Integrating simulation and decision trees through blockchain-enabled data sharing to prevent the cash flow bullwhip effect in supply chains

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Annals of Operations Research
https://doi.org/10.1007/s10479-025-06858-4

ORIGINAL RESEARCH

Integrating simulation and decision trees through blockchain-enabled data sharing to prevent the cash flow bullwhip effect in supply chains

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Received: 13 November 2024 / Accepted: 15 September 2025

Abstract
Working capital mismanagement poses significant challenges to supply chain (SC) operations, threatening the stability and viability of businesses worldwide. One manifestation of this issue is the cash flow bullwhip (CFB) effect, which refers to the amplification of working capital variability relative to demand variability as it propagates upstream in the SC. Blockchain-enabled data sharing and decision trees trained on data generated by discrete-event simulation are potential yet unexplored solutions to address the CFB effect. This study fills this gap by investigating the effectiveness of blockchain-enabled data sharing and the integration of discrete-event simulation with decision trees in mitigating the CFB effect. The analysis focuses on a three-echelon manufacturing-retail SC. However, the findings are applicable to other SC types that experience the CFB effect. Blockchain provides visibility into end-customer demand and working capital policies across SC tiers by enabling data sharing. The shared data serve as inputs into a discrete-event simulation model that generates dynamic scenarios to train decision trees. Findings demonstrate that demand forecasting based on end customers' needs, facilitated by blockchain, significantly reduces the CFB effect. Additionally, combining this forecasting with uniformly applied, increasing cash collection policies across all SC members, also coordinated by blockchain, can prevent the CFB effect. Decision trees provide interpretable and actionable rules for setting working capital policies, highlighting the importance of regulating inventory policies at the middle echelon of the SC to prevent the CFB effect. This study offers managerial recommendations to address the CFB effect in SCs.

Keywords Simulation · Decision trees · Blockchain · Machine learning (ML) · Cash flow bullwhip effect

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Published online: 06 October 2025

1 Introduction

Working capital management refers to the efficient management of a company's short-term assets and liabilities. Mismanagement of working capital has wreaked havoc on supply chains (SCs), paralyzing operations and threatening the survival of businesses worldwide (Bal & Pawlicka, 2021). High-profile bankruptcies, such as those of Converse in 2001, Toys "R" Us in 2017, and Esprit Belgie Retail in 2024, underscore the severe consequences of ineffective working capital management. These catastrophic events extend beyond the companies facing bankruptcy, affecting suppliers and customers within the SC (Gibilaro & Mattarocci, 2019). This highlights the crucial importance of viewing working capital management from a SC perspective rather than from the perspective of a single company (Badakhshan et al., 2022).

Effective working capital management in SCs involves the rigorous monitoring and analysis of inventory, cash, receivables, and payables within a network of interconnected entities engaged in the production, distribution, and sale of goods and services (Pei et al., 2023). This management serves as the lifeblood that keeps the entire SC ecosystem functioning smoothly, directly influencing an organization's ability to meet financial obligations, maintain liquidity, and sustain day-to-day operations (Badakhshan & Bahadori, 2024; Wuttke et al., 2013).

A significant obstacle to effective working capital management is the cash flow bullwhip (CFB) effect, a phenomenon that amplifies working capital fluctuations as one moves upstream in the SC, leading to increased financial strain and risk for upstream members (Tangsucheeva & Prabhu, 2013). The CFB effect arises from a combination of operational, financial, and informational factors. Demand variability is identified as one of its primary causes. For instance, even a small shift in consumer demand, whether upward or downward, can trigger disproportionately large fluctuations in upstream orders, as each tier adjusts inventory levels to manage uncertainty. Additionally, asymmetric payment terms (where upstream suppliers experience immediate cash outflows but receive delayed payments from downstream partners), order batching practices, extended or uncertain lead times, and limited visibility into actual consumer demand collectively exacerbate the CFB effect (Lamzaouek et al., 2021).

The automotive sector provides a real-world illustration of the CFB effect. During the COVID-19 pandemic, as consumer demand rebounded unexpectedly in late 2020, automakers rapidly increased replenishment orders. This sudden escalation forced Tier 1 and Tier 2 suppliers to incur immediate expenses to restart production lines, procure raw materials, and rehire labor. However, delayed payments from automakers led to a rise in accounts receivable for these upstream suppliers. As a result, they experienced amplified working capital volatility, exemplifying the CFB effect through disproportionate fluctuations in working capital relative to changes in demand (PwC, 2021).

Empirical studies further underscore the significance of this issue. For example, Drissi et al. (2023) analyzed data from 51 Moroccan fast-moving consumer goods companies, revealing that small and medium-sized enterprises (SMEs) experienced an average 43% increase in accounts receivable due to extended trade credit periods imposed by downstream SC partners. These disruptions intensified working capital variability relative to changes in demand, highlighting the presence of the CFB effect. Similarly, Patil and Prabhu (2024a), in their analysis of 763 U.S. public companies from 2010 to 2019, found that the CFB effect impacted 37% of retailing, 43% of wholesaling, and 81% of manufacturing firms. Their findings emphasize that upstream SC members, who often experience delayed cash inflows and heightened liquidity constraints, are particularly vulnerable. This underscores the need for strategies that address the structural causes of the CFB effect across SC tiers.

Traditional approaches to addressing the CFB effect, such as demand forecasting, have often failed due to persistent data silos, limited visibility, and a lack of trust among participants (Riahi et al., 2023). Data silos occur when different entities within a SC, such as suppliers, manufacturers, distributors, and retailers, fail to effectively share critical data (Alzoubi & Yanamandra, 2020). Each entity operates autonomously with its own objectives, priorities, and internal systems, creating barriers to data exchange (Kembro & Näslund, 2014; Nurhayati et al., 2023). Technological disparities can contribute significantly to data silos; entities often utilize disparate Enterprise Resource Planning (ERP) systems or other technological platforms. These systems may employ different data formats, structures, or protocols, complicating the integration and exchange of data across the SC (Chen et al., 2015; Tavana et al., 2020). This lack of effective data sharing results in fragmented landscapes where each participant only has a partial view of the overall SC operations (Khanuja & Jain, 2020).

Moreover, a lack of trust among participants exacerbates persistent data silos, as firms are often reluctant to share sensitive financial and operational data with their partners (Müller et al., 2020). This distrust undermines the effectiveness of traditional working capital strategies, such as demand forecasting, leading to decision-making based on incomplete, outdated, or inaccurate data. The reluctance to collaborate across organizational boundaries hinders coordinated responses and perpetuates inefficiencies throughout the SC (Gligor et al., 2019).

Blockchain technology offers a novel solution to the problems of data silos, limited visibility, and distrust among SC participants. Its decentralized architecture ensures that all SC members have access to the same data on product, order, and cash flows, thereby eliminating data silos (Wan et al., 2020; Xue et al., 2025). Blockchain maintains an immutable and cryptographically secured ledger, ensuring data integrity and authenticity while preventing unauthorized modifications (Dahal, 2023). This transparency reduces information asymmetry, fosters trust among participants, and promotes accountability, making blockchain uniquely suited to overcoming the data silos, limited visibility, and distrust that hinder traditional approaches to working capital management. By enhancing trust and visibility simultaneously, blockchain enables more reliable demand forecasting and the coordinated execution of working capital policies across SC tiers (Gazzola et al., 2023).

Data shared through blockchain must be effectively utilized to mitigate the CFB effect in SCs. Accurately measuring the CFB effect is essential, and simulation modeling is widely used for assessing SC performance indicators, including the CFB, because it captures the dynamics of product, order, and cash flows (Jahani et al., 2023; Xu et al., 2024). However, simulation models mainly identify policies to mitigate the CFB effect through what-if analysis, which can become cumbersome when evaluating numerous scenarios (Badakhshan et al., 2024). Machine learning (ML) offers a means to analyze large datasets and extract meaningful patterns (Mehdiyev et al., 2024). This enables decision-makers to identify effective strategies to prevent the CFB effect. However, ML models require substantial volumes of data, which can be generated through simulation.

Integrating simulation with decision trees enhances efforts to prevent the CFB effect in SCs. Simulation captures the complex dynamics of financial and operational flows within the SC, generating extensive data under a variety of policy and environmental conditions. This data is then used to train decision trees, which produce transparent, rule-based outputs. For example, a decision rule might state: *"If the desired inventory at the middle echelon exceeds X, then reduce the desired work-in-progress at the lower and middle echelons to Y and Z, respectively, to avoid the CFB effect."* These if–then rules are directly interpretable by non-technical stakeholders, including supply chain managers, and offer clear, actionable guidance for adjusting inventory decisions, cash collection policies, and trade credit terms. By making ML outputs interpretable, this integration provides a practical decision-support framework that enables managers to implement targeted interventions to prevent the CFB effect.

Despite the significant potential of blockchain technology to mitigate the CFB effect in SCs, its application in this context remains largely unexplored. Existing studies on blockchain for working capital management in SCs have primarily focused on enhancing transparency, automating transactions via smart contracts, and improving security (e.g., Bhusari et al., 2023; Chen et al., 2024). Additionally, although there is a growing body of literature on the integration of simulation models with ML techniques for SC management (e.g., Badakhshan & Ball, 2024), their application to addressing the CFB effect remains limited.

To address these gaps, this study is guided by two research questions: (1) How can blockchain-enabled data sharing contribute to mitigating the CFB effect and stabilizing financial flows in SCs? (2) How effective is the integration of simulation and machine learning techniques in preventing the CFB effect in SCs? These questions aim to explore the potential of emerging digital technologies in enhancing transparency, coordination, and financial stability across SC networks.

This research contributes by offering a transformative approach to managing cash flow in SCs, aligning with the broader trend of digitalization, and enhancing visibility and transparency (Cui et al., 2023a; Dolgui & Ivanov, 2022; Iftikhar et al., 2024; Ivanov, 2021). The findings will provide valuable insights for both academic researchers and industry practitioners focused on ensuring the financial stability of SCs.

This paper is structured as follows: Sect. 2 offers a comprehensive review of existing literature, identifying research gaps. In Sect. 3, the simulation modeling of the CFB effect in a multi-stage SC is described. Section 4 discusses the proposed Frameworks for addressing the CFB effect. Section 5 presents experimental results and provides recommendations for practitioners. Finally, Sect. 6 summarizes the findings and suggests directions for future research.

2 Literature review

This study covers three major research domains: the CFB effect, hybrid simulation-ML for supply SC management, and blockchain-based solutions for working capital management in SCs. Accordingly, the literature review is organized around these themes. These research strands are integrated to evaluate the effectiveness of hybrid simulation-ML, enabled by blockchain-based data sharing, in mitigating the CFB effect.

2.1 CFB effect

The CFB effect refers to a phenomenon analogous to the traditional bullwhip effect observed in material flows, but it pertains specifically to cash flows. While the bullwhip effect captures the amplification of demand variability as it propagates upstream, resulting in inventory and production inefficiencies, the CFB effect reflects the amplification of working capital volatility under similar conditions. It is also conceptually linked to the ripple effect, which describes the cascading impact of disruptions whether operational or financial across multiple tiers of a SC (Dolgui et al., 2020a, 2020b; Ivanov, 2020, 2025a).

Tangsucheeva and Prabhu (2013) defined the ratio of variability in the cash conversion cycle to variability in demand as an indicator of the CFB effect. They identified demand variability and lead time as the primary contributors to the CFB effect in an inventory system utilizing the order-up-to replenishment policy. Goodarzi et al. (2017) further recognized rationing and shortage gaming as principal causes of the CFB effect in inventory systems employing the order-up-to replenishment policy. Chen et al. (2022) expanded on this by measuring the CFB effect in parallel SCs. Their results indicated that competition and market share significantly impact the CFB effect. Sim and Prabhu (2022) investigated the influence of credit risk on the CFB effect, finding that considering credit risk increases the flow of cash from downstream to upstream in a SC, thereby alleviating the CFB effect.

The CFB effect results in inefficiencies such as inventory imbalance and financial strain on upstream SC members. Several studies have identified strategies to mitigate the CFB effect. For instance, Badakhshan et al. (2020) suggest reducing the CFB effect by determining the optimal inventory and financial decisions. Sim and Prabhu (2017) demonstrate that a SC microfinance scheme, where the manufacturer acts as the lender and the supplier as the borrower, can reduce the CFB effect. Lamzaouek et al. (2023) state that reliable SCs are at a lower risk of encountering the CFB effect because they can more effectively manage and predict cash flows, reducing the likelihood of significant variability in cash flow. Drissi et al. (2023) recommend enhancing collaboration among SC members and implementing internal control mechanisms for collecting receivables, paying payables, and managing inventory to reduce the CFB effect. Lamzaouek et al. (2021) highlight the role that digitalization can play in controlling the operational causes of the CFB effect, namely poor demand forecasting, price fluctuations, order batching, lead times, and rationing and shortage gaming.

Patil and Prabhu (2024a) argue that the formula presented by Tangsucheeva and Prabhu (2013) does not accurately measure the CFB effect, as it divides the variance of the cash conversion cycle, which is in time units, by the variance of demand, which is either in monetary or product units. To address this shortcoming, they propose substituting the cash conversion cycle with working capital in the formula presented by Tangsucheeva and Prabhu (2013). Therefore, in the new formulation, the CFB effect is defined as the ratio of variability in working capital to variability in demand. Patil and Prabhu (2024b) employ the new formula to calculate the CFB effect for 786 companies over a 10-year period and verified its existence in real-world SCs.

While previous studies have explored strategies like optimizing inventory and financial decisions to address the CFB effect within SCs, none have specifically investigated blockchain-based solutions for reducing this effect. To address this gap, our research aims to assess the effectiveness of blockchain in mitigating the CFB effect. Additionally, no studies have integrated simulation and ML to tackle the CFB effect in SCs. To fill this gap, we propose an approach that combines simulation and ML to address the CFB effect.

2.2 Hybrid simulation-ML for SC management

Hybrid simulation-ML refers to the integration of simulation models with ML techniques to address complex decision-making tasks in dynamic environments (Badakhshan et al., 2024; Brailsford et al., 2019). This approach has garnered significant attention in SC management for its ability to enhance decision-making and operational efficiency. By combining the strengths of simulation methods and ML algorithms, hybrid approaches offer dynamic and adaptive solutions to the complexities of SCs. Simulation models, such as discrete-event or agent-based simulations, capture the intricate interactions and behaviors within SCs, while ML leverages data-driven insights to optimize decision variables, predict demand patterns, and detect anomalies (Mustafee & Fakhimi, 2024). This literature review explores the growing body of work on hybrid simulation-ML applications in SC management, highlighting key contributions and gaps in existing research. The review categorizes the literature into three groups based on the three main ML techniques: supervised learning, unsupervised learning, and reinforcement learning.

