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Assessing the Bullwhip effect in supply chain: trends, gaps, and overlaps

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Abstract: Due to operational and behavioral factors, the Bullwhip effect (BWE) arises with variations in the logistics flow, yielding uncertainty and disturbances along the supply chain (SC). Previous studies have discussed isolated approaches, underestimating the influence of behavioral aspects over operational ones, and multi-factor analysis, which helps to measure and diminish the BWE. This study systematically assesses the bodies of knowledge to identify new trends, emphasizing gaps and overlaps to underly behavioral-operational links and multi-factor scenarios through a unified frame of reference built during the paper review. The results from this research spot new BWE trends like COVID and closed-loop supply chain (CLSC) driven by disruption and return flows; the influence of behavioral causes over pricing, returning flows, production capacity, and batching; the combination of multi-factor topics like pricing, production capacity, synchronization, and order batching. This overview contributes to understanding new trends and connections in the issues, highlighting logistic challenges and opportunities to explore future studies with a broader scope. It also elucidates the BWE causes and how to handle them, which could assist in comprehending its effects and advantages on the technical elements of logistics.

1 Introduction

Supply chain (SC) is a complex system with actors making multiple decisions influenced by behaviors, feedback information, non-linearity, delays, deviations, and uncertainty to satisfy the demand of retailers and customers [1,2]. Lack of synchronization between SC members yields demand variations, batch size oscillations [3], and thus BWE, where SC actors mitigate fluctuations and resource shortages through a misguided decision-making process by reacting and changing the capacity to meet peak demands. This effect increases safety stock level investments, transportation costs, unstable planning, unmet service acceptance levels (SAL), running out of products, and revenue loss, affecting the company profit between 10%-30 % and the inventory balance, increasing holding and shortage costs [4-6].

The behavioral BWE describes stakeholders' interventions and decision-making processes reflected in operational aspects [7]. Although there has been an increasing interest in studying human behavioral factors associated with the BWE, most of this analysis is still at the individual level. It is necessary to extrapolate these factors to a cultural and societal level, including more case studies that replicate a real-world business scenario with complexity instead of the beer game simulation [8].

Previous studies addressed variables that compound the BWE effects from different viewpoints to describe, measure, and reduce the impact on the SC [9], highlighting the need to close the gap between theoretical definitions and complex systems. Analytical, empirical, and experimental methodologies have been implemented in different components related to demand, replenishment policy, and coordination to rethink the SC role, structure, product type, price strategy, competition, and sustainability. This trend to enhance the scope of the BWE analysis has led to include econometric variables like costs and price to improve the outcome [10] and influence demand through communication strategies to align consumers with the level of the stocks to increase or decrease orders. Furthermore, multiple components have explored new pricing models like marketing techniques, technologies, inventory policies, forecasting methods, and multi-echelon SC [11,12]. Information exchange and vendor-managed replenishment schemas to reduce the BWE have evolved into synchronized SC. However, integration complexity, lead time, lack of trust, and transferred information delays are challenges to overcome [13,14].

Including a multi-factor approach to the BWE is an overdue opportunity to explore topic combinations to analyze closer-to-reality studies with multivariable causes; future studies may research complex systems, pricing strategies, service chains, and competitiveness factors [10]. Despite previous studies addressing bodies of knowledge, trends, assessing the status of repetitive topics, mitigation strategies, and behavioral-operational factors [15-17], this

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paper identifies overlapping issues, gaps, synergies, future research, updating existing taxonomy, and combining frameworks to relate BWE causes. This study also shows strategies for SC decision-makers to identify and mitigate the BWE.

This research guides answering the question: How can the BWE issues be synthesized by clustering topics to illustrate existing links in the literature to identify gaps, trends, and future works? This paper builds a holistic view to contributing new insights, point likenesses, and BWE mitigation benefits.

This article is structured as follows: the methodology used to find the clustered topics and trends about BWE supply chains from the existing literature is presented in Section 2. Using the frameworks proposed by Bhattacharya et al. [15], Geary et al. [16], and Wang et al. [10] during the refinement phase addressed in Section 3, the problem, solution, and future research are extracted to identify trends, gaps, and overlaps. Section 4 depicts a visual analysis explaining overlapped operational and behavioral studies and the connection between causes, mitigation strategies, clustered topics, trends, and future research. Finally, the conclusions and future works are reported in Section 5.

2 Methodology

This paper presents a systematic literature review on BWE based on the methodology developed by Hosseini, Dmitry, and Dolgui [18]. The iterative process applies different criteria to filter pertinent contributions aligned with the goals of this study, carry out the analysis, and categorize the results, as illustrated in (Figure 1). The following sections present more detail on the methodology applied.

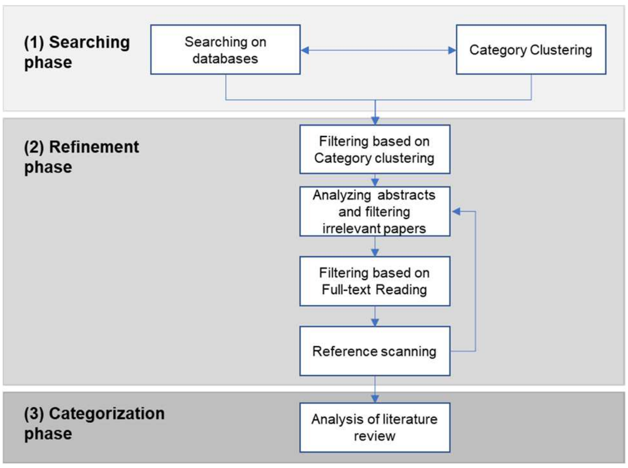

Figure 1 Literature-review methodology flow chart

2.1 Searching phase

The Web of Science and Scopus citation databases were used to build an overview of the topics, applying a search equation. TITLE-ABS-KEY(“bullwhip effect”) AND (EXCLUDE (SUBJAREA, “SOCI”) OR EXCLUDE (SUBJAREA, “MATE”) OR EXCLUDE (SUBJAREA, “ENVI”) OR EXCLUDE (SUBJAREA, “PHYS”) OR EXCLUDE (SUBJAREA, “MULT”) OR EXCLUDE (SUBJAREA, “ENER”) OR EXCLUDE (SUBJAREA, “CENG”) OR EXCLUDE (SUBJAREA, “MEDI”) OR EXCLUDE (SUBJAREA, “CHEM”) OR EXCLUDE (SUBJAREA, “EART”) OR EXCLUDE (SUBJAREA, “ARTS”) OR EXCLUDE (SUBJAREA, “AGRI”) OR EXCLUDE (SUBJAREA, “PSYC”) OR EXCLUDE (SUBJAREA, “BIOC”) OR EXCLUDE (SUBJAREA, “HEAL”) OR EXCLUDE (SUBJAREA, “IMMU”) OR EXCLUDE (SUBJAREA, “PHAR”)).

The initial abroad exploration includes all the search results related to the “Bullwhip Effect” keyword, excluding non-English articles, and areas like Physics and Chemistry to zoom in on areas like Management, Operation Research, Logistics, and Economy. Secondly, both sources of information are joint, excluding duplicates to select 1,522 papers.

