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BADAKHSHAN, Ehsan <<http://orcid.org/0000-0002-5298-764X>> and IVANOV, Dmitry <<http://orcid.org/0000-0003-4932-9627>>

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Integrating Digital twin and Blockchain for Responsive Working Capital Management in Supply Chains Facing Financial Disruptions

Ehsan Badakhshan^{a*}, Dmitry Ivanov^b

^a Sheffield Business School, Sheffield Hallam University, Sheffield, UK.

^b Berlin School of Economics and Law, Department of Business Administration
Professor for Supply Chain and Operations Management, 10825 Berlin, Germany
Phone: +49 308771155; E-Mail: divanov@hwr-berlin.de

*Corresponding author: e.badakhshan@shu.ac.uk

Abstract

Financial disruptions, such as extended trade credit periods and reduced down payments, pose significant challenges to effective working capital management in supply chains. While the benefits of blockchain and digital twin technologies have been studied independently in supply chain finance, their combined potential to optimize working capital performance during disruptions remains underexplored. Our study addresses this research gap by proposing an integrated blockchain and digital twin framework to enhance financial resilience in disrupted supply chains. Blockchain facilitates secure, decentralized data sharing, providing visibility into product, order, and cash flows across supply chain stages. The digital twin complements blockchain by offering predictive capabilities and enabling dynamic adjustments to working capital policies in response to disruptions. Within this framework, discrete-event simulation assesses the impact of financial disruptions on working capital performance, while machine learning models generate decision rules for adaptive working capital management. The study highlights the critical role of inventory adjustments in mitigating financial disruptions and reducing working capital variability relative to demand fluctuations. By demonstrating the effectiveness of integrating blockchain with a digital twin for financial decision-making, this research contributes to both theory and practice. It provides actionable insights for supply chain managers seeking to improve working capital stability amid disruptions and offers a data-driven approach to financial resilience in modern supply chains.

Keywords: Digital twin, Blockchain, Working capital management, Supply chain, Simulation, Machine learning.

SDG 9: Industry, innovation and infrastructure.

1. Introduction

Financial disruptions in supply chains (SCs), such as extended trade credit periods and reduced down payments, create significant challenges for working capital management and production continuity (Ghadge et al., 2021; Moretto & Caniato, 2021). These financial practices, often adopted

to accommodate downstream cash flow constraints, impose liquidity strains on upstream suppliers, jeopardizing their ability to procure raw materials and maintain production (Badakhshan & Ball, 2023; Li et al., 2022). For instance, extended trade credit cycles increase suppliers' working capital risks, as seen in automotive SCs, potentially disrupting production (Esenduran et al., 2022; Huang et al., 2022). Similarly, reducing down payments shifts the financing burden to suppliers, forcing them to prioritize short-term liquidity over long-term investments in production capacity (Ivanov, 2024a).

Blockchain-enabled data sharing offers a potential solution to these financial flow challenges by providing end-to-end visibility into product, order, and cash flows across all SC stages (Kucukaltan et al., 2024). Its decentralized and immutable ledger ensures secure and transparent data exchange, allowing stakeholders to monitor these flows effectively (Zheng et al., 2024). This visibility is particularly valuable in managing financial disruptions, such as extended trade credit periods and reduced down payments (Chang et al., 2020; Gupta et al., 2023). By establishing a single, shared source of truth, blockchain reduces information silos and minimizes the risk of data manipulation or inaccuracies resulting from fragmented record-keeping (Van Nguyen et al., 2023). However, despite these advantages, blockchain lacks predictive capabilities, as it primarily records and validates transactions rather than proactively analyzing disruptions (Kamble et al., 2020; Patel et al., 2024). This limitation makes blockchain insufficient for dynamic working capital management in rapidly evolving SC conditions.

Digital twin technology complements blockchain by providing predictive capabilities for working capital management in SCs during financial disruptions. In the context of our study, an SC digital twin is a virtual replica of a physical SC able to simulate financial and operational scenarios using data shared via blockchain (Ivanov, 2024b; Nguyen et al., 2022; Park et al., 2021). By continuously analyzing product, order, and cash flow data, an SC digital twin allows stakeholders to forecast potential disruptions, assess their impact, and adjust working capital strategies accordingly (Ivanov, 2023; Lin et al., 2024). This synergy between blockchain's data-sharing infrastructure and the analytical power of an SC digital twin fosters a responsive working capital management framework, enhancing the financial stability of SC participants during disruptions.

Despite the increasing adoption of blockchain and digital twin technologies in SC financial management, their combined application for responsive working capital management under financial disruptions remains unexplored. Existing research primarily investigates these technologies in isolation. Studies on blockchain emphasize its role in enhancing financial transparency, automating transactions via smart contracts, and reducing inefficiencies in financial operations (e.g., Yang, 2021; Du et al., 2020; Liu, L. et al., 2023; Yang et al., 2023). Meanwhile, research on digital twin technology focuses on its potential to optimize production, storage, and transportation costs (e.g., Büchele et al., 2024; Raja et al., 2024; Voipio et al., 2023; Li & Li, 2024).

This fragmented approach overlooks the synergistic benefits of combining blockchain's secure data-sharing capabilities with the predictive analytics of a digital twin. An integrated approach could more effectively mitigate financial disruptions' impact on working capital performance. Given the increasing frequency of global SC disruptions, such a framework holds substantial value for firms seeking greater financial stability and efficiency.

To address this gap, this paper develops an integrated blockchain and SC digital twin framework for working capital management in financially disrupted SCs, guided by two research questions: (1) What are the impacts of extended trade credit periods and reduced down payments on SC working capital performance? and (2) How effective is an integrated blockchain-digital twin framework in minimizing the impact of these disruptions on working capital performance? To address the first question, the framework employs discrete-event simulation (DES), a component of the SC digital twin, to model SC disruptions and examine their effects. To answer the second question, the framework utilizes machine learning, another component of the SC digital twin, to analyze the relationships between controllable working capital policies and performance. Blockchain serves as a data source for the SC digital twin, supporting the analysis for both questions. By demonstrating the effectiveness of this framework, the study offers actionable insights for decision-makers seeking to leverage advanced digital technologies to improve working capital management amid disruptions.

Our contributions advance production research in three ways. First, we extend the digital twin literature by applying it to working capital management in SCs under financial disruptions, addressing the limitation of a single-company perspective in prior studies. Instead, we adopt a SC-wide perspective, capturing financial interdependencies among SC participants during disruptions, as highlighted by Huang et al. (2022) and Moretto and Caniato (2021). Second, we enhance blockchain's role in SC finance by integrating it with an SC digital twin, which provides predictive analytics to support financial decision-making. This integration overcomes blockchain's inherent limitation of lacking predictive capabilities, as noted by Patel et al. (2024) and Saberi et al. (2019). Third, we demonstrate how DES and machine learning, embedded in the SC digital twin, enable dynamic working capital adjustments in response to financial disruptions, advancing SC resilience strategies (Pu et al., 2024a; Ruel & El Baz, 2023).

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and identifies research gaps. Section 3 describes modeling a multi-echelon SC and examines how disruption scenarios affect working capital performance. Section 4 presents an integrated blockchain-digital twin framework to enhance working capital management during disruptions. Section 5 evaluates the effectiveness of this framework in managing disruptions and provides practical recommendations. Finally, Section 6 summarizes the findings and suggests directions for future research.

2. Literature review

This study encompasses four major research domains: digital twin technology in SCs, blockchain technology in SCs, financial management in SCs under disruptions, and the integration of blockchain and digital twin technology in SCs. Accordingly, the literature review is structured to explore each domain. This organization allows for a systematic assessment of how these technologies individually contribute to financial management and how their integration can enhance working capital management during SC disruptions.

2.1. Digital twin technology in SCs

Digital twin technology is central to digital transformation in SCs, enabling real-time monitoring, predictive analytics, and optimization (Park et al., 2021). Unlike traditional models relying on static inputs or historical data for "what-if" analyses, digital twins continuously incorporate real-time data from IoT and ERP systems, allowing proactive and reactive decision-making in dynamic environments (Badakhshan & Ball, 2024; Huang et al., 2024).

In production systems, digital twins significantly improve operational efficiency by enabling real-time, data-driven simulations that optimize production planning and scheduling (Lin et al., 2024; Luo et al., 2023). This allows managers to anticipate bottlenecks, dynamically adjust resources, and reduce downtime. Additionally, digital twins facilitate predictive maintenance by continuously analyzing machinery sensor data to forecast potential malfunctions, enabling proactive repairs that prevent costly production halts (Lim et al., 2024; Wang et al., 2021). Further, advanced analytics within digital twins identify sources of inefficiencies, reducing material wastage (Wang & Wang, 2019; Yuan et al., 2024). For instance, Al-Saeed et al. (2020) demonstrated that shop-floor digital twins substantially reduced manufacturing costs by streamlining processes and minimizing waste.

Digital twin technology significantly enhances financial performance in SCs by enabling continuous monitoring, simulation, and optimization of financial flows, leading to improved cost management, risk mitigation, and overall financial outcomes (Ivanov, 2019; Ivanov & Dolgui, 2021). For instance, Hezam et al. (2024) developed an SC digital twin integrating financial risk factors to improve supplier selection and align financial performance with sustainability goals. Similarly, Qiu et al. (2024) incorporated financial metrics into digital twin frameworks for semiconductor SCs, optimizing resource allocation toward sustainability objectives. Additional studies have highlighted digital twins' ability to reduce production, storage, and transportation costs, and improve the cash conversion cycle (CCC). Büchele et al. (2024) demonstrated significant reductions in horticultural storage costs via real-time environmental monitoring, while Li and Li (2024) emphasized measurable improvements in enterprise financial performance. Further supporting these benefits, Raja et al. (2024) and Voipio et al. (2023) reported digital twins' effectiveness in lowering transportation and warehousing expenses in manufacturing SCs.

Digital twins are critical in mitigating financial losses from SC disruptions. Klöckner et al. (2022) highlighted their role in reducing disruption-related losses, further supported by Badakhshan and Ball (2023), who demonstrated how SC digital twins minimize adverse financial impacts. Additionally, Badakhshan et al. (2022) applied digital twin technology to reduce the CCC, emphasizing further financial benefits. Perez et al. (2022, 2021) also showed that digital twin technology can forecast disruptions and optimize revenue across SC operations.

Despite extensive literature highlighting the financial benefits of digital twin technology in SCs, two gaps remain. First, most studies emphasize cost or risk reduction, overlooking digital twin technology's potential to optimize working capital management during disruptions, when firms often prioritize internal liquidity over broader SC needs (Huang et al., 2022; Moretto & Caniato, 2021). Second, although blockchain has proven valuable for data integrity, existing research has not integrated blockchain with digital twin technology to enhance working capital management. Blockchain can provide immutable data, thereby improving the accuracy and reliability of real-time digital twin updates.

To address these gaps, our study presents a framework that combines blockchain and an SC digital twin to improve working capital management during disruptions. This integrated approach leverages blockchain's data-sharing capabilities and the predictive analytics of digital twin to offer a robust solution for optimizing financial performance and enhancing SC resilience.

2.2. Blockchain technology in SCs

Blockchain technology has gained attention in SCs for enhancing resource allocation, transparency, and cost efficiency through secure, real-time data sharing. Its immutable ledger reduces transaction costs by improving stakeholder collaboration and minimizing reliance on intermediaries (Queiroz et al., 2021; Pournader et al., 2020).

Trust is crucial for SC efficiency, and blockchain significantly fosters trust across SC networks. Blockchain-enabled transparency can increase consumer trust, enhancing market demand (Liu et al., 2024). Kamble et al. (2019) found that perceived usefulness and ease of implementation drive blockchain adoption, strengthening trust and transparency in Indian SCs. Similarly, Yavaprabhas et al. (2024) highlighted blockchain's role in enhancing trust through trust-transfer mechanisms. However, Song et al. (2024) argue that although blockchain internally promotes trust, external factors such as governance restructuring can be even more influential.

Blockchain technology significantly supports sustainable SCs by verifying sustainability claims through raw material provenance tracking and environmental compliance enforcement, thereby enhancing environmental performance (Saberli et al., 2019; Bai & Sarkis, 2020; Manupati et al., 2020; Messina et al., 2024). Similarly, Wang, B et al. (2023) demonstrated blockchain's application in ensuring compliance with sustainability standards in healthcare SCs.

Integrating sustainability with production efficiency has become a central theme in contemporary production research, aligning with industry trends toward greener manufacturing. Zeng et al. (2023) proposed a blockchain-enabled SC scheduling framework to minimize production and transportation costs while maximizing carbon emission reductions. Additionally, blockchain contributes to resource management and waste reduction, promoting economic, social, and environmental sustainability (Upadhyay et al., 2021). Its role in facilitating environmentally and socially responsible practices is emphasized by Yontar (2023), while Du et al. (2022) identify blockchain-driven sustainable management as essential for long-term SC viability and ethical standards.

Despite blockchain's benefits, its adoption in SCs faces challenges including scalability, interoperability, and high computational demands (Kouhizadeh et al., 2021; Li et al., 2023; Liu, J. et al., 2023; Sharabati & Jreisat, 2024). Regulatory uncertainties, governance complexities, and blockchain's high energy consumption also complicate integration (Bak et al., 2023; Choi et al., 2023). Additional barriers include data ownership issues, implementation complexity, and participant readiness (Bogucharskov et al., 2018; Negi, 2024).

Numerous studies highlight blockchain's benefits and challenges in managing SC financial flows, emphasizing enhanced transparency as a key advantage. Blockchain's immutable ledger improves stakeholders' ability to audit financial activities, fostering trust among SC partners (Chen et al., 2020; Guo et al., 2022; Zuo et al. 2022). Scott et al. (2024) and Yoon and Pishdad-Bozorgi (2022) further demonstrate its application in minimizing late payments within construction SCs, improving financial reliability and predictability.

Blockchain enhances SC financial security by eliminating single points of failure and preventing unauthorized alterations to financial records (Habib et al., 2022). Bhusari et al. (2023) and Natanelov et al. (2022) emphasize blockchain's effectiveness in mitigating cyber-attacks and fraud. Additionally, Yang et al. (2023) developed a non-linear programming model balancing security and efficiency in blockchain-based SC finance systems.

Smart contracts optimize SC financial processes by automating transactions, thus reducing manual intervention, minimizing errors, and enhancing cash flow management (Han & Fang, 2024; Khan et al., 2021). Chen et al. (2020) and Wise et al. (2020) illustrate how smart contracts streamline invoicing, payments, and compliance, accelerating transactions and improving financial reliability.

Blockchain's role in financial SC management extends to cash flow optimization. Raj et al. (2022) and Yigit and Dag (2024) demonstrate that Ethereum-based blockchain systems can significantly enhance transaction processing in SCs. In practice, integrating Ethereum into a financial SC involves deploying smart contracts on the Ethereum network to automate and enforce financial

transactions such as payments and credit terms. Each SC participant operates a node that records every transaction immutably on the blockchain. This setup enables real-time data sharing and immediate verification of transactions, reducing delays and errors, which in turn leads to improved liquidity and financial stability across the SC. Zhao et al. (2024) suggest blockchain can mitigate fraud issues common in traditional SC finance, typically reliant on firm reputation. Additionally, Liu, L. et al. (2023) found blockchain platform finance more efficient than independent finance in scenarios involving capital-constrained retailers facing high production costs.

Despite extensive research on blockchain's financial applications in SCs, limited studies explore its integration with digital twin technology to optimize working capital. Blockchain enhances financial transparency, automates transactions via smart contracts, and reduces operational inefficiencies. Meanwhile, digital twin technology provides real-time monitoring, scenario analysis, and predictive capabilities. Yet, research combining these technologies for working capital optimization remains scarce.

Integrating blockchain with an SC digital twin presents a promising avenue for improving financial resilience and adaptability. By utilizing blockchain's secure and immutable ledger, a digital twin can access verified and real-time financial and operational data, facilitating both proactive and reactive decision-making. This integration would allow firms to optimize cash flow, predict financial bottlenecks, and dynamically adjust financial strategies in response to disruptions. Such capabilities are particularly crucial during crises, where liquidity management and financial continuity play a vital role in maintaining SC resilience.

To address this gap, our study proposes a novel framework combining blockchain and digital twin technology to improve working capital management in SCs. The framework aims to enhance financial agility, reduce capital constraints, and ensure seamless financial flows among SC partners, particularly during disruptions. Our contribution advances knowledge on financial strategies in disrupted SCs and provides practical insights for organizations seeking improved resilience through emerging technologies.

2.3. Financial management in SCs under disruptions

SCs frequently face disruptions impacting financial stability (Yu et al., 2019), arising from factors such as natural disasters, pandemics, political instability, and economic downturns (Tukamuhabwa et al., 2015). Consequently, firms increasingly emphasize financial decision-making, focusing on liquidity management, resource allocation, and financial resilience to mitigate disruptions' adverse impacts.