The first group of studies integrated simulation with supervised learning methods to address SC problems. For instance, Le and Xuan-Thi-Thu (2024) combined the predictive capabilities of an artificial neural network (ANN) with the dynamic modeling capabilities of simulation to develop a comprehensive tool for analyzing and improving sustainable SC operations in the seafood industry. Zhang et al. (2024) coupled simulation modelling with an ANN to conduct pre-crisis performance assessment in a humanitarian SC. Similarly, Ogunsoto et al. (2025) employed simulated data to train an ANN for predicting production network recovery time following disruptions.

Yang et al. (2023) combined simulation with an ANN to identify process-switching strategies that enable firms to promptly adjust their production lines in response to global SC disruptions. Similarly, Roozkhosh et al. (2023) and Liebenberg and Jarke (2023) used data generated by simulations to train ANNs, enhancing resilience and improving production scheduling in SCs, respectively. In another study, Gružauskas et al. (2019) applied an ANN to forecast demand and incorporated these predictions into a simulation model to reduce food waste. Additionally, Badakhshan and Ivanov (2025) and Badakhshan and Ball (2024) used simulation to train decision tree models for SC master planning and responsive working capital management, respectively, under disruption scenarios. Bodendorf et al. (2022) used data generated by discrete-event and Monte Carlo simulations to train a deep neural decision tree (DNDT), a supervised learning model that integrates neural networks with decision tree structures, to optimize operational decisions in automotive SCs. Sankaran et al. (2022) and Behnamfar et al. (2022) employed data from discrete-event and system dynamics simulations to train ANNs for forecasting dynamic behavior and supporting decision-making in complex SC networks under uncertainty.

The second group of studies integrated simulation with unsupervised learning methods to address SC problems. For example, Weihrauch et al. (2018) used simulation to assess the impact of disruptions identified through clustering analysis on SC performance. Wang et al. (2020) employed discrete-event and system dynamics simulation to generate data for principal component analysis (PCA), which was then used to detect SC disruptions. Similarly, Jacobson et al. (2021) and Karimi-Mamaghan et al. (2020) combined simulation models with the K-means clustering algorithm to tackle SC configuration and production planning problems, respectively.

The third group of studies integrated simulation with reinforcement learning to address SC problems. For example, El Shar et al. (2022), Mehta and Yamparala (2014), and Wang et al. (2022) utilized simulation to facilitate the training of reinforcement learning models for inventory planning in SCs. Additionally, Gutierrez-Franco et al. (2021) developed a simulation environment for a reinforcement learning agent to learn optimal routes in a vehicle route planning problem. Pouri (2025) developed a simulation environment for a reinforcement learning agent focused on predictive maintenance. Clark and Kulkarni (2021) integrated discrete-event, agent-based, and system dynamics simulations to train an RL agent for inventory planning. Similarly, Gros et al. (2020) combined discrete-event and Monte Carlo simulations to train an RL agent for production planning.

While previous studies have integrated simulation and ML techniques, including supervised, unsupervised, and reinforcement learning, to address various SC challenges such as demand forecasting, inventory optimization, and disruption recovery, these efforts have primarily focused on performance improvement using black-box models. Few studies have explored the use of interpretable machine learning methods in conjunction with simulation, and none have examined this integration in the context of preventing the CFB effect. This study fills these gaps by combining discrete-event simulation with decision trees to produce transparent, rule-based insights. The resulting framework supports financially informed decision-making by aligning operational policies with cash flow stability objectives across the supply chain.

2.3 Hybrid simulation for SC management

In recent years, researchers have increasingly adopted hybrid simulation, which involves integrating two or more modeling approaches such as discrete-event simulation (DES), agent-based simulation (ABS), and system dynamics (SD) to capture different aspects of SC dynamics (Kar et al., 2025). Hybrid simulation has been applied across various domains of SC management.

Hybrid simulation has been applied to manufacturing networks to evaluate long-term performance and sustainability. Barbosa et al. (2023) presented a tri-method model (SD + DES + ABS) for an aerospace make-to-order chain, showing that greener configurations can be assessed without sacrificing process detail. Complementing this, Ferreira et al. (2025) integrated DES material-flow blocks with ABS autonomous machines to test “Supply-Chain 4.0” levers, finding that smart factory investments reduce emissions without harming service levels. Kamal et al. (2025) coupled SD price dynamics with ABS farmer and trader agents in the global coffee chain, illustrating that fair-profit-sharing stabilizes prices and supports smallholders. Fani et al. (2022) employed a hybrid DES-ABS model to quantify how fashion-rental logistics and refurbishment cycles alter carbon footprints compared to traditional “buy-and-keep” models. Similarly, Farsi et al. (2019) developed a modular ABS-DES framework for a regulated cell and gene therapy manufacturing system, enabling scalable simulation of repeated production modules under stochastic and dynamic conditions. The developed model demonstrated high accuracy in performance estimation and supported resource planning under uncertainty.

In the agri-food domain, Vempiliyath et al. (2021) built an ABS-DES framework for the Atlantic salmon SC, where autonomous farmer-agents interact with detailed fish-growth and processing processes. Harvest-scheduling experiments showed improved throughput and inventory balance, demonstrating how hybrid simulation bridges micro-level behavior and process-flow analysis.

Operational logistics networks have also benefited from hybrid simulation to optimize performance under complexity. Farhan et al. (2023) created a cloud-based ABS-DES yard model for Amazon fulfillment centers, enabling what-if experiments that reduce congestion and cut costs. Similarly, Gu and Kunk (2020) employed an ABS-DES model to optimize omnichannel retail operations, where agent-based modeling captures individual customer purchasing and delivery decisions, and discrete-event simulation handles fulfillment logistics. Their model demonstrates the importance of integrating behavioral dynamics with logistical processes for effective strategy evaluation in modern retail SCs. Xu et al. (2021) integrated an ABS of additive-manufacturing decision-makers with a DES spare-parts flow for fighter jet maintenance, revealing that decentralized 3D printing cuts lead time and boosts readiness. Luevano and Barrientos (2022) combined DES order-processing blocks with courier and customer agents, showing how last-mile capacity bottlenecks erode e-commerce service levels.

Hybrid simulation has also emerged as a powerful analytical approach for modeling and stress-testing SC resilience to pandemic and other disruption shocks. Camur et al. (2023) developed a SD model to generate non-stationary, pandemic-driven demand signals that feed a DES representation of an end-to-end oxygen concentrator SC, enabling rapid evaluation of capacity expansion and inventory policies under surge conditions. Mahachi et al. (2022) fed an SD pandemic-infection loop into an ABS semiconductor production network and showed that flexible capacity and higher safety stocks mitigate COVID-19-induced chip shortages.

Hybrid simulation has further proven valuable in humanitarian SCs, where multiple agencies and resource flows must be coordinated. Krejci (2015) proposed an ABS–DES framework that represents both the decision-making behaviors of humanitarian actors and the stochastic flow of relief goods, arguing that such a hybrid lens is essential for analyzing how coordination mechanisms affect long-term efficiency and effectiveness. Building on this foundation, Sharif et al. (2023) integrated an ABS of emergency-response actors with a SD model of societal dynamics to test post-earthquake relief strategies, finding that stronger inter-agency coordination accelerates infrastructure restoration and service delivery.

Collectively, these studies demonstrate the versatility of combining DES, ABS, and SD. By capturing multi-scale feedback, heterogeneous agent decisions, and detailed process dynamics in unified models, hybrid simulation delivers richer insights for designing resilient, sustainable, and efficient SCs in an increasingly uncertain world.

Despite its growing adoption, hybrid simulation for SC analysis still inherits a well-known limitation of simulation in general: insights depend on what-if experiments, which explore only a narrow set of scenarios (Badakhshan et al., 2024). Integrating simulation modeling with ML algorithms can address this shortcoming. In such an integrated framework, the simulation generates large volumes of data, which ML algorithms can analyze to identify broader patterns and predictive rules. Explainable ML techniques, such as decision trees, are preferable because they produce transparent, rule-based insights that decision-makers can readily interpret (Puthanveettil Madathil et al., 2025). Accordingly, this study combines decision trees with simulation modeling to address the CFB effect in SCs.

2.4 Blockchain-based solutions for working capital management in SCs

Blockchain technology has gained considerable attention as a potential solution for enhancing working capital management in SCs. Several studies have explored the advantages and challenges associated with implementing blockchain-based solutions for managing working capital within SCs.

A primary advantage of blockchain technology is its capacity to enhance transparency and trust within SCs, which directly supports more effective working capital management. Natanelov et al. (2022) emphasize that blockchain's immutable record-keeping reduces fraud and dispute risks. Blockchain-driven platforms for SC working capital management, as explored by Chen et al. (2024), Chen et al. (2020), Guo et al. (2022), and Zuo et al. (2022) leverage blockchain's trust mechanisms to establish a reliable, transparent business environment. These platforms improve visibility and accountability, ultimately creating more efficient and secure processes in SC working capital management. In particular, the transparency provided by blockchain has led to innovative applications to minimize late payments in SCs, improving cash flow reliability and predictability (Luo et al., 2019; Scott et al., 2024; Yoon & Pishdad-Bozorgi, 2022).

Furthermore, blockchain enhances product traceability within SCs, increasing supplier accountability for quality issues. Cui et al. (2023b) examine blockchain’s role in SC quality contracting, demonstrating how the technology can identify sources of quality issues and enable firms to implement contingent payment systems based on quality metrics. This approach optimizes working capital allocation by linking cash flows to product quality.

Blockchain-based solutions also improve efficiency and security in SC working capital workflows. Studies by Pushpa et al. (2024), Choi (2023) and Bhusari et al. (2023) suggest that blockchain-based working capital management outperforms traditional methods in terms of speed and security, while Chen et al. (2020) demonstrate how smart contracts facilitate partial automation of SC working capital processes. Wise et al. (2020) propose a blockchain-based approach that enables the derivative trade of mineral stockpiles through smart contracts, allowing for earlier access to working capital tied to underlying assets.

Blockchain can mitigate SC working capital risks by addressing information asymmetries that often lead to inefficient working capital allocation. Li et al. (2019) review limitations in traditional SC working capital risk management, suggesting that blockchain's transparency could address these challenges. Wang and Wang (2022) also highlight blockchain's role in optimizing risk control systems and reducing costs. Dahdal et al. (2020) notes blockchain's potential in managing cash flows and reducing counterparty risk, which is crucial for small and medium-sized enterprises (SMEs).

In times of systemic disruption, blockchain can support SC cash flow stability. For instance, Yang (2021) examines the impact of COVID-19 pandemic, including cash flow crises, and introduces blockchain-based approaches, such as accounts receivable financing, to alleviate cash flow challenges for SMEs. Hamledari and Fischer (2021) explore disruptions in the construction industry, proposing blockchain-based crypto assets to synchronize product and payment flows, thereby improving integration and supporting working capital continuity during disruptions.

Despite its potential benefits, implementing blockchain-based solutions for working capital management in SCs presents several challenges. Natanelov et al. (2022) highlight the need to ensure data privacy and security, integrate blockchain with existing systems, address scalability issues, navigate regulatory hurdles, and establish trust among SC participants. Sangari et al. (2025) indicate that, although discussions primarily emphasize the technological drivers of blockchain adoption for working capital management, practitioners place greater importance on non-technological factors, including peer adoption and innovation promotion.

Tsai (2023) and Bhusari et al. (2023) also caution about limited adoption and regulatory constraints, suggesting a cautious approach to the use of blockchain in SC working capital management. Additionally, the inherent complexity of blockchain and concerns about participant readiness may further hinder its adoption (Bogucharskov et al., 2018). Hamledari and Fischer (2021) underscore the need for further investment in data-driven solutions to fully capitalize on blockchain's benefits, such as data accuracy and completeness.

While prior research has emphasized the advantages of blockchain, such as enhanced transparency and traceability in SC working capital management, there remains a notable gap in the literature regarding its potential to reduce the CFB effect within SCs. To bridge this gap, our study seeks to evaluate the effectiveness of blockchain-based solutions in mitigating the CFB effect. We adopt a blockchain framework that functions as a data-sharing infrastructure and enables the implementation of adaptive financial controls across the SC. These controls are informed by insights generated through simulation modeling and explainable ML techniques.

2.5 Summary of literature review

A review of the literature on the CFB effect, hybrid simulation-ML approaches for SC management, and blockchain-based solutions for working capital management in SCs reveals two key gaps: (1) the effectiveness of blockchain in mitigating the CFB effect in SCs has not been explored; (2) the effectiveness of integrated simulation-ML modeling in preventing the CFB effect in SCs has not been investigated. To address the first gap, we propose a blockchain framework and assess its impact on the CFB effect in SCs. To address the second gap, we develop an integrated simulation-ML framework that combines discrete-event simulation (DES) and decision trees to identify working capital policies aimed at preventing the CFB effect. Notably, the simulation-ML framework leverages data sharing facilitated by the blockchain framework.

Table 1 presents an overview of existing research on the CFB effect, hybrid simulation-ML in SC management, and blockchain-based solutions for working capital management in SCs. A key observation is that while some studies, such as Patil and Prabhu (2024a, 2024b), analyze the CFB effect across industries and discuss mitigation strategies, they do not provide methods to prevent this undesirable effect. Other studies, such as Badakhshan and Ball (2024) and Ogunsoto et al. (2025), employ hybrid simulation-ML techniques, yet focus on SC disruptions and resilience strategies rather than the financial instability caused by the CFB effect. Similarly, several studies including Chen et al. (2024) and Scott et al. (2024) explore blockchain applications in SC working capital management but do not address the CFB effect.

Table 1 Summary of Literature review

References	Study focus	CFB effect addressed	Blockchain-enabled data sharing	Hybrid simulation-ML	Relevance to our study
Patil and Prabhu (2024a)	Empirical analysis of CFB effect across industries	✓	–	–	Demonstrates that CFB varies by industry but does not prevent the CFB effect
Patil and Prabhu (2024b)	Measuring CFB effect in SCs	✓	–	–	Analyzes mitigation strategies but does not prevent the CFB effect
Badakhshan and Ball (2024)	Hybrid simulation-ML for SC disruption management	–	–	✓	Integrate simulation and ML but do not address the CFB effect
Le and Xuan-Thi-Thu (2024)	Assessing sustainable SC operations in Vietnam's seafood industry	–	–	✓	Integrate simulation and ML but do not address the CFB effect
Zhang et al. (2024)	Coupling simulation and ML for predictive analytics in SCs	–	–	✓	Integrate simulation and ML but do not address the CFB effect
Pouri (2025)	Coupling simulation and ML to enhance maintenance scheduling	–	–	✓	Integrate simulation and ML but do not address the CFB effect
Ogunsoto et al. (2025)	Digital supply chain twin framework for resilience and recovery	–	–	✓	Integrate simulation and ML but do not address the CFB effect
Sangari et al. (2025)	Blockchain adoption in SC working capital management	–	✓	–	Examines blockchain adoption but does not address the CFB effect
Chen et al. (2024)	Blockchain's impact on SC working capital management	–	✓	–	Examines blockchain in SC working capital management but does not address the CFB effect
Scott et al. (2024)	Blockchain for payment automation	–	✓	–	Uses blockchain for payment automation but does not address the CFB effect
Pushpa et al. (2024)	Blockchain integration into SC working capital management through IoT-based automation	–	✓	–	Uses blockchain for financial transparency but does not address the CFB effect

Table 1 (continued)

References	Study focus	CFB effect addressed	Blockchain-enabled data sharing	Hybrid simulation-ML	Relevance to our study
This study	Integrating simulation and decision trees via blockchain-enabled data sharing to prevent the CFB effect in SCs	✓	✓	✓	Integrate simulation, decision trees, and blockchain to prevent the CFB effect, filling a key research gap

This study makes a novel contribution by integrating blockchain-enabled data sharing, decision trees, and DES to prevent the CFB effect in SCs. Unlike prior research, it presents a proactive solution that leverages blockchain for financial transparency and hybrid simulation–decision trees for informed decision-making. This approach addresses a critical gap in the literature and offers a practical roadmap for mitigating financial instability in SCs.

