
  - Delivery Time (LTSC)
  - Integration and Transparency (ITSC)
  - Coordination and Collaboration (CCSC)
  - Order Volume (OVSC)
  - Information Sharing Capability (ISC)
  - Visibility Capability (VC)

These enablers play a vital role in mitigating the Bullwhip Effect in the automotive supply chain.

Other outputs of the FCM analysis include three key indicators: outdegree (influence), indegree (dependence), and centrality—summarized in Table 10. Outdegree reflects the cumulative absolute impact of an enabler on others. Indegree represents the extent to which a given enabler is influenced by the others. Centrality, being the sum of both, reflects the overall systemic interaction of each enabler.

Table 9. Indices of Core Dimensions in the FCM Model

Dimension	Code	Outdegree	Indegree	Centrality
Supply Chain Flexibility	A1	2.69	3.44	6.14
Trust in the Supply Chain	A2	2.58	2.58	5.17
Information Quality in the Supply Chain	A3	2.72	4.73	7.45
Supply Chain Agility	A4	1.36	0.61	1.97
Customer Relationship Management	A5	3.00	3.00	5.99
Delivery Time	A6	2.08	2.08	4.17
Integration & Transparency	A7	0.00	0.00	0.00
Coordination & Collaboration	A8	0.60	0.60	1.19
Order Volume	A9	1.18	0.60	1.77
Information Sharing Capability	A10	1.16	0.60	1.75
Visibility Capability	A11	1.46	0.60	2.06
Business Intelligence	A12	1.49	0.60	2.09
Big Data	A13	2.68	4.64	7.38

The Interpretive Structural Modeling (ISM) algorithm is an iterative process where interconnected elements are systematically structured into a comprehensive model. A specially designed questionnaire based on the BD and BI variables (determined earlier via Delphi method) was used to identify directional relationships among enablers. Experts evaluated these relationships using symbolic indicators, and the results were analyzed and compiled into the Structural Self-Interaction Matrix (SSIM).

Using the structural matrix and ordering rules, the matrix was constructed according to the following principles:

1. If the relationship between elements *i* and *j* is **V**, then the matrix elements are (i, j) = 1 and (j, i) = 0.
2. If the relationship between elements *i* and *j* is A, then the matrix elements are (i, j) = 0 and (j, i) = 1.
3. If the relationship between elements *i* and *j* is X, then the matrix elements are (i, j) = 1 and (j, i) = 1.
4. If there is no relationship, then the matrix elements are (i, j) = 0 and (j, i) = 0.

Table 10. Initial Reachability Matrix (IRM)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	0	1	1	1	0	0	1	1	0	0	1	1	1

3	0	0	1	0	0	1	1	1	1	0	0	1	1
4	0	0	1	1	0	1	0	1	1	0	0	1	1
5	0	1	0	1	1	1	0	0	0	0	0	1	1
6	0	1	0	0	1	1	0	0	0	0	0	1	1
7	0	0	0	0	0	0	1	0	0	0	0	1	1
8	0	0	0	0	1	0	0	1	0	0	0	0	1
9	0	1	0	0	1	0	0	1	1	0	0	1	1
10	0	1	1	0	0	1	1	0	0	1	1	1	1
11	0	0	1	0	0	0	1	0	0	0	1	1	1
12	0	0	0	0	0	0	0	0	0	0	0	1	1
13	0	0	0	0	0	0	1	0	0	1	1	0	1

This table presents the reachability matrix derived from expert input, where each variable represents one of the 13 core enablers for reducing the Bullwhip Effect.

To ensure transitive consistency between elements, the initial matrix must be internally consistent. If such consistency is achieved, the matrix is called the Final Reachability Matrix (FRM). Otherwise, the questionnaire must be completed again by the experts until consistency is reached, or the matrix must be raised to the (k+1) power until a steady state is achieved. In such a case, some of the zero elements in the matrix convert to one, denoted as (1*). In this study, the second method was used.