Category clustering: A clustering algorithm is applied to have a high-level view of relevant terms linked to the BWE studies using VOSviewer. This software extracts information from the title and abstracts to match and group topics. The full counting method calculates occurrences of keywords in the documents. The initial result was 20,813 terms, applying a minimum of 10 occurrences refines to 1,083 - the relevance score selected is 60%, equivalent to 650 terms. Finally, the list is cleaned-up to remove irrelevant terms to obtain 305 clustered topics.

Network visualization: The clustered topics network built (Figure 2a) explains the recurrency and links between the terms divided by colors. There are nine clusters: first [red], 63 items, agglomerates inventory, ordering, synchronization, reverse logistics, and distribution processes. The second [green], 47 items, combine technology, communication, and optimization. Third [blue], 42 items, brackets demand, pricing, and the market. Fourth [yellow], 40 items, links demand, costs, and stocks. Fifth [purple], 39 items, connects the beer game, supply chain structure, and simulation. Sixth [sky blue], 24 items, groups behavior, inventory information, and knowledge. Seventh [orange], 22 items, groups algorithm, vendor, and market. Eighth [brown], 16 items, associates closed-loop supply chain, control strategy, and inventory variance. Ninth [pink], 16 items, correlates COVID, supply chain risk, and inventory stock-out.

Overlay Visualisation: The clustered topics timeline (Figure 2b) exemplified when the BWE issues appeared, explaining it through the intensity of the purple and yellow colors. Since the first decade of the 2000s, terms like VMI (vendor-managed inventory), inventory policy, demand process, forecasting method, and beer game have been present, while new topics like COVID, price, disruption, Big Data, closed supply chain, information transparency, resilience, supply agility, and market share emerged since 2016.

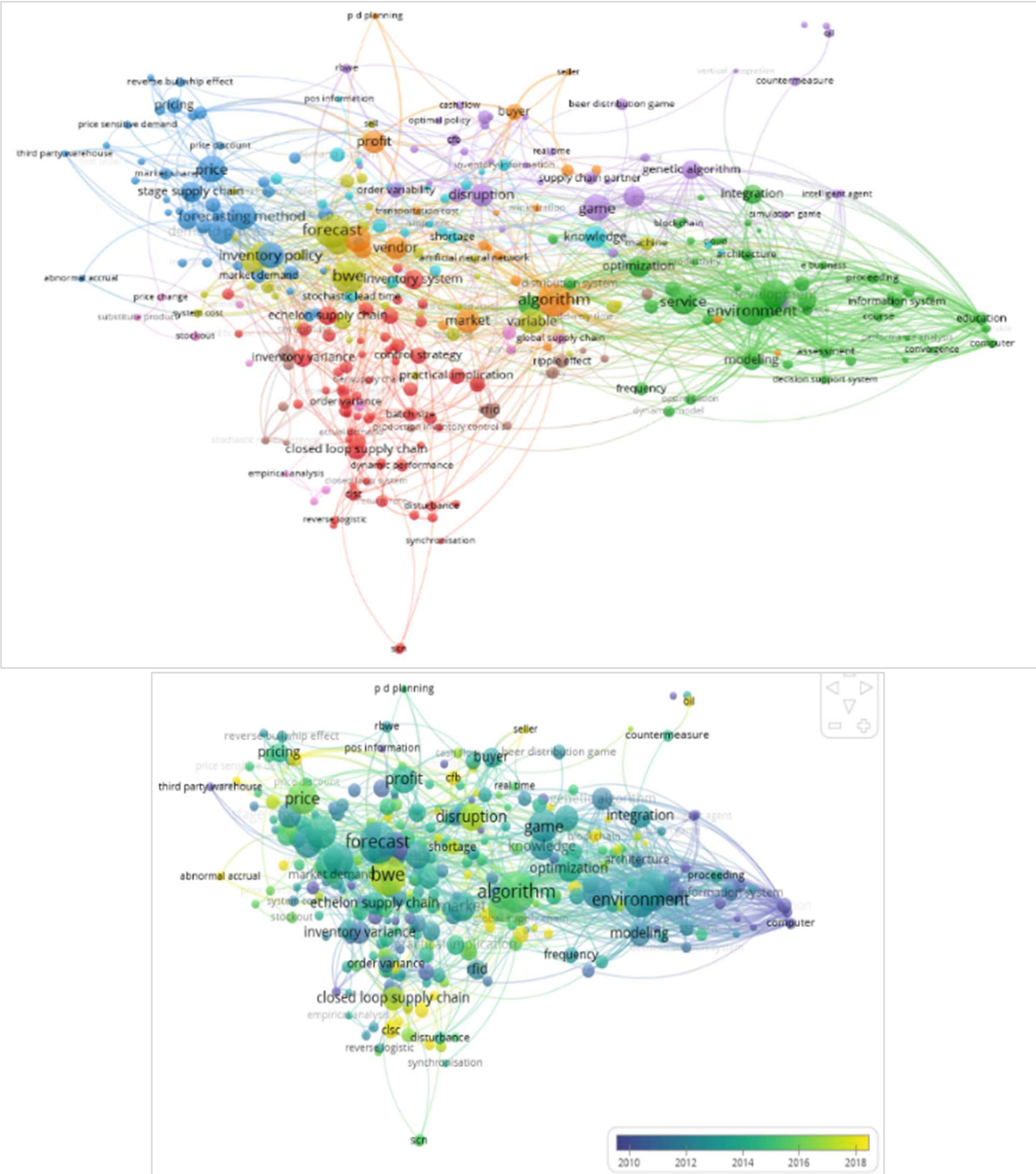

Figure 2 Category clustering timeline

2.2 *Refinement phase*

Refining the articles aims to understand how BWE issue has evolved, detecting recent trend topics and prominent contributing authors to concentrate on insightful research. The iterative process includes an abstract analysis, full-text reading, and reference scanning, applying the clustering categories to filtered documents (Figure 3). An H-index author filter was also used to optimize the balance between publications and citations [19].