3 SC simulation modeling

Conceptual modeling is the first step in developing a simulation model. The purpose of conceptual modeling is to define the structure and operation of the SC being analyzed. It is crucial for creating an abstract, high-level representation of the SC system, focusing on critical elements such as product flow, inventory management, and cash flow dynamics (Robinson, 2020). Conceptual modeling involves simplifying the system to highlight its key components and interactions while omitting unnecessary details (Robinson, 2015). Effective conceptual modeling requires a clear understanding of how each component in the system interacts, which is vital for building a simulation model that accurately reflects real-world dynamics (Gabriel et al., 2022).

For this study, we analyze a three-echelon, single-product SC comprising a manufacturer, two distributors, and three retailers. The manufacturer delivers products to both distributors, with distributor 1 supplying retailers 1 and 2, and distributor 2 supplying retailer 3. This structure is represented in the network diagram (Fig. 1), which is a key part of the conceptual model. The diagram visually represents the echelons and their interactions, where each node corresponds to a SC member (manufacturer, distributor, or retailer), and directed arrows between the nodes illustrate the flow of orders, products, and cash.

In addition to showing the relationships between echelons, the network diagram incorporates key operational parameters, such as lead times and production capacity. Shipments from the manufacturer to distributors and from distributors to retailers involve a one-week lead time, while customer pickups at retailers are instantaneous. The manufacturer can produce up to 50,000 units per week. Customer demand is uniformly distributed, with retailer 1 receiving between 5000 and 10,000 units per week, retailer 2 between 4000 and 8000 units, and retailer 3 between 6000 and 12,000 units.

The network diagram also reflects the cash collection policy within the SC. Sales transactions are a mix of cash and credit, with each SC member paying 10% of the order value in

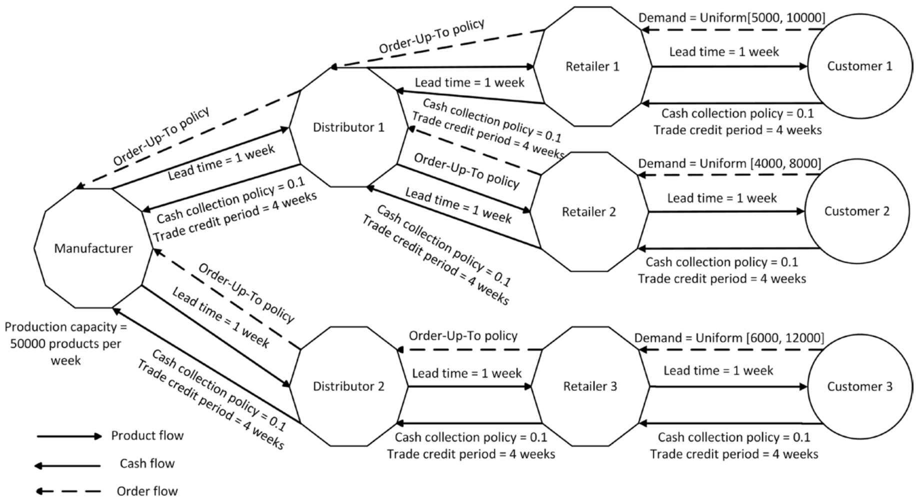

Fig. 1 SC network diagram (Adapted from Badakhshan & Ivanov, 2025)

cash up front and the remaining 90% after a four-week trade credit period. Additionally, the diagram illustrates an Order-Up-To (OUT) inventory policy with a weekly review period. These elements form the basis for the next phase of the modeling process, where the system's behavior will be simulated to evaluate the effects of various operational strategies.

Building on the conceptual model, the next step is model building, where a simulation model is developed to analyze and test the SC's performance. We use discrete event simulation (DES) to simulate the dynamics of inventory management, demand fulfillment, and cash flow within the SC. During this stage, interactions defined in the conceptual model, such as order placement, are formalized in a simulation structure that tracks SC performance over time. DES is widely applied in SC studies due to its ability to capture complex interactions and dependencies among SC entities (Dagkakis & Heavey, 2016; Ivanov, 2019). By simulating discrete SC events, DES provides insights into how various factors influence performance metrics and supports the evaluation of strategies to improve SC performance (Ivanov, 2017, 2025b; Tako & Robinson, 2012).

The DES model is built on the conceptual representation shown in Fig. 1, with each SC member's activities modeled as discrete events occurring over time. The three SC echelons follow a periodic review inventory policy with a weekly review period. Each SC member proceeds through the following steps in every period:

1. Deliveries from the previous period arrive after a one-week lead time and are added to the current stock, with storage capacity assumed to be unrestricted.
2. Available inventory is first allocated to satisfy downstream requests and to clear any pending backlogs.
3. Shipments are dispatched to the next echelon, inventory records are updated, and any unfulfilled demand is recorded as a new backlog.
4. The replenishment order for the upstream partner is determined using the order-up-to (OUT) policy described in Eq. (1).

Each SC member determines its order quantity (O) to meet the anticipated demand from the next downstream node ($\overline{D}$) and to correct any discrepancies between actual inventory and work-in-progress (WIP) levels and their respective desired values. The demand forecast is computed using a historical averaging method in which each SC member calculates the arithmetic mean of all past demand observations received from its immediate downstream partner. For example, retailers forecast future customer demand based on the average of previous customer orders, distributors use the average demand received from retailers, and the manufacturer relies on the average of aggregated distributor orders. This cumulative averaging method is particularly suitable under the assumption of stationary and uniformly distributed demand as it effectively smooths out random fluctuations over time.

To compute the inventory gap, the net inventory (NI), calculated as available stock minus any pending backorders (B), as expressed in Eq. (2), is compared with the target inventory (DI). The WIP gap is evaluated in the same way by taking the difference between the desired WIP and the current WIP, which accounts for items ordered from the supplier but not yet received. Because these discrepancies cannot be completely resolved in one review cycle, a smoothing approach is applied where the gap contributions are weighted by α and β. Larger values of α and β amplify the effect of the inventory and WIP gaps, respectively, on the resulting order decision.

$$O_t = Max(0, \overline{D} + \alpha \underbrace{(DI - NetI_t)}_{Inventory\,gap} + \beta \underbrace{(DWIP - WIP_t)}_{WIP\,gap} \tag{1}$$

$$NetI_t = I_t - B_t \tag{2}$$

Upon placing an order, each SC member is required to make an advance payment (AP), as determined by Eq. (3), which is calculated by multiplying the upstream member's cash collection policy (UCP) by the total order value. The total order value is the product of the order quantity (O) and the price per item charged by the upstream member (P1). The remaining portion of the order value is recorded as a credit purchase (CP), as defined by Eq. (4), and is settled once the trade credit period agreed upon with the upstream partner expires. Simultaneously, each SC member receives an advance payment (AC) from its downstream partner, as calculated by Eq. (5), by multiplying its cash collection policy (CP) by the downstream member's demand value. Any remaining balance of that demand is considered a credit sale (CS), as expressed in Eq. (6), which will be collected after the negotiated trade credit period (TCP) with the downstream partner.

$$AP_t = UCP * O_t * P1 \tag{3}$$

$$CP_t = (1 - UCP) * O_t * P1 \tag{4}$$

$$AC_t = CP * D_t * P \tag{5}$$

$$CS_t = (1 - CP) * D_t * P \tag{6}$$

The simulation model is developed using Simpy, a process-based discrete-event simulation library in Python, to examine CFB effect dynamics within the SC. By leveraging Simpy, the model can replicate the sequence and timing of key SC operations, including inventory replenishment, cash flow transactions, and demand fulfillment, allowing for a granular analysis of SC behavior.

To measure the CFB effect, we use the ratio of working capital (WCL) variability to demand (D) variability as defined by Patil and Prabhu (2024a) and formalized in Eq. (7). This metric is essential for assessing how demand fluctuations amplify throughout the SC, impacting the working capital required by each SC member. Using variability rather than a static metric captures both the magnitude and responsiveness of SC members' financial and operational resources to external changes, offering a comprehensive measure of the CFB effect.

Working capital, detailed in Eq. (8), comprises inventory (I), cash (CH), receivables (R), and payables (P), each of which contributes to the SC member’s operational stability and demand fulfillment capabilities. This broad perspective on working capital allows the simulation to examine how each component fluctuates with demand variability, highlighting which factors most significantly impact working capital needs.

$$CFB_t = \frac{Var(WCL)}{Var(D)} \tag{7}$$

$$WCL_t = I_t + CH_t + R_t - P_t \tag{8}$$

The simulation runs over a 52-week period (one fiscal year) with a 20-week warm-up period to ensure the system reaches a steady operational state before data collection begins, mitigating potential biases from initial conditions (Mahajan & Ingalls, 2004). This setup enables the model to track working capital fluctuations accurately while assessing SC strategies designed to mitigate the CFB effect. By adjusting parameters such as cash collection policies, the model provides insights into how different working capital strategies influence the extent of the CFB effect. Ultimately, this analysis aids in designing targeted interventions to enhance SC financial stability, aiming to keep CFB values below 1 for SC members amidst demand variability.

To support methodological clarity, Fig. 2 presents a simulation process flow diagram that illustrates the sequential steps involved in executing the model. The diagram outlines the configuration of key input parameters, the generation of stochastic demand from three customers, inventory updates, order placement using the Order-Up-To (OUT) policy, execution of financial transactions, and the calculation of working capital and CFB values.

It also highlights verification and validation steps. 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 (Manuj et al., 2009). This process includes monitoring the simulation runs to detect any discrepancies or anomalies and analyzing the output data to ensure alignment with anticipated patterns. This proactive approach helps to identify and resolve potential coding errors, logic flaws, or parameter inconsistencies that may affect model fidelity.

To validate the simulation results, we conduct 100 replications for each set of simulation parameters. This entails running the simulation multiple times with varying random seeds and input values to capture the inherent variability and randomness in the system (Sargent, 2010). By comparing the results across these replications, we assess the consistency and

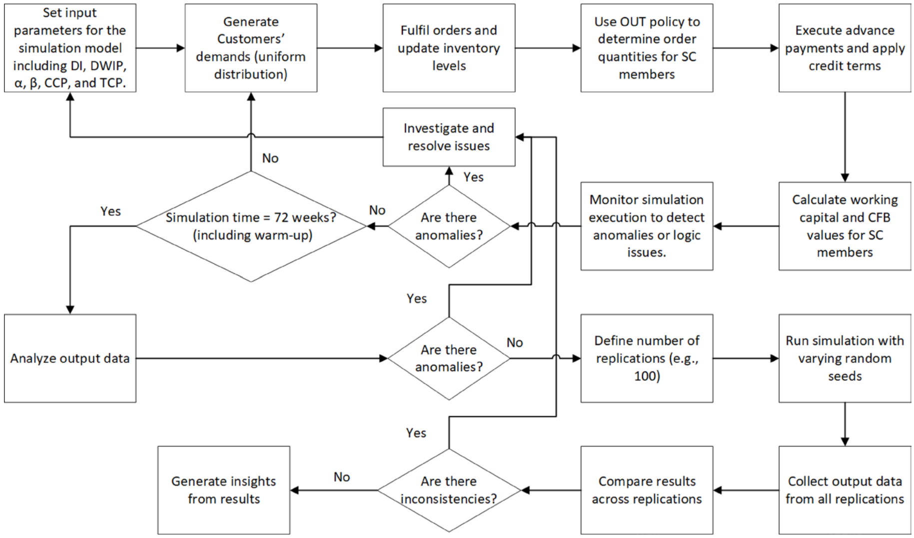

Fig. 2 Simulation process flow diagram

robustness of the simulation output. Any significant discrepancies among replication results are investigated to maintain model reliability and accuracy.

This thorough verification and validation approach strengthens the model's credibility, ensuring it provides a sound basis for analyzing and testing SC strategies aimed at mitigating the CFB effect.

To complement the existing description of verification and validation procedures, Table 2 presents a structured verification and validation matrix detailing the procedures applied to each major model component. The matrix specifies the relevant inputs and outputs, and delineates the techniques employed to verify correct implementation and to validate behavioral accuracy.

4 Frameworks for improving SC transparency and addressing the CFB effect

This section introduces two key frameworks designed to improve SC operations. The first framework leverages blockchain technology to enhance transparency by providing visibility into order and cash flows. The second framework integrates simulation and ML to address the CFB effect. By simulating SC dynamics and generating decision rules, this framework aims to identify working capital policies that prevent the CFB effect. Notably, the simulation-ML framework leverages data sharing facilitated by the blockchain framework.

4.1 Blockchain framework for enhanced SC transparency

Several blockchain frameworks such as Hyperledger Fabric (Androulaki et al., 2018) and Corda (Brown et al., 2016) have been developed for SC management. These frameworks provide foundational infrastructure for building distributed, permissioned networks that

Table 2 Simulation model verification and validation matrix

Model component	Inputs	Outputs	Verification method(s)	Validation method(s)
Customer demand generation	Demand distribution parameters (uniform)	Weekly customer demand per retailer	Time series generation trace	Comparison with theoretical distribution
Order quantity calculation (OUT policy)	Inventory gap, WIP gap, $\overline{D}$, α, β	Order quantity per SC member per week	Boundary checks, logical rule consistency	Output consistency with known inventory dynamics
Inventory update	Order quantities, deliveries, initial inventory	Updated inventory/WIP levels per member	Mass balance and negative inventory tests	Consistency with expected WIP flow under stable input
Working capital calculation	Inventory, receivables, payables, cash	Weekly working capital values	Formula consistency with accounting rules	Comparison with benchmark case outputs
CFB ratio computation	Working capital, demand	CFB values per SC member	Code logic checks	Checks for CFB pattern consistency across runs
Payment and credit execution	Trade credit parameters, cash payment policy	Cash flow position after payments	Time alignment in transaction logging	Tracing cash flow updates over time in sample scenarios
Multi-run replication logic	Random seed, number of replications	Distribution of CFB and working capital statistics	Consistent seed initialization and replication control	Convergence testing across replications
Output analysis and insight generation	Output data from all replications	Validated interpretations of trends and anomalies	Output format and unit consistency	Scenario-based trend evaluation and sensitivity checks

enable secure, verifiable data exchange among SC participants. A range of enterprise-grade solutions have been implemented using these frameworks. For instance, IBM Food Trust, built on Hyperledger Fabric, has been deployed to improve traceability and food safety by enabling end-to-end visibility of product flows across the agri-food SC (Kamath, 2018). Similarly, TradeLens, also based on Fabric, was designed to streamline maritime logistics by digitizing shipping documents and enhancing data interoperability among carriers, ports, and customs authorities (Jovanovic et al., 2022). In the financial services domain, Corda has been used to develop platforms such as Marco Polo (Chaudhury et al., 2023) and Contour (Rijanto, 2021), which support digital trade finance by connecting banks and corporate clients to automate invoicing, payment commitments, and letter of credit issuance.