The COVID-19 pandemic, for instance, caused unprecedented SC disruptions, intensifying the focus on managing their financial impacts (Ruel & El Baz, 2023). Effective working capital management, i.e., handling short-term assets and liabilities, becomes particularly crucial in this

context. By optimizing operating cash, firms can build financial buffers to absorb shocks and ensure operational continuity. Companies with robust working capital reserves are better equipped to pay suppliers, seek alternative sources, or expedite shipments during disruptions (Wu et al., 2024). Conversely, inadequate working capital hinders daily operations, leading to poorer performance, highlighting the importance of healthy working capital for financial resilience (Pant et al., 2024).

A key aspect of working capital management in disrupted SCs is liquidity management, ensuring sufficient cash flow for immediate operational needs. Disruptions typically require companies to adjust financial components such as inventories, receivables, and payables to sustain liquidity. Empirical research confirms a strong correlation between SC disruption exposure and proactive adjustments in net working capital (Huynh & Le, 2025).

Using data from 51 Moroccan fast-moving consumer goods companies, Drissi et al. (2023) found that small and medium-sized enterprises (SMEs) faced the most severe financial impacts during COVID-19. Specifically, SMEs experienced an average increase of 43% in accounts receivable due to extended trade credit periods from downstream SC partners. These disruptions intensified working capital fluctuations, creating a cash flow bullwhip (CFB) effect, characterized by amplified variability in working capital relative to demand fluctuations.

Patil and Prabhu (2024), studying 763 U.S. public companies, found that following the 2008 financial crisis, 37% of retailing, 43% of wholesaling, and 81% of manufacturing firms experienced the CFB effect. Their results highlight that the effect is particularly pronounced for upstream SC members facing delayed cash inflows and increased liquidity constraints, emphasizing the importance of robust working capital policies to mitigate financial instability during disruptions.

Working capital management also influences broader financial decisions by determining the trade-offs firms can make during disruptions. Companies with robust working capital reserves have greater flexibility for proactive actions, such as early procurement of materials or investing in redundant suppliers to mitigate disruption impacts. In contrast, firms with limited working capital may resort to reactive strategies, including order cancellations, expense deferrals, or emergency financing, potentially destabilizing the SC. Empirical evidence from the COVID-19 pandemic indicates that firms with higher working capital levels performed better and recovered faster than those with insufficient reserves (HOSSAIN & Zariyawati, 2022).

Building on these insights, prior studies have proposed several strategies to enhance working capital management during SC disruptions. Ivanov and Dolgui (2020) highlighted how the pandemic prompted firms to adopt comprehensive financial planning for SC resilience. Before disruptions, firms should improve forecasting and maintain sufficient cash reserves as buffers (Ivanov et al., 2017). Supervised learning methods to predict disruptions (Ye et al., 2015) and

postponement strategies (Carbonara & Pellegrino, 2018) further support these efforts. During disruptions, firms can manage financial exposure by assessing potential losses, optimizing inventory, and implementing cost-saving measures (Elluru et al., 2019; Ivanov, 2024a). Reinforcement learning helps identify optimal recovery policies (Bussieweke et al., 2024), and prioritizing downstream SC members is advised due to their significant financial influence (Olivares-Aguila & ElMaraghy, 2021).

To strengthen financial resilience, companies increasingly adopt diversification and integration strategies. Diversifying products, suppliers, and customers reduces dependency and enhances flexibility (Wang, Q et al., 2023), while multi-sourcing yields higher net present value compared to single sourcing (Gaur et al., 2020). Additionally, integrating processes and products and enhancing coordination among SC partners have proven effective for improving financial stability (Ebrahimi et al., 2024; Hendijani & Norouzi, 2022; Zaefarian et al., 2024).

Digital twin technology is recognized as an essential tool for managing finances in disrupted SCs. An SC digital twin provides operational visibility, enabling firms to simulate disruption scenarios and assess financial impacts. By analyzing operational and financial data continuously, it forecasts risks such as increased costs, cash shortages, or resource allocation issues (Badakhshan & Ball, 2024; Ivanov, 2023; Klöckner et al., 2022). This predictive capability supports informed financial decisions, including adjustments in budgets, inventory, and investments. Badakhshan and Ball (2023) demonstrated that an SC digital twin can dynamically adjust inventory and payment policies during disruptions, enhancing financial resilience.

Blockchain technology has emerged as a robust tool for improving financial transparency and security in SCs, particularly during disruptions (Etemadi et al., 2021). Its decentralized ledger ensures transparent and immutable recording of transactions, reducing fraud, misreporting, and payment delays (Javaid et al., 2022). Wang et al. (2019) note that blockchain promotes trust among SC participants by providing real-time, verifiable financial data, enhancing cash flow management and financing efficiency. During the COVID-19 pandemic, blockchain proved valuable in addressing cash flow and financing challenges; for example, Pu et al. (2024b) and Yang (2021) proposed blockchain-based solutions like receivable financing and advance payments, benefiting SMEs with liquidity constraints. Additionally, Hamledari and Fischer (2021), Sigalov et al. (2021), and Nanayakkara et al. (2021) demonstrated blockchain's capability to streamline cash flow during payment disruptions. Smart contracts on blockchain platforms automate payments, reduce financial friction, and ensure timely obligations, enhancing financial reliability across global SCs (Wang & Wang, 2022).

While previous research has separately investigated the use of digital twin and blockchain technologies for financial decision-making in disrupted SCs, their integrated potential remains

underexplored, particularly in working capital management. Individually, each technology offers valuable solutions for SC disruptions, but their combined strengths in enhancing visibility, streamlining financial flows, and improving financial resilience have not been fully realized. To address this gap, our study proposes a framework integrating SC digital twin and blockchain technologies to optimize working capital management during disruptions.

2.4. Integrating blockchain and digital twin technology in SCs

The integration of blockchain and digital twin technology in SCs has attracted growing attention due to its potential to enhance security, transparency, traceability, data integrity, efficiency, and sustainability (Hemdan et al., 2023; Zhen & Yao, 2024). Three main integration patterns have emerged.

The first integration pattern employs blockchain as a tamper-proof source of accurate data for the digital twin. Firms record essential milestones or verified transactions such as shipment departures, arrivals, and quality checks on-chain to ensure that the digital twin modeling uses accurate and trustworthy data (Wang et al., 2020). This method effectively addresses trust issues common in multi-stakeholder SCs, allowing stakeholders to confidently utilize on-chain data for decision-making (Suhail et al., 2022). Industrial applications of this pattern span across sectors. For instance, Maersk's TradeLens platform logs container events on a permissioned blockchain, with verified records subsequently used by third-party logistics providers to feed digital models, optimizing routing and reducing delays (Jovanovic et al., 2022). Similarly, in the aircraft industry, manufacturers record every transaction in the metal additive manufacturing process on the blockchain. This creates an immutable audit trail that the digital twin utilizes to simulate, validate, and optimize production processes, ensuring compliance with stringent technical standards while reducing time-to-market and costs (Mandolla et al., 2019).

In the second integration pattern, digital twin technology generates real-time sensor data, analytics, or predictive alerts, which are then stored on the blockchain, ensuring transparency and non-repudiation of key events (Fernández-Caramés & Fraga-Lamas, 2018; Yaqoob et al., 2020). Recording these outputs on-chain supports automated smart contracts that trigger payments or penalties based on digital twin insights (Queiroz et al., 2021). For example, Lee et al. (2021) implemented this approach in construction projects by transmitting near real-time positioning data of prefabricated elements to update Building Information Modeling (BIM), subsequently timestamping and recording this information on blockchain. This ensured traceability and accountability, facilitating efficient stakeholder collaboration.

A third integration pattern involves bidirectional data sharing between blockchain and digital twin technology. In this approach, the digital twin retrieves immutable data from blockchain, such as authenticated maintenance records or verified shipment rates, and concurrently pushes simulation

results or updated operational states back onto the ledger (Hasan et al., 2020). This continuous exchange supports transparency, predictive maintenance, and collaborative decision-making. García-Valls and Chirivella-Ciruelos (2024) demonstrated this pattern in the CoTwin framework, where digital twin models are continuously refined through interaction with a blockchain-based collaborative space, both retrieving and storing data for ongoing model improvements. Similarly, Zhang et al. (2024) proposed a blockchain-digital twin framework for synchronizing production logistics, where the digital twin retrieves logistics data and updates real-time production statuses onto the blockchain, facilitating resource optimization. Additionally, Botta et al. (2023) developed a digital twin for food SC history management, retrieving blockchain-stored provenance and temperature logs, and subsequently recording quality metrics back onto the blockchain to enhance accountability and traceability.

Beyond these three central patterns, additional integration variants include partial on-chain/off-chain storage, where only essential data such as hashes, timestamps, or milestones are stored on-chain, while larger IoT datasets remain off-chain (Zheng, Z. et al., 2018). Another variant positions blockchain primarily as a governance layer controlling access to digital twin data (Putz et al., 2021). A more experimental concept involves creating digital twins of blockchain networks themselves to optimize performance prior to deployment (Diamantopoulos et al., 2024).

Despite evidence supporting the integration benefits of blockchain and digital twin technology in SCs, literature addressing their joint impact on working capital management remains sparse. Our study addresses this gap by proposing a blockchain-digital twin framework to optimize working capital management under disruptions. This integrated approach leverages blockchain's secure data-sharing and the digital twin's predictive analytics, thus enhancing SC financial resilience.

2.5. Literature summary

Recent research highlights digital twin technology's ability to enhance SC financial performance by reducing costs and risks. However, literature largely overlooks its potential to optimize working capital, particularly crucial during disruptions when firms prioritize internal liquidity needs over broader SC considerations. Meanwhile, blockchain technology has been recognized for improving data integrity, automating transactions through smart contracts, and enhancing financial transparency. Yet, the literature lacks studies integrating blockchain with digital twin technology specifically for responsive working capital management during financial disruptions.

An integrated blockchain-digital twin framework can significantly improve SC visibility, streamline financial flows, and enhance financial resilience. Blockchain provides immutable, verified data for digital twin analytics, allowing firms to optimize cash flow, forecast financial bottlenecks, and adjust financial strategies dynamically. To address this gap, our study proposes a novel framework combining blockchain's secure data sharing with the predictive capabilities of an SC digital twin.

This framework aims to optimize working capital management, enhance financial agility, reduce capital constraints, and strengthen overall SC resilience.

3. SC modeling and disruption impact analysis

In this section, we first detail modeling a multi-echelon SC and then examine the impact of disruption scenarios on working capital performance.

3.1. SC structure and modeling technique

In this study, a single-product SC is analyzed. The SC contains three echelons: one manufacturer, two distributors, and three retailers, as illustrated in Figure 1. Distributor 1 supplies Retailers 1 and 2, while Distributor 2 serves Retailer 3. The distribution lead times between the manufacturer and distributors and between the distributors and retailers are one week. There is no lead time between the retailers and customers since customers collect their orders directly from the retailers. The manufacturer's production capacity is 50,000 products per week. Customers' demands are stochastic and uniformly distributed: between 5,000 and 10,000 products per week for customer 1, between 4,000 and 8,000 products per week for customer 2, and between 6,000 and 12,000 products per week for customer 3. Suppose the retailers' inventories cannot fully meet their corresponding customer demand. In that case, the unmet orders are backlogged, adversely affecting the retailer's service level, defined as the ratio of the retailer's sales rate to its customer demand. Sales transactions are a mix of cash and credit, with a cash collection policy of 0.3, meaning each SC member pays 30% of the order value in cash in advance, with the remaining 90% paid after a trade credit period of four weeks.

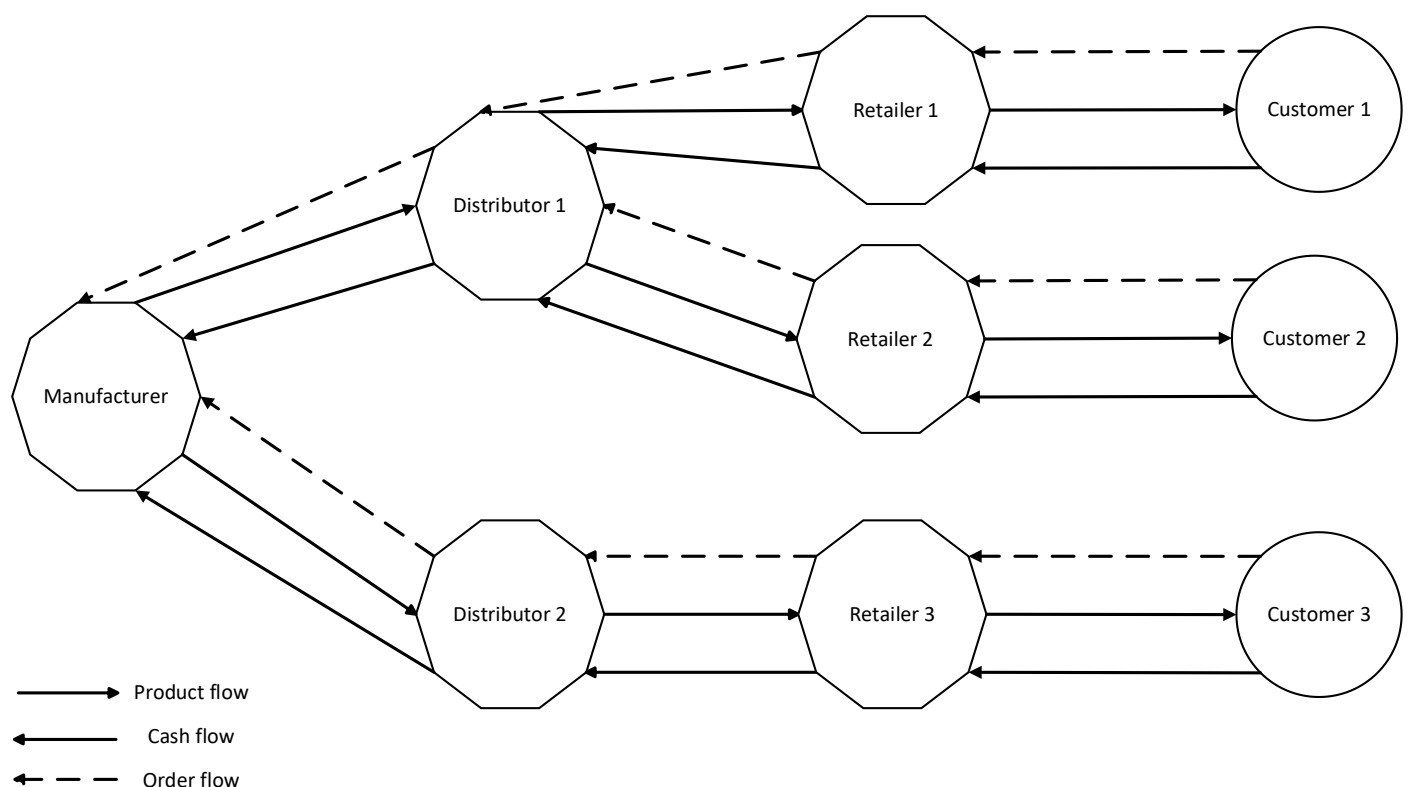


Figure 1. SC structure.

Figure 1. Alt text. The figure illustrates the flow of product, order, and cash across the SC.

We assume that the three SC nodes operate according to a periodic review inventory policy with a review period of one week. This means that each SC member reviews its inventory and work-in-progress (WIP) weekly and places an order with its upstream member. The sequence of events for each SC member is as follows: (1) Products ordered the previous week are received (lead time = 1) and added to the inventory. We assume unlimited storage capacities for SC members. (2) Inventory is used to fulfill orders from downstream members and to address any existing backlogs. (3) Products are sent downstream, the inventory level is updated, and a backlog is generated if necessary. (4) The order-up-to (OUT) policy is used to place an order with the upstream member. The order amount is defined by Eq. (1).

To calculate the order quantity (O), each SC member aims to fulfill the forecasted demand of its downstream partner ($\bar{D}$) while adjusting for any differences between current and desired levels of inventory and work-in-progress (WIP). Demand is forecasted based on an averaging function.

The inventory gap is determined by subtracting the net inventory (NI), defined as the current inventory minus unfilled orders (B) per Eq. (2), from the desired inventory (DI). Similarly, the WIP gap is calculated as the difference between the actual and desired WIP, where WIP includes supplier orders that have been sent but not yet received. Since it is impractical to close these gaps in a single review period, smoothing replenishment rules are applied, assigning weights (α and β) to the inventory and WIP gap terms. Higher values of α and β increase the influence of the inventory and WIP gaps, respectively, on the order quantity.

$$O_t = \text{Max}(0, \bar{D} + \alpha \underbrace{(DI - NI_t)}_{\text{Inventory gap}} + \beta \underbrace{(DWIP - WIP_t)}_{\text{WIP gap}}) \quad (1)$$

$$NI_t = INV_t - B_t \quad (2)$$

When placing an order, each SC member must make an advance payment (AP) as specified in Eq. (3). This is calculated by multiplying the upstream member's cash collection policy (UCCP) by the total order value, which is determined by the order quantity (O) and the unit price charged by the upstream member (UP). The unpaid portion of the order value is recorded as a credit purchase (CP), as defined in Eq. (4), to be paid after the agreed-upon trade credit period with the upstream partner.