Table 11. Final Reachability Matrix (FRM)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	Driving Power
1	1	1	1	1	1	1	1	1	1	1	1	1	1	13
2	0	1	1	1	1*	1*	1	1	1*	1*	1	1	1	12
3	0	1*	1	0	1*	1	1	1	1	1*	1*	1	1	11
4	0	1*	1	1	1*	1	1*	1	1	1*	1*	1	1	12
5	0	1	1*	1	1	1	1*	1*	1*	1*	1*	1	1	12
6	0	1	1*	1*	1	1	1*	1*	0	1*	1*	1	1	11
7	0	0	0	0	0	0	1	0	0	1*	1*	1	1	5
8	0	1*	0	1*	1	1*	1*	1	0	1*	1*	1*	1	10
9	0	1	1*	1*	1	1*	1*	1	1	1*	1*	1	1	12
10	0	1	1	1*	1*	1	1	1*	1*	1	1	1	1	12
11	0	1*	1	1*	0	1*	1	1*	1*	1*	1	1	1	11
12	0	0	0	0	0	0	1*	0	0	1*	1*	1	1	5
13	0	1*	1*	0	0	1*	1	0	0	1	1	1*	1	8

This matrix shows the final structural interrelationships between the 13 enablers. The last column indicates each enabler's driving power, i.e., the number of other elements it influences.

After determining the reachability set, antecedent set, and intersection set, the reachability set for each element includes all rows where the value is 1, while the antecedent set includes all columns where the value is 1. The intersection of these two sets yields the common set. Elements for which the reachability and intersection sets are identical are assigned the first-level priority. This process is repeated for all other elements until all levels are classified.

Based on the variable levels and their relationships, the factors of Big Data (BD) and Business Intelligence (BI) in the automotive supply chain were classified into five levels using the Interpretive Structural Modeling (ISM) approach. This classification and the interrelationships demonstrate how these variables affect the automotive supply chain.

Specifically, variables 7, 10, 12, and 13—known as first-level variables—are placed in level one. Variables 2, 6, 8, and 11 are in level two. Variables 3, 5, and 9 are in level three. The remaining parameters are assigned to other levels as shown in Table 12.

Table 12. Final Levels of Core Enablers for Reducing the Bullwhip Effect

Level	Intersection Set	Antecedent Set	Reachability Set	Variable
5	1	1,4	1,4	1
2	2,3,4,5,6,8,9,11	1,2,3,4,5,6,8,9,11	2,3,4,5,6,8,9,11	2
3	3,5,9	1,3,4,5,9	3,5,9	3

4	4	1,4	4	4
3	3,4,5,9	1,3,4,5,9	3,4,5,9	5
2	2,3,4,5,6,8,11	1,2,3,4,5,6,8,9,11	2,3,4,5,6,8,11	6
1	7,10,11,12,13	1,2,3,4,5,6,7,9,10,11,12,13	7,10,11,12,13	7
2	2,4,5,6,8,11	1,2,3,4,5,6,8,9,11	2,4,5,6,8,11	8
3	3,4,5,9	1,3,4,5,9	3,4,5,9	9
1	2,3,4,5,6,7,8,9,10,11,12,13	1,2,3,4,5,6,7,8,9,10,11,12,13	2,3,4,5,6,7,8,9,10,11,12,13	10
2	2,3,4,6,8,9,11	1,2,3,4,5,6,8,9,11	2,3,4,6,8,9,11	11
1	7,10,11,12,13	1,2,3,4,5,6,7,8,9,10,11,12,13	7,10,11,12,13	12
1	2,3,6,7,10,11,12,13	1,2,3,4,5,6,7,8,9,10,11,12,13	2,3,6,7,10,11,12,13	13

In this study, 13 enablers were identified as the main variables and operators for reducing the performance of the Bullwhip Effect in the automotive supply chain through BD and BI, using both the Fuzzy Cognitive Mapping (FCM) and Interpretive Structural Modeling (ISM) approaches.

First, our research showed that the structural modeling behavior validated the results of fuzzy cognitive mapping. Second, the interactions revealed by both models were consistent. Third, based on the outputs of both models, the variables and operators identified were confirmed as the fundamental drivers for reducing the Bullwhip Effect in the automotive supply chain via BD and BI.