Despite these advancements, the existing blockchain-based SC management solutions primarily focus on traceability, regulatory compliance, and transactional efficiency, with an emphasis on improving visibility and reducing manual reconciliation. However, they largely overlook the CFB effect. In contrast, our proposed framework targets the mitigation of the CFB effect by enabling real-time sharing of operational and financial indicators (e.g., inventory levels, WIP levels, trade credit terms). This approach not only enhances transparency but also supports adaptive coordination of cash flow and inventory policies, offering a novel contribution to blockchain-enabled working capital management in SCs.

From a ledger architecture perspective, blockchain frameworks typically adopt either a global or channelized (local) model (Taherdoost, 2022). Frameworks such as VeChainThor use a global ledger, granting all participants access to a common ledger. While this promotes transparency and immutability, it raises concerns about confidentiality, competitive sensitivity, and data governance, particularly in SCs handling proprietary information (Chang et al., 2020). In contrast, Hyperledger Fabric employs a channelized architecture, sharing data only within predefined subgroups. This enhances privacy but introduces coordination complexity, data silos, and fragmented analytics, hindering end-to-end visibility (Abang et al., 2024).

To address these limitations, our framework adopts a hybrid ledger architecture that balances privacy with selective transparency (Alkhateeb et al., 2022). Built on a unified permissioned network, it enforces fine-grained access control and cryptographic safeguards to regulate data visibility. Shared data includes working capital policy parameters such as inventory levels, work-in- WIP levels, and trade credit terms as well as customer demand information which is critical for synchronized planning and forecasting. These data elements are accessible to authorized members, while sensitive financial data such as unit costs and profit margins remains restricted to bilateral or consortium-level access. This design enables stakeholders to collaborate on mitigating the CFB effect by exchanging relevant operational and financial indicators without exposing sensitive information across the entire network.

Building on this, the proposed blockchain framework supplies shared ledger data to an integrated simulation and ML framework which dynamically adjusts trade credit periods, cash collection policies, and inventory control parameters based on evolving conditions. This data-driven mechanism aims to mitigate the CFB effect in the SC and represents an innovative application of blockchain technology in the domain of working capital management.

The proposed framework leverages a permissioned blockchain to securely share critical data within the studied SC, which includes one manufacturer, two distributors, and three retailers. The use of a permissioned blockchain ensures that only authorized participants can access and modify the shared data, thereby enhancing both security and privacy (Thantharate & Thantharate, 2023). Figure 3 shows the sequence of steps in the proposed blockchain framework designed to enhance SC transparency.

4.1.1 Identity verification by Certificate Authority

In the first step, each participant's identity and role within the SC are verified through a Certificate Authority (CA) which issues digital certificates to authenticate the nodes. The CA plays a critical role in establishing trust within the network by ensuring that only legitimate SC members can participate. This mechanism prevents unauthorized access and ensures that

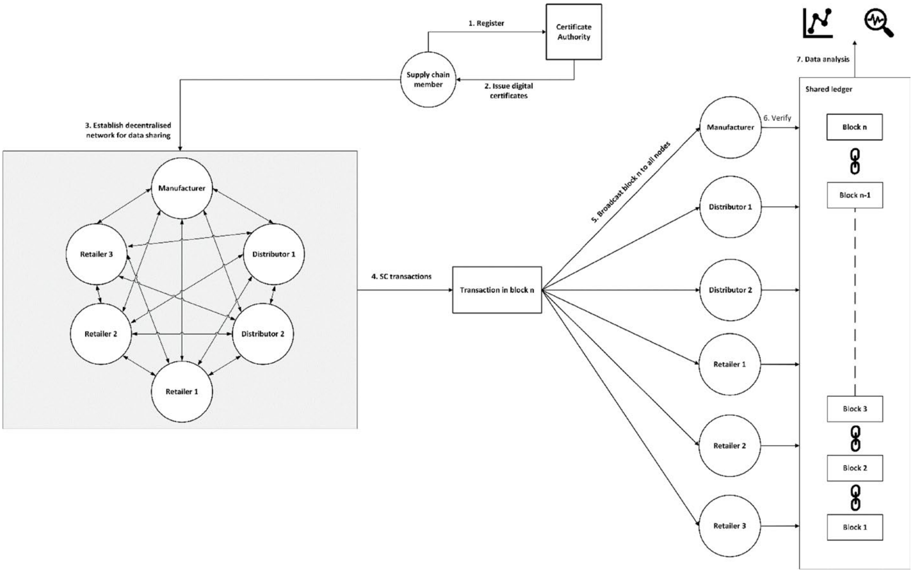

Fig. 3 Blockchain framework for enhanced SC transparency

all data transactions are traceable and verifiable (Centobelli et al., 2022). The CA must be trusted by all SC members. In the proposed blockchain framework, an independent third-party CA is selected to manage the issuance and validation of digital certificates.

An independent third-party CA provides neutrality, ensuring that no single participant within the SC holds disproportionate influence over the network's security infrastructure. This impartiality is critical for maintaining trust among all members, as each participant can be confident that the CA operates without bias or favoritism (Durach et al., 2021). This neutrality fosters trust among SC members and mitigates conflicts of interest within the network (Alsadi et al., 2023). Moreover, third-party CAs possess specialized expertise in digital identity verification and cybersecurity, ensuring robust processes for issuing and managing digital certificates (Dos Santos et al., 2021). Compliance with regulatory requirements, facilitated by the CA's expertise, ensures alignment with legal mandates such as GDPR, enhancing overall security and regulatory compliance (Sunny et al., 2020). By outsourcing certificate management to an independent third-party CA, SC members can optimize operational efficiency and focus on core business activities (Chang et al., 2020). This approach enables scalable security solutions while reducing the burden of managing complex security processes internally.

4.1.2 Establishment of decentralized network and data sharing

In the second step, the SC network is established to facilitate data sharing among its members. In this blockchain-enabled ecosystem, each SC participant functions as a node within the network, creating a decentralized and collaborative environment where data integrity and transparency are prioritized. The manufacturer, distributors, and retailers share data on their desired inventory levels, desired work-in-progress (WIP) levels, inventory proportional controllers, WIP proportional controllers, cash collection policies, and trade credit periods, promoting transparency and collaboration throughout the SC. Additionally, retailers share customer demand data, enriching the collective understanding of market dynamics that is essential for accurate demand forecasting across the SC.

4.1.3 Transaction initiation and validation

Following the establishment of the decentralized network and data sharing infrastructure within the blockchain-enabled ecosystem for the SC, the subsequent step involves transaction initiation and validation. In this phase, SC participants use the decentralized network to initiate transactions by submitting various types of data, such as desired inventory levels, which are then recorded on the blockchain ledger. These transactions serve as the mechanism through which data are exchanged between participants in the SC ecosystem. Upon submission, the transactions undergo a validation process to ensure their integrity and compliance with network rules. This validation typically occurs through a consensus mechanism, where network nodes collectively verify the validity of transactions before they are added to the blockchain.

In the proposed blockchain framework for SC, the Reputation-Based Proof of Cooperation (RPoC) consensus mechanism is employed to ensure secure, efficient, and trustworthy validation of transactions among known participants. RPoC is specifically designed for permissioned blockchain networks composed of identified and vetted entities such as the manufacturer, distributors, and retailers in the studied SC (Sarfaraz et al., 2023). Unlike traditional consensus mechanisms that rely on computational power (e.g., Proof of Work) or strict fault-tolerance protocols (e.g., PBFT), RPoC leverages a reputation system that evaluates participants based on their historical behavior, cooperation level, and compliance with network protocols (de Oliveira et al., 2020).

This consensus mechanism offers several advantages aligned with the operational and financial needs of the SC. First, it enhances scalability and transaction throughput by limiting consensus participation to high-reputation nodes, reducing communication overhead while maintaining trust (Hussain et al., 2025; Zhou et al., 2025). Second, by encouraging cooperative behavior, RPoC supports the collaborative nature of SC processes, particularly in contexts involving real-time sharing of sensitive operational and financial data (Li et al., 2020). Third, RPoC is energy-efficient, avoiding the computational intensity of PoW-based systems and making it a sustainable solution for enterprise environments (Aluko & Kolonin, 2021). Finally, its design ensures network resilience and data integrity, as the consensus is achieved through a trust-weighted process rather than equal node voting, reducing the risk posed by dishonest actors (Bao et al., 2023). Given these attributes, RPoC is particularly well-suited to the goals of the proposed blockchain framework, which seeks to enable secure, transparent, and adaptive coordination in working capital management and mitigate the CFB effect in SCs.

4.1.4 Data recording and auditing

Following transaction initiation and validation in the proposed blockchain framework for the SC, the subsequent step is data recording and auditing. In this phase, validated transactions are cryptographically secured and appended to the blockchain ledger in a sequential, immutable manner, ensuring the integrity of the chain (Politou et al., 2019). All network nodes update their copies of the distributed ledger to maintain synchronization and consistency across the network. Continuous verification processes check the cryptographic hashes to detect and prevent any tampering attempts, while compliance and reporting mechanisms provide transparent and auditable records of all transactions, facilitating regulatory adherence (Akanfe et al., 2024). This process ensures that all transactions are transparent, tamper-proof, and traceable, thereby establishing a trusted record of events within the SC ecosystem.

4.1.5 Data analysis and decision making

Following data recording and auditing in the blockchain framework for the SC, the subsequent step involves data analysis and decision-making. This phase focuses on leveraging securely recorded and audited data to derive actionable insights and improve SC operations (Dolgui et al., 2020a, 2020b). The transparent and reliable data provided by the blockchain framework fosters collaborative decision-making among SC partners, enabling alignment of strategies and achievement of shared objectives (Rejeb et al., 2021). For instance, SC members may continuously monitor CFB values across the chain and refine working capital policies accordingly to mitigate the CFB effect.

4.2 Integrated simulation and decision trees framework for addressing CFB effect

To address the CFB effect, combining simulation with decision trees offers a promising approach to improving decision-making. In this study, we propose an integrated simulation-decision trees framework, as shown in Fig. 4. Data shared through the blockchain is input into the simulation model, which mirrors the physical SC by capturing the dynamics of product, order, and cash flows. The simulation generates data on working capital policies and their corresponding average CFB values for the SC, which is then used by the decision tree model. The decision tree model, in turn, provides decision rules for establishing working capital policies, enabling decision-makers to identify policies that eliminate the CFB effect in the SC.

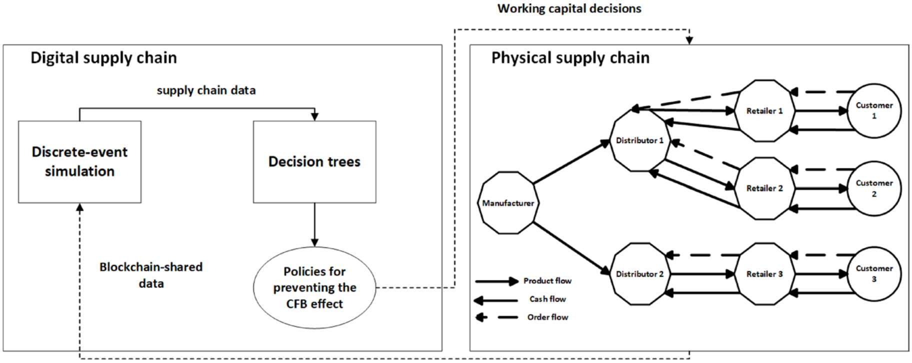

Fig. 4 Integrated simulation and decision trees framework

4.2.1 Inherent versus post-hoc Interpretability

ML interpretability methods fall into two categories: inherently interpretable models and post-hoc explanation techniques (Rudin, 2019). Inherently interpretable models, such as decision trees are self-explanatory by design. Their internal decision structure can be directly examined to understand the rationale behind each prediction. Post-hoc explainability tools, including SHAP (Lundberg & Lee, 2017) and LIME (Ribeiro et al., 2016) approximate the behavior of complex black-box models (e.g., ensembles or neural networks) by generating local surrogate explanations.

We adopted decision trees for three main reasons. First, they offer global interpretability, meaning that the entire decision logic can be directly inspected from input to output. This property is essential in SC contexts, where transparency defined as the ability for stakeholders to understand how and why a decision is made is critical for operational trust and policy auditability (Bhargavi et al., 2025).

In contrast, post-hoc explainability methods such as SHAP and LIME provide only local approximations of complex model behavior. While these tools are valuable for interpreting black-box models, they can suffer from fidelity issues. That is, the explanations they generate may not accurately reflect the model's true internal reasoning (Slack et al., 2020). Such discrepancies can lead to misleading interpretations, particularly in high-stakes domains like SC management. In our setting, where both interpretability and transparency must align with actual model behavior, decision trees offer a more appropriate and reliable solution.

Second, computational efficiency was essential for our deployment scenario. Post-hoc methods introduce non-trivial inference overheads and additional layers of abstraction, making them less suitable for low-latency, resource-constrained applications (Arya et al., 2019). Third, decision trees present logic in the form of explicit rule paths which are generally easier to interpret than attribution-based explanations that require interpreting abstract statistical outputs (Lipton, 2018). These considerations led us to select decision trees as a practical balance between interpretability, efficiency, and predictive performance for identifying policies that prevent the CFB effect in SCs.

5 Results and discussion

In this section, we first examine the existence of the CFB effect in the SC by running the simulation model described in Sect. 3, with the results presented in Sect. 5.1. We then assess the effectiveness of the blockchain framework illustrated in Fig. 3 in mitigating the CFB effect, with findings reported in Sects. 5.2 through 5.6. In Sect. 5.7, we evaluate the integrated simulation–ML framework shown in Fig. 4, analyzing its effectiveness in preventing the CFB effect in the SC. Finally, in Sect. 5.8, we present both theoretical and practical perspectives.