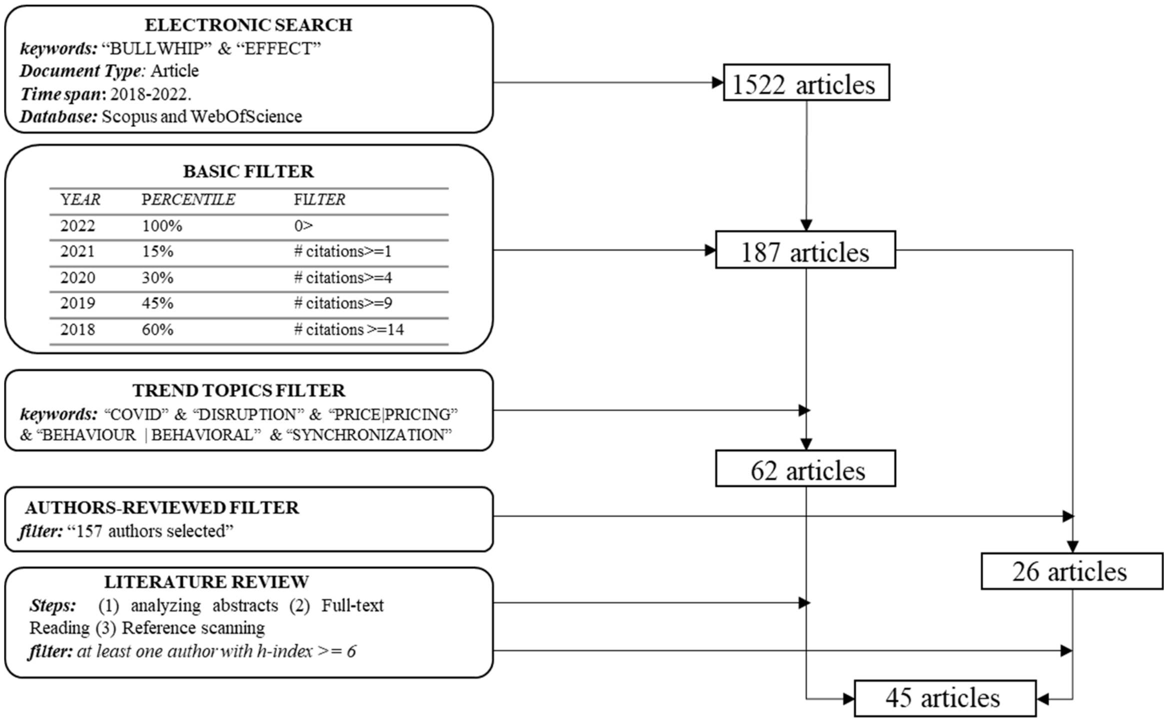

Figure 3 Refinement process

Filtering based on Category clustering: The search phase identifies papers regarding relevance and time, filtering by year, citations, trend recent topics, and authors to identify the bodies of knowledge. The basic filters include English documents from 2018 until 2022, filtering relevant studies by the number of citations using percentile values. The trend and historical topics are searched in the title, abstract, author, and keywords. The authors-reviewed filters no-trend topics studies through a bibliographic analysis of co-authorship to cluster authors with at least four published documents and follow a line of research. From the initial 2,381 authors, 157 are selected.

3 Results and discussion

This research adopts three main frameworks to identify the problem, approach, solution, result, and future studies. First, Bhattacharya et al. [15] classified the BWE into two main categories, operational and behavioral. The operational causes are characteristics inherent to the SC operation, while behavioral ones are decision-makers' reactions that increase fluctuations in the network. Second, Geary et al. [16] designed a five routes framework to reduce the BWE minimizing costs through difference equation (OR theory), a control law approach to solving fluctuations, exchanging SC structure problems to get the desired response, causal loops approach with system dynamics simulation, and previous practical experience (Ad-Hocacy). Third, Wang et al. [10] identified six trends that explain how the topics are evolving: SC structure studies from linear and simple networks to no linear and complex ones, from tangible to intangible products, financial and information flows beside the logistic ones, market power approaches including competing scenarios, sustainability including environmental perspective beyond the economic one, and the operational BWE concept incorporating finance and regulatory subjects.

3.1 Price fluctuations

The price effect on the SC's actors creates fluctuations in demand and the BWE, analyzing the price stability, price-sensitive demand streams, stochastic purchase prices, and scenarios of multiple products interacting with price-sensitive demands [20,21]. However, more studies on how price contributes to BWE propagation are needed [10,15]. Tai et al. [22] developed a linear combination autocorrelated (LCA) demand function to measure the BWE in a two-echelon SC; with an order-up-to (OUT) policy, deterministic lead time, autoregressive demand, retail prices, and customer reference prices. Price and demand correlation explains the customer's decision-making process to stockpile influenced by inventory level and retailer's actions over price reference through fluctuations and discounts; suppliers who implement promotional strategies adjusting price span can reduce the BWE. Communication of external factors influencing reference price rather than retailer and adoption of reference price models may be explored.

Feng et al. [12] investigated disruption and panicking with price fluctuations, analyzing pricing strategies to adjust order variance through an econometric model (EM) to reduce the BWE. The "naïve" model defines price based on capacity and demand-price function, omitting customers' reactions and having the best relation between order variability and profit, followed by the historical regression prices and customer orders model. The "One-period correction" model tunes price value with customer deviation in the last period less effectively. A fixed price model eliminates order fluctuations whit non-profit results. Customer behavior deep knowledge helps to formulate the best pricing strategy under disruption. Short gaming, where limited resources influence panicking, can be explored.

Ma et al. [23] include price-sensitive and substitute products using a minimum mean square error (MMSE) demand function. A growing lead time does not increase the BWE proportionally; however, a better one enables pricing strategies to reduce it. The competitors' information improves the making-decision process and pricing strategy according to substitute product performance—a higher degree of substitution leads to more impact. The correlated influence of competitors' pricing strategies can amplify the BWE; a strong self-correlation price coefficient with a weak mutual-correlation price coefficient with competitors may amplify the BWE to the opponent. The BWE can be mitigated with a low self-correlation and high mutual-correlation price and a neutral BWE when high or low levels pair self and mutual correlation prices. Multi-substitute products, pricing strategies, and profit could be explored.

The Cash Flow BWE (CFBE) impacts competencies' conditions and market share, Chen et al. [24] compare two-parallel SC with a retailer, a supplier, two products, and an autoregressive demand process (AR). The CFBE is present in substitutable products or no-null price cross-sensitivity coefficient, improving forecast accuracy and service client increases market share and reduces CFBE. Healthy competitiveness and cooperative relationship partners decrease fluctuations. CFBE with multiple suppliers, distributors, forecasting, sales channels, and retailers may be explored.

Ponte et al. [25] provide an SC mathematical model (MM) to reflect the quantity discounts influence in the BWE and the NSA ratios by analyzing logistic costs like purchase, inventory, stock-out, opportunity, and overtime. The model optimizes discounts in upstream decision-making to implement it and downstream to calculate it. The discount encourages a mismatch in demand and orders, yielding distorted information, waste, capacity costs, and underperformed inventory. However, it could reduce purchase costs for upstream decision-makers and increase benefits for downstream SC actors. Future studies can explore: pricing strategies' influence based on markup, skimming, and penetration, Consumption psychology and pricing affecting the behavioral BWE, Closed-loop supply chain (CLSC) in pricing mechanisms, and the link between pricing decisions and disruptions like Ripple Effect (RE).

Kumar et al. [11] propose a data-driven framework to collect and process demand data and customer behavior patterns, increasing accuracy forecasting, marketing efficiency, tracking advertising, and return reductions. The historical demand is ingested and decomposed into factors to forecast future demand using seasonality and trends. The optimal demand is shaped using consumer insights, promotions, advertising, sales, pricing effects, advertising plan, and ROI to run scenarios to adjust and orchestrate the final demand. The data-driven fuzzy classifier-based (FCB) improves the forecasting process, inventory costs, and profitability, enabling a feature to evaluate hypothetical scenarios for new products. Future studies may optimize hidden layers and nodes in the fuzzy neural network model, including intermittent demand and information like weather forecasting, shipping, marketing, and customer profile.

Ma et al. [26] propose a four-channel SC network with one manufacturer and two retailers, using a price game model to simulate BWE response to changing discount conditions. The price adjustment speed and discount sensitivity infer the system's reaction. A moderate price discount keeps the system stable, but discount disruption could amplify the BWE to a chaotic state. SC actors should reduce price discount sensitivity and increase customer loyalty. Multiple channels, inventory, and discount strategies could be explored. Zhang et al. [27] simulate the BWE in a complex system with dynamic price, decision schemas, service value, and coordination process, approaching profit discrepancies in a multi-channel SC influenced by centralization levels. Centralized models have a smaller price gap between the retailer and direct channel, yielding stable market conditions. A framework to coordinate mechanisms and contract agreements under discount conditions may pair decentralized and centralized states. The BWE may increase long-term service costs. Direct channel's service value and multiple manufacturers and retailers could be explored.