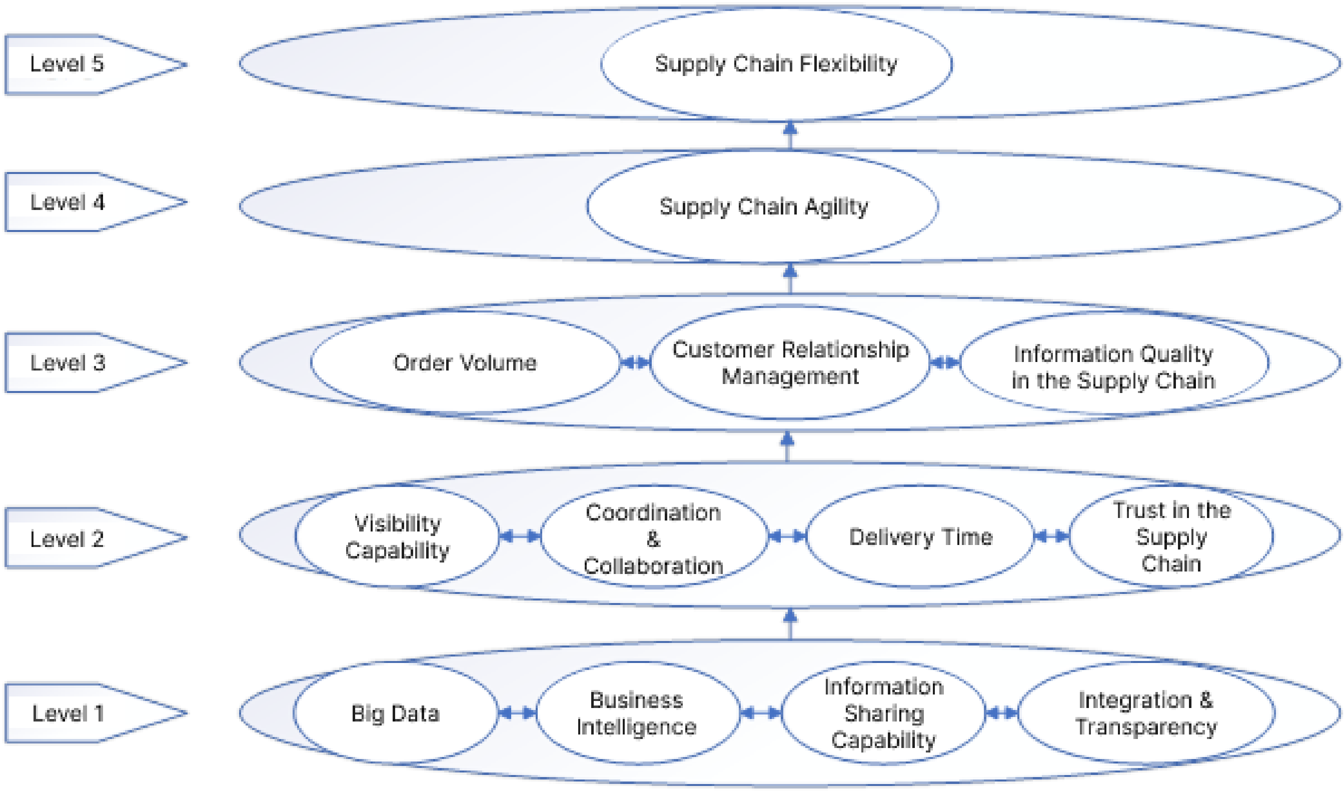

Figure 1. Proposed ISM Model of Core Enablers in Reducing the Bullwhip Effect in the Supply Chain

4. Discussion and Conclusion

The primary objective of this study was to identify and structurally analyze the main enablers for reducing the Bullwhip Effect (BE) in the automotive supply chain through the integrated application of Big Data (BD) and Business Intelligence (BI), using a hybrid methodological approach of Fuzzy Cognitive Mapping (FCM) and Interpretive Structural Modeling (ISM). The findings from both FCM and ISM converged on a set of 13 enablers, among which "information sharing capability," "visibility capability," "customer relationship management," and "trust in the supply chain" emerged as particularly influential based on their high centrality and driving power.