5.1 Scenario 0. No data sharing

We run the simulation model for 52 weeks. The input parameters are set as follows: The proportional controllers for inventory and WIP (α and β) for all SC members are set to 0.5, consistent with previous literature (e.g., Aslam & Ng, 2016). The desired inventory and WIP levels for retailers are defined based on the peak customer demand, for instance, 8000 units for retailer 2. For distributors and the manufacturer, these desired levels are set at 1.5 times the peak demand. Sensitivity analysis with factors ranging from 1 to 1.5 times the maximum demand indicated that values below 1.5 lead to insufficient inventory across SC members, limiting their ability to meet downstream demand and reducing the service level below the 95% target.

This setup serves as a baseline scenario, showing CFB values for SC members without data sharing through blockchain. We then compare the impact of blockchain-enabled data sharing on CFB values against this baseline.

Figure 5 illustrates the working capital and CFB values for different SC members. Working capital increases as we move upstream in the SC because upstream members hold higher inventory levels than their downstream counterparts.

All three retailers exhibit CFB values below 1, demonstrating that fluctuations in their working capital are not magnified relative to variations in customer demand. In contrast, the average CFB values for distributor 1, distributor 2, and the manufacturer exceed 1, suggesting that these upstream members experience amplified cash flow oscillations. This pattern confirms the presence of the CFB effect in upstream SC members, with the highest intensity observed at the manufacturer.

To assess the impact of different lead times on CFB values of SC members, we vary lead times between SC members from 1 to 4 weeks. Table 3 reports the results, showing that all SC members experience rising CFB values as lead times increase. The retailers' values, though starting below 1, eventually rise to values above 1, indicating the presence

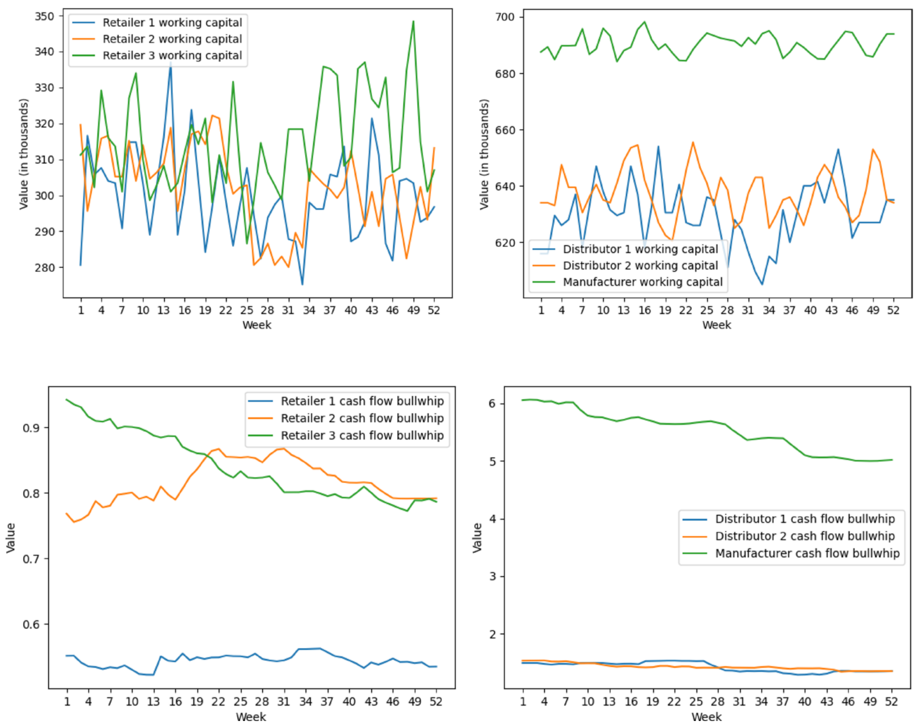

Fig. 5 Experiment results. No data sharing scenario

Table 3 Average CFB values for SC members under different lead times

Average CFB	Lead time (L)			
	L=1	L=2	L=3	L=4
Retailer 1	0.55	0.86	1.22	1.46
Retailer 2	0.83	1.05	1.39	1.53
Retailer 3	0.86	1.14	1.35	1.69
Distributor 1	1.62	1.94	2.27	2.95
Distributor 2	1.83	2.16	2.48	3.11
Manufacturer	5.41	5.62	5.87	6.34

of the CFB effect. The primary driver behind this result is that longer lead times amplify inventory variability, which in turn magnifies working-capital variability relative to demand variability.

In the following scenarios, SC members utilize the blockchain framework presented in Fig. 2 and described in Sect. 4.1 to share data on end customers' demands, desired inventory levels, desired work-in-progress (WIP) levels, inventory proportional controllers, WIP proportional controllers, cash collection policies, and trade credit periods.

5.2 Scenario 1. Forecasting using end customers' demands

Blockchain-enabled data sharing ensures that each party within the SC has access to the same set of data. Consequently, they can generate forecasts directly from end customers' demands rather than relying on demand received from immediate downstream members. Figure 6 illustrates the impact of forecasting using end customers' demands by SC members on working capital and CFB values across various SC members.

There is no significant reduction in the working capital levels for retailers because, similar to Scenario 0, their demand forecasts are based on actual customer demand. However, noticeable reductions in working capital occur for the manufacturer and distributors. For instance, in this scenario, the average working capital of the manufacturer is 644, whereas it is 685 in Scenario 0. This reduction is attributed to distributors and the manufacturer using customer demand in their forecasts instead of the demand received from retailers and distributors, respectively.

Consistent with Scenario 0, all retailers exhibit CFB values below 1, reflecting that their working capital is effectively managed in relation to fluctuations in customer demand. Upstream in the SC, we observe a reduction in CFB values compared to Scenario 0. For instance, the average CFB value for the manufacturer decreases from 5.4 in Scenario 0 to 2.3 in the current scenario.

The impact of forecasting using end customers' demands on CFB reduction is more pronounced for upstream SC members due to increased demand distortion. The reduction in CFB values for the manufacturer and distributors demonstrates the effectiveness of forecasting using end customers' demands in mitigating the CFB effect, leading to more stable and efficient working capital management across the SC.

5.3 Scenario 2. Increasing cash collection policies for upstream members

In this scenario, SC members with an average CFB value greater than 1, namely the manufacturer and distributors, request a proportional increase to their cash collection policy. For

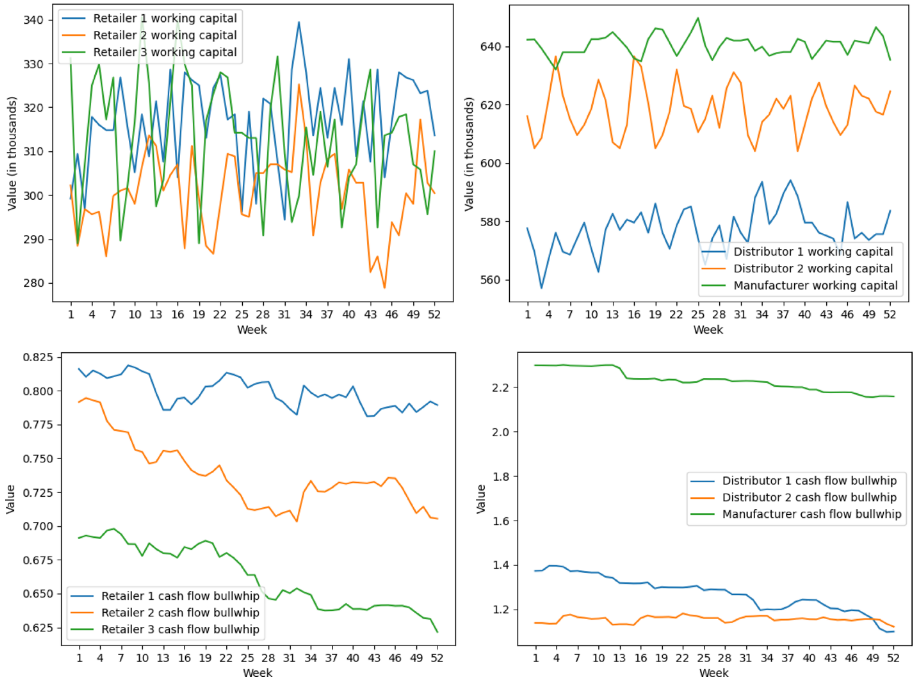

Fig. 6 Experiment results. Forecasting using end customers' demands scenario

example, a member with an average CFB value of 5 requests a five-fold increase to its cash collection policy. This adjustment in the cash collection policy must be approved and recorded on the blockchain.

In Scenario 0, the average CFB values for distributor 1, distributor 2, and the manufacturer are 1.6, 1.8, and 5.4, respectively. Consequently, distributor 1, distributor 2, and the manufacturer request a 1.6-fold, 1.8-fold, and 5.4-fold increase to their original cash collection policy of 0.1.

Figure 7 illustrates the impact of increasing cash collection policies for the manufacturer and distributors on working capital and CFB values across various SC members. There is no significant change in the average working capital levels for retailers because their cash collection policies remain unchanged at 0.1. However, there is a noticeable reduction in the average working capital for the manufacturer, which increases its cash collection policy. Compared to Scenario 0, the average working capital for the manufacturer reduces by 25% in this scenario, from 685 to 511.

Although distributors 1 and 2 increased their cash collection policies, their average working capital levels increased. This result arises because the effects of the 1.6 and 1.8-fold increases for distributors 1 and 2, respectively, were negated by the manufacturer's substantial 5.4-fold increase in its cash collection policy.

Regarding the CFB values, the manufacturer experiences a decrease compared to Scenario 0, indicating an improvement. However, the CFB values for distributors 1 and 2 increases. This outcome shows that while Scenario 2 helps reduce the CFB for the manufac-

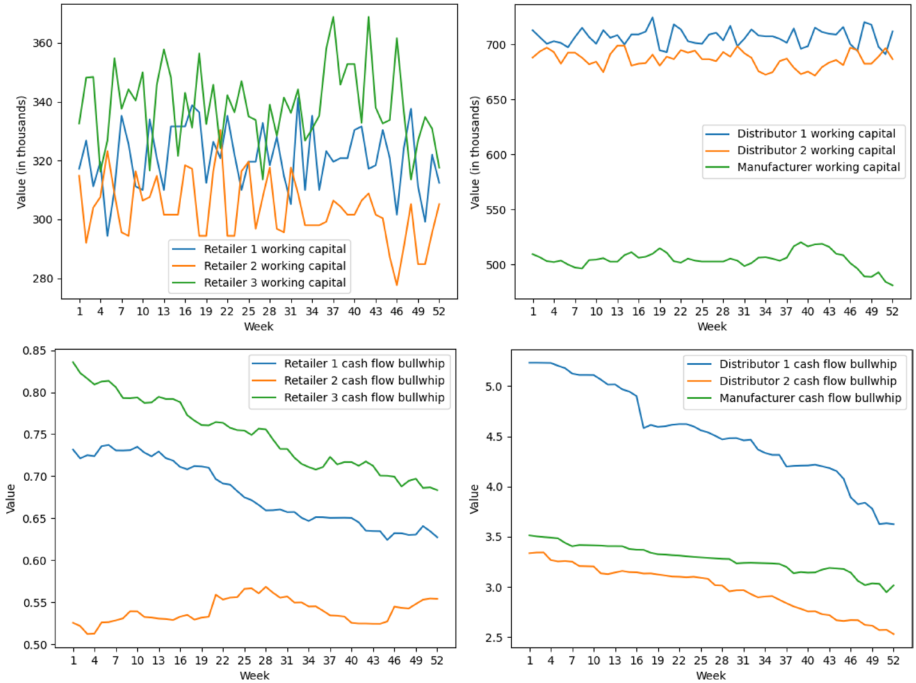

Fig. 7 Experiment results. Increasing cash collection policies for upstream members scenario

turer, it does not achieve an overall reduction in CFB values for all SC members. Instead, it merely transfers the CFB burden from the manufacturer to the distributors.

5.4 Scenario 3. Uniformly increasing cash collection policies for all SC members

In this scenario, the average CFB within the SC network is measured, and a proportional increase in the cash collection policies of all SC members is proposed via the blockchain. In Scenario 0, the average CFB for SC members, including manufacturers, distributors, and retailers, is 2.2. Therefore, a 2.2-fold increase to the original cash collection policies of 0.1 is requested, resulting in a cash collection policy of 0.22 for all SC members.

Figure 8 illustrates the impact of uniformly increasing cash collection policies for all SC members on working capital and CFB values across various SC members. There is no significant change in the working capital levels for retailers and distributors, as the cash collection policy increases by these members are offset by the cash collection policy increases by their upstream SC members. However, the average working capital for the manufacturer, which did not face a cash collection policy increase from its suppliers, reduces by 6% in this scenario compared to Scenario 0, decreasing from 690 to 651. This occurs because increasing the cash collection policy reduces the receivables of the manufacturer while its payables remain unchanged, consequently decreasing its average working capital. With a cash collection policy of 0.22, the average receivables for the manufacturer are 432, compared to 694 in Scenario 0.

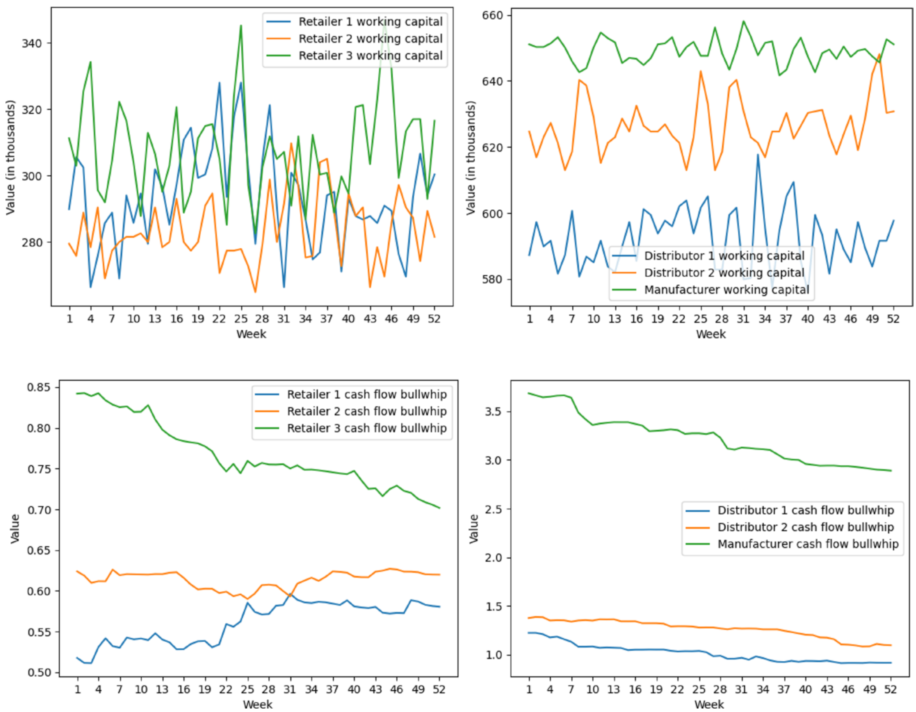

Fig. 8 Experiment results. Uniformly increasing cash collection policies for all SC members scenario

CFB values for retailers remain below 1, indicating the absence of a CFB effect at the retail level. Moreover, CFB values at distributors and manufacturers reduce compared to Scenario 0. For instance, the average CFB value for the manufacturer dropped from 5.4 in Scenario 0 to 3.4 in this scenario. This demonstrates that a uniformly increasing cash collection policies for all SC members leads to a reduction in CFB values for all SC members. In contrast, as shown in Scenario 2, increasing cash collection policies for only manufacturers and distributors merely transfers the CFB burden from the manufacturer to the distributors.