Tai et al. [28] explore the price fluctuation impact on the BWE in two-echelon SC with an OUT policy and price-sensitive AR demand. The BWE is calculated with demand and order variation due to price fluctuations. A steady-limited price strategy is better for increasing demand variation. A dynamic price strategy could decrease the BWE in negative relations. This work could be extended, including deviations in the forecast and price promotions.

The trends include new flow types like strategy pricing, price sensitivity, promotions, and discounts (Table 1), adding complexity like substitute products, multiple competitors, panicking demand, marketing, financial, and customer behaviors, critical to understanding the BWE under the price lens.

Table 1 Price fluctuation literature review

Category [15]	**Solution Method.** [16]	**Technique**	**Trend** [10]	**(ME) Measure/ (MI) Mitigate**	**Sources**
O/B	OR	LCA	FTy	ME	Tai et al.[22]
O/B	OR	EM	FTy	ME & MI	Feng et al. [12]
O/B	OR	MMSE	FTy	ME & MI	Ma et al. [23]
O/B	OR	AR	FTy/C	ME & MI	Chen et al. [24]
O	OR	MM	FTy	ME	Ponte et al. [25]
O/B	CT	big data-driven FCB	FTy	ME & MI	Kumar et al. [11]
O	FT	bifurcation model	Fty/SCs	ME & MI	Ma et al. [26]
O	S	numerical simulation (NS)	Fty/SCs/MP	ME	Zhang et al. [27]
O	S	NS	FTy	ME	Tai et al. [28]

- **Category**: Operational (O), Behavioural(B).
- **Solution Method:** OR Theory (OR), filter theory (FT), control theory (CT), Simulation (S), Ad-Hocacy (AdH).
- **Trend:** SC structure (SCs), Product Type (PT), Flow Type (FTy), Market Power (MP), Sustainability (S), and Concept (C).

3.2 COVID-19, disruption, and Ripple effect

COVID-19 produced unprecedented effects in different sectors affecting downstream and upstream material flows, rethinking the globalization state, lean and local production, and risk fallbacks [29]. These fluctuations combined the demand variations due to the customers' lockdowns with a downstream propagation of the unfulfillment demand during the severe disruption, joining the BWE with the Ripple effect (RE) and affecting the SC stability significantly [30].

Dolgui et al. [31] analyze the RE influence over the BWE through discrete and agent-based simulation. The shipment, production capacity disruption, and order recoveries are simulated as discrete events, while customers and communication use agent-based and multi-agent frameworks. Supply interruptions, backorder accumulations, and late recovering periods to restore downstream flows can trigger the RE and hamper the BWE; communication and coordination reduce ordering, inventory, and production deviations. Inventory policies to control backlogs during disruption could be explored. Scarpin et al. [32] combined BWE and RE to measure the COVID-19 outbreak impact through financial and non-financial variables. The Efficient Market Hypothesis (EMH) and the Capital Asset Pricing Model (CAPM) reveal the effect on the stock market where a node represents the airline companies, comparing buyers' and suppliers' performance. Financially, BWE and RE affect more companies with high operating leverage and debt-to-assets ratio. The degree of centrality has an impact proportional to the number of suppliers and buyers. Global airline stock index (GASI) could be extrapolated to Nasdaq, S&P 500, Dow Jones, and other industries.

Ghadir et al. [33] rank COVID-19 risks, using Failure Mode and Effects Analysis (FMEA) and Best–Worst Method (BWM). The model combines Best–Worst Method (BWM) to define weights in strategies to reduce disruption. The risks include deficient customer demand information, shortages, BWE, intermittent delivery, delays, restrictions, and supply cut-off. SC visibility and information shared are crucial to reducing unpredictable market conditions' impact.

Hu [34] uses differential equations with a Markov supply-demand matrix to measure oscillations' impact and disruptions in the network, demonstrating that small fluctuations are rather than larger ones. The SC stability responds to an aligned order strategy. The Hopf bifurcation analysis calculates estimated logistic costs when the network loses the optimal point and tries to achieve it again.

Xu et al. [35] use control system theory, super-twisting (STW), and sliding mode control (SMC) algorithm to design a master entity in the system to synchronize a chaotic SC, reducing fluctuations and disturbances. Evaluating parameters like delivery efficiency, customer demand satisfaction, distortion rate, and safety stock coefficient. The model can support technology to the decision-maker. Future research can extend the scope to operations management with a depth dynamical analysis in a multi-echelon chaotic SC, using fractional-order optimal control.

COVID-19 disrupted the SC, creating an economic impact, panicking, influencing SC actors' decisions, and spreading fluctuations. Future studies can collect more information to validate current conclusions. Information sharing (IS) is insightful in reducing fluctuating conditions and uncertainty during a disruptive scenario (Table 2).

Table 2 COVID-19, disruption, and RE literature review

Category [15]	**Solution Method.** [16]	**Technique**	**Trend** [10]	**Measure/ Mitigate**	**Sources**
O	S	agent-based simulation	Fty/SCs	ME	Dolgui et al. [31]
O	OR	EMH/ CAPM	C/SCs	ME	Scarpin et al. [32]
O/B	FT	FMEA/ BWM	FTy	ME & MI	Ghadir et al. [33]
B	FT	Hopf bifurcation analysis	FTy	ME & MI	Hu [34]
O	CT	STW/SMC	FTy	ME & MI	Xu et al. [35]

3.3 Closed loop Supply chain model

The CLSC topic is growing due to an increasing interest in circular economies and their impact on profit, sustainability, and SC integration. However, there is a gap between the research and the real world to improve the current decision-making frameworks, coordinate actors efficiently, handle complex flows, and include SC dynamics [36-40]. Giri et a. [41] consider the BWE as an inventory fluctuation with large wives flowing from the consumer to the producer and replicated through the demand. The anti-bullwhip effect has an opposite dynamic, having more minor wives and not always disseminated from upstream to downstream. A variance in the market price can suppress an order amplification at each part of SC. Future studies can explore incentive systems for customers to increase the purchase of remanufacturing products, including customers' information and behaviors.

Ponte et al. [42] study a CLSC with a control system, proportional order-up-to (POUT) policy, and a quality-grading scheme to classify returning products, smoothing order rate, and BWE. A quality-grading policy increases inventory performance in low-quality returns and low-frequency demand conditioned to manufacturing and remanufacturing lead times differences. The quality-grading mechanisms benefit the work-in-progress, balancing lead time, customer service, and inventory levels; future studies: nonlinear models, remanufacturing markets, and multi-quality grades.

Dominguez et al. [43] ponder centralized or decentralized schemas in a CLSC using multi-agent-based simulation with multiple-return flows. The remanufacturer consolidates the returning flow in a centralized model, while the retailer has a remanufacturer per customer in a decentralized one. Transparency information, returning flow, remanufacturing configuration, and the number of retailers influence the BWE. A centralized model reduces reverse flow uncertainty, smoothing new product orders with operational and logistic efficiencies through information to minimize configuration effects. A decentralized model fits better in an SC with few independent markets and downstream organizations. An echelon to use reverse flow as raw material could be explored.