The results from the FCM model revealed that "information quality," "big data," and "business intelligence" are among the most central variables with the highest combined influence and dependence scores, suggesting that the effective management of information flow is crucial in mitigating the amplifying demand distortions characteristic of the Bullwhip Effect. This is consistent with the findings of Al-Sukhni and Migdalas (2021), who proposed a blockchain architecture to enhance end-to-end visibility by sharing backlog data among partners, significantly reducing BE through secure and transparent data exchange [18]. Likewise, Ghode et al. (2022) emphasized the potential of blockchain-enabled distributed ledgers in allowing all supply chain partners to access real-time demand data, thereby enhancing planning accuracy and dampening demand variability [10].

In terms of structural hierarchy derived from ISM, variables such as "integration and transparency," "information sharing," and "coordination and collaboration" occupied lower levels, denoting foundational status in the hierarchy. Their role as root drivers of system-wide improvement highlights the necessity of addressing these elements first when planning interventions. Sarfaraz et al. (2021) underscored the importance of such transparency and inter-organizational trust, noting that complete visibility of demand data combined with collaborative behavior among partners minimizes BE and optimizes supply chain efficiency [34]. The finding that these foundational factors lead to cascading improvements in agility, flexibility, and performance aligns with previous research by Hsu et al. (2021), who showed that agility is strengthened when supported by robust big data systems [11].

Additionally, the role of "customer relationship management" and "trust" emerged strongly as mediating enablers in both the FCM and ISM models. These findings confirm the importance of human and relational dimensions within technological ecosystems. Similarly, Sarfaraz et al. (2023) validated the positive impact of blockchain-facilitated trust-building mechanisms, which ultimately reduce uncertainty and variability in supply-demand dynamics [35].

The study also found that enablers such as "agility," "flexibility," and "order volume control" held significant influence, especially in the mid-levels of the ISM hierarchy. These are more operational or executional enablers that depend heavily on foundational inputs such as BD, BI, and information sharing. Nyamukoroso (2022) and Zeng et al. (2022) both proposed that enhancing agility through improved big data analytics enables firms to respond faster to fluctuations, thus smoothing out disruptive spikes in order flows [7, 15]. Our findings resonate with this logic, showing that agility and flexibility are dependent constructs that materialize only when foundational data systems and organizational cooperation mechanisms are in place.

From a comparative methodological standpoint, the FCM results provided nuanced insights into the causal loops and strength of relationships, while ISM confirmed the structural order and interdependency levels among the enablers. The mutual validation of these two models enhances the reliability of the conceptual framework presented. Notably, this dual confirmation aligns with the results of Jafari et al. (2023), who used a combination of qualitative and quantitative approaches to confirm the reinforcing roles of BI, integration, and agility in optimizing supply chain performance. They similarly concluded that BI had the strongest direct effect, a finding mirrored in our FCM centrality rankings [21].

Moreover, the current research affirms the relevance of emerging technologies such as blockchain and artificial intelligence (AI) in supply chain coordination strategies. Raj et al. (2023) emphasized that AI, when integrated within a structured managerial framework, serves as a potent tool for smoothing demand signals and enhancing planning responsiveness. Though AI was not directly modeled in our current enabler set, the presence of BI and BD as proxies for advanced analytics echoes the call for data-driven architectures to address BE [14]. Similarly, Rossi (2022) compared traditional coordination contracts with data-intensive systems and concluded that, while collaboration-based methods are complex, big data approaches offer scalable and impactful alternatives for BE mitigation [5].

Interestingly, the results also indicated some reluctance among firms to adopt digital technologies unless there is a direct and visible benefit or a contractual framework that supports such adoption. This insight reflects the findings of Ran et al. (2020), who observed that suppliers and retailers often hesitate to use digital tools like blockchain or big data in the absence of mutual incentives, even in cost-sharing or revenue-sharing arrangements. This behavioral barrier further underscores the need for well-aligned incentives and trust-building mechanisms—particularly when deploying transformative technologies across the supply chain [32].

Finally, the integration of digital tools such as BD and BI with relational capabilities—like trust, coordination, and transparency—results in a synergistic framework that significantly contributes to BE reduction. Sundarakani et al. (2021) contextualized this within the realm of Industry 4.0, showing that such integration offers not just technological advancement but also strategic alignment, thus enhancing both short-term responsiveness and long-term resilience [19]. These insights collectively strengthen the argument that technological adoption alone is insufficient; rather, the success of digital transformation depends on how well these technologies are embedded within human and organizational processes.