Each SC member also collects an advance payment (AC) from its downstream member, calculated in Eq. (5) by applying its cash collection policy (CCP) to the downstream demand value.

The remaining amount of the demand value is noted as a credit sale (CS), as shown in Eq. (6), to be collected after the trade credit period arranged with the downstream member.

$$AP_t = UCCP * O_t * UP \quad (3)$$

$$CP_t = (1 - UCCP) * O_t * UP \quad (4)$$

$$AC_t = CCP * D_t * P \quad (5)$$

$$CS_t = (1 - CCP) * D_t * P \quad (6)$$

We employ DES methodology to model the dynamics of the studied SC. DES simulation is a widely used technique for studying SC performance, allowing for the examination of complex interactions and dependencies among various entities within the SC (Ivanov, 2019). By simulating discrete events, such as order placements, product movements, and financial transactions, DES enables a detailed understanding of how different factors affect SC behavior and performance metrics. This methodology facilitates the exploration of various scenarios and the evaluation of strategies to improve efficiency and enhance overall performance (Ivanov, 2017).

The simulation model is developed using the Simpy library in Python to analyze working capital performance in the SC. We measure SC's working capital performance using CFB values. To quantify CFB for SC members, we apply the ratio of working capital (WC) variability to demand (D) variability, as proposed by (Patil & Prabhu, 2024) and represented in Eq. (7). A CFB value greater than 1 indicates the presence of the CFB effect, while a value below 1 signifies its absence. Working capital, as defined in Eq. (8), includes inventory (I), cash (C), receivables (R), and payables (P). The simulation spans 52 weeks (one year), with a 20-week warm-up period. To compute the CFB values, we collect weekly time series data on working capital (WC) and demand (D) for each supply chain member over the simulation period after the warm-up phase. Variability is measured as the statistical variance of these series, and CFB is calculated by dividing the variance of WC by the variance of D.

$$CFB_t = \frac{Var(WC)}{Var(D)} \quad (7)$$

$$WC_t = I_t + C_t + R_t - P_t \quad (8)$$

Additionally, we measure SC's working capital performance using the CCC and inventory turnover. The CCC is a key indicator of working capital efficiency, representing the time required for a company to convert its investments in inventory and other resources into cash flows from sales. As defined in Eq. (9), the CCC consists of three components: Days Inventory Outstanding (DIO), Days Sales Outstanding (DSO), and Days Payables Outstanding (DPO).

$$CCC_t = DIO_t + DSO_t - DPO_t \quad (9)$$

The DIO, as defined in Eq. (10), represents the average number of days inventory is held before being sold. It is calculated by dividing the inventory value, which is the product of inventory levels and sales price, by the daily cost of goods sold (COGS). Daily COGS is obtained by multiplying units sold (US) by unit cost (UC) and dividing by 7 to convert weekly data into a daily measure.

The DSO, as defined in Eq. (11), measures the average time taken to collect payments from customers after a sale. It is determined by dividing accounts receivable (R) by daily sales revenue, where daily sales revenue is calculated as the product of units sold (US) and sales price (SP), divided by 7.

The DPO, as defined in Eq. (12), quantifies the average number of days a company takes to pay its suppliers. It is computed by dividing accounts payable (P) by daily COGS, ensuring consistency with the time-based calculations used in DIO and DSO.

The inventory turnover defined in Eq. (13) indicates how efficiently inventory is converted into sales. A higher ratio signifies more effective inventory management.

Beyond working capital performance indicators, we also assess total cost (TC), which represents the financial burden associated with inventory management, unfulfilled demand, and logistics. The total cost defined in Eq. (14), is the sum of inventory holding cost (IC), backlog cost (BC), and shipment cost (SHC). In addition, we evaluate service level, a key performance metric that measures the effectiveness of order fulfillment. Service level defined in Eq. (15), is the ratio of a retailer's sales (S) to the corresponding customer demand (D), expressed as a percentage.

$$DIO_t = \frac{I_t \times SP_t}{\frac{US_t \times UC_t}{7}} \quad (10)$$

$$DSO_t = \frac{R_t}{\frac{US_t \times SP_t}{7}} \quad (11)$$

$$DPO_t = \frac{P_t}{\frac{US_t \times UC_t}{7}} \quad (12)$$

$$IT_t = \frac{COGS_t}{I_t} \quad (13)$$

$$TC_t = IC_t + BC_t + SHC_t \quad (14)$$

$$SL_t = \frac{S_t}{D_t} \times 100 \quad (15)$$

In our simulation, we explicitly model financial disruptions by adjusting key financial parameters. For instance, extended trade credit periods are simulated by delaying the receipt of cash payments from downstream partners, while reductions in down payments are represented by

decreasing the proportion of cash collected in advance. These disruptions directly impact working capital by altering cash flow timings and liquidity levels across the SC. To quantitatively evaluate these financial disruptions, our simulation model tracks key performance indicators, such as the CFB effect (Eq. (7)), the CCC (Eq. (9)), inventory turnover (Eq. (13)), and total cost (TC) (Eq. (14)).

For model verification, we employ simulation run monitoring and output data analysis techniques to ensure that the simulation behaves as expected and accurately represents the system under study. This involves monitoring the simulation runs to identify discrepancies or anomalies and analyzing the output data to verify that it aligns with the expected behavior. To validate the simulation results, we conduct 100 replications of the simulation for each set of simulation parameters. This process involves running the simulation multiple times with different random seeds and input values to account for variability and randomness inherent in the system. By comparing the results of these replications, we can assess the consistency and robustness of the simulation output. Any discrepancies or inconsistencies among the replication results are investigated to ensure the reliability and accuracy of the simulation model.

3.2. Impact of disruption scenarios

In this section, we examine the impact of three disruption scenarios—trade credit extension, down payment reduction, and a combination of both—on working capital performance in the SC by running the simulation model described in Section 3.1. We conduct a 52-week simulation using the following input parameters: Inventory and Work-In-Progress (WIP) proportional controllers (α and β) for all SC members are both set to 0.5, aligning with previous studies (e.g., Aslam & Ng, 2016). The retailer's desired inventory and WIP levels are set to match peak customer demand, such as 10,000 units for retailer 1. For distributors and manufacturers, desired inventory and WIP levels are set at 1.4 times the peak demand. Testing factors between 1 and 1.4 times the maximum demand showed that values under 1.4 times resulted in inventory shortages, causing SC members to fall short of the 95% target service level.

3.2.1. Scenario 0. No disruption

This scenario serves as the baseline, displaying the CFB values for SC members without disruptions. Disruption events are later evaluated against this baseline to determine their impact on CFB values. Figure 2 presents the working capital and CFB values across various SC members. As expected, retailer 3, serving the customer with the highest demand, holds more working capital compared to retailers 1 and 2. Moving upstream in the SC, an increase in working capital is observed, which is primarily due to higher inventory levels at upstream members compared to those downstream.

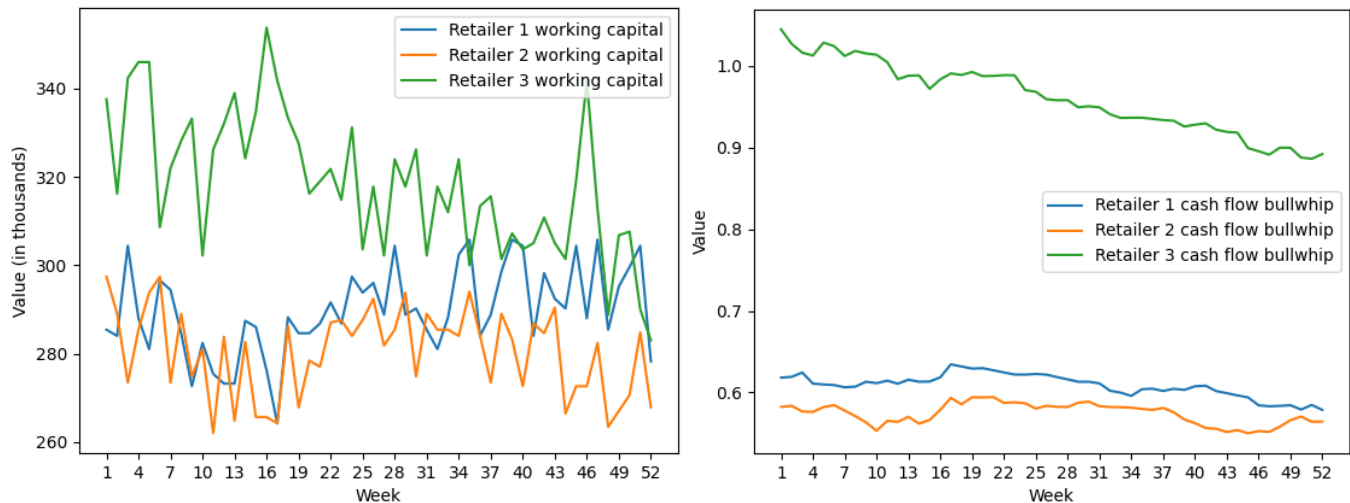
Throughout the simulation, the CFB values for all three retailers remain below 1, indicating that the variability in their working capital is lower than the variability in customer demand. This means the

fluctuations in working capital at the retailers are not amplified relative to customer demand fluctuations, demonstrating effective working capital management.

The average CFB values for distributor 1 and distributor 2 are 1.2 and 1.1, respectively, suggesting a slight CFB effect. The manufacturer, however, holds the highest average CFB value of 2.3, indicating more pronounced cash flow fluctuations. This confirms the presence of the CFB effect at upstream SC members, with the effect intensifying further upstream.

The simulation results reveal an interplay among inventory management, cash conversion, and cost performance throughout the SC. Retailers operate with lower inventory levels and higher inventory turnovers, translating into lower CCCs. In contrast, distributors and the manufacturer maintain higher inventories and exhibit lower turnover rates, resulting in higher CCC values. For example, Retailer 1 records an average inventory of 12,714 units, an inventory turnover of 3.4, and a CCC of 242 days, whereas the manufacturer holds an average inventory of 57,372 units, an inventory turnover of 0.54, and a CCC of 271 days.

Cost analysis further reinforces these observations. Total cost escalates progressively from retailers to distributors, reaching a peak at the manufacturer. For instance, Retailer 2 incurs a total cost of £35,726, compared to the manufacturer's total cost of £78,230. Despite these differences in financial indicators, the overall SC sustains an outstanding service level of 99.87%.



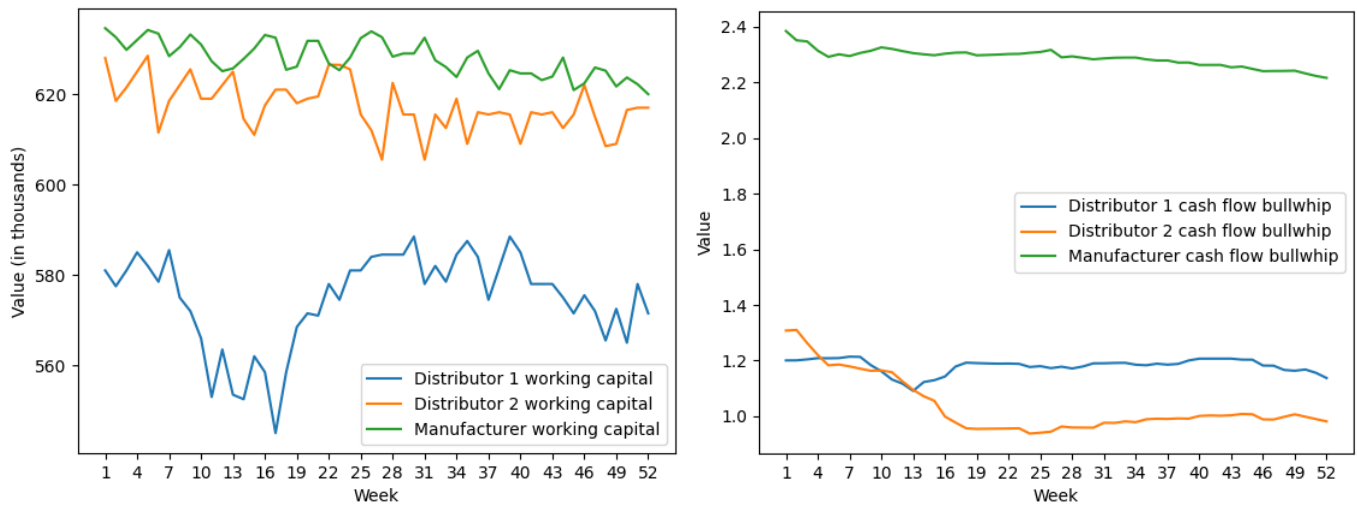


Figure 2. No disruption scenario.

Figure 2 Alt text. The figure presents the working capital and CFB values across SC members under no disruption.

3.2.2. scenario 1. Trade credit extension

In this scenario, customers extend their trade credit periods to retailers from 4 to 8 weeks to improve their financial position. Similarly, SC members extend their trade credit periods with their upstream partners from 4 to 8 weeks. Figure 3 illustrates the impact of extending the trade credit period for 10 weeks, from week 15 to week 24, on the working capital levels of the SC members.

The extension of the trade credit period increases both accounts receivable and accounts payable for retailers. However, since the purchasing price for retailers is lower than the price they charge customers, the increase in receivables exceeds the increase in payables. This imbalance results in a net rise in the retailers' working capital requirements, as more capital is tied up in customer outstanding payments than in the amounts owed to suppliers. Additionally, the extended trade credit period amplifies the CFB effect for retailers, leading to CFB values greater than 1. In contrast, under Scenario 0, where no trade credit extension was applied, retailers maintained CFB values below 1 throughout the simulation, indicating no CFB effect.

Similarly, distributors and manufacturer experience a significant increase in working capital levels due to the extended trade credit period. Even in Scenario 0, without any trade credit extension, distributors and the manufacturer experienced the CFB effect. However, the extended trade credit period further exacerbates their CFB values. In this scenario, the average CFB values for distributor 1, distributor 2, and the manufacturer are 7.9, 4.3, and 28.3, respectively, demonstrating a substantial increase compared to Scenario 0.

Based on the simulation results, there is no significant difference in average inventory levels, inventory turnovers, total costs, or the overall service level of the SC between scenarios 0 and 1. However, extending the trade credit period increases the DSO, which raises the CCC for SC members. For instance, in the extended trade credit scenario, Retailer 1's average CCC is 261

days compared to 242 days in the baseline scenario. Similarly, the manufacturer's average CCC increases from 271 days in the baseline scenario to 302 days in the extended trade credit scenario.

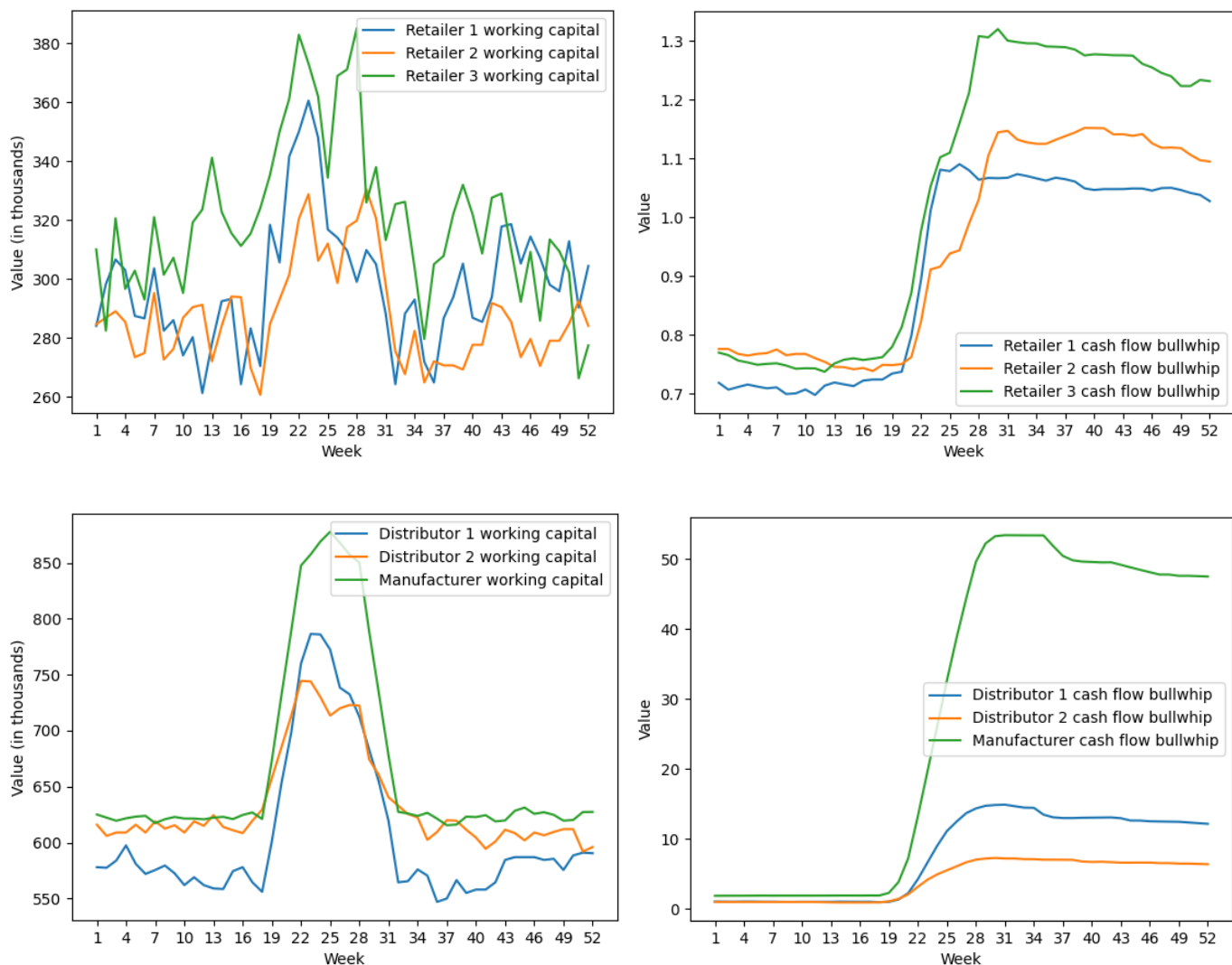


Figure 3. Trade credit extension scenario.