5.5 Scenario 4. Forecasting using end customers' demands and uniformly increasing cash collection policies for all SC members

This scenario integrates scenarios 1 and 3. SC members utilize end customers' demands for forecasting and propose a 2.2-fold increase in the original cash collection policies, from 0.1 to 0.22, for all SC members. The 2.2-fold increase reflects the average CFB value across all SC members.

Figure 9 illustrates the impact of forecasting using end customers' demands and uniformly increasing cash collection policies for all SC members on working capital and CFB values across various SC members. There is no significant change in the average working capital levels for retailers, as retailers' demand forecasts are based on actual customer demand even in the absence of data sharing. Moreover, the cash collection policy increases by retailers are offset by the cash collection policy increases by their upstream SC mem-

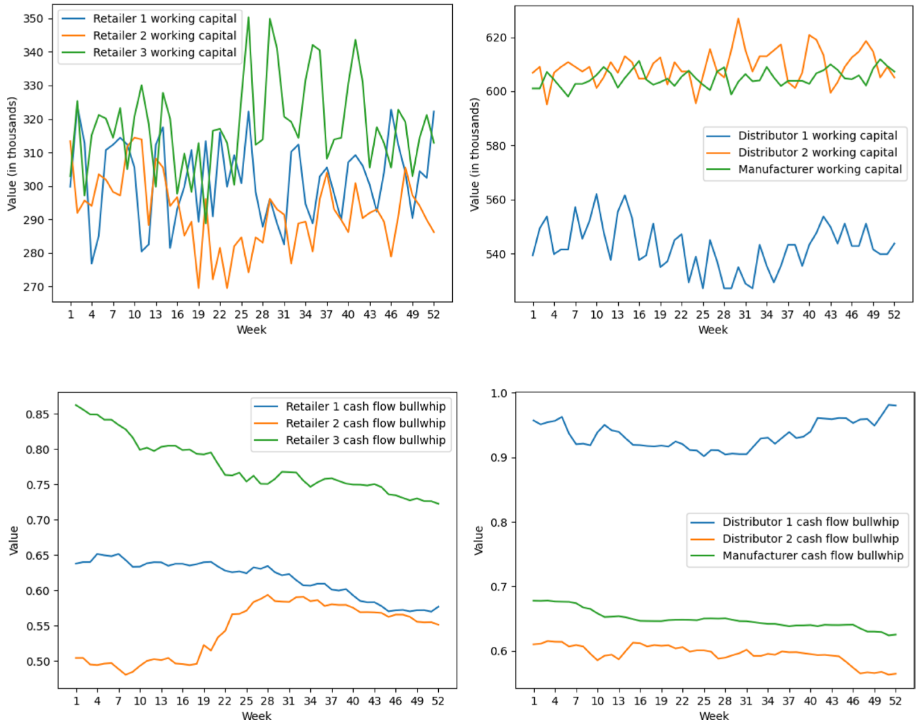

Fig. 9 Experiment results. Forecasting using end customers' demands and uniformly increasing cash collection policies for all SC members scenario

bers, i.e., distributors. However, the average working capital levels for distributors and the manufacturer decrease as they use customer demand in their forecasts instead of the demand received from retailers and distributors, respectively. Additionally, the manufacturer increases its cash collection policy but does not face a cash collection policy increase from its suppliers. The average working capital levels of distributor 1, distributor 2, and the manufacturer reduce by 13%, 7%, and 12%, respectively, in this scenario compared to scenario 0.

CFB values for all SC members remain below 1, indicating the absence of the CFB effect in the SC. The reduction in CFB values is significant for upstream SC members. For instance, the average CFB value for the manufacturer dropped from 5.4 in Scenario 0 to 0.65 in this scenario. This demonstrates that forecasting using end customers' demands and uniformly increasing cash collection policies for all SC members eliminate the CFB effect in the SC.

5.6 Sensitivity analysis

The results of scenario 3 indicate that increasing the cash collection policies of all SC members by a factor equal to the average CFB for SC members reduces the CFB effect. However, this strategy does not eradicate the CFB effect. In this section, we conduct sensitivity analysis on the cash collection policy to explore the impact of further increases on the

CFB effect. We incrementally increase the factor multiplying cash collection policies for SC members by 0.1, starting from the average CFB of the SC (i.e., 2.2), to investigate potential thresholds associated with eliminating the CFB effect. Table 4 presents the results of the sensitivity analysis. In scenarios 0, 1, 2, and 3, distributors and the manufacturer experience CFB values greater than 1. Therefore, the average CFB values for these members are used as indicators of the CFB effect.

5.6.1 Scenario 5. Uniformly increasing cash collection policies for all SC members by 2.6-fold

In this scenario, a 2.6-fold increase in the original cash collection policies, from 0.1 to 0.26, is proposed for all SC members. The reason for choosing the 2.6-fold increase is that at this threshold, the CFB value for the manufacturer drops below 2, as illustrated in Table 1.

Figure 10 illustrates the impact of this increase on working capital and CFB values across the SC. Similar to scenario 3, there is no significant change in the working capital levels for retailers and distributors, as the cash collection policy increases by these members are offset by the cash collection policy increases by their upstream SC members. However, the average working capital for the manufacturer, which did not face a cash collection policy increase from its suppliers, decreased by 4% in this scenario compared to Scenario 3, reducing from 651 to 623. This reduction occurs because increasing the cash collection policy reduces the receivables of the manufacturer while its payables remain unchanged, leading to a decrease in the average working capital of the manufacturer. The average receivables for the manufacturer with a cash collection policy of 0.26 is 410, whereas in scenario 3, the average receivables for the manufacturer is 432.

Similar to scenario 3, the average CFB values for retailers remain below 1, indicating the absence of a CFB effect at the retail level. Moreover, the average CFB value for the manufacturer decreases compared to Scenario 3. Specifically, the average CFB value for

Table 4 Impact of increasing cash collection policies for upstream SC members

Factor multiplier for cash collection policy	Average CFB for distributor 1	Average CFB for distributor 2	Average CFB for manufacturer
2.2	1.08	1.54	3.40
2.3	1.02	0.96	2.83
2.4	1.19	1.06	2.60
2.5	1.39	0.83	2.02
2.6	1.15	1.12	1.47
2.7	1.39	0.76	1.88
2.8	1.14	0.78	1.86
2.9	1.57	0.88	1.54
3	1.19	1.12	1.58
3.1	1.20	1.05	1.30
3.2	1.40	1.06	1.41
3.3	1.56	1.07	1.42
3.4	0.94	0.86	1.37
3.5	1.21	0.63	1.32
3.6	1.24	0.69	1.10
3.7	0.87	0.82	0.95

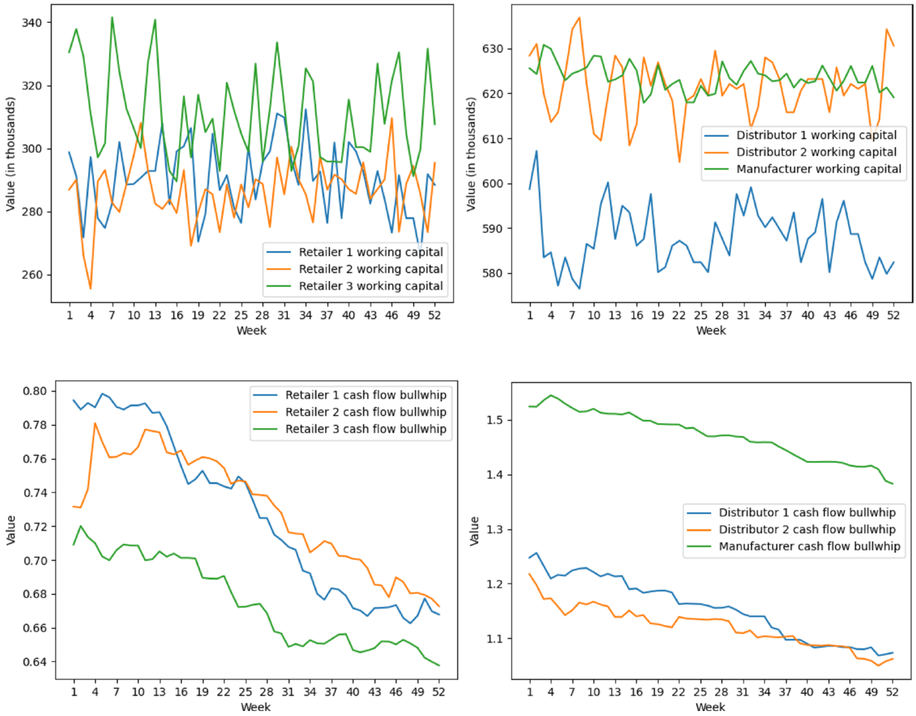

Fig. 10 Experiment results. 2.6-fold increase in the original cash collection policies scenario

the manufacturer drops from 3.4 in Scenario 3 to 1.47 in this scenario, while there is no considerable change in the CFB values for the distributors.

5.6.2 Scenario 6. Uniformly increasing cash collection policies for all SC members by 3.7-fold

In this scenario, a 3.7-fold increase in the original cash collection policies of 0.1 is requested for all SC members. The reason for choosing the 3.7-fold increase is that at this threshold, the CFB value for the manufacturer drops below 1, as illustrated in Table 3.

Figure 11 illustrates the impact of this increase on working capital and CFB values across the SC. Similar to scenario 5, there is no significant change in the working capital levels for retailers and distributors, as the cash collection policy increases by these members are offset by the cash collection policy increases by their upstream SC members. However, the average working capital for the manufacturer, which did not face a cash collection policy increase from its suppliers, decreased by 8% in this scenario compared to scenario 5, decreasing from 623 to 575. This reduction occurs because increasing the cash collection policy reduces the receivables of the manufacturer while its payables remain unchanged, leading to a decrease in the average working capital of the manufacturer. The average receivables for the manufacturer in this scenario is 374, while in scenario 5, the average receivables for the manufacturer is 410.

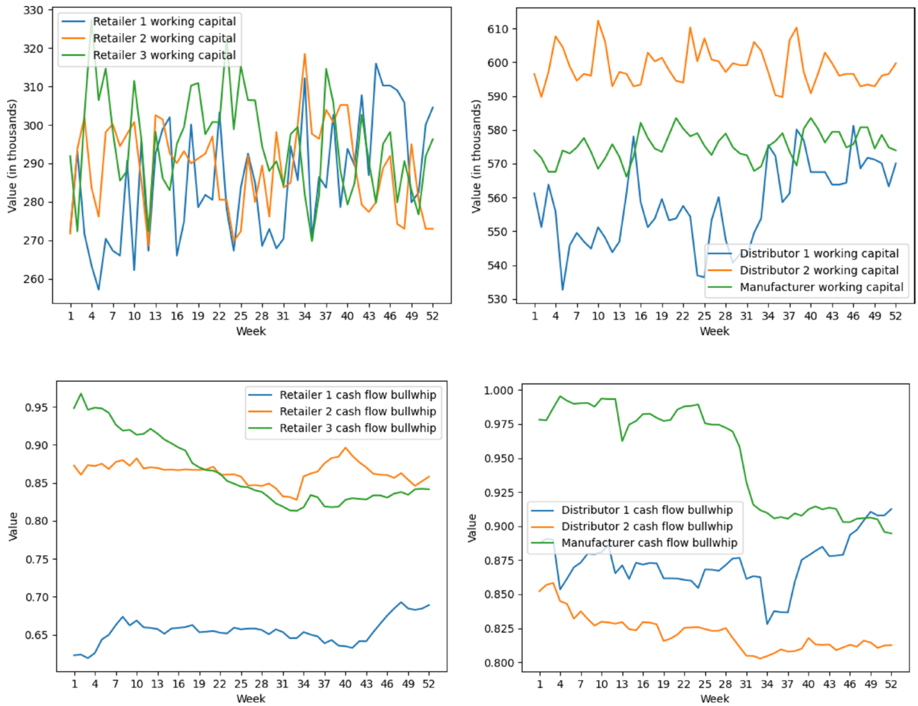

Fig. 11 Experiment results. 3.7-fold increase in the original cash collection policies scenario

Similar to scenario 5, the average CFB values for retailers remain below 1, indicating the absence of a CFB effect at the retail level. Moreover, the average CFB value for the manufacturer decreases compared to scenario 5. Specifically, the average CFB value for the manufacturer drops from 1.47 in scenario 5 to 0.95 in this scenario. Although, the average CFB values for the distributors dropped below 1 in this scenario. We cannot claim that this was caused by the cash collection policy of 0.37, as this also occurs in previous cash collection policies. For instance, the average CFB value for distributor 2 is below 1 with a cash collection policy of 0.23. Similarly, the average CFB value for distributor 1 falls below 1 with a cash collection policy of 0.34.

It is important to note that the results reported in Sects. 5.1–5.6 are derived under the assumption of unlimited storage capacity. This assumption was adopted to isolate the influence of policy parameters on CFB behavior and to simplify model complexity. However, it introduces a limitation that may affect the simulation outcomes. Finite storage capacity can influence working capital dynamics in multiple ways. On one hand, storage constraints may lead to stockouts, which could amplify fluctuations in cash flows and increase the observed CFB effect. On the other hand, SC members may rationally adjust their ordering policies to remain within capacity limits, resulting in leaner inventories and reduced holding costs, which could dampen cash flow variability. Therefore, the net effect of finite storage constraints on cash flow behavior is context-dependent and warrants further investigation.

5.7 Integrating simulation and ML

In this section, we apply the framework outlined in Fig. 4 and described in Sect. 4.2 to derive decision rules for working capital management. The data shared through the blockchain is inputted into the simulation model, which is then run for 10,000 weeks to generate data on working capital policies and their corresponding average CFB values for the SC. We classify the average CFB value into two classes: (1) no CFB effect, defined as an average CFB value less than or equal to 1; and (2) CFB effect, where the average CFB value is greater than 1.

We determine the class of the average CFB value using: (1) demands from customers and SC members (3) inventory policies of SC members, including desired inventory, desired work-in-progress (WIP), inventory proportional controller (α), and WIP proportional controller (β); and (4) cash collection policies and trade credit periods for all SC members.