This study, while comprehensive in modeling the enablers of Bullwhip Effect reduction using BD and BI, is limited by its focus on the automotive supply chain in Iran, which may affect the generalizability of the findings to other industrial sectors or global supply chain contexts. The expert sample, though experienced, was relatively small and concentrated within a specific region, which may have introduced regional or sectoral bias in the weightings and causal assessments. Additionally, while the hybrid use of FCM and ISM adds rigor, the models are still dependent on subjective expert judgment, which, despite efforts to reach consensus, can introduce variability and limit replicability.

Future studies could expand the scope of the current research by including cross-industry and multi-national comparative analyses to test the validity of the proposed model across different sectors and geographies. A longitudinal design could also be employed to evaluate how changes in digital maturity and trust dynamics influence the structural relationships among enablers over time. Moreover, integrating simulation-based methods or system dynamics modeling could provide further depth by analyzing how specific interventions (e.g., adoption of a new BI tool) influence the temporal behavior of the Bullwhip Effect under varying market conditions.

For practitioners, the study highlights the need to prioritize investments in foundational enablers such as data integration, information visibility, and trust-building before focusing on advanced agility tools. Supply chain managers should adopt a phased approach to digital transformation, ensuring that relational and organizational capacities are developed in tandem with technological upgrades. Establishing formal mechanisms for information sharing and data governance, supported by blockchain or BI systems, can facilitate smoother coordination and foster trust. These efforts, in turn, are likely to result in a more responsive, resilient, and BE-resistant supply chain ecosystem.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

References

[1] F. Liu, M. Fang, S. Xiao, and Y. Shi, "Mitigating bullwhip effect in supply chains by engaging in digital transformation: the moderating role of customer concentration," *Annals of Operations Research*, pp. 1-22, 2024, doi: 10.1007/s10479-019-03363-3.

[2] J. Gao, Y. Gao, T. Guan, S. Liu, and T. Ma, "Inhibitory influence of supply chain digital transformation on bullwhip effect feedback difference," *Business Process Management Journal*, vol. 30, no. 1, pp. 135-157, 2024, doi: 10.1108/BPMJ-01-2023-0029.

[3] M. Wiedenmann and A. Größler, "The impact of digital technologies on operational causes of the bullwhip effect-a literature review," *Procedia CIRP*, vol. 81, pp. 552-557, 2019, doi: 10.1016/j.procir.2019.03.154.

[4] M. Rezaeefard, N. Pilevari, F. F. Razi, and R. Radfar, "Factors Affecting Demand Predict to Reduce Bullwhip Effect in Supply Chain," *Iranian Journal of Operations Research*, vol. 13, no. 2, pp. 96-120, 2022.

[5] R. Rossi, "Big data solutions towards the mitigation of the Bullwhip effect," 2022.

[6] M. J. Alvarado-Vargas and K. J. Kelley, "Bullwhip severity in conditions of uncertainty: regional vs global supply chain strategies," *International Journal of Emerging Markets*, vol. 15, no. 1, pp. 131-148, 2020, doi: 10.1108/IJOEM-02-2017-0050.

[7] J. Y. Zeng, C. H. Hsu, and X. Chen, "Using Agility to Reduce the Bullwhip Effect of Supply Chains," Advances in Intelligent Systems and Computing, 2022, doi: 10.1007/978-981-16-8048-9_5.

[8] P. Borja, D. Roberto, C. Salvatore, and M. F. Jose, "The implications of batching in the bullwhip effect and customer service of closed-loop supply chains," *International Journal of Production Economics*, vol. 244, p. 108379, 2022, doi: 10.1016/j.ijpe.2021.108379.

[9] G. Gaalman, S. M. Disney, and X. Wang, "When bullwhip increases in the lead time: An eigenvalue analysis of ARMA demand," *International Journal of Production Economics*, vol. 250, p. 108623, 2022, doi: 10.1016/j.ijpe.2022.108623.