Figure 3 Alt text. The figure presents the working capital and CFB values across SC members under trade credit extension.

3.2.3. Scenario 2. Down payment reduction

In this scenario, customers shift from a 30% down payment at the time of order placement to a no down payment. This means 100% of the payment is made after the trade credit period. Similarly, SC members adopt this change with their upstream partners, moving from a 30% down payment to 0%. Figure 4 illustrates the impact of reducing the down payment for 10 weeks, from week 15 to week 24, on the working capital levels of the SC members.

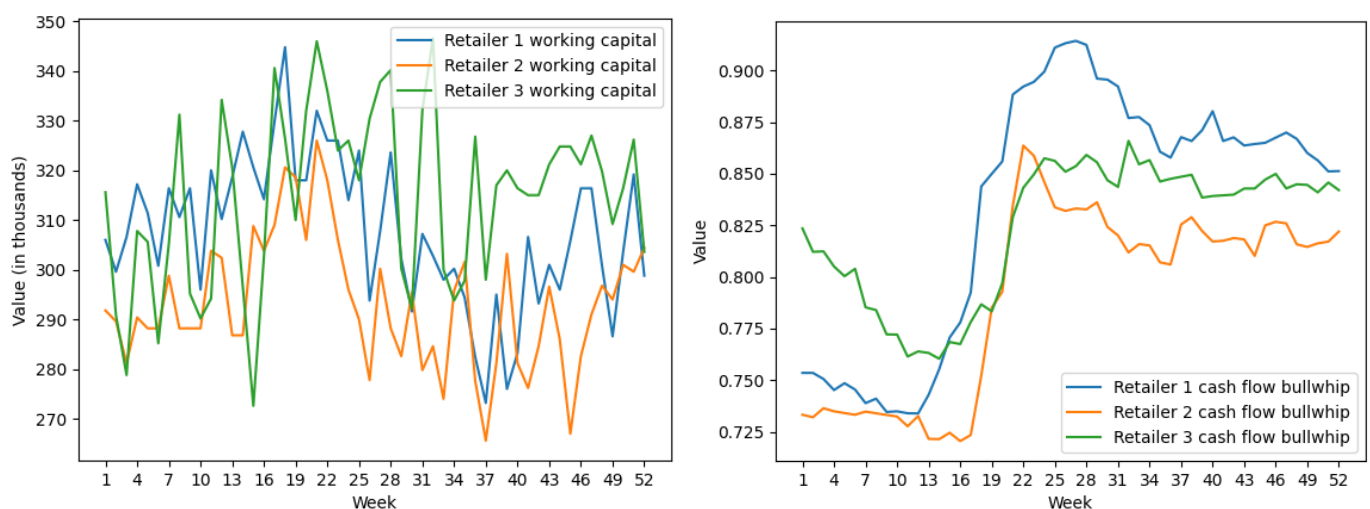
Reducing the down payment increases accounts receivable for retailers, thereby raising their working capital requirements as more capital becomes tied up in unpaid customer orders. Although the down payment reduction leads to a slight increase in the CFB values for retailers,

these values remain below 1 throughout the simulation, indicating the absence of the CFB effect similar to scenario 0, where a 30% down payment was required from customers.

Distributors and the manufacturer experience a significant increase in working capital due to the reduced down payment. Even in scenario 0, with a 30% down payment, they faced the CFB effect. However, the reduction in down payment exacerbates their CFB values. In this scenario, the average CFB values for distributor 1, distributor 2, and the manufacturer are 3.2, 1.7, and 10.2, respectively, showing a substantial increase compared to scenario 0.

Reducing down payment does not lead to a significant difference in average inventory levels, inventory turnovers, total costs, or the overall service level of the SC compared to a no-disruption scenario. However, reducing the down payment increases the day's sales significantly, which in turn raises the CCC for SC members. For instance, in the down payment reduction scenario, Retailer 1's average CCC is 268 days compared to 242 days in the baseline scenario. Similarly, the manufacturer's average CCC increases from 271 days in the baseline scenario to 351 days in the down payment reduction scenario.

It should be noted that the impact of the down payment reduction on the CCC is stronger than the impact of the trade credit extension. This is because reducing or eliminating the portion of the sale price paid upfront places a larger share of the total receivable into the credit period, thereby significantly increasing DSO. In contrast, simply extending the trade credit period from, for example, four weeks to eight weeks only adds a smaller delay to the receipt of the balance, resulting in a comparatively smaller effect on the DSO. Consequently, removing or lowering the down payment prolongs the operating cycle more substantially than adjusting credit terms alone, which leads to a greater overall impact on the CCC.



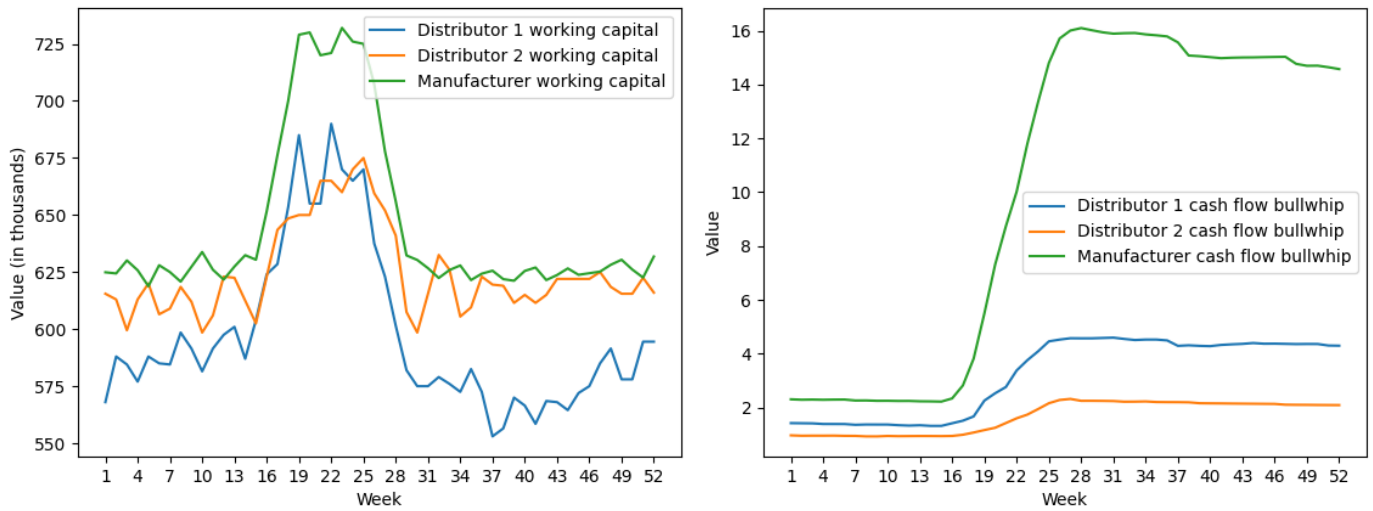


Figure 4. Down payment reduction scenario.

Figure 4 Alt text. The figure presents the working capital and CFB values across SC members under down payment reduction.

3.2.4. Scenario 3. Trade credit extension and down payment reduction

This scenario combines scenarios 1 and 2 to investigate the simultaneous impact of trade credit extension and down payment reduction on the working capital levels of SC members. Figure 5 illustrates this impact.

As with the individual effects of trade credit extension and down payment reduction, their combined impact increases accounts receivable, thereby raising working capital levels for retailers compared to the no-disruption scenario 0. Similar to Scenario 1, in this combined scenario, the CFB values for retailers exceed 1, indicating the presence of the CFB effect.

Likewise, distributors and manufacturers experience a significant increase in working capital levels, as observed in scenarios 1 and 2. The simultaneous trade credit extension and down payment reduction exacerbates the CFB effect for distributors and the manufacturer. In this scenario, the average CFB values for distributor 1, distributor 2, and the manufacturer are 22.4, 15.9, and 97.8, respectively, showing a substantial increase compared to scenarios 1 and 2.

Combining trade credit extension with down payment reduction does not significantly affect average inventory levels, inventory turnovers, total costs, or the overall service level of the SC when compared to a no-disruption scenario. However, it does increase the day's sales outstanding, which in turn raises the CCC for SC members. As expected, the combined impact of these two measures on the CCC is stronger than the impact of either measure individually. For example, in the combined scenario, Retailer 1's average CCC is 281 days, compared to 268 days in the down payment reduction scenario and 261 days in the trade credit extension scenario. Likewise, the manufacturer's average CCC in the combined scenario is 401 days, compared to 351 days in the down payment reduction scenario and 302 days in the trade credit extension scenario.

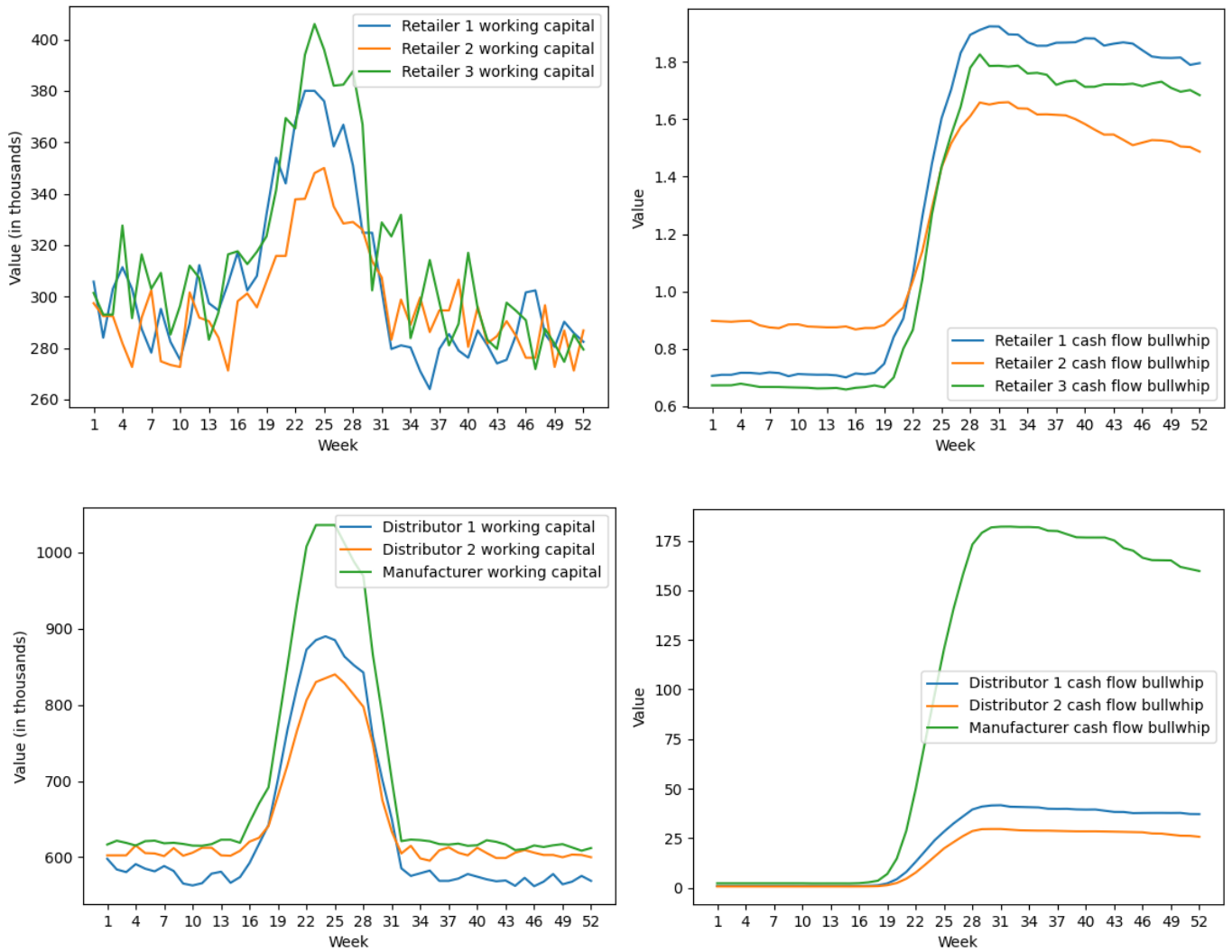


Figure 5. Trade credit extension and down payment reduction scenario.

Figure 5 Alt text. The figure presents the working capital and CFB values across SC members under trade credit extension and down payment reduction.

4. Integrated digital twin and blockchain framework for enhancing working capital management in SCs during disruptions

Combining digital twin and blockchain technologies for working capital management in disrupted SCs offers significant advantages. An SC digital twin replicates SC operations and finances, enabling decision-makers to analyze how disruptions and uncertainties affect working capital. Blockchain enhances transparency and trust by securely recording operational and financial data on a shared ledger. Together, these technologies empower firms to better control working capital and make timely adjustments to their working capital policies in response to disruptions, ultimately strengthening financial stability and liquidity in volatile SC environments.

The synergistic relationship between blockchain and digital twin is manifested in several key areas. Blockchain's decentralized and immutable ledger guarantees that the data fed into the digital twin is both accurate and trustworthy, creating a high-quality foundation that enables the digital twin to generate more reliable simulations and predictions. This robust integration of secure

data with simulation closely aligns with Cyber-Physical Systems (CPS) theory (Napoleone et al., 2023), which emphasizes the seamless interaction between the physical world and its digital counterpart. CPS theory underscores the necessity of maintaining data integrity to ensure that the virtual model mirrors real-world conditions (Porter & Heppelmann, 2014). By ensuring that only reliable, high-integrity data informs digital twin, blockchain plays a critical role in achieving the accuracy and responsiveness essential for effective CPS implementation.

Beyond basic data exchange, our framework leverages machine learning to process simulation outputs alongside blockchain-recorded data, yielding optimized working capital policies. This advanced integration informs strategic financial decisions by reducing information asymmetry, a key concern addressed by SC Finance theory, which emphasizes enhanced visibility and coordination between financial and operational flows to optimize liquidity and working capital (Gelsomino et al., 2016).

Moreover, by continuously updating its simulation model with high-integrity, real-time data and dynamically processing these inputs, our framework enables highly responsive working capital management. This rapid adjustment capability extends the principles of Dynamic Capabilities Theory (Teece, 2007), which posits that organizations must sense and swiftly respond to environmental changes to maintain a competitive advantage, from the firm level to the broader SC context. In our framework, this means that companies can quickly adapt their financial strategies to counteract disruptions, ensuring liquidity across the SC and preserving its financial stability even under stressful conditions.

Figure 6 illustrates the proposed framework for enhancing working capital management in disrupted SCs through the integration of digital twin and blockchain technologies. The framework is divided into four main steps, each of which can be adapted to specific SC contexts:

Step 1: Decentralized data sharing via blockchain

This step involves implementing a secure, immutable ledger to enhance transparency and traceability in SC operations. To ensure that blockchain's key characteristics, i.e., transparency, decentralization, and immutability, are maintained in practice, each SC member (manufacturers, distributors, and retailers) operates an independent blockchain node within a consortium-based, permissioned network. Although many industry solutions tend toward centralized implementations, our framework is designed to preserve decentralization by ensuring that no single entity controls the ledger.