The CLSC is aligned with the SC structure trend (Table 3) that seeks to model the SC dynamics and return flows. The new U-shaped relations in the network create interactions, contributing to potential disturbances and fluctuations, increasing complexity, and helping to reduce costs and waste. Other BWE fields include the CLSC structure topic due to the growing interest in sustainability, complexity, and real-world problems.

Table 3 Closed-loop Supply chain model

Category [15]	**Solution Method.** [16]	**Technique**	**Trend** [10]	**Measure/Mitigate**	**Sources**
O	OR	MMSE	SCs	ME	Giri et a. [41]
O	CT	control system model	Fty/SCs	ME & MI	Ponte et al. [42]
O	S	Multi-agent-based	Fty/SCs	ME & MI	Dominguez et al. [43]

3.4 Order policy and batching

The batch size growth and unaware decisions in the order process may yield erratic dynamics in the SC and the BWE [44]. A batch size value divisor of the mean demand mitigates the BWE [45]. The policy order-up-to (OUT) has evolved to the proportional order-up-to (POUT), in which the orders are issued partially and proportional to the difference between the target and the available inventory, reducing the BWE [46-48].

Ponte et al. [49] deepen the well-known implication of batching in CLSC, being a booster for the BWE and including service level (SL). The mathematical model represents a hybrid manufacturing-remanufacturing system (HMRS) with discrete events, including inventory policies and backlogging system. The batch size should be divisors of the mean production rate [45]. Omitting the batch size increases the BWE and decreases the SL, as the OUT policy does. The POUT policy may reduce the BWE, increasing SL, inventory holding, and stock-out costs.

Cannella et al. [50] studied the POUT policy in a CLSC, decreasing the BWE. POUT policy surpasses the OUT policy with production efficiency, SL balance, and economic benefits. The OUT policy is better with high return volume and low BWE cost. Inventory controls balance the optimal difference between the target and current inventory, considering production costs, inventory, and SL. An inventory controller in the CLSC optimizes underestimated values to reduce return rates and costs.

A stochastic forecast with the POUT policy limits the BWE, satisfying the demand.

Lin et al. [51] study a push-pull hybrid system with CLSC attributes using a nonlinear control theory and discrete-time simulation. The demand frequency and return rate strongly influence the BWE due to returning orders' boomerang effect. An optimal stage linking capacity constraints to a recoverable inventory with a cost function could be explored.

Order Policy and batching size studies have increased the sophistication of the analysis by concepts like POUT policy, reduction of the BWE through the batch size divisor mean, and the influence of CLSC. The principal considerations are sustainability, finances, and SL (Table 4).

Table 4 Order policy and batching

Category [15]	**Solution Method.** [16]	**Technique**	**Trend** [10]	**Measure/Mitigate**	**Research Works**
O	OR	MM	SCs/FTy	ME & MI	Ponte et al. [49]
O	OR	difference equation	SCs/FTy	ME & MI	Cannella et al. [50]
O	CT/S	Nonlinear control/ simulation	Fty/SCs	ME	Lin et al. [51]

3.5 Information shared and synchronization

Organizations with complex-large and decentralized SCs are dynamic structures exchanging asymmetric information and lack coordination [52], adopting inefficiencies that lead to waste of resources, supply discrepancies, financial losses, and suboptimal performance [53,54]. Synchronization strategies use information sharing (IS) as the main component to align the SC at strategic, tactical, and operational levels, vertically and horizontally, to mitigate the BWE [55,56]. The collaboration schemas have two main scenarios; cooperation, where organizations have mutual commitment, goals, and dedicated resources [57]; coordination which joins the decision-making process and IS, to enhance cross-organizational performance [58].

Dominguez et al. [59] research the impact of partial, accurate, timely, and vertical IS in multi-echelons SC using the decentralized concept where not all members collaborate. Regardless of its position, the number of echelons sharing information is critical in the BWE propagation. The collaborative approach throughout IS is more effective in the downstream than upstream direction. The average lead time may reduce the BWE in IS models, particularly at upstream echelons. Future research could explore different IS types and structures with deviation.

Papanagnou [60] simulates a CLSC using a control system model to mathematically describe the complex relationships in a four-echelon network, demonstrating that high product return rates with aggressive ordering policies amplify the BWE. The model accomplished the information asymmetry in a CLSC, including the Internet of Things (IoT) concept in the customer-to-retailer loop to share accurate information about the returned products and replenishment policies to mitigate the variations in the demand and the BWE.

Ponte et al. [61] model a CLSC influenced by information transparency in order variance and inventory, defining marketing and remanufacturing archetypes with visibility levels. The return rate, lead time, and information visibility degree compose BWE functions and net stock amplification (NSA) ratio to analyze holding requirements and stock-out trade-offs with a cost structure. Increasing returns flatten production positively or negatively, depending on inventory underperformance's available information. The information transparency in the remanufacturing pipeline decreases order variance and inventory depending on market pipeline data; the market one decreases order variability and increases inventory independently. Include other forecasting models and demand attributes could be explored.

Dominguez et al. [62] simulate a four-echelon SC with a multi-agent system (MAS), with partial IS scenarios, influencing SC performance, BWE, and inventory level. Homogeneous retailers collaborating and sharing information generate equal benefits with more impact than heterogeneous ones. However, prioritizing an IS strategy benefits heterogonous retailers with poor forecasting, high demand variance, and long lead time. The full IS model should implement in highlighted retailers due to the additional costs yielded by the strategy.

Li et al. [63] represent a dynamic multi-echelon coordination scenario with material or information flows connected or interrupted. A multiagent-based framework and a consensus control system (H_∞) simulate a switching system to evaluate stock levels in sub-chains and consensus protocols. The study assesses total activation time in stable and unstabilizable subsystems, including delays in transmitting information and materials. The control technique (H_∞) mitigates the BWE mainly for isolated sub-chains, minimizing uncertainty demand. Future research could include stochastic production delays, nonlinear SC with fuzzy control, and backorders accumulated in sub-chains.

Shaban et al. [64] model a coordination mechanism to reduce the BWE through an Info-Smooth based on order smoothing and information sharing transferred upstream. The inventory policy (R,S) seeks to cover the gap between current and target inventory levels, reducing inventory variance and costs and decreasing adverse effects due to order parameters such as lead time. Future research could include order batching in collaboration models.

IS groups topics to optimize the actors' interactions and mitigate the BWE, enhancing inventory decision-making, demand management, and SC flow. Complexity is a trend in the IS (Table 5), studying the progressive amount of information shared. IS includes synchronization or schemas of collaboration to coordinate actions at different levels to mitigate the BWE, especially in disruption periods.

Table 5 Information Shared and Synchronization

Category [15]	**Solution Method.** [16]	**Technique**	**Trend** [10]	**Measure/ Mitigate**	**Sources**
O	S	computer simulation	FTy	ME & MI	Dominguez et al. [59]
O	CT	control systems model	FTy /SCs	ME & MI	Papanagnou [60]
O	OR	MM	FTy /SCs	ME & MI	Ponte et al. [61]
O	S	MAS	FTy /SCs	ME & MI	Dominguez et al. [62]
O	S	(H_∞)	FTy /SCs	ME & MI	Li et al. [63]
O	S	simulation	FTy /SCs	ME & MI	Shaban et al. [64]

3.6 Behavioral BWE

Human factors have been studied widely, such as line underweighting, phantom ordering, and coordination risk; these can be present without operational causes [65]. The BWE behavioral causes are associated with decision-makers' cognitive limitations and SC underweight [66]. SC's actors who decompose problems based on a two consecutive echelon approach tend to underestimate the BWE [67]. The BWE mitigation via behavioral factors involves an adjustment on the operational side, such as keeping inventory levels at a certain quantity [68].