To obtain the decision rules on working capital management, we employ the CN2 rule induction and C4.5 algorithms. The CN2 rule induction algorithm is specifically designed for generating rules from a set of examples and excels in producing human-readable rules that facilitate better understanding and interpretation of the data (Kumar & Kumar, 2022). It identifies the most significant patterns and relationships within the dataset, which can help decision-makers make informed choices regarding working capital policies. On the other hand, the C4.5 algorithm constructs a decision tree based on information gain, allowing us to visualize the decision-making process and understand how different factors influence working capital management (Cherfi et al., 2018). By leveraging these two algorithms, we can generate robust decision rules that enhance our ability to manage working capital effectively and prevent the CFB effect in the SC.

We use the tenfold cross-validation method to validate the results. This approach randomly divides the dataset into 10 subsets, using 9 for training and knowledge extraction, and repeats the process 10 times. It then reports the average result called accuracy, which represents the performance of the ML algorithm (Badakhshan et al., 2022). We measured the accuracy for different sizes of the training dataset, ranging from 700 to 10,000 examples. The accuracy improves with an increase in the number of examples. However, it stabilizes within a narrow range of 85% to 88% after 1,000 examples for the C4.5 algorithm. The accuracy for the CN2 rule induction algorithm is higher than that of the C4.5 algorithm and ranges from 89 to 93%. The slight variability is mainly due to the randomness of the selected examples in the cross-validation process. Overall, the C4.5 and CN2 rule induction algorithms effectively capture the factors impacting the average CFB values in the SC.

5.7.1 Insights from the C4.5 algorithm

The C4.5 algorithm derives 132 decision rules from 1500 examples. For illustration, Table 5 presents some of these rules, each followed by the number of examples correctly classified out of the total examples meeting the conditions of that rule. These 132 rules form a complex decision tree. To improve clarity, Fig. 12 presents a simplified version of the tree, highlighting the branches generated from the seven control factors, with the class of average CFB value displayed at the bottom of each branch.

A key insight from the decision tree is the hierarchy of factor relevance. The tree identifies distributor 2's desired inventory as the most significant control factor, followed by

Table 5 Extract of the decision rules generated by the C4.5 algorithm

Rule	If	Then	Rule accuracy
1	D2DI < 18 and D1DWIP < 27 and α_m < 0.5 and R3DWIP < 18	No CFB effect	38/38
2	D2DI < 18 and D1DWIP < 27 and α_m < 0.5 and R3DWIP ≥ 18 and R2D-WIP ≥ 10 and R1DWIP < 15	No CFB effect	12/12
3	D2DI < 18 and D1DWIP < 27 and α_m < 0.5 and R3DWIP ≥ 18 and R2D-WIP ≥ 10 and R1DWIP ≥ 15 and β_m ≥ 0.5	No CFB effect	6/6
4	D2DI < 18 and D1DWIP < 27 and α_m ≥ 0.5 and β_{d2} < 0.5	No CFB effect	39/52
5	D2DI < 18 and D1DWIP < 27 and α_m ≥ 0.5 and β_{d2} < 0.5 and MDI ≥ 45 and MDWIP ≥ 45	No CFB effect	17/17
6	D2DI < 18 and D1DWIP < 27 and α_m ≥ 0.5 and β_{d2} < 0.5 and MDI < 45 and R1DWIP ≥ 15 and MDI ≥ 45	CFB effect	4/4
7	D2DI < 18 and D1DWIP ≥ 27 and R1DWIP < 15 and α_{r1} < 0.5 and R3D-WIP ≥ 18 and β_{d1} ≥ 0.5 and β_{r1} < 0.5	CFB effect	6/6
8	D2DI < 18 and D1DWIP ≥ 27 and R1DWIP < 15 and α_{r1} ≥ 0.5 and α_{d1} ≥ 0.5	CFB effect	4/4
9	D2DI < 18 and D1DWIP ≥ 27 and R1DWIP < 15 and α_{r1} < 0.5 and R3D-WIP < 18 and CCP < 0.5	No CFB effect	8/8
10	D2DI < 18 and D1DWIP ≥ 27 and R1DWIP < 15 and α_{r1} < 0.5 and R3D-WIP < 18 and CCP > 0.5	CFB effect	5/5
…			
64	D2DI ≥ 18 and MDWIP < 45 and R1DWIP ≥ 15 and α_{d2} ≥ 0.5 and α_m ≥ 0.5	No CFB effect	19/19
65	D2DI ≥ 18 and MDWIP ≥ 45 and β_{d2} < 0.5 and α_{r1} < 0.5 and R1DI ≥ 15	No CFB effect	25/26
66	D2DI ≥ 18 and MDWIP ≥ 45 and β_{d2} ≥ 0.5 and R1DWIP ≥ 15 and β_{r2} ≥ 0.5	CFB effect	7/7
…			
131	D2DI ≥ 18 and MDWIP ≥ 45 and β_{d2} ≥ 0.5 and R3DWIP ≥ 18 and D1DI < 27	No CFB effect	9/9
132	D2DI ≥ 18 and MDWIP ≥ 45 and β_{d2} ≥ 0.5 and R3DWIP ≥ 18 and D1DI < 27	CFB effect	4/4

Lower echelon controllers: R3DWIP: retailer 3 desired WIP; R2DWIP: retailer 2 desired WIP; R1DWIP: retailer 1 desired WIP; β_{r1}: retailer 1 WIP proportional controller; α_{r1}: retailer 1 inventory proportional controller; R1DI: retailer 1 desired inventory; CCP: cash collection policy; β_{r2}: retailer 2 WIP proportional controller; TCP: trade credit period

Middle echelon controllers: D2DI: distributor 2 desired inventory; D1DWIP: distributor 1 desired WIP; β_{d2}: distributor 2 WIP proportional controller; β_{d1}: distributor 1 WIP proportional controller; α_{d1}: distributor 1 inventory proportional controller; α_{d2}: distributor 2 inventory proportional controller; D1DI: distributor 1 desired inventory

Upper echelon controllers: α_m: manufacturer inventory proportional controller; β_m: manufacturer WIP proportional controller; MDI: manufacturer desired inventory; MDWIP: manufacturer desired WIP

distributor 1's and the manufacturer's desired WIP levels. This suggests that the inventory replenishment policies of upstream SC echelons have a substantial impact on the average CFB value for the SC. Other important factors include the manufacturer's inventory proportional controller (α_m), retailer 1's desired WIP (R1DWIP), and distributor 2's WIP proportional controller (β_{d2}). Interestingly, cash collection (CCP) and trade credit (TCP) controllers rank much lower, indicating that the average CFB value for the SC is more heavily influenced by inventory decisions than by cash flow decisions.

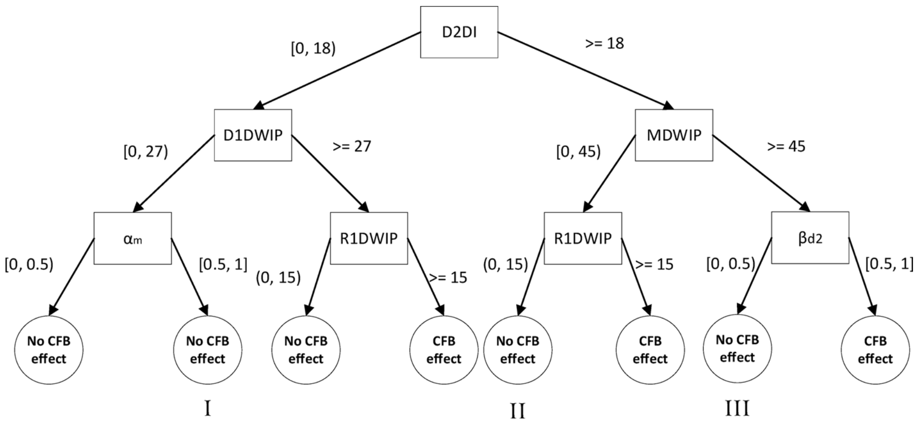

Fig. 12 Simplified decision tree produced by the C4.5 algorithm

Additionally, the decision tree helps decision-makers understand the cause-effect relationships between attribute values and their corresponding CFB class. For instance, Rule I highlights that when D2DI < 18 and D1DWIP < 27, the CFB effect can be avoided even if $\alpha_m \geq 0.5$, indicating that regulating desired inventory and WIP levels at the middle echelon (i.e., distributors) is key to preventing the CFB effect. This is because lower desired inventory and WIP values at the middle echelon lead to reduced demand at the upper echelon, resulting in lower production at the manufacturer level. On the other hand, Rule II indicates that when D2DI ≥ 18, MDWIP and R1DWIP should be set below 45 and 15, respectively, to avoid the CFB effect in the SC. This demonstrates that high desired inventory at the middle echelon must be offset by lower inventory levels at both the upper and lower echelons to prevent the CFB effect. Similarly, Rule III shows that when D2DI ≥ 18 and MDWIP ≥ 45, representing 1.5 times customer 3 demand and 1.5 times total customer demand, respectively, β_{d2} should be set below 0.5 to avoid the CFB effect. This suggests that increasing the desired inventory and WIP levels for the middle and upper echelons should be counterbalanced by reducing the WIP proportional controller for the upper echelon to prevent the CFB effect.

5.7.2 Insights from the CN2 rule induction algorithm

The CN2 rule induction algorithm generates 147 decision rules from 1,500 examples. For illustration, Table 6 presents some of these rules, each followed by a probability, which indicates the likelihood that the rule correctly classifies an instance into a specific class.

Rule 1 generated by the CN2 rule induction algorithm indicates that, to avoid the CFB effect, D2DI, D1DWIP, and R3DWIP should be set to values below 1.5 times customer demand. Additionally, α_m should remain below 0.5 to prevent the CFB effect. This insight aligns with findings from the C4.5 algorithm. Rule 2 recommends setting D2DI and R3DWIP below 1.5 times customer demand and α_{r3} below 0.5 to avoid CFB effect. Additionally, TCL should be kept under 2.5 weeks to prevent the CFB effect.

Rules 3 and 4 from the CN2 rule induction algorithm reveal that overstocking in the middle echelon (i.e., D1DWIP ≥ 27 and D2DWIP ≥ 18) and aggressive strategies for bridging

Table 6 Extract of the decision rules generated by the CN2 rule induction algorithm

Rule	If	Then	Probability (rule accuracy)
1	D2DI < 18 and D1DWIP < 27 and α_m < 0.5 and R3DWIP < 18	No CFB effect	0.98
2	D2DI < 18 and α_{r3} < 0.5 and TCP < 2.5 and R3DWIP < 18	No CFB effect	0.96
3	$\beta_m \geq 0.5$ and D1DWIP ≥ 27 and $\beta_{d2} \geq 0.5$ and $\alpha_{r2} \geq 0.5$	CFB effect	0.90
4	$\beta_m \geq 0.5$ and D1DWIP ≥ 27 and D2DWIP ≥ 18 and $\alpha_{r1} \geq 0.5$	CFB effect	0.89
…			
73	D2DI < 18 and $\alpha_{r1} \geq 0.5$ and α_{d1} < 0.5 and $\beta_m \geq 0.5$	No CFB effect	0.86
…			

inventory and WIP gaps (i.e., α_{r1}, α_{r2}, β_{d2}, $\beta_m \geq 0.5$) across all SC echelons lead to the CFB effect. To counterbalance the aggressiveness of the manufacturer and retailer 1 in bridging the inventory gaps, Rule 73 suggests setting D2DI below 18 and α_{d1} below 0.5. This mirrors Rule I from the C4.5 algorithm, which emphasizes the critical role of inventory policies at the middle echelon (i.e., distributors) in preventing the CFB effect.

To enhance the interpretability and practical relevance of the decision rules extracted using interpretable ML algorithms (C4.5 and CN2), Table 7 presents a policy rule matrix. This matrix consolidates the recommended actions for preventing the CFB effect under various conditions, along with their anticipated impacts on cash flow dynamics. It offers a structured and transparent reference for stakeholders aiming to align inventory and credit control policies with cash flow stability objectives in SCs.

5.8 Theoretical and practical perspectives

The simulation outcomes from scenarios 1–6 along with the decision rules obtained from the C4.5 and CN2 rule induction algorithms offer novel theoretical and managerial insights. Table 8 compiles the major theoretical implications and the corresponding managerial recommendations.

The first insight is that forecasting using end customers' demands reduces the CFB effect, especially for upstream SC members experiencing higher demand distortion. This implies that SC members should prioritize sharing data on inventory levels, work-in-progress (WIP), and customer demand to reduce the CFB effect. This insight extends the existing body of knowledge on the CFB effect (e.g., Badakhshan et al., 2020; Goodarzi et al., 2017; Patil & Prabhu, 2024b).

The second insight reveals that increasing cash collection policies specifically for SC members with a CFB value greater than 1 does not lead to an overall reduction in CFB values across all SC members. Instead, this approach merely shifts the CFB burden from one echelon within the SC to another. Consequently, our recommendation is to avoid selectively increasing cash collection policies for only certain SC members. Instead, consider increasing the cash collection policies for all SC members collectively.

Thirdly, increasing cash collection policies for all SC members based on the average CFB value within the network results in a reduction in CFB values throughout the SC.

Table 7 Policy rule matrix

Rule	Conditions	Recommended Action	Impact on CFB
R1	Upper echelon: $\alpha m \geq 0.5$; Middle echelon employs high desired inventory or WIP	Set middle echelon desired inventory and WIP to < 1.5 × demand	Mitigates amplification caused by upstream aggressiveness
R2	Lower echelon: $\alpha r1 \geq 0.5$; Middle echelon employs high desired inventory	Set middle echelon inventory proportional controller ($\alpha d1$) to < 0.5	Balances policy tension between upstream and downstream nodes
R3	Middle echelon overstocking ($\geq$1.5x)	Lower desired WIP at upper and lower echelons to offset middle overstocking	Avoids system-level inventory saturation and cash flow distortion
R4	TCP ≥ 2.5 weeks; Overstocking at lower & middle echelons; $\alpha r1 \geq 0.5$	Set TCP < 2.5 weeks, lower middle DI and lower echelon WIP; $\alpha r1 < 0.5$	Prevents the CFB effect triggered by credit and inventory imbalances
R5	Lower echelon: $\alpha r1 \geq 0.5$ AND Upper echelon: $\beta m \geq 0.5$	Lower desired inventory at the middle echelon and set middle echelon inventory proportional controller ($\alpha d1$) to < 0.5	Dampens amplification caused by downstream and upstream aggressiveness
R6	Upper echelon overstocking: (MDI ≥ 45 AND MDWIP ≥ 45)	Lower desired inventory at the lower and middle echelons and set lower and middle echelon inventory proportional controllers ($\alpha r1$, $\alpha d1$) to < 0.5	Mitigates volatility induced by aggressive policies at upper echelon

Therefore, we recommend implementing a uniform increase in cash collection policies for all SC members based on the average CFB value within the network.