Smart contracts are deployed to govern key financial terms, such as cash collection policies and credit periods, automatically recording and managing deviations due to disruptions. SC members have control over their participation, including decisions on data sharing and update frequency, making these variables integral to the network's operation. The system employs strict security

protocols, robust data integrity measures, and a consensus mechanism such as proof-of-authority suitable for private blockchain environments. This design ensures that even in a controlled, permissioned setting, the benefits of transparency, decentralization, and immutability are maintained, providing a trustworthy foundation for managing financial transactions in the SC.

Step 2: Simulation and performance monitoring

The objective of this step is to develop a simulation model that accurately represents the operational and financial dynamics of the physical SC. This is achieved by integrating data inputs from the blockchain, including customer demand, production capacities, production and distribution lead times, desired inventory and work-in-progress (WIP) levels, inventory and WIP proportional controllers (α and β), cash collection policies, and trade credit periods.

The simulation model also incorporates disruption events (e.g., trade credit extensions, down payment reductions) to account for real-world uncertainties. As the simulation runs, key performance indicators such as the CFB effect and overall working capital variability are measured to evaluate the financial resilience of the SC. Decision variables in this stage include the selection of performance metrics to monitor and the frequency of data capture and updates.

Step 3: Machine Learning- Based Policy Optimization

The objective of this step is to develop actionable decision rules for optimizing working capital policies using data generated by the simulation model. This is achieved by training a machine learning (ML) model on the simulation data to determine optimal settings for key policy parameters, such as cash collection policies and inventory proportional controllers.

The decision variables in this process include the choice of ML algorithm, the selection of relevant features, and the tuning of model parameters, all of which significantly impact the model's predictive accuracy and practical applicability. The ML model operates within constraints related to the quality and volume of available data, as well as the requirement that its recommended policies remain feasible within the operational and financial framework of the SC.

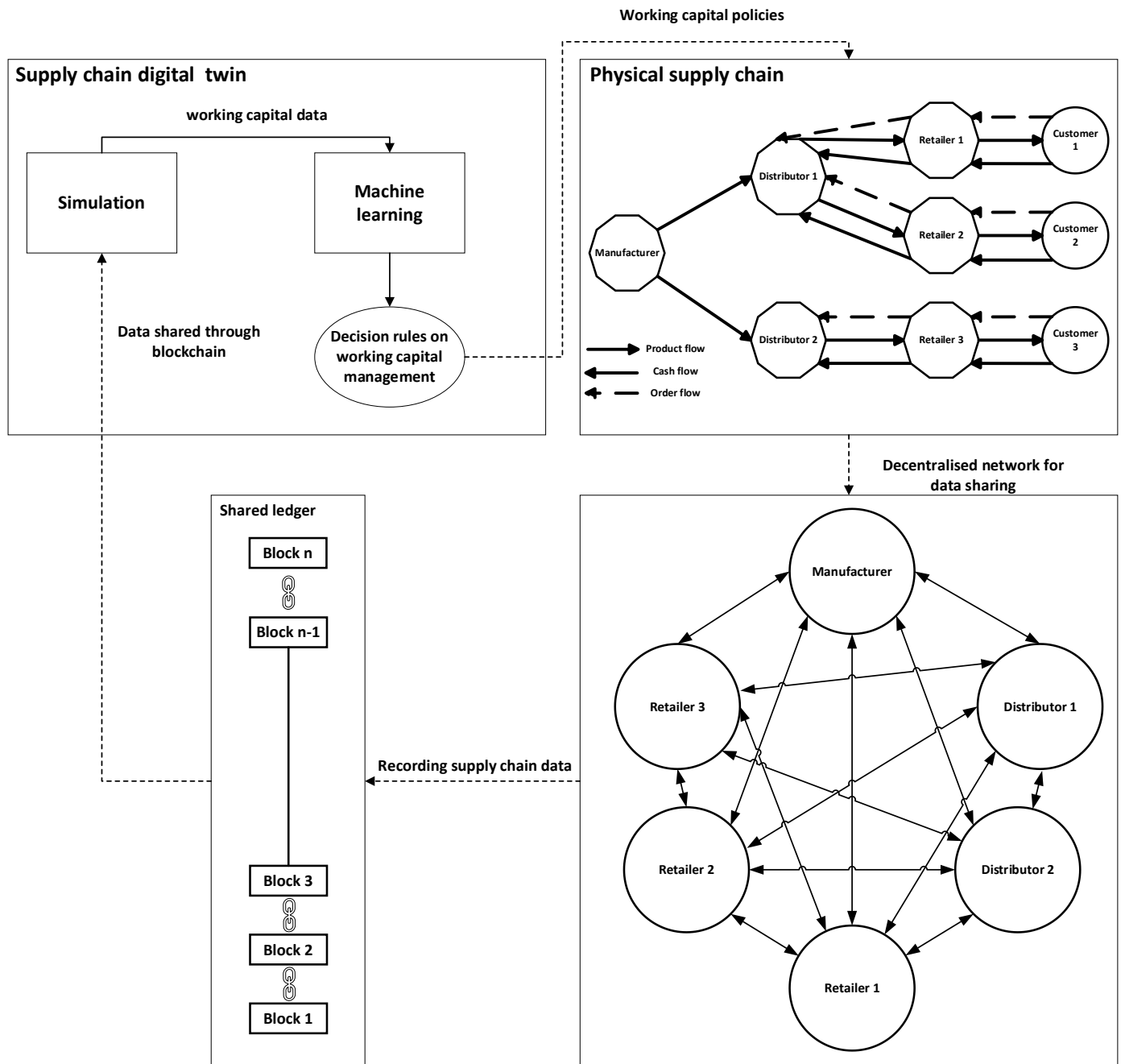


Figure 6. Integrated blockchain-digital twin framework for working capital management in SCs.

Figure 6. Alt text. Figure 6 illustrates the proposed framework for enhancing working capital management in disrupted SCs through the integration of digital twin and blockchain technologies.

Step 4: Real-Time Disruption Response

The objective of this final step is to dynamically adjust operational and financial policies in real time when SC disruptions occur. This is achieved by leveraging real-time notifications from the blockchain to update the simulation model with new disruption conditions. The simulation model is then refreshed, generating an updated dataset that is fed into the ML model. The ML model subsequently produces revised policy recommendations tailored to the emerging situation.

Key decision variables include the thresholds for triggering a disruption response, the frequency of simulation updates, and the ML model's sensitivity to changes in input data. The effectiveness of

this real-time adaptation is constrained by data processing speed, the responsiveness of the integrated blockchain-digital twin system, and the practical capacity of the SC to implement rapid policy adjustments.

Algorithm 1 outlines the complete pseudocode for our proposed framework, demonstrating the step-by-step process used to dynamically adjust SC policies.

Our framework is designed to incorporate multiple sources of uncertainty, ensuring adaptability to real-world SC conditions. The current implementation already integrates demand uncertainty. Additionally, the framework has the potential to incorporate financial uncertainty, such as fluctuations in trade credit periods, down payments, and liquidity constraints, as well as operational uncertainty, including variations in lead times, production disruptions, and supplier reliability.

```

// Initialization Phase
1. InitializeBlockchainNetwork()
    For each SupplyChainMember:
        Deploy blockchain node
        Load smart contracts (cash collection policies, credit periods)
2. InitializeSimulationModel()
    Set simulation parameters (production capacities, lead times, desired inventory/WIP,  $\alpha$  and  $\beta$ )
3. InitializeMLModel()
    Configure ML algorithm parameters

// Main Loop: While system is active
4. While (SystemIsActive) do:
    For each SupplyChainMember:
        Collect operational & financial data
        Store data on blockchain via smart contracts
    blockchainData  $\leftarrow$  FetchDataFromBlockchain()
    disruptionData  $\leftarrow$  FetchDisruptionEventData()
    simulationInput  $\leftarrow$  MergeData(blockchainData, disruptionData)
    simulationResults  $\leftarrow$  RunSimulation(simulationInput)
    performanceMetrics  $\leftarrow$  EvaluatePerformanceMetrics(simulationResults)
    If (SufficientData(simulationResults)) then:
        MLModel  $\leftarrow$  TrainOrUpdateMLModel(simulationResults)
        optimalPolicyParams  $\leftarrow$  MLModel.PredictOptimalPolicy(simulationResults)
        UpdateSupplyChainPolicies(optimalPolicyParams)
    Else:
        WaitForAdditionalData()
    If (DisruptionDetected()) then:
        newDisruptionData  $\leftarrow$  FetchLatestDisruptionData()
        UpdateSimulationModel(newDisruptionData)
        updatedInput  $\leftarrow$  MergeData(FetchDataFromBlockchain(), newDisruptionData)
        simulationResults  $\leftarrow$  RunSimulation(updatedInput)
        MLModel  $\leftarrow$  RetrainOrUpdateMLModel(simulationResults)
        revisedPolicyParams  $\leftarrow$  MLModel.PredictOptimalPolicy(simulationResults)
        UpdateSupplyChainPolicies(revisedPolicyParams)
    End If
    Wait(simulationInterval)
5. End While

Return "Enhanced Working Capital Management Achieved"

```

Algorithm 1. Integrated blockchain-digital twin framework for working capital management in SCs.

5. Comparative analysis

This section presents a rigorous evaluation of our proposed framework by comparing its performance against two state-of-the-art models for working capital management: a no-data-sharing model and a blockchain-enabled data sharing model. In our evaluation, we use key performance indicators including the CFB effect, the CCC, total cost, inventory turnover, and service level. The analysis is structured in four parts. In Section 5.1, we evaluate the impact of blockchain-enabled data sharing versus a no-data-sharing alternative, using the CFB effect as a primary performance metric. Section 5.2 extends this comparison by benchmarking our integrated digital twin and blockchain framework, as illustrated in Figure 6, against the blockchain-enabled data sharing model in mitigating the CFB effect under both disrupted and non-disrupted conditions. Section 5.3 presents the results of a statistical analysis using ANOVA and post-hoc tests to determine whether the observed differences across the three models are statistically significant across multiple performance indicators. Finally, in Section 5.4, we summarize the theoretical implications derived from Sections 3.2, 5.1, 5.2, and 5.3, and provide managerial recommendations based on these insights.

5.1. No data sharing vs. data sharing using blockchain

This section corresponds to steps 1 and 2 of the proposed framework and compares the impact of blockchain-enabled data sharing with a no-data-sharing alternative on working capital performance indicators. Blockchain-enabled data sharing ensures that all SC members have access to a consistent dataset. As a result, forecasts can be generated directly from end-customers' demands rather than relying on demand information from immediate downstream members. Figure 7 illustrates how SC members' forecasting based on end-customer demand affects working capital performance across various SC members under no disruption condition.

In line with Scenario 0, CFB values for all retailers remain below 1, signifying effective management of working capital relative to customer demand variability. Additionally, blockchain-enabled data sharing prevents the CFB effect for distributors. While this approach reduces the manufacturer's average CFB value compared to Scenario 0, it does not fully eliminate it. Specifically, the average CFB value for the manufacturer decreases from 2.3 in Scenario 0 to 1.49 in this scenario.

Blockchain-enabled data sharing provides distributors and manufacturers with visibility into end customers' demand, enhancing their demand forecasting. More accurate forecasts enable them to better align supply with actual demand, reducing average inventory levels while maintaining sales and increasing inventory turnover. For example, distributor 1's inventory turnover improves from 1.5 in the no-blockchain, no-disruption scenario (scenario 0) to 2.3 in the blockchain-enabled, no-disruption scenario.

Additionally, lower average inventory levels shorten the CCC by reducing DIO, which in turn lowers total cost. For instance, in the blockchain-enabled scenario, the manufacturer's CCC decreases from 271 days to 247 days, while total cost drops from £78,230 to £75,174. Notably, blockchain-enabled data sharing does not lead to a significant difference in the overall service level of the SC compared to the no-blockchain scenario, with average service level remaining above 99%.



Figure 7. Impact of blockchain-enabled data sharing under no disruption.

Figure 7. Alt text. The figure illustrates the Impact of blockchain-enabled data sharing under no disruption on working capital and CFB values across SC members.

Figure 8 illustrates the impact of SC members' forecasting based on end-customer demand on working capital performance across various SC members under trade credit extension and downpayment reduction. Consistent with Scenario 3, the extension of trade credit and reduction of downpayment lead to CFB values greater than 1 for all retailers, indicating the presence of the CFB effect among retailers. This outcome was expected, as retailers forecast using end-customers' demands data, even in the absence of blockchain-enabled data sharing. Moving upstream in the SC, we observe a reduction in CFB values compared to Scenario 3. For instance,

the average CFB value for the manufacturer decreases from 97.8 in Scenario 3 to 77.6 in the current scenario.

The improved visibility provided by blockchain-enabled data sharing enhances demand forecasting, reducing average inventory levels while maintaining sales and increasing inventory turnover. For example, distributor 2's inventory turnover improves from 0.9 in the no-blockchain scenario with trade credit extension and down payment reduction (scenario 3) to 1.4 in the blockchain-enabled data-sharing scenario under the same conditions.

Additionally, lower average inventory levels shorten the CCC and reduce total costs for the distributors and the manufacturer. For instance, in the blockchain-enabled data-sharing scenario with trade credit extension and down payment reduction, the manufacturer's CCC decreases from 401 days in scenario 3 to 309 days, while total cost drops from £78,596 to £76,863. Notably, blockchain-enabled data sharing does not significantly impact the SC's service level, which remains above 99%.

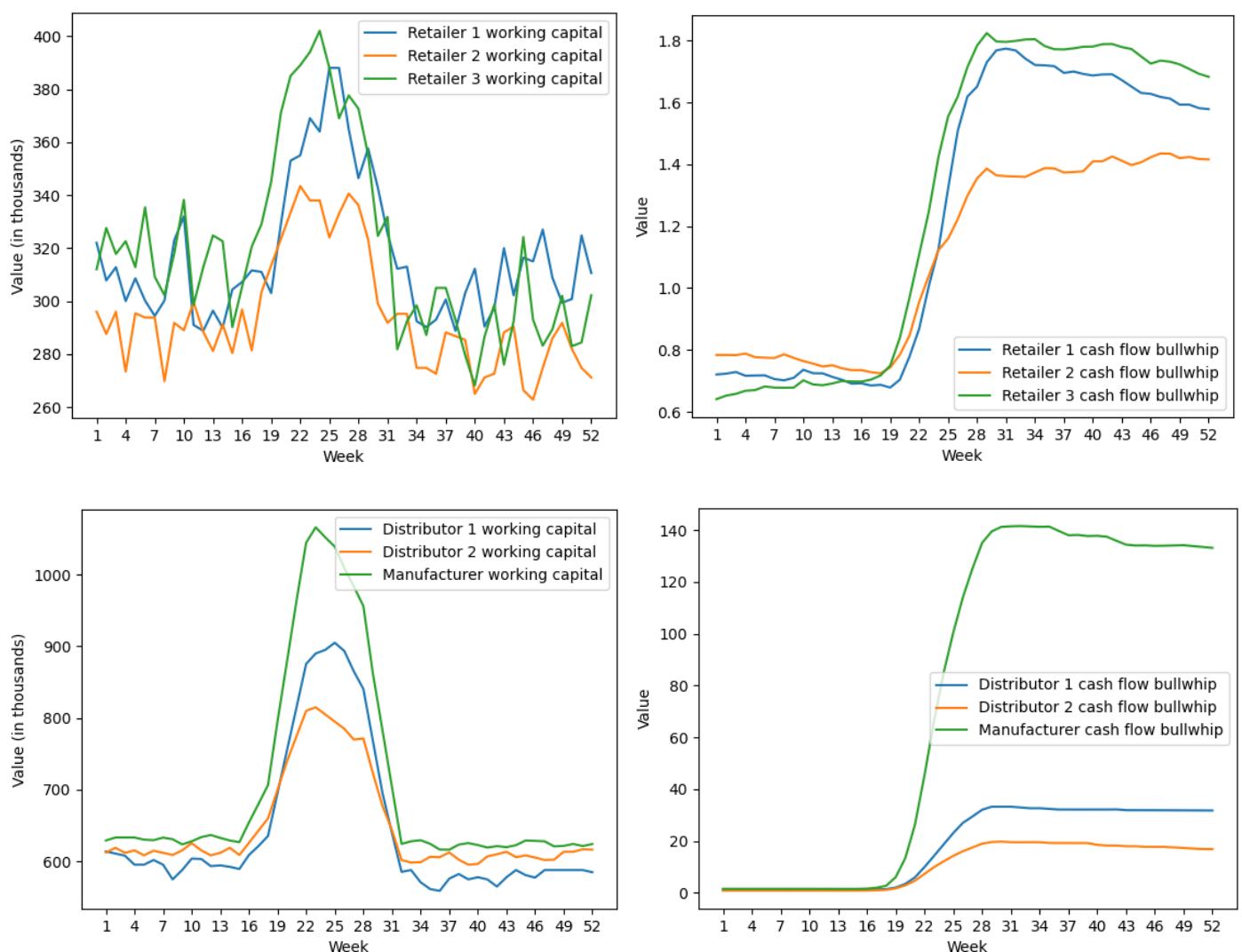


Figure 8. Impact of blockchain-enabled data sharing under trade credit extension and down payment reduction.