Moritz et al. [69] simulate line underweighting, naïve forecasting, hoarding, phantom orders, anchoring and heuristic adjustment to classify irrational orders via experimental data, applying particle swarm (PS) optimization, beer game (BG), and cognitive reflection test (CRT). In a multi-echelon SC, decision-makers with ordering bias increase ordering costs unequally in SC actors, being worse when a retailer has it. Increasing downstream ordering raises excess inventory and logistic costs, while the upstream increases production inventory and cost to customers, reducing distributors' stock levels and decision-makers' intervention. The model rejects the naïve behavior that uses the most recent demand to forecast orders; a cognitive process shapes the making-decision process improving outcomes and reducing costs. Optimizing the forecast process can support decision-makers in disruptions with signals, data, and suggested values.

Narayanan et al. [70] use BG to design a metric-alignment framework with a coordination approach, including panicking and phantom orders. Synchronizing the decision-making process mitigates back-ordering and costs. Financial penalties related to on-time, in-full conditions to deliver orders turn a cooperative environment into a punitive one. The metric-alignment approach includes synchronization, goal congruence, and IS. In a four-echelon SC participants receive demand information from downstream partners aligned with inventory and backorder costs. Even IS reduces the BWE, unnecessary information entangles decision-making, creating sub-performance. Decision-makers' alignment with retailers mitigates the BWE, improving performance and effectiveness. Profitability, customer satisfaction, market share, SC configurations, vertical integration, and ordering incentives schema could be explored.

Shabany et al. [71] researched the negotiation process using token-based (TB) to classify current demand orders and token volume from inventory shortages; the model incorporates cooperation throughout IS where only retailers access customers' demands. The multi-agent system performs negotiation between retailer and manufacturer agents, using reverse ultimatum game (RUG) and fuzzy logic to solve ambiguities. Implementing no-bias system negotiation reduced the BWE by 30%. Developing trust variables and revenue contracts can enhance negotiation studies.

Villa [72] studied a limited supply where competitors boost placed orders volume, evaluating the BWE on supplier responsiveness, customer overreaction, and retailer efficiency through heuristics. Retailers tend to increase orders to reinforce a safety stock, expecting a shortage scenario with no signal in demand and ignoring canceled orders. The model incentivizes outstanding retailers proportional to effective orders to discourage over-stocks. Asymmetric competition's influence over decision-making, performance, and collaboration could be explored.

Xu et al. [73] simulate a chaotic four-echelon CLSC distorting sales markets and orders through differential equations, including a fractional order sliding mode control (FO-SMC) synchronization algorithm to control SC's fluctuations and tracking variances in error with a control law—a master-slave configuration with a slave system's synchronized behavior to reduce disturbances. The algorithm provides insights to the decision-makers to understand a chaotic SC and recalculate targets. Coming studies may include demand changes, promotions, and disruptions risks.

Narayanan et al. [74] run an empirical experiment to assess ordering strategies flexibility and SC underweighting. Demand variations and constrained downstream ordering limit decision-makers to handle fluctuations, impacting lead times and SL. Flexible orders reduce variations and lead time costs, keeping the SL, and allowing decision-makers to accumulate orders irrationally. A low flexible ordering increases the cost per order, while a high one has a "minimal" one—disincentivizing irrational orders. Hard-constrained supply reduces underweighting behavior where decision-makers assess lead time to reduce order size, reducing order variation and SL. Flexible models may dampen the BWE.

Close capital relations in SC actors can build trust and benefits flow information [75]; which may lead to opportunistic or gaming behavior [76]. Zhao et al. [77] use a multivariate regression analysis (MRA) to evaluate capital relations, identify SC's links through financial statements to assess the capital relation net value, analyzing relationship length and dependency between customer and supplier. Mutual dependence increases the BWE, selling costs, order backlog shocks, and gross margin variations. However, the length of the relationships can mitigate it.

Bray et al. [78] apply a dynamic discrete mathematical model (DDMM), a Markov-modulated demand process, and a Nested Pseudo-Likelihood (NPL). The analysis identified higher variance in shipments than customers and the rational gaming action of upstream scarcity over stores accumulating stocks to avoid shortages. Rational gaming affects inventory and the BWE. SC visibility could be inadequate; the final decision depends on the decision-makers' criteria.

Operational and behavioral factors focus on physical and institutional structures. However, behavioral factors add actors' mental models, bundling rational decision-making with heuristics [7] and spreading the BWE in the SC through operational aspects. Methodologies like the beer game [79] include a holistic view of the problem to understand how behavioral and operational aspects are linked (Table 6).

Table 6 Behavioural BWE

Category [15]	**Solution Method.** [16]	**Technique**	**Trend** [10]	**Measure/ Mitigate**	**Sources**
O/B	OR/S	PS/BG/CRTt	FTy/ MP, SCs	ME & MI	Moritz et al. [69]
O/B	OR/S	BG	FTy /MP/SCs/C	ME & MI	Narayanan et al. [70]
O/B	S	TB/MAS/RUG/CBR	FTy /SCs	ME & MI	Shabany et al. [71]
O/B	OR	MM	FTy /SCs	ME & MI	Villa [72]
O/B	OR/CT	FO-ASMC/ASMC)	FTy /MP	ME & MI	Xu et al. [73]
O/B	AdH	Empirical	FTy /SCs	ME & MI	Narayanan et al. [74]
O/B	OR	MRA	FTy /SCs	ME	Zhao et al. [77]
O/B	OR	DDMM/NPL	FTy /SCs	ME	Bray et al. [78]

3.7 Lead time, demand forecasting, replenishment policies, and inventory policy

Orders are placed based on previous demand, subsequent lead times, and the amount defined by the stock policy and replenishment orders upstream. At the same time, SC's actor attempts to boost benefits regardless of overall efficiency, increasing BWE and logistic inefficiencies [80]. Deterministic or stochastic lead time influences BWE combined with different demand forecasting methods and stock and replenishment policies [81].

Michna et al. [82] measure the BWE in an SC with random autocorrelated demand and lead times, adopting the moving average method (MA) to forecast. Lead time forecasting influences BWE, increasing the stimulus when it combines forecasting and correlation demand. The volume of no-biased forecasting data is crucial to reduce the BWE. Lead time correlation and BWE propagation in a multi-echelon SC could be explored.

Dominguez et al. [83] model uncertain returns quality effects over variable lead times, inventory, and stock in CLSC through a MAS, analyzing return, information transparency, inventory performance, and the BWE. Uncertain returns fluctuations affect inventory. Avoiding the lead-time paradox where the production lead time is longer than the remanufactured one benefits CLSC performance. Incentivizing lower levels IS enhances SC's upstream performance. Order policies, stochastic returns, and returning product values determined by customer perception could be explored.

Shaban et al. [84] simulate a single-echelon SC with correlated demand, OUT policy, and returning flow, analyzing performance measures: order variance ratio (OVR), NSA, and average SL. The model includes lead time, forecasting, and order parameters. Correlated demand with OUT policy optimizes performance measures and is impacted by order parameters, tunning control parameter reduces the BWE. Future research could study time series and new adaptive forecasting methods that obey correlated demand, optimizing forecasting and order policy.