Insights 2 and 3 align with studies emphasizing the need for integrated SC strategies to improve overall efficiency and effectiveness, rather than localized adjustments (Fahimnia et al., 2015; Ivanov & Dolgui, 2021, 2025; Lee & Billington, 1992; Dolgui et al., 2025; Ivanov, 2025c).

The fourth insight derived from our analysis is that forecasting using end customers' demands, combined with uniformly increasing cash collection policies for all SC members, eliminates the CFB effect within the SC. This dual approach addresses both the data asymmetry and the coordination gaps that exacerbate the CFB effect. Based on this finding, we recommend implementing a synchronized strategy that involves both forecasting based on end customers' demands and uniformly increasing cash collection policies across all SC members to eradicate the CFB effect. This insight extends the existing body of knowledge on the CFB effect (e.g., Drissi et al., 2023; Lamzaouek et al., 2023; Sim & Prabhu, 2017).

The fifth insight underscores that the most upstream member of a SC experiences the greatest benefits from enhanced cash collection policies across all SC participants due to not facing cash collection policy increases from their suppliers. Consequently, it is advisable to uniformly elevate cash collection policies for all members of the SC by employing

Table 8 Theoretical and practical perspectives obtained from scenarios 1–6, C4.5 and CN2 rule induction algorithms

Source	Theoretical implications	Managerial recommendations
Scenario 1	Forecasting using end customers' demands reduces the CFB effect, especially for upstream SC members experiencing higher demand distortion	Forecast using end customers' demands to reduce the CFB effect and stabilize working capital for SC members
Scenario 2	Increasing cash collection policies for SC members with a CFB value greater than 1 does not achieve an overall reduction in CFB values for all SC members. Instead, it merely transfers the CFB burden from one echelon to another echelon	Refrain from increasing cash collection policies for selected but not all SC members
Scenario 3	Increasing cash collection policies for all SC members based on the average CFB value within the network results in a reduction in CFB values throughout the SC	Implement a uniform increase in cash collection policies for all SC members based on the average CFB value within the network
Scenario 4	Forecasting using end customers' demands alongside a simultaneous increase in cash collection policies for all SC members eliminates CFB effect in the SC	Forecast using end customers' demands and uniformly increase cash collection policies for all SC members
Scenario 5	The most upstream member of the SC benefits the most from the increase in cash collection policies for all SC members	Increase cash collection policies uniformly for all SC members by a factor multiplier that reduces the CFB value for the most upstream SC member to your desired level
Scenario 6	Uniformly increasing cash collection policies for all SC members beyond an identifiable threshold eradicates the CFB effect in the SC	Perform sensitivity analysis on cash collection policy to identify the threshold factor multiplier that eradicates the CFB effect in the SC
C4.5 and CN2 rule induction algorithms	Regulating inventory policies at the middle echelon (i.e., distributors) is key to preventing the CFB effect in the SC	Set the desired inventory and WIP levels at the middle echelon to below 1.5 times customer demand if the upper echelon employs an aggressive policy to bridge the inventory gap (i.e., $\alpha_m \geq 0.5$) Set the desired inventory at the middle echelon to below 1.5 times customer demand, and exercise caution when establishing the inventory proportional controller (i.e., $\alpha_{d1} < 0.5$) if the lower echelon employs an aggressive policy to bridge the inventory gap (i.e., $\alpha_{r1} \geq 0.5$) Exercise caution in setting the WIP proportional controller at the middle echelon (i.e., $\beta_{d2} < 0.5$) if the desired inventory and WIP levels at the middle and upper echelons are set equal to or above 1.5 times customer demand
C4.5 and CN2 rule induction algorithms	Avoiding overstocking at the lower and middle echelons, along with exercising caution in bridging the inventory gap at the upper echelon, prevents the CFB effect in the SC	Set the desired inventory and WIP levels for the lower and middle echelons to below 1.5 times the customer demand, and the inventory proportional controller for the upper echelon to below 0.5
C4.5 algorithm	Overstocking at the middle echelon should be offset by lowering inventory levels at both the upper and lower echelons to prevent the CFB effect in the SC	Set the desired WIP levels for the lower and upper echelons to below 1.5 times customer demand if the desired inventory for the middle echelon is set equal to or above 1.5 times customer demand

Table 8 (continued)

Source	Theoretical implications	Managerial recommendations
CN2 rule induction algorithm	Regulating trade credit period and avoiding overstocking at the lower and middle echelons, along with exercising caution in bridging the inventory gap at the lower echelon, prevents the CFB effect in the SC	Set the trade credit period to below 2.5 weeks, the desired inventory for the middle echelon and the desired WIP for the lower echelon to below 1.5 times customer demand, and the inventory proportional controller for the lower echelon to below 0.5

a multiplier that mitigates the CFB value for the most upstream SC member to a predefined threshold. This approach aligns with studies emphasizing the critical importance of maintaining the financial health of upstream SC members, as their financial instability could jeopardize the overall viability of the SC (Badakhshan & Ball, 2023; Ivanov, 2024; Kroes & Manikas, 2014).

The sixth insight is that uniformly increasing cash collection policies for all SC members beyond an identifiable threshold eradicates the CFB effect in the SC. This implies that it is feasible to eliminate the CFB effect even without forecasting using end customers' demands by SC members. We recommend conducting sensitivity analysis on cash collection policy to identify the threshold factor multiplier that eradicates the CFB effect in the SC. This insight extends the literature on CFB effect in line with previous studies that highlight the reluctance for data sharing among SC members (Hannibal et al., 2022; Inderfurth et al., 2013; Mahmud et al., 2021). It should be noted that if SC customers do not accept the collection policy that eliminates the CFB effect in the SC, cash collection policies should be uniformly increased for all SC members to reduce the CFB value for the most upstream member to a desired level, as derived from insight 5.

The seventh insight reveals that the CFB effect can be avoided by regulating inventory policies at the middle echelon. This suggests that even if the upper echelon employs an aggressive policy to bridge the inventory gap (i.e., $\alpha_m \geq 0.5$), as shown by rule I in Fig. 11, the middle echelon can still prevent the CFB effect in the SC by setting the desired inventory and WIP levels to below 1.5 times customer demand. Similarly, if the lower echelon employs an aggressive policy to bridge the inventory gap (i.e., $\alpha_{r1} \geq 0.5$), as shown by rule 73 in Table 3, the middle echelon can prevent the CFB effect by setting the desired inventory to below 1.5 times customer demand and by exercising caution when establishing the inventory proportional controller (i.e., $\alpha_{d1} < 0.5$). In the same way, as shown by rule III in Fig. 11, if the desired inventory and WIP levels at the middle and upper echelons are set equal to or above 1.5 times customer demand, the middle echelon can still prevent the CFB effect by exercising caution in setting the WIP proportional controller (i.e., $\beta_{d2} < 0.5$).

The eighth insight derived from rule 1 in Table 3 demonstrates that avoiding overstocking at the lower and middle echelons (i.e., D2DI, R3DWIP < 18 and D1DWIP < 27), along with exercising caution in bridging the inventory gap at the upper echelon (i.e., $\alpha_m < 0.5$), prevents the CFB effect in the SC. The C4.5 algorithm generated a similar rule as shown in Fig. 11. Therefore, we recommend setting the desired inventory and WIP levels for the lower and middle echelons to below 1.5 times customer demand and keeping the inventory proportional controller for the upper echelon below 0.5.

These insights underscore a critical trade-off in inventory management at the middle echelon. Overstocking creates buffers that enhance service levels and reduce stockouts, but it also ties up capital and increases working capital variability, thereby fueling the CFB effect. Understocking, on the other hand, reduces capital tied up in inventory and improves cash flow stability but raises the risk of SC disruptions due to unmet demand. Therefore, striking an appropriate balance, guided by empirical rules generated through decision trees, is essential for maintaining SC resilience while minimizing financial volatility.

The ninth insight obtained from rule II in Fig. 11 shows that overstocking at the middle echelon should be offset by lowering inventory levels at both the upper and lower echelons to prevent the CFB effect. Therefore, we suggest setting the desired WIP levels for the lower and upper echelons to below 1.5 times customer demand if the desired inventory for the middle echelon is set equal to or above 1.5 times customer demand.

The tenth and final insight obtained from rule 2 in Table 3 indicates that regulating trade credit period (TCP) and avoiding overstocking at the lower and middle echelons, along with exercising caution in bridging the inventory gap at the lower echelon, prevents the CFB effect in the SC. consequently, we recommend setting the trade credit period to below 2.5 weeks, the desired inventory for the middle echelon and the desired WIP for the lower echelon to below 1.5 times customer demand, and the inventory proportional controller for the lower echelon to below 0.5.

Importantly, the trade credit period interacts with inventory policies and payment terms by influencing the timing of cash flows across the supply chain. Shorter trade credit periods improve liquidity for upstream members by accelerating receivables but may restrict the ability of downstream partners to maintain sufficient inventory levels, particularly in capital-constrained environments. This constraint can elevate the risk of understocking and service level deterioration. Conversely, longer trade credit periods alleviate financial pressure on downstream members, enabling more flexible inventory strategies, but may heighten working capital variability for upstream firms. Therefore, a carefully balanced trade credit policy is critical.

While our findings support shorter trade credit periods to prevent the CFB effect, we acknowledge that excessively short credit terms could strain supplier–buyer relationships or affect liquidity in certain industries. For example, in the apparel industry, companies often rely on extended credit terms to manage seasonal demand fluctuations and working capital requirements (Aloina et al., 2019). Similarly, in agribusiness, long production lead times and regulatory delays can necessitate extended payment windows to sustain operations (Detthamrong & Chansanam, 2023). Hence, trade credit policies must be tailored to industry-specific financial dynamics and supply chain characteristics.

Insights seven to ten extend the existing body of knowledge on strategies to avoid CFB effect in the SC (e.g., Badakhshan et al., 2020; Lamzaouek et al., 2023; Sim & Prabhu, 2017).

The insights presented in this study highlight the critical role of digital coordination (Ivanov, 2025d) in preventing the CFB effect. However, these strategies introduce operational and financial trade-offs that must be carefully managed. For instance, uniformly increasing cash collection policies across all SC members can reduce overall cash flow variability but may also impose liquidity constraints on financially weaker downstream partners, potentially resulting in service-level failures or customer attrition in price-sensitive industries. Similarly, forecasting based on end-customer demand enhances informational accuracy but depends on robust data-sharing infrastructures, which may be absent or infeasible in practice.

Furthermore, policies such as reducing desired inventory levels and tightening proportional control parameters improve cash flow stability but may elevate the risk of stockouts, replenishment delays, and service degradation. Conversely, maintaining high inventory to protect against demand uncertainty increases working capital variability, exacerbating the CFB effect. These tensions are particularly pronounced at the middle echelon, which serves as a coordination buffer between upstream and downstream actors. As shown in the rule-based analysis, middle-echelon policies must strike a balance between responsiveness to partners' aggressive replenishment behaviors and internal efficiency goals. Similarly, while shorter trade credit periods enhance upstream liquidity, they can restrict the financial flexibility of downstream members, especially in capital-constrained environments. Therefore, the design and implementation of CFB prevention strategies should be context-sensitive and account for trade-offs between financial resilience and operational robustness.

6 Conclusion

This study bridges a gap in the literature concerning the effectiveness of blockchain-enabled data sharing and the integration of simulation with ML in preventing the CFB effect. While previous studies (e.g., Patil & Prabhu, 2024a, 2024b) analyze the CFB effect across industries and discuss mitigation strategies, they do not propose concrete methods to prevent this undesirable phenomenon. Similarly, although there is growing interest in applying hybrid simulation-ML models and blockchain technology to SC problems (e.g., Ogunsoto et al., 2025; Scott et al., 2024), there is a lack of studies that specifically examine the effectiveness of blockchain-enabled data sharing or the integration of simulation and ML in addressing the CFB effect.

Our study first examines the impact of data sharing using blockchain on the CFB effect. We employed discrete-event simulation to evaluate the CFB effect in a no-data-sharing scenario (Scenario 0) and in six blockchain-enabled data-sharing scenarios (Scenarios 1–6). Scenario 0 revealed the existence of the CFB effect in the SC. Key findings indicate that forecasting based on end-customer demands reduces the CFB effect. Conversely, increasing cash collection policies for SC members with a CFB value greater than 1, approved via the blockchain, does not result in an overall reduction of CFB values for all SC members. Instead, it merely shifts the burden from one echelon to another. Therefore, we recommend implementing a uniform increase in cash collection policies for all SC members, based on the average CFB value within the network, to reduce the CFB effect. Furthermore, combining end-customer demand forecasting with a simultaneous increase in cash collection policies for all SC members eliminates the CFB effect. Sensitivity analysis reveals that uniformly increasing cash collection policies for all SC members beyond a specific threshold eradicates the CFB effect, as seen in Scenario 6. We recommend identifying and implementing this threshold as the standard collection policy for all SC members. If SC customers cannot accept this threshold, cash collection policies should be uniformly increased to reduce the CFB value for the most upstream member to the desired level, as demonstrated in Scenario 5.

Next, we assess the effectiveness of integrating simulation with decision trees, enabled by blockchain-shared data. Decision trees provide valuable insights, emphasizing the role of inventory policies at the middle echelon of the SC in preventing the CFB effect. Specifically, avoiding overstocking and exercising caution when bridging inventory gaps at the middle echelon helps prevent the CFB effect. Additionally, regulating trade credit period and balancing inventory levels across the SC help avoid the risk of the CFB effect.

Several limitations exist in this research. Firstly, the study focuses on the CFB effect in the absence of SC disruptions. Future studies could explore the dynamics of the CFB effect under disrupted conditions. Secondly, while this research integrates discrete-event simulation with decision trees, future work could incorporate other ML techniques to eliminate the CFB effect in SCs. In particular, combining high-performing black-box models with post-hoc explainability techniques such as SHAP or LIME represents a promising direction for balancing predictive performance with interpretability. Thirdly, the study overlooks uncertainties that affect working capital components and consequently the CFB effect. Future research could investigate how uncertainties such as fluctuations in economic conditions influence the dynamics of the CFB effect. Fourthly, this research assumes unlimited storage capacity to isolate the impact of digital interventions. Future research could extend the model by incorporating storage constraints, thereby assessing their effect on working capital variability and the CFB effect. Fifthly, although this study demonstrates the effectiveness of blockchain technology and two AI methods, simulation and ML, in mitigating the CFB effect, future research could explore the potential of other Industry 4.0 technologies such as Digital Twins for eliminating the CFB effect. Lastly, our model relies on a demand forecasting approach based on historical averages. Future research could explore the use of alternative forecasting techniques such as ARIMA models or neural networks particularly under conditions of non-stationary or seasonal demand to assess whether improved forecasting accuracy enhances system robustness and mitigates the CFB effect.

Declarations

Conflict of interest The authors have no conflicts of interest to declare that are relevant to the content of this article. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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