Figure 8. Alt text. The figure illustrates the Impact of blockchain-enabled data sharing under trade credit extension and down payment reduction on working capital and CFB values across SC members.

Based on the results shown in Figures 7 and 8, in the absence of disruptions, blockchain-enabled data sharing prevents the CFB effect for distributors but only reduces the CFB values for the manufacturer. When trade credit extension and downpayment reduction are applied, blockchain-enabled data sharing continues to reduce CFB values for both distributors and the manufacturer, but it does not fully prevent the CFB effect for either. These findings underscore the limitations of blockchain-enabled data sharing in mitigating the CFB effect within the SC. In other words, steps 1 and 2 of the proposed framework are insufficient to prevent the CFB effect for both distributors and the manufacturer, highlighting the need to integrate blockchain with digital twin technology.

5.2. Blockchain-enabled data sharing vs. integrated digital twin and blockchain

This section compares the impact of integrating blockchain and digital twin technology (steps 1-4 of the framework) with an alternative approach that excludes the digital twin (steps 1 and 2 of the framework). As shown in Figure 6, the SC digital twin employs machine learning to identify working capital policies that prevent the CFB effect in the SC. Additionally, the SC digital twin updates these policies in response to disruptions to sustain the prevention of the CFB effect.

Our proposed framework employs eight supervised learning algorithms, i.e., Decision Trees, Random Forests, K-Nearest Neighbours (kNN), Support Vector Machines (SVM), Logistic Regression, Naive Bayes, AdaBoost, and Neural Networks, to analyze simulation outputs and distinguish between the presence and absence of the CFB effect. The primary data source for these algorithms is the extensive output generated by our DES model. We classify the CFB effect into two categories, i.e., "no CFB effect" for a CFB value less than or equal to 1, and "CFB effect" for a CFB value greater than 1. The explanatory attributes used to determine these classes include customers' demands and the working capital policies of all SC members, such as desired inventory levels, desired work-in-progress (WIP), inventory proportional control (α), WIP proportional control (β), trade credit periods, and cash collection policies.

The 10-fold cross-validation method is employed to validate the results. In this approach, the dataset is randomly divided into 10 equal subsets; in each of the ten iterations, nine subsets are used for training while the remaining subset is reserved for testing. The process is repeated ten times, and the average performance across these iterations, known as the classification accuracy, is reported. We tested classification accuracy for different sizes of the training dataset (between 700 and 2000 examples). As expected, classification accuracy improves as the number of examples increases; however, this indicator stabilizes in a narrow range when the training set exceeds 1000 examples for all employed algorithms. Based on these findings, we chose 1000

examples for training the models, as this size provides a good balance between sufficient training data and computational efficiency.

Table 1 presents the performance of eight supervised learning algorithms in predicting the presence or absence of the CFB effect in the SC under no disruption. The area under the curve (AUC) metric indicates each model's ability to distinguish between the two classes, "CFB effect" and "no CFB effect." A higher AUC suggests superior classification performance. Among the algorithms, the random forest achieved the highest AUC of 0.920, indicating the best classification performance, while the AdaBoost algorithm had the lowest AUC at 0.791.

Classification accuracy (CA) measures the overall proportion of correct predictions, while precision indicates the proportion of true positives among all positive predictions made by the model. Recall reflects the proportion of actual positives correctly identified, and the F1 score, as the harmonic mean of precision and recall, provides a balanced metric when both are important. Among the algorithms, Logistic Regression and Naive Bayes achieved the highest values in classification accuracy, precision, recall, and F1 score.

Table 1. Performance of eight supervised learning algorithms under no disruption.

Model	AUC	CA	Precision	Recall	F1 Score
Decision tree	0.847	0.809	0.807	0.809	0.807
Random forest	0.920	0.889	0.907	0.889	0.890
K-nearest neighbours (kNN)	0.919	0.880	0.893	0.880	0.881
Support vector machines (SVM)	0.884	0.807	0.807	0.807	0.807
Logistic Regression	0.902	0.893	0.916	0.893	0.894
Naive Bayes	0.898	0.893	0.916	0.893	0.894
AdaBoost	0.791	0.807	0.806	0.807	0.806
Neural Network (NN)	0.917	0.847	0.847	0.847	0.847

Feature importance assessments from the Logistic Regression model indicate that inventory decisions including desired inventory, desired WIP, inventory proportional controller (α), and WIP proportional controller (β) across SC echelons significantly impact the presence or absence of the CFB effect in the SC. Among these factors, desired WIP and desired inventory at the retailer level, as well as desired inventory and inventory proportional controllers at the distributor level, have the greatest influence on the CFB effect. In comparison, financial decisions, including trade credit periods and cash collection policies, are less influential in determining the presence or absence of the CFB effect, although the trade credit period plays a more significant role than the cash collection policy.

Although feature importance assessment helps identify the most influential factors, it does not provide clear decision rules for decision makers. Rule-based models, such as decision tree, create

“if-then” rules that directly describe the paths to classification outcomes. These rules are easy to interpret, as they explicitly lay out the conditions leading to each decision. Based on the performance metrics reported in Table 1, the decision tree model demonstrates acceptable performance in predicting the presence or absence of the CFB effect in the SC.

Figure 9 presents a simplified version of the tree generated by the decision tree model, showing the branches derived from the seven control factors, with the class of CFB value for the SC displayed at the end of each branch. For instance, Rule I highlights that when distributor 2’s desired inventory and distributor 1’s desired WIP are both below 1.5 times customer demand (CD), and the inventory proportional controller for the manufacturer (α_m) is below 0.5, the CFB effect will not occur in the SC. A key insight from this tree is the hierarchy of factor significance. Distributor 2’s desired inventory emerges as the most influential control factor, followed by the desired WIP levels for distributor 1 and the manufacturer. Other notable factors include the manufacturer’s inventory proportional controller (α_m), retailer 1’s desired WIP, and distributor 2’s WIP proportional controller (β_{d2}). This finding aligns with the feature importance analysis from the Logistic Regression model, which also indicated that inventory decisions across SC echelons substantially impact the presence or absence of the CFB effect. Furthermore, cash collection policies and trade credit periods are shown to be less influential, underscoring that inventory decisions play a more significant role than cash flow decisions in determining the CFB effect in the SC, as also observed in the feature importance results of the Logistic Regression model.

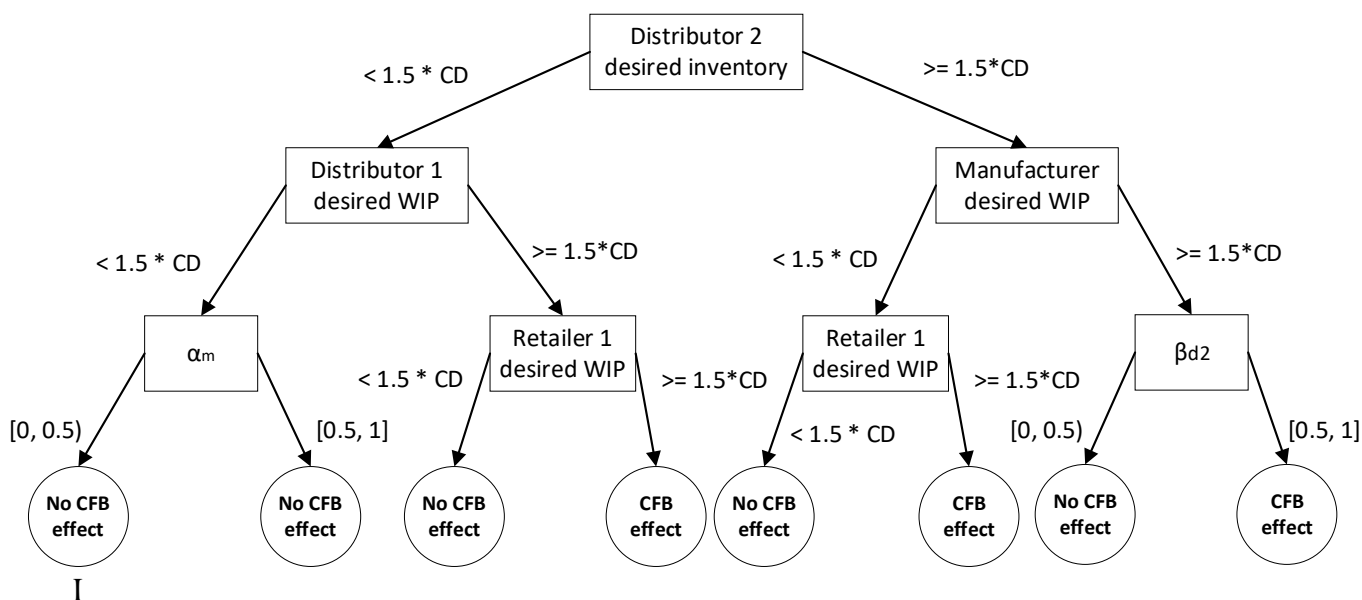


Figure 9. Decision tree under no disruption.

Figure 9. Alt text. The figure presents a simplified version of the tree generated by the decision tree model under no disruption.

Decision rules generated by the decision tree algorithm help reduce average inventory levels across SC members while maintaining sales and increasing inventory turnover. For example, distributor 1's inventory turnover improves from 2.3 in the blockchain-enabled scenario to 2.6 in the integrated digital twin and blockchain scenario.

Additionally, lower average inventory levels shorten the CCC by reducing DIO, which in turn lowers total cost. For instance, in the integrated digital twin and blockchain scenario, the manufacturer's CCC decreases from 247 days in the blockchain-enabled data-sharing scenario to 228 days, while total cost declines from £75,174 to £73,253.

Notably, the integrated digital twin and blockchain scenario does not lead to a significant difference in the overall service level of the SC compared to the blockchain-enabled data-sharing scenario, with service levels consistently remaining above 99%.

Table 2 presents the performance of eight supervised learning algorithms in predicting the presence or absence of the CFB effect in the SC under conditions of trade credit extension and down payment reduction. Among these algorithms, the neural network achieved the highest AUC (0.949), indicating the best classification performance, while the AdaBoost algorithm had the lowest AUC at 0.841. It is notable that the classification performance of AdaBoost improved by 0.05, from an AUC of 0.791 under no disruption to 0.841 under trade credit extension and down payment reduction. Additionally, the neural network and Naïve Bayes algorithms achieved the highest classification accuracy, Naïve Bayes showed the highest precision, and AdaBoost demonstrated the highest recall and F1 score.

As neural networks do not intrinsically provide feature importance, we derive feature importance from the Logistic Regression model, the second-best model in terms of AUC. Similar to the no-disruption scenario, inventory decisions including desired inventory, desired WIP, inventory proportional controller (α), and WIP proportional controller (β) across SC echelons significantly impact the presence or absence of the CFB effect in the SC. However, the importance of these factors under trade credit extension and down payment reduction differs from the no-disruption condition. Among these factors, desired WIP and desired inventory at the retailer level, as well as inventory proportional controllers at the distributor and manufacturer levels, have the greatest influence on the CFB effect. Consistent with the no-disruption case, the trade credit period has a more significant impact than the cash collection policy in determining the presence or absence of the CFB effect.

Table 2. Performance of eight supervised learning models under trade credit extension and down payment reduction.

Model	AUC	CA	Precision	Recall	F1 Score
Decision tree	0.847	0.834	0.835	0.834	0.834
Random forest	0.942	0.830	0.830	0.830	0.830
K-nearest neighbours (kNN)	0.935	0.825	0.825	0.825	0.825
Support vector machines (SVM)	0.866	0.768	0.773	0.768	0.767
Logistic Regression	0.947	0.831	0.831	0.831	0.831
Naive Bayes	0.941	0.835	0.846	0.835	0.833
AdaBoost	0.841	0.841	0.841	0.841	0.841
Neural Network (NN)	0.949	0.835	0.835	0.835	0.835

To provide clear decision rules for decision-makers, Figure 10 presents a simplified decision tree generated by the decision tree model under conditions of trade credit extension and down payment reduction. Similar to the no-disruption case, inventory decisions such as distributor 2's desired WIP, the inventory proportional controller for retailer 3, and the WIP proportional controller for the manufacturer emerge as the most influential control factors. However, the importance of trade credit policy in determining the presence or absence of the CFB effect has increased, as it appears higher in the tree. This underscores the value of an SC digital twin that responds to trade credit extensions and dynamically updates decision rules to prevent the CFB effect. For instance, Rule II indicates that when distributor 2's desired WIP exceeds 1.5 times customer demand (CD), retailer 3's inventory proportional controller (α_{r3}) should be set below 0.5, and the trade credit period should be limited to less than 2.5 weeks to avoid the CFB effect in the SC.

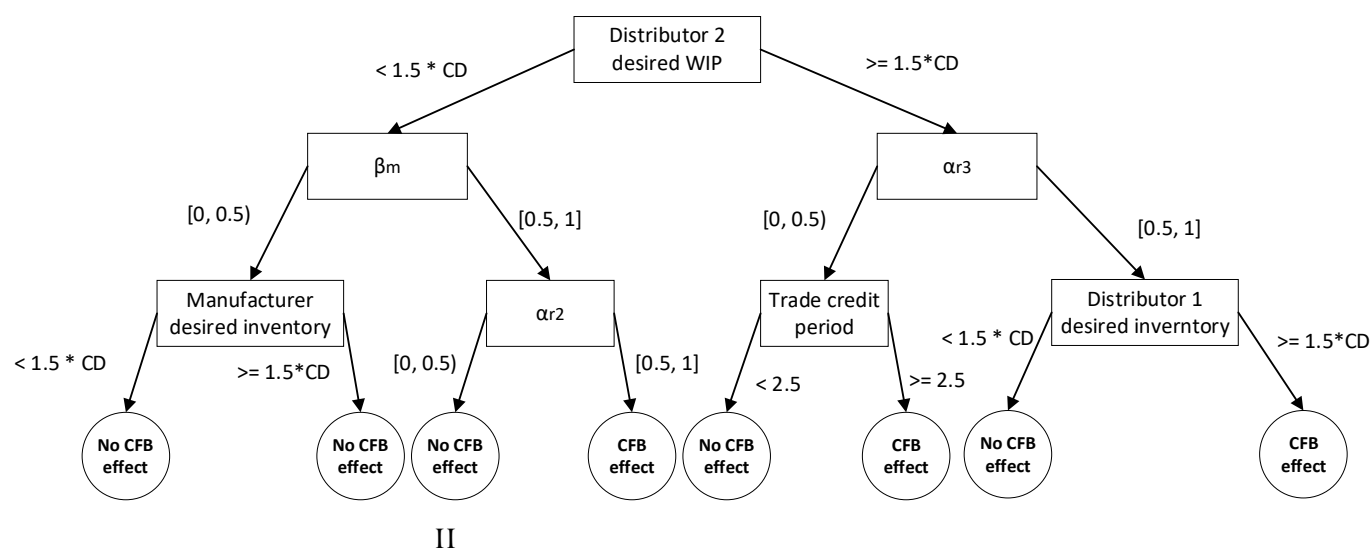


Figure 10. Decision tree under trade credit extension and down payment reduction.

Figure 10. Alt text. The figure presents a simplified version of the tree generated by the decision tree model under trade credit extension and down payment reduction.

Decision rules generated by the decision tree algorithm help reduce average inventory levels across SC members, thereby increasing inventory turnover. For example, distributor 2's inventory turnover improves from 1.4 in the blockchain-enabled data-sharing scenario with trade credit extension and down payment reduction to 1.6 in the integrated digital twin and blockchain scenario under the same conditions. Lower average inventory levels also contribute to cost reductions for SC members. For instance, total cost for the manufacturer declines from £76,863 in the blockchain-enabled data-sharing scenario with trade credit extension and down payment reduction to £75,591 in the integrated digital twin and blockchain scenario.

Additionally, the CCC is shortened by reducing both DIO and DSO. For example, the manufacturer's CCC decreases from 309 days in the blockchain-enabled data-sharing scenario with trade credit extension and down payment reduction to 278 days in the integrated digital twin and blockchain scenario under the same conditions. Notably, blockchain-enabled data sharing does not significantly impact the SC's service level, which remains consistently above 99%.

5.3. ANOVA and post-hoc analysis of performance indicators

This section presents an analysis of key SC performance indicators across three working capital management models: no-data sharing, blockchain-enabled data sharing, and integrated digital twin–blockchain. Our objective is to assess whether these models significantly affect performance metrics, specifically, the CFB effect, CCC, total cost, inventory turnover, and service level. These indicators are essential for evaluating the impact of the proposed integrated framework on supply chain finance and operational efficiency.