Campuzano et al. [85] research a system dynamics simulation in a single-echelon SC with variable deadlines, uncertain demand, and a rolling horizon (RH) updating information and plans, reducing inventory and logistic costs. Lot-sizing, variable lead times, and RH hence the performance, using logistic costs, SL, and the BWE as metrics. Storage and production capacities constrain the lot size, which a collaborative system such as VMI should be considered.

Bayraktar et al. [86] measure order fulfillment and the retailer's performance in a two-echelon SC with seasonal demand using discrete events, mathematics models, and SEM causal effects analysis. The retailer prioritizes SL, lead time, and forecast accuracy over the BWE; whether decision-makers underestimate backorder cost and the BWE amplification affects fill rate and total inventory cost. The decision-maker should try to decrease lead time and improve forecast accuracy; the SL seasonality affects inventory cost.

Oroojlooyjadid et al. [87] applied a BG with a reinforcement learning algorithm, comparing a basic stock policy with sub-optimal solutions and considering a decentralized information case in the decision-making process. The investigation develops a shaped-reward data-driven algorithm (SRDQR) in a cooperative environment, including information about independent actions and minimizing SC costs in the training phase. Besides, trained agents by SRDQR learn sub-optimal solutions and reduce costs compared to agents using a base-stock policy. The network design definitions may influence seasonal demand functions to increase the response [88]; Future studies can consider a network design aligned with the SRDQR framework, improving the decision-making demand process.

Disney et al. [89] studied a nonlinear inventory system with OUT policy and lost sales, comparing sales and backlogging to measure the BWE and inventory amplification and recovery. The lost sales model mitigates the BWE, contrasting with a backlogging system under some demand and forecasting conditions. No-negative conditions affect inventory variance metrics to measure control, reducing backorder accuracy or lost sales visibility. Complete demand visibility handles lost sales, out-of-stock, and total rate; the safety stock absorbs fluctuation and hidden demand from lost sales. Dynamic replenishment policies, no-linear capacity, and returns could be explored.

Lead time, demand forecasting, replenishment policies, and inventory policy studies have included CLSC structures, models, and policies. Capturing the problems' complexity results in the sophistication of some models (Table 7) proposed. Additionally, metrics like lost sales and service level balance the financial assessment, aligning the solution with different organizational objectives besides the evident economic benefit of reducing the BWE.

Table 7 Lead time, demand forecasting, replenishment policies, and inventory policy

Category [15]	**Solution Method.** [16]	**Technique**	**Trend** [10]	**Measure/ Mitigate**	**Sources**
O	OR	MA	FTy	ME	Michna et al. [82]
O	S	MAS	FTy /SCs	ME & MI	Dominguez et al. [83]
O	S	AR	FTy /SCs	ME & MI	Shaban et al. [84]
O	S	dynamic simulation	FTy	ME & MI	Campuzano et al. [85]
O	S	SEM/ discrete simulation	FTy	ME	Bayraktar et al. [86]
O	S	BG/ RL	FTy /SCs	ME & MI	Oroojlooyjadid et al. [87]
O	OR	MMSE	SCs	ME	Disney et al. [89]

3.8 Production capacity

Constrained capacity impacts lead times directly; a high volume of orders increases time and replenishment. Shrinking the capacity increases lead times, spreading fluctuations along the SC while the actors try to shield themselves from uncertain demand and periods, having a cycle that produces the BWE [90].

Cannella et al. [91] study the production capacity effect on operational performance linked to nonlinear manufacturing lead times, work in progress, and responsiveness. A two-echelon SC simulated with demand variance, safety stock, and proportional controller influencing order variance, inventory level, and SL. Opposite to other studies, increasing manufacturing capacity has positive effects by keeping a lower constant lead time, while decreasing capacity has a negative effect mitigated by SC responsiveness to work under saturation. Stochastic lead time with divergent and convergent CLSC and limited/amplified upstream affecting a downstream capacity/responsiveness could be explored.

Dominguez et al. [92] study a single-echelon CLSC with capacity restrictions and uncertainty in stock demand and returning units through differential equations, tracking the BWE on net stock and production variances. Remanufacturing forward flow fluctuations affect the whole system. Tuning correct capacity constraints, market environment, and uncertainty degree dampen BWE. However, low capacity can affect inventory holding costs and SL. Ponte et al. [93] formulate a mathematical model of impact returns in a CLSC system, considering a U-shaped dynamic between inventory performance and returns. Additionally, unknown return fluctuations affect the SC stability, increasing the BWE and the costs. The returns policy is an effective mechanism to hamper the variable effect.

CLSC schemas are linked to production capacity due to return flows and the SC dynamics' complexity fluctuations, increasing the BWE. Policies could handle these variations, funneling raw materials in the SC to reduce waste. Production capacity flexibility linked to downstream/upstream disturbances is still an open topic.

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Table 8 Production capacity

Category [15]	**Solution Method.** [16]	**Technique**	**Trend** [10]	**Measure/ Mitigate**	**Sources**
O	OR	mathematical model	SCs	ME	Cannella et al. [91]
O	OR	difference equation	SCs	ME& MI	Dominguez et al. [92]
O	OR	mathematical model	SCs	ME	Ponte et al. [93]

4 Overlapping topics, future research, and trends

Figure 4 shows how cluster topics, BWE causes, mitigation strategies, flows, trends and future research are interconnected using the SC structure. Bhattacharya et al. [15] review is used as a framework for BWE causes, adding the trends from the closed topics, such as CLSC returning flows and COVID-19 disruptions. Forrester [94] identified three mitigation strategies: fast order handling, distributor echelon-level elimination, and inventory policy. Recently, researchers have considered lead time [95] and collaborative SC actors relationships [96] accurate forecasting [82], and pricing strategy. [28], IS [61], capacity production tunning [84], and handling CLSC returning flow [60] as strategies to mitigate the BWE. This paper used the framework proposed by Wang et al. [10] to connect trends, found concepts, and future studies discerned by authors.