[10] D. J. Ghode, V. Yadav, R. Jain, and G. Soni, "Lassoing the bullwhip effect by applying blockchain to supply chains," *Journal of Global Operations and Strategic Sourcing*, vol. 15, no. 1, pp. 96-114, 2022, doi: 10.1108/JGOSS-06-2021-0045.

[11] C. H. Hsu, X. H. Yang, T. Y. Zhang, A. Y. Chang, and Q. W. Zheng, "Deploying big data enablers to strengthen supply chain agility to mitigate bullwhip effect: An empirical study of China's electronic manufacturers," *Journal of Theoretical and Applied Electronic Commerce Research,* vol. 16, no. 7, pp. 3375-3405, 2021, doi: 10.3390/jtaer16070183.

[12] P. Ignaciuk and A. Dziomdziora, "Bullwhip effect-supply chain stability examination in the presence of demand uncertainty and delay," 2020 24th International Conference on System Theory, Control and Computing (ICSTCC), 2020, doi: 10.1109/ICSTCC50638.2020.9259768.

[13] M. H. Khan, S. Ahmed, and D. Hussain, "Analysis of Bullwhip effect: A Behavioral Approach," *Supply Chain Forum: An International Journal*, pp. 1-22, 2019, doi: 10.1080/16258312.2019.1661756.

[14] R. Raj, V. Kumar, and P. Verma, "Big data analytics in mitigating challenges of sustainable manufacturing supply chain," *Operations Management Research,* vol. 16, no. 4, pp. 1886-1900, 2023, doi: 10.1007/s12063-023-00408-6.

[15] M. Nyamukoroso, "How big data characteristics can help the manufacturing industry mitigate the bullwhip effect in their supply chain," 2022.

[16] D. Ojha, F. Sahin, J. Shockley, and S. V. Sridharan, "Is there a performance tradeoff in managing order fulfillment and the bullwhip effect in supply chains? The role of information sharing and information type," *International Journal of Production Economics,* vol. 208, pp. 529-543, 2019, doi: 10.1016/j.ijpe.2018.12.021.

[17] C. I. Papanagnou, "Measuring and eliminating the bullwhip in closed loop supply chains using control theory and Internet of Things," *Annals of Operations Research*, vol. 310, no. 1, pp. 153-170, 2022, doi: 10.1007/s10479-021-04136-7.

[18] M. Al-Sukhni and A. Migdalas, "Blockchain Technology for Information Sharing and Coordination to Mitigate Bullwhip Effect in Service Supply Chains," International Congress and Workshop on Industrial AI, 2021, doi: 10.1007/978-3-030-93639-6_17.

[19] B. Sundarakani, A. Ajaykumar, and A. Gunasekaran, "Big data driven supply chain design and applications for blockchain: An action research using case study approach," *Omega,* vol. 102, p. 102452, 2021, doi: 10.1016/j.omega.2021.102452.

[20] M. Sarkar, B. K. Dey, B. Ganguly, N. Saxena, D. Yadav, and B. Sarkar, "The impact of information sharing and bullwhip effects on improving consumer services in dual-channel retailing," *Journal of Retailing and Consumer Services,* vol. 73, p. 103307, 2023, doi: 10.1016/j.jretconser.2023.103307.

[21] T. Jafari, A. Zarei, A. Azar, and A. Moghaddam, "The impact of business intelligence on supply chain performance with emphasis on integration and agility-a mixed research approach," *International Journal of Productivity and Performance Management,* vol. 72, no. 5, pp. 1445-1478, 2023, doi: 10.1108/IJPPM-09-2021-0511.

[22] S. Yang and L. Chen, "Bullwhip effect analysis for supply chains using a fuzzy forecast approach," 2021 33rd Chinese Control and Decision Conference (CCDC), 2021, doi: 10.1109/CCDC52312.2021.9602212.

[23] R. Watson, "Interpretive structural modeling—A useful tool for technology," *Technological Forecasting and Social Change,* vol. 11, no. 2, pp. 165-185, 1978, doi: 10.1016/0040-1625(78)90028-8.