Data were collected from extensive simulation runs, with each model independently tested over multiple iterations and performance indicators recorded for all SC members (retailers, distributors, and the manufacturer). Here, the working capital model (with three levels) is the independent variable, and the performance metrics are the dependent variables.

A one-way ANOVA was performed to compare the group means across the three models. Prior to analysis, assumptions of normality, homogeneity of variances, and independence of observations were verified. Descriptive statistics (mean $\pm$ standard deviation) for each performance indicator, along with the ANOVA results (F-values, degrees of freedom, and p-values), are summarized in Table 3.

The ANOVA results indicate that significant differences among the three working capital models are primarily observed for upstream SC members. For example, the manufacturer's CFB yielded an F-value of 7.14 ($df_1 = 2$, $df_2 = 147$; $p = 0.001$), signifying that at least one model differs significantly. Because ANOVA is an omnibus test, we conducted Tukey's HSD post-hoc tests to pinpoint the specific differences. For the manufacturer's CFB, the comparisons showed that:

- The no-data sharing model had a significantly higher CFB than the blockchain-enabled model (mean difference = 0.82; 95% CI: 0.55–1.09; $p = 0.002$).
- The no-data sharing model also had a significantly higher CFB than the integrated digital twin–blockchain model (mean difference = 1.38; 95% CI: 1.10–1.66; $p = 0.001$).
- Additionally, the blockchain-enabled model exhibited a significantly higher CFB than the integrated model (mean difference = 0.56; 95% CI: 0.30–0.82; $p = 0.041$).

Similarly, post-hoc Tukey's HSD comparisons for distributors revealed that the integrated digital twin–blockchain model achieved significantly lower CFB values compared to both the no-data sharing and blockchain-enabled models.

For the CCC, the ANOVA did not detect significant differences among the retailer groups (p -values between 0.155 and 0.243); however, significant differences were found for Distributor 1 ($F = 3.42$, $p = 0.035$), Distributor 2 ($F = 4.56$, $p = 0.012$), and the Manufacturer ($F = 4.24$, $p = 0.016$). Tukey's HSD tests confirmed that the integrated model produced significantly lower CCC values for these upstream members, underscoring its effectiveness in accelerating cash flow conversion.

Inventory turnover differences followed a similar pattern. Although the retailer segment showed no significant differences, significant improvements were observed for Distributor 1 ($F = 3.75$, $p = 0.026$), Distributor 2 ($F = 3.22$, $p = 0.043$), and the Manufacturer ($F = 3.46$, $p = 0.034$). Post-hoc analysis indicated that the integrated digital twin–blockchain model achieved higher turnover rates, implying more efficient inventory management, compared to the other models for these upstream SC members.

Total cost analyses revealed that the integrated model significantly reduces costs for Distributor 1 ($F = 5.33$, $p = 0.006$), Distributor 2 ($F = 5.76$, $p = 0.004$), and the Manufacturer ($F = 6.20$, $p = 0.003$), whereas no significant differences were detected among retailers. Tukey's HSD post-hoc comparisons confirmed that the integrated digital twin–blockchain model results in substantially lower total costs for these upstream SC members compared to the alternatives.

Service level performance, assessed for retailers only, did not differ significantly among the models ($F = 0.98$, $p = 0.378$), indicating that all models maintain high levels of customer order fulfillment under no disruption conditions.

Collectively, these findings demonstrate that under no disruption conditions, the integrated digital twin–blockchain working capital model significantly enhances financial and operational performance for distributors and the manufacturer by reducing the CFB effect, shortening the CCC, improving inventory turnover, and lowering total cost. These improvements clearly support the superiority of the integrated approach in optimizing working capital management and overall SC efficiency.

Table 3. ANOVA results and descriptive statistics for performance indicators under no disruption.

Performance indicator	SC member	No-data sharing (Mean (M) $\pm$ standard deviation (SD))	Blockchain-enabled data sharing (M $\pm$ SD)	Integrated digital twin-blockchain (M $\pm$ SD)	F-value (2, 147)	p-value
Cash Flow Bullwhip (CFB)	Retailer 1	0.58 $\pm$ 0.08	0.59 $\pm$ 0.10	0.63 $\pm$ 0.08	1.38	0.255
	Retailer 2	0.43 $\pm$ 0.06	0.62 $\pm$ 0.09	0.62 $\pm$ 0.07	1.67	0.192
	Retailer 3	0.95 $\pm$ 0.03	0.61 $\pm$ 0.05	0.58 $\pm$ 0.11	1.85	0.161
	Distributor 1	1.24 $\pm$ 0.09	0.92 $\pm$ 0.06	0.95 $\pm$ 0.02	4.66	0.011
	Distributor 2	1.13 $\pm$ 0.10	0.84 $\pm$ 0.08	0.87 $\pm$ 0.06	4.32	0.015
	Manufacturer	2.31 $\pm$ 0.15	1.49 $\pm$ 0.12	0.93 $\pm$ 0.04	7.14	0.001
Cash Conversion Cycle (CCC)	Retailer 1	242 $\pm$ 11	243 $\pm$ 13	243 $\pm$ 15	1.43	0.243
	Retailer 2	258 $\pm$ 6	256 $\pm$ 11	255 $\pm$ 12	1.89	0.155
	Retailer 3	246 $\pm$ 8	244 $\pm$ 7	246 $\pm$ 10	1.85	0.161
	Distributor 1	256 $\pm$ 7	224 $\pm$ 10	225 $\pm$ 9	3.42	0.035
	Distributor 2	268 $\pm$ 4	236 $\pm$ 14	241 $\pm$ 11	4.56	0.012
	Manufacturer	271 $\pm$ 9	247 $\pm$ 8	228 $\pm$ 9	4.24	0.016
Inventory Turnover	Retailer 1	3.41 $\pm$ 0.11	3.38 $\pm$ 0.10	3.35 $\pm$ 0.12	2.05	0.132
	Retailer 2	2.73 $\pm$ 0.09	2.86 $\pm$ 0.07	2.81 $\pm$ 0.06	1.27	0.284
	Retailer 3	3.72 $\pm$ 0.12	3.79 $\pm$ 0.11	3.77 $\pm$ 0.13	0.94	0.393
	Distributor 1	1.58 $\pm$ 0.08	2.31 $\pm$ 0.14	2.64 $\pm$ 0.08	3.75	0.026
	Distributor 2	1.03 $\pm$ 0.10	1.47 $\pm$ 0.09	1.52 $\pm$ 0.15	3.22	0.043
	Manufacturer	0.54 $\pm$ 0.07	0.73 $\pm$ 0.15	0.96 $\pm$ 0.07	3.46	0.034
Total cost (£)	Retailer 1	39,058 $\pm$ 234	39,146 $\pm$ 261	39,079 $\pm$ 255	1.24	0.292
	Retailer 2	35,726 $\pm$ 152	35,528 $\pm$ 193	35,739 $\pm$ 168	1.58	0.209
	Retailer 3	43,929 $\pm$ 154	43,989 $\pm$ 125	43,901 $\pm$ 157	1.21	0.301
	Distributor 1	63,502 $\pm$ 249	61,434 $\pm$ 214	60,258 $\pm$ 244	5.33	0.006
	Distributor 2	67,819 $\pm$ 186	64,118 $\pm$ 174	63,866 $\pm$ 133	5.76	0.004
	Manufacturer	78,230 $\pm$ 257	75,174 $\pm$ 288	73,253 $\pm$ 226	6.20	0.003
Service level (%)		99.87 $\pm$ 0.09	99.64 $\pm$ 0.13	99.52 $\pm$ 0.16	0.98	0.378

Table 4 summarizes the descriptive statistics for each performance indicator along with the ANOVA results under the trade credit extension and down payment reduction condition.

For the CFB effect, the ANOVA revealed significant differences across all SC members. For instance, Retailer 1 recorded an F-value of 4.48 ($p = 0.013$) and Distributor 1 an F-value of 5.26 ($p = 0.006$). Tukey's HSD post-hoc comparisons indicated that the integrated digital twin–blockchain model produced significantly lower CFB values than both the no-data sharing and blockchain-enabled models.

Similarly, for the CCC, the ANOVA results were statistically significant across all members. Retailers exhibited F-values ranging from 3.69 to 4.02 (p-values between 0.020 and 0.027), while distributors and the manufacturer showed F-values between 4.42 and 5.16 (p-values between 0.007 and 0.014). Post-hoc tests confirmed that the integrated model yielded significantly lower CCC values than the other two models for every SC member.

Regarding inventory turnover, significant differences were found for the upstream members only. Specifically, Distributor 1 had an F-value of 3.91 ($p = 0.022$), Distributor 2 an F-value of 3.84 ($p = 0.024$), and the Manufacturer an F-value of 3.46 ($p = 0.034$). Tukey's HSD analyses indicated that the integrated model achieved higher turnover rates, reflecting improved efficiency, compared to the other models, whereas no significant differences were observed among the retailers.

For total cost, significant differences were observed at the distributor and manufacturer levels. The ANOVA produced F-values of 4.88 ($p = 0.009$) for Distributor 1, 5.19 ($p = 0.007$) for Distributor 2, and 5.47 ($p = 0.005$) for the Manufacturer. Tukey's HSD post-hoc tests confirmed that the integrated digital twin–blockchain model resulted in substantially lower total costs than both the no-data sharing and blockchain-enabled models, while differences among retailers were not statistically significant.

In contrast, service level performance did not differ significantly among the three models ($F = 0.81$, $p = 0.447$). Although the integrated model reported a slightly lower mean service level (99.15%) compared to no-data sharing (99.71%) and blockchain-enabled (99.78%), these differences are not statistically significant. This indicates that all models maintain robust customer order fulfillment under these conditions.

Overall, the combined ANOVA and post-hoc analyses demonstrate that, under trade credit extension and down payment reduction conditions, the integrated digital twin–blockchain working capital model significantly reduces the CFB effect and CCC across all SC members. In addition, this integrated approach enhances inventory turnover and substantially lowers total costs for both distributors and the manufacturer. These results support the conclusion that the integrated model offers a more effective solution for optimizing working capital management and improving overall SC performance under disruptive financial conditions.

Table 4. ANOVA results and descriptive statistics for performance indicators under trade credit extension and down payment reduction.

Performance indicator	SC member	No-data sharing (Mean (M) $\pm$ standard deviation (SD))	Blockchain-enabled data sharing (M $\pm$ SD)	Integrated digital twin-blockchain (M $\pm$ SD)	F-value (2, 147)	p-value
Cash Flow Bullwhip (CFB)	Retailer 1	1.28 $\pm$ 0.05	1.32 $\pm$ 0.07	0.68 $\pm$ 0.07	4.48	0.013
	Retailer 2	1.22 $\pm$ 0.08	1.18 $\pm$ 0.06	0.55 $\pm$ 0.08	4.65	0.011
	Retailer 3	1.25 $\pm$ 0.04	1.22 $\pm$ 0.08	0.61 $\pm$ 0.06	4.33	0.015
	Distributor 1	22.45 $\pm$ 0.10	14.84 $\pm$ 0.09	0.92 $\pm$ 0.04	5.26	0.006
	Distributor 2	15.93 $\pm$ 0.07	11.36 $\pm$ 0.07	0.89 $\pm$ 0.07	4.32	0.015
	Manufacturer	97.86 $\pm$ 0.12	77.6 $\pm$ 0.11	0.95 $\pm$ 0.03	7.28	0.001
Cash Conversion Cycle (CCC)	Retailer 1	281 $\pm$ 7	280 $\pm$ 11	248 $\pm$ 13	3.85	0.023
	Retailer 2	277 $\pm$ 9	275 $\pm$ 6	243 $\pm$ 10	3.69	0.027
	Retailer 3	285 $\pm$ 10	281 $\pm$ 8	246 $\pm$ 11	4.02	0.020
	Distributor 1	374 $\pm$ 8	305 $\pm$ 10	261 $\pm$ 10	4.42	0.014
	Distributor 2	368 $\pm$ 5	286 $\pm$ 14	263 $\pm$ 11	4.74	0.010
	Manufacturer	401 $\pm$ 12	309 $\pm$ 10	278 $\pm$ 9	5.16	0.007
Inventory Turnover	Retailer 1	3.32 $\pm$ 0.14	3.41 $\pm$ 0.13	3.32 $\pm$ 0.13	2.36	0.098
	Retailer 2	2.61 $\pm$ 0.11	2.73 $\pm$ 0.06	2.72 $\pm$ 0.08	2.27	0.107
	Retailer 3	3.59 $\pm$ 0.15	3.65 $\pm$ 0.12	3.64 $\pm$ 0.12	1.55	0.216
	Distributor 1	1.67 $\pm$ 0.09	2.28 $\pm$ 0.11	2.61 $\pm$ 0.07	3.91	0.022
	Distributor 2	0.92 $\pm$ 0.13	1.42 $\pm$ 0.07	1.63 $\pm$ 0.15	3.84	0.024
	Manufacturer	0.51 $\pm$ 0.08	0.64 $\pm$ 0.13	0.82 $\pm$ 0.06	4.56	0.012
Total cost (£)	Retailer 1	39,194 $\pm$ 218	39,257 $\pm$ 241	39,086 $\pm$ 255	2.35	0.099
	Retailer 2	35,883 $\pm$ 171	35,797 $\pm$ 182	35,757 $\pm$ 168	1.64	0.198
	Retailer 3	44,202 $\pm$ 169	44,009 $\pm$ 138	43,968 $\pm$ 127	1.39	0.252
	Distributor 1	63,576 $\pm$ 214	61,594 $\pm$ 237	60,357 $\pm$ 219	4.88	0.009
	Distributor 2	67,912 $\pm$ 158	64,888 $\pm$ 161	63,956 $\pm$ 111	5.19	0.007
	Manufacturer	79,358 $\pm$ 225	76,863 $\pm$ 266	75,591 $\pm$ 231	5.47	0.005
Service level (%)		99.71 $\pm$ 0.10	99.78 $\pm$ 0.12	99.15 $\pm$ 0.14	0.81	0.447

5.4. Theoretical and practical implications

Table 5 summarizes the major theoretical implications along with corresponding managerial recommendations. The insights below derived from Sections 3.2, 5.1, and 5.2 cover both the influence of financial disruptions on the CFB effect and the mitigating role of blockchain-enabled data sharing and digital twin technology.

5.4.1. Financial Disruptions and the CFB Effect

The theoretical implications from Section 3.2 highlight the varying impact of the CFB effect across SC members under different conditions. In the absence of disruptions, only distributors and the manufacturer experience the CFB effect, with its intensity increasing further upstream. Trade Credit Extension and Down Payment Reduction independently contribute to the CFB effect, again amplifying as one moves upstream. When these two factors are combined, the CFB effect extends to all SC members, intensifying from downstream to upstream.

These findings underscore the importance of managing financial interactions, particularly trade credit and down payments, to mitigate the CFB effect, especially for upstream players such as manufacturers and distributors. These findings extend the existing body of knowledge on the financial management in SCs under disruptions reviewed in Section 2.3 (e.g., Ebrahimi et al., 2024; Ivanov, 2024a; Zaefarian et al., 2024).

From a managerial perspective, these insights emphasize improving working capital management throughout the SC, with particular attention to upstream echelons where financial inefficiencies have a more pronounced impact. Effective working capital practices at these upstream tiers are critical to maintaining overall operational continuity. This may involve reconfiguring trade credit terms and adjusting down payment policies to prevent or lessen the CFB effect, thereby bolstering the financial resilience of the entire SC.

5.4.2. The Role of Blockchain-Enabled Data Sharing

The theoretical implications from Section 5.1 show that blockchain-enabled data sharing plays a significant role in mitigating the CFB effect under different conditions. In the absence of disruptions, blockchain-enabled data sharing prevents the CFB effect for retailers and distributors, though it only reduces, rather than fully prevents, the CFB effect for manufacturers. Under trade credit extension and down payment reduction, blockchain-enabled data sharing lowers CFB values for distributors and the manufacturer; however, it does not completely eliminate the CFB effect for either group.

These findings demonstrate that blockchain-enabled data sharing offers a varying degree of protection against the CFB effect, depending on SC tier and disruption type. They build on prior research into blockchain in SCs reviewed in Section 2.2 (e.g., Scott et al., 2024; Song et al., 2024; Yontar, 2023)

From a practical standpoint, SC managers can leverage blockchain technology to achieve real-time visibility into orders, transactions, and outstanding payments, thereby reducing information lags that contribute to cash flow distortions. For instance, a manufacturer of consumer electronics could deploy a private blockchain network with key distributors and third-party logistics (3PL) providers, sharing transaction data and credit terms in near real time. This approach allows upstream actors to spot potential cash flow imbalances early. By integrating such blockchain data

with predictive tools (e.g., an SC digital twin), managers can preemptively adjust working capital policies, mitigating the CFB effect even when disruptions arise.