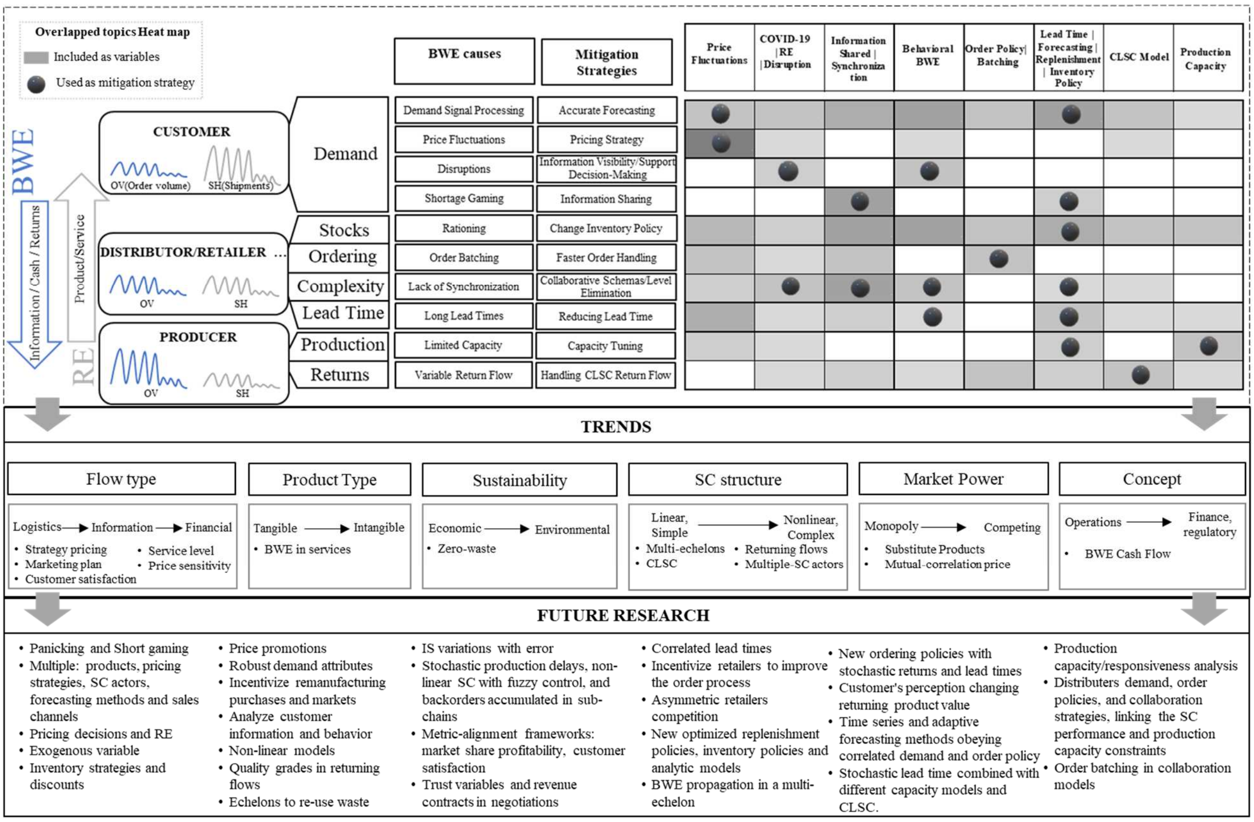

Figure 4 Overlapping topics, future research, and trends

Disney et al. [17] mapped operational and behavioral through a Venn diagram, comprehending the intersection of behavioral and operational causes. The taxonomy is updated with the new clustered topics, showing the number of behavioral studies intersected with blue numbers (Figure 5), including cross-cutting topics involved in the BWE causes.

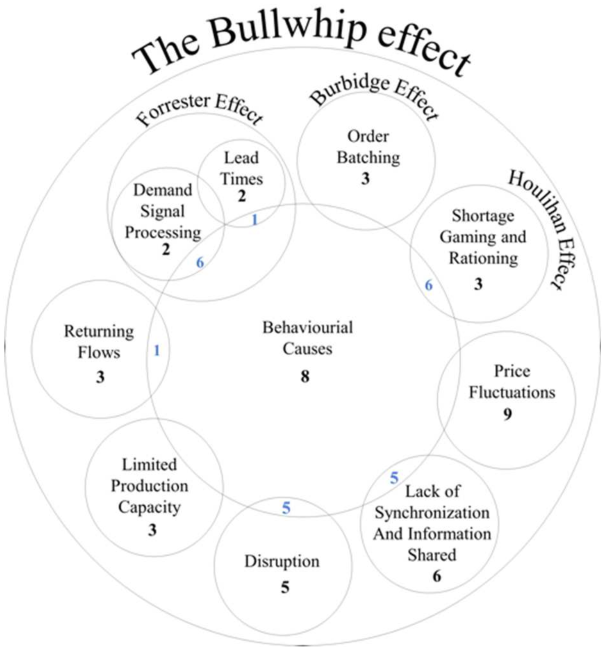

Figure 5 Overlapping behavioral and operational BWE causes [17]

5 Conclusion

How can the BWE issues be synthesized by clustering topics to illustrate existing links in the literature to identify gaps, trends, and future works?: Forecasting Demand has been the dominant topic in upstreaming variations from customers due to its relation with the BWE origin; there is an increasing necessity to improve the information collected at this point to explain and influence customers' behavior, yielding trends like pricing strategy, IS, and disruptions like the COVID-19 pandemic. At the middle network level, distributors and retailers interact through inventory policies to dampen the BWE, including order batching and lead times to further understand the ordering process factors; complexity has a relevant role, requiring collaborative schemas to sync multiple actors and changing elements. In the last level, where the BWE wave is highly amplified, adapting capacity constraints are a normal response. Nevertheless, the SC progression to CLSC models and returning flows add disturbances and new dynamics to the BWE, increasing the relevance of managing this boomerang effect.

The pricing is evolving intrinsically to strategies and complemented concepts to increase the influence over customers' behaviors. However, it is necessary to extrapolate the pricing strategy to other approaches to mitigate the BWE. Price components have been included in stocks, ordering, lead time, complexity, and production; future studies may combine it with disruptions, short gaming, IS, and CLSC schemas.

COVID-19 increased the interest in disruption topics; multiple fluctuations along the network, like BWE and RE. Information visibility and collaborative schemas mitigate the BWE in these scenarios, actively including variables from different topics. Future studies may corroborate the hypothesis around the COVID-19 disruptions, including the shortage gaming and new BWE mitigation strategies to control upstream and downstream flows influencing SC actors' behavior under panicking, like pricing, tuning capacity, and inventory policies.

Understanding and reducing returning flow disturbance is challenging in CLSC structures, representing complexity variations in some lines of research. This growing topic provides economic benefits and sustainability. Nevertheless, none of the selected papers addressed CLSC combined with pricing. There are opportunities to research more about this U-shape model, considering a new level in the SC to explore remanufacturing purchasing incentives, markets, quality classifiers, and zero-waste scenarios.

Order policy and batching include demand forecasting, stock information, and CLSC return flows as variables. Nevertheless, more BWE causes, and mitigation strategies could be linked to order batching.

The papers reviewed frequently mentioned IS to mitigate the BWE; its functionality has been strongly associated with synchronization and collaboration schemas, extending the strategy scope to influence SC actors' dynamics. There are opportunities to combine the IS with topics like pricing strategy, production capacity, and its contribution during disruption events.

The literature review found BWE behavioral causes reflected in operational factors. However, no behavioral study included order batching, shortage gaming, price fluctuations, and limited capacity. Synchronization, lead time, and information visibility were strategies to mitigate BWE. Future studies may explore ordering incentive mechanisms, competing retailers' asymmetries, promotions, and disruptions risk.

Lead time, demand forecasting, replenishment, and inventory policy influence each other, exploring the CLSC model in recent studies. Future studies could include pricing strategy, correlated and stochastic variables in demand, lead times, and non-linearities in the SC, like capacity constraints or returns. Production capacity has been a hard constraint in BWE causes and mitigation strategies. Future research may explore production capacity flexibility to handle downstream and upstream disturbances and CLSC influence over the production capacity.

Integral solutions to remove local optimizations and benefit the whole network have joined topics and sophisticated solutions to include new variables and insights to improve the SC members' decision-making processes. Complex models conceptualize problems and solutions from real-world applications.

Previous authors emphasized the opportunity to extend the BWE research to topics like pricing, behavioral BWE, financial analysis, marketing process, multi-echelon SC, inventory policies, and advanced algorithms [8,97]. This paper review recognizes emerging subjects like COVID-19 and CLSC, distinguishing them from the previous work due to the unified and updated review to visualize trends, gaps, and overlaps.

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