[24] P. H. Chen and P. L. P. Rau, "Evaluating Trust, Trustworthiness and Bullwhip Effect: A Three-Echelon Supply Chain Interactive Experiment," Cross-Cultural Design. User Experience of Products, Services, and Intelligent Environments, 2020, doi: 10.1007/978-3-030-49788-0_33.

[25] A. Dolgui, D. Ivanov, and M. Rozhkov, "Does the ripple effect influence the bullwhip effect? An integrated analysis of structural and operational dynamics in the supply chain," *International Journal of Production Research,* vol. 58, no. 5, pp. 1285-1301, 2020, doi: 10.1080/00207543.2019.1627438.

[26] G. Jiang, F. Liu, W. Liu, S. Liu, Y. Chen, and D. Xu, "Effects of information quality on information adoption on social media review platforms: Moderating role of perceived risk," *Data Science and Management,* vol. 1, no. 1, pp. 13-22, 2021, doi: 10.1016/j.dsm.2021.02.004.

[27] W. Jiang, "An intelligent supply chain information collaboration model based on Internet of Things and big data," *IEEE access,* vol. 7, pp. 58324-58335, 2019, doi: 10.1109/ACCESS.2019.2913192.

[28] G. Kankam, E. Kyeremeh, G. N. K. Som, and I. T. Charnor, "Information quality and supply chain performance: The mediating role of information sharing," *Supply Chain Analytics,* vol. 2, p. 100005, 2023, doi: 10.1016/j.sca.2023.100005.

[29] E. Al Humdan, Y. Shi, and M. Behnia, "Supply chain agility: a systematic review of definitions, enablers and performance implications," *International Journal of Physical Distribution & Logistics Management,* vol. 50, no. 2, pp. 287-312, 2020, doi: 10.1108/ijpdlm-06-2019-0192.

[30] V. P. Lele, S. Kumari, and G. White, "Streamlining Production: Using Big-Data's CRM & Supply Chain To Improve Efficiency In High-Speed Environments," *IJCSPUB-International Journal of Current Scienc (IJCSPUB),* vol. 13, no. 2, pp. 136-146, 2023.

[31] Z. Michna, S. M. Disney, and P. Nielsen, "The impact of stochastic lead times on the bullwhip effect under correlated demand and moving average forecasts," *Omega,* vol. 93, p. 102033, 2020, doi: 10.1016/j.omega.2019.02.002.

[32] W. Ran, Y. Wang, L. Yang, and S. Liu, "Coordination mechanism of supply chain considering the bullwhip effect under digital technologies," *Mathematical Problems in Engineering,* vol. 2020, pp. 1-28, 2020, doi: 10.1155/2020/3217927.

[33] K. Ravi, O. Jan, A. Tarun Kumar, and W. Magnus, "The ABCDE of supply chain visibility: A systematic literature review and framework," *International Journal of Production Economics,* vol. 248, p. 108464, 2022, doi: 10.1016/j.ijpe.2022.108464.

[34] A. Sarfaraz, R. K. Chakrabortty, and D. L. Essam, "A blockchain-coordinated supply chain to minimize bullwhip effect with an enhanced trust consensus algorithm," 2021.

[35] A. Sarfaraz, R. K. Chakrabortty, and D. L. Essam, "The implications of blockchain-coordinated information sharing within a supply chain: A simulation study," *Blockchain: Research and Applications,* vol. 4, no. 1, p. 100110, 2023, doi: 10.1016/j.bcra.2022.100110.

[36] L. Tang, T. Yang, Y. Tu, and Y. Ma, "Supply chain information sharing under consideration of bullwhip effect and system robustness," *Flexible Services and Manufacturing Journal,* 2020, doi: 10.1007/s10696-020-09384-6.

[37] E. Weisz, D. M. Herold, and S. Kummer, "Revisiting the bullwhip effect: how can AI smoothen the bullwhip phenomenon?," *The International Journal of Logistics Management,* vol. 34, no. 7, pp. 98-120, 2023, doi: 10.1108/IJLM-02-2022-0078.

[38] R. L. Bray, Y. Yao, Y. Duan, and J. Huo, "Ration Gaming and the Bullwhip Effect," *Operations Research,* pp. 1-15, 2019, doi: 10.1287/opre.2018.1774.