5.4.3. Impact of Inventory Decisions on the CFB Effect

Section 5.2 reveals that, in the absence of disruptions, inventory decisions such as desired inventory levels, desired work-in-progress (WIP), inventory proportional controllers (α), and WIP proportional controllers (β) significantly influence the presence or absence of the CFB effect. Logistic regression and decision tree algorithms confirm that these inventory decisions are pivotal in determining whether the CFB effect arises. These findings corroborate existing research emphasizing the critical role of inventory policies in mitigating the CFB effect (e.g., Badakhshan et al., 2020; Goodarzi et al., 2017; Patil & Prabhu, 2024).

Managers should prioritize data-driven inventory policies across all echelons. For example, a global distributor in the automotive industry could employ a digital twin to simulate different α and β settings under realistic demand conditions. By fine-tuning these parameters iteratively with machine learning, the distributor can maintain a balanced inventory position that supports downstream demand without generating excessive holding costs or exacerbating the CFB effect.

An SC digital twin, combining simulation and machine learning, adds unique value beyond traditional simulation models. It synthesizes complex data relationships and offers predictive, real-time decision rules for working capital management. This capability is particularly useful for multinational SCM operations, where logistical complexities and financial disruptions can vary widely across regions.

5.4.4. Inventory Decisions Amid Disruptions

When trade credit extension and down payment reduction are introduced, inventory decisions continue to be crucial in determining the CFB effect (Section 5.2). However, the relative importance of these decisions shifts compared to the no-disruption scenario. Insights revealed by logistic regression and decision tree show that While inventory decisions remain critical, prioritization may need to adapt to disruptions. An SC digital twin that employs a decision tree can dynamically update decision rules to preempt or curtail the CFB effect, even in response to sudden financial policy changes (e.g., extended credit periods).

From a practical application perspective, consider a large food and beverage manufacturer faced with unexpected credit extensions from upstream ingredient suppliers. By continuously retraining its machine learning algorithms on the digital twin's simulation data, the manufacturer can fine-tune inventory targets to reduce cost overruns and maintain healthy cash flows. This example highlights how digital twin technology allows real-time, adaptive inventory adjustments that help stabilize the SC financially.

These outcomes advance the literature on digital twin technology in SCs reviewed in section 2.1 (e.g., Hezam et al., 2024; Perez et al., 2022; Raja et al., 2024). They showcase the synergy between simulation and machine learning in supporting adaptive policy recommendations, underscoring how digital twin offer a proactive means of mitigating the CFB effect in disruption-prone SC environments.

5.4.5. Summary and Managerial Outlook

Collectively, these theoretical and practical insights demonstrate how blockchain technology and an SC digital twin, incorporating machine learning and simulation, can interact to manage and mitigate financial disruptions in modern SCs. The integration of these technologies allows SC members to enhance visibility, improve forecasting accuracy, and dynamically adjust financial and operational policies in response to disruptions.

In practice, this framework can be tailored to specific industries such as automotive, consumer electronics, or fast-moving consumer goods (FMCG). Adapting the system to industry-specific requirements involves configuring blockchain nodes, establishing data-sharing protocols, and setting simulation parameters that reflect real-world constraints, including supplier credit terms and logistics lead times. By aligning the framework with sector-specific dynamics, companies can ensure that the blockchain-digital twin integration effectively supports financial decision-making and SC resilience.

Beyond industry-specific adaptation, the framework also facilitates continuous monitoring through a digital twin that updates in real time using blockchain-derived data. This real-time integration enables SC members to detect early signals of financial disruptions, such as delayed payments or unexpected fluctuations in trade credit and take proactive measures to adjust working capital policies. By leveraging machine learning-driven insights, businesses can optimize financial strategies dynamically, mitigating risks associated with cash flow imbalances and ensuring financial stability across the SC.

By illustrating these real-life scenarios, our study highlights the feasibility of integrating blockchain data with an SC digital twin to manage financial disruptions effectively. This underlines the framework's practical relevance, offering managers evidence-based strategies to mitigate the CFB effect, enhance working capital performance, and foster a more resilient SC.

Table 5. Theoretical implications and managerial recommendations.

Section	Theoretical implications	Managerial recommendations
3.2.1	In the absence of disruptions, only the distributors and the manufacturer experience the CFB effect, with its intensity increasing as we move further upstream.	Managers should prioritize working capital management across the supply SC, with a particular focus on upstream echelons, where financial inefficiencies
3.2.2	Trade credit extension results in the CFB effect for all SC	

	members, with its intensity increasing further upstream.	are often more pronounced. Effective working capital management in these echelons is essential, as they play a critical role in maintaining the operational continuity of the SC. This requires adopting strategies to avoid the CFB effect, ensuring financial stability across the SC.
3.2.3	Down payment reduction leads to the CFB effect, with the distributors and the manufacturer experiencing the effect, and its intensity increasing as we move further upstream.	
3.2.4	Trade credit extension and down payment reduction collectively lead to the CFB effect for all SC members, with its intensity increasing as we move upstream.	
5.1	In the absence of disruptions, blockchain-enabled data sharing prevents the CFB effect for retailers and distributors, while it only reduces the CFB effect for the manufacturer.	Managers should leverage blockchain data alongside predictive tools, such as an SC digital twin. Blockchain provides real-time visibility into SC flows, while an SC digital twin offers predictive insights. Together, these technologies enable managers to proactively adjust working capital policies, effectively preventing the CFB effect.
5.1	In the presence of trade credit extension and down payment reduction, blockchain-enabled data sharing reduces the CFB values for both distributors and the manufacturer but does not prevent the CFB effect for either.	
5.2	In the absence of disruptions, logistic regression and decision tree algorithms show that inventory decisions, including desired inventory, desired WIP, inventory proportional controller (α), and WIP proportional controller (β), across SC echelons, significantly impact the presence or absence of the CFB effect in the SC. This highlights the value of an SC digital twin which generates decision rules for working capital management by integrating simulation and machine learning.	Managers should prioritize inventory decisions across SC echelons. Utilizing data-driven models, such as machine learning algorithms, can help them understand the impact of these decisions and fine-tune working capital policies to prevent the CFB effect.
5.2	In the presence of trade credit extension and down payment reduction, logistic regression and decision tree algorithms show that inventory decisions across SC echelons significantly impact the presence or absence of the CFB effect in the SC. However, the importance of these factors differs from the no-disruption scenario. This highlights the value of an SC digital twin which dynamically updates decision rules to prevent the CFB effect in response to trade credit extension and down payment reduction.	Managers should update inventory decisions in response to SC disruptions to prevent the CFB effect. This requires retraining the machine learning models that identify working capital policies to prevent the CFB effect.

5.4.6. Implementation Challenges and Managerial Implications

This section examines the practical considerations of implementing the proposed framework, including its costs and benefits, technical and organizational requirements, and strategies to overcome adoption barriers. It also offers tailored recommendations for businesses of different sizes and financial configurations and critically reflects on the challenges that may arise during implementation.

While the framework enhances working capital efficiency and financial resilience, managers must carefully assess the associated implementation costs. Investment in technology infrastructure may be required to set up private blockchain networks, establish simulation environments, and integrate these systems with existing enterprise resource planning (ERP) platforms. Organizations may also need to train existing staff or hire specialists in blockchain technology, data analytics, and machine learning. Additionally, ongoing resources will be necessary to maintain blockchain nodes and digital twin models. However, the benefits including improved working capital visibility and reduced DIO can offset these costs if managed effectively. A structured cost-benefit analysis, aligned with the organization's size, complexity, and strategic priorities, is essential to ensure a justified return on investment (ROI).

Successful implementation also depends on strong technical and organizational capabilities. From a technical perspective, a private or permissioned blockchain network can provide real-time data visibility while maintaining confidentiality among authorized SC partners. Establishing a digital twin environment requires robust simulation capabilities and continuous machine learning updates to ensure accurate financial forecasting and operational decision-making. Data security is also critical, necessitating encryption, access controls, and standardized data formats to enable seamless integration across systems. Organizationally, cross-functional collaboration is key, as financial, operational, and IT teams must align on policy adjustments related to credit terms, inventory targets, and cash flow management. Without clear governance structures and proactive change management, firms risk implementation delays or resistance from stakeholders.

Adoption barriers may stem from concerns about technology readiness, cost, and data-sharing reluctance. Managers can address these challenges through phased adoption strategies. Small pilot implementations that demonstrate tangible benefits, such as more stable cash flows and improved forecasting accuracy, can build trust among internal stakeholders and SC partners. Concerns about data security and confidentiality can be mitigated by employing role-based permissions, encryption protocols, and clear agreements on data ownership. Additionally, a gradual scaling approach starting with select business units or partners allows firms to refine processes, address unforeseen challenges, and ensure a smoother transition to full implementation.

Different business sizes require tailored implementation approaches, but cloud-based solutions offer flexibility for both SMEs and large enterprises. SMEs can leverage fully managed, cloud-hosted blockchain and digital twin services to enhance financial visibility without significant upfront investments. Pay-as-you-go cloud models enable both SMEs and larger enterprises to scale resources based on demand, ensuring cost efficiency and flexibility.

Larger multinational corporations, with more complex SCs and in-house IT expertise, may adopt a hybrid or multi-cloud strategy to integrate blockchain nodes and digital twin models across multiple regions and product categories. While enterprises may use pay-as-you-go for dynamic workloads, they often combine it with reserved pricing or enterprise agreements to optimize long-term costs. Regardless of size, cloud-based deployment allows businesses to scale financial visibility and improve SC resilience.

When allocating funds for these initiatives, SMEs are advised to engage in incremental budgeting, allocating a small percentage of available funds in each cycle to pilot testing without overextending limited reserves. By concentrating on targeted working capital ROI metrics such as improved CCCs, reduced inventory holding costs, optimized accounts receivable and payable, and enhanced liquidity, firms can effectively demonstrate tangible financial improvements. These metrics help justify the broader scaling of blockchain-based digital twin models, ensuring that each investment delivers measurable gains in working capital efficiency and contributes to a more robust financial position.

For larger corporations, a similar incremental budgeting approach can be adopted but with a greater allocation of available funds due to their enhanced financial capacity. In each budgeting cycle, these firms can commit a more significant portion of funds to pilot projects that serve as a testbed for blockchain-based digital twin models, while still safeguarding overall capital reserves. Alongside this, dedicated R&D budgets can support extensive initial testing and rapid scaling of successful initiatives. Emphasis should be placed on targeted ROI metrics such as improvements in working capital efficiency, reductions in DIO, and enhanced cash flow stability to justify subsequent scaling and broader enterprise-wide deployment.

Despite its advantages, the proposed framework faces several challenges that may affect its adoption. Data integration remains a key obstacle, particularly for organizations relying on legacy systems that lack real-time interoperability. Scalability is another concern, as expanding the framework across multiple SC partners or product lines may introduce coordination complexities and data consistency issues. Additionally, organizational resistance to AI-driven financial policy adjustments could slow adoption, particularly in companies with rigid financial structures or low technological readiness. These challenges underscore the importance of careful planning, phased implementation, and continuous monitoring to ensure data quality, operational efficiency, and long-term financial stability.

6. Conclusions and future research

In this study, we first employ DES to analyze the impact of trade credit extension, down payment reduction, and their combination on working capital in the SC. This analysis addresses Research

Question 1, revealing that both trade credit extension and down payment reduction contribute to the CFB effect, with their impact intensifying further upstream in the SC. When both disruptions occur simultaneously, the CFB effect propagates across all SC members, becoming more severe at higher echelons. Additionally, both disruptions lead to an increase in the CCC, with down payment reduction exerting a stronger effect than trade credit extension. Notably, the combined impact of these two financial policies on CCC is greater than their individual effects.

To mitigate the impact of these financial disruptions on working capital performance, we propose an integrated blockchain–digital twin framework consisting of four steps. This framework addresses a critical research gap concerning the integration of blockchain and SC digital twin to enhance working capital management during disruptions. Our analysis shows that blockchain-enabled data sharing (Steps 1 and 2 of the framework) increases inventory turnover, shortens the CCC by reducing DIO, and lowers total costs for both the distributors and the manufacturer. Additionally, it reduces CFB values for both distributors and the manufacturer by improving financial visibility. However, while blockchain enhances transparency, it does not fully eliminate the CFB effect, underscoring the need for a predictive tool such as an SC digital twin to dynamically adjust working capital policies in response to disruptions.

In other words, fully eliminating the CFB effect requires the complete integration of blockchain and an SC digital twin (Steps 1-4 of the framework). Our analysis demonstrates that combining blockchain with an SC digital twin not only eliminates the CFB effect but also enables real-time policy adjustments in response to SC disruptions. This integration further increases inventory turnover, shortens CCCs, and reduces total costs for both distributors and the manufacturer compared to cases where only blockchain-enabled data sharing is employed. These findings address Research Question 2, emphasizing the importance of a data-driven, adaptive approach to working capital management in SCs.

While our proposed framework shows significant potential for enhancing financial resilience and operational efficiency, several limitations present opportunities for further research. One key area for exploration is the impact of physical flow disruptions, such as lead time variability and capacity constraints, on the CFB effect. Future studies could investigate how disruptions in inventory and production processes interact with financial decision-making, offering a more comprehensive perspective on working capital management in SCs.

A valuable avenue for future research is the expansion of our framework to incorporate additional sources of uncertainty beyond the demand variability already integrated into the current implementation. While our model effectively captures demand uncertainty, future studies could extend it to include financial uncertainty, such as fluctuations in trade credit periods, down

payments, and liquidity constraints, as well as operational uncertainty, including variations in lead times, production disruptions, and supplier reliability. By integrating these elements, the framework could provide a more comprehensive decision-support system, enabling firms to proactively adjust financial and operational policies in response to unpredictable disruptions. This enhancement would further strengthen SC resilience and improve the robustness of working capital management strategies under uncertain conditions.

Additionally, alternative modeling approaches could further refine the framework's predictive capabilities. For instance, integrating DES with reinforcement learning could allow SCs to develop adaptive strategies that dynamically mitigate the CFB effect. Moreover, incorporating optimization techniques and unsupervised learning methods could improve disruption detection and response, enabling SC managers to make more proactive, data-driven decisions.

Another promising research avenue involves integrating federated learning within digital twin frameworks. Federated learning enables multiple organizations or SC nodes to collaboratively train machine learning models on local data without sharing sensitive information. This approach enhances predictive accuracy while maintaining data privacy and security, making it particularly valuable in industries with strict regulatory requirements or competitive constraints. Future research could explore how federated learning can be leveraged to optimize working capital management in decentralized SCs and examine its interaction with blockchain-enabled data sharing.

Importantly, while our proposed architecture emphasizes the integration of blockchain and digital twins, future research could further explore the comparative benefits of decentralized versus centralized alternatives. For instance, centralized IoT-based analytics systems may offer simpler architectures for real-time data visibility. However, such systems may struggle with issues related to trust, data silos, and scalability, challenges that blockchain is specifically designed to address. Blockchain ensures data immutability, decentralized consensus, and selective transparency, enabling secure and trustworthy sharing of operational and financial information across organizational boundaries. This is especially critical for managing sensitive policies such as trade credit terms and cash collection, which require both coordination and confidentiality. Future studies could perform comparative analyses of financial and operational outcomes under different architectural configurations to evaluate the unique contribution of blockchain in such hybrid frameworks.

From a methodological standpoint, while this study relies on one-way ANOVA and Tukey's post-hoc tests to assess the statistical significance of performance improvements across different simulation scenarios, we acknowledge that additional statistical methods could provide deeper

insights. Future research could apply alternative techniques such as regression modeling, multivariate analysis, or bootstrapping to validate the robustness and generalizability of the results. These methods may be particularly useful in capturing complex interactions between financial and operational policies and in supporting causal inference.

Similarly, while this study evaluates the proposed framework against baseline scenarios of no data sharing and blockchain-enabled data sharing, future work could compare our approach with real-world systems such as ERP platforms with predictive analytics or digital control towers to further benchmark its practical relevance and effectiveness.

Finally, practical implementation challenges must be addressed to facilitate real-world adoption of the framework. These include data integration issues with legacy systems, interoperability between different digital platforms, and organizational resistance to AI-driven financial decision-making. Future studies should conduct field research or case studies to assess the framework's feasibility, identify best practices for large-scale deployment, and develop strategies for overcoming adoption barriers. Investigating the cost-benefit trade-offs across different industries would also provide valuable insights for practitioners seeking to implement blockchain-integrated digital twin solutions. While this study does not evaluate blockchain scalability parameters such as transaction throughput, latency, or energy consumption, we recognize their importance particularly in time-sensitive SC environments and identify them as essential considerations for future research and real-world implementation. Although a full-scale pilot or implementation is beyond the scope of this study, we acknowledge the importance of validating our assumptions under real-world conditions and identify this as a priority for future research.

By addressing these research gaps, future studies can refine integrated digital twin and blockchain applications in SC finance, enhance financial resilience, and promote a more adaptive and data-driven approach to working capital management.

Data Availability Statement

Data related to this paper is available from the authors and will be provided upon reasonable request.

Conflict of Interest

The authors report there are no competing interests to declare.

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