Revisiting the bullwhip effect: how can AI smoothen the bullwhip phenomenon?

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Abstract

Purpose – Although scholars argue that artificial intelligence (AI) represents a tool to potentially smoothen the bullwhip effect in the supply chain, only little research has examined this phenomenon. In this article, the authors conceptualize a framework that allows for a more structured management approach to examine the bullwhip effect using AI. In addition, the authors conduct a systematic literature review of this current status of how management can use AI to reduce the bullwhip effect and locate opportunities for future research.
Design/methodology/approach – Guided by the systematic literature review approach from Durach *et al.* (2017), the authors review and analyze key attributes and characteristics of both AI and the bullwhip effect from a management perspective.
Findings – The authors' findings reveal that literature examining how management can use AI to smoothen the bullwhip effect is a rather under-researched area that provides an abundance of research avenues. Based on identified AI capabilities, the authors propose three key management pillars that form the basis of the authors' Bullwhip-Smoothing-Framework (BSF): (1) digital skills, (2) leadership and (3) collaboration. The authors also critically assess current research efforts and offer suggestions for future research.
Originality/value – By providing a structured management approach to examine the link between AI and the bullwhip phenomena, this study offers scholars and managers a foundation for the advancement of theorizing how to smoothen the bullwhip effect along the supply chain.

Keywords Bullwhip effect, Supply chain, Artificial intelligence, Literature review
Paper type Literature review

1. Introduction

The bullwhip effect and its implications on supply chains have been studied by numerous academics, but it still represents one of the most contemporary operational and logistics problems in supply chain research (Forrester, 1961; Wang and Disney, 2016). In simple terms, the bullwhip effect refers to amplifications in orders along the supply chain, meaning that small variances in customer demand lead to increasing oscillations in the supply chain when moving upstream (Yang *et al.*, 2021). In other words, a bullwhip effect occurs due to a lack of coordination along the supply chain, as members pursue individual strategies instead of seeing the supply chain as a single unit, which not only leads to a "distortion" (Lee *et al.*, 1997b) of demand and related orders, but also results in significant negative operational and financial impacts for businesses and organizations (Pournader *et al.*, 2021).

However, as businesses rely on global and increasingly complex supply chains to satisfy their customers, they regard the supply chain as "an integrated process which includes all activities associated with the flow and transformation of goods from raw materials stage through to the end user" (O'Donnell *et al.*, 2006, p. 1523). In the past, the respective supply chain stages and its related operational processes were often managed independently in their own organizational structures, but technological shifts and the use of artificial intelligence (AI) question the self-sufficient approach and reinforce the interdependence along the supply chain. We argue that the use of AI, which refers to systems capable to perform tasks usually associated with human intelligence such as learning or problem solving (Nilsson, 1971; Pournader *et al.*, 2021), has a significant impact on the way how information, goods and financial flows are managed in an integrated supply chain (Herold *et al.*, 2021a; Pournader *et al.*, 2021; Raisch and Krakowski, 2021).

While initial AI applications focused on the automation of routine tasks, the technological advances in new machine learning techniques, big data availability and the exponential increase of computational power allow organizations today to apply AI-based solutions to complex management problems that was originally reserved for human intelligence (Brynjolfsson and Mcafee, 2017). Scholars argue that the management of AI is unlike information technology (IT) management in the past and the associated machine learning technologies "have greater autonomy, deeper learning capacity, and are more inscrutable than any of the intelligent IT artifacts that have come before" (Berente *et al.*, 2021, p. 1433). In particular, current AI technologies, including facial recognition, autonomous vehicles, robots and natural language processing are developed and adopted in and for various problem domains with more than half of firms implementing these new technologies in some form in their supply chain processes (Balakrishnan *et al.*, 2020). As a consequence of this fusion and interconnection between data and knowledge in the cyber- and physical space, the "information environment surrounding AI development has changed profoundly" (Pan, 2016, p. 410).

In fact, studies show that managers are increasingly using AI to tackle operational problems along the supply chain (Baryannis *et al.*, 2019; Sharma *et al.*, 2022). For example, the use of AI leads to more flexible, reliable and accurate forecasts compared to classic forecast techniques, in particular in the area of demand forecasting which can help to reduce demand variability and thus the bullwhip effect (Jaipuria and Mahapatra, 2014; Prakash and Pandey, 2014). In other words, AI can be seen as enabler to enhance current forecasting techniques and to better react to changing environmental conditions by integrating multiple sources such as vacations, weather, life cycle phases or seasonality (e.g. Helo and Hao, 2021; Kiefer *et al.*, 2019; Singh and Challa, 2016).

AI and its methods of machine learning and deep learning in combination with big data analysis techniques provides an opportunity to smoothen the bullwhip effect in supply chains in ways that is different to former technologies. In particular, AI in and for supply chains differentiates itself from known and existing technologies in three ways: First, the information environment has changed, i.e. sensing and wearable devices enable networks and data transfer among groups and individuals resulting in aggregated knowledge and capabilities in a ternary space [cyber, physics and human society or (CPH)] (Balakrishnan *et al.*, 2020; Pan, 2016). Second, combing machines and humans knowledge, i.e. instead of using a computer to simulate human intelligence, AI builds hybrid intelligence systems by to optimize data flows for greater collaboration along the supply chain (Pournader *et al.*, 2021). Third, the change in data resources can be observed, i.e. the data-driven algorithms are incorporating big data sets, networks as well as intra- and interorganizational information flows (Bresciani *et al.*, 2021). In contrast to the traditionally fragmented and thus not "intelligent" enough IT solutions, AI provides an opportunity to establish effective business systems as a response to the increasing dynamic nature of supply chains (Helo and Hao, 2021).

But although AI and AI applications have become an increasingly prevalent research topic in management research, supply chain scholars have been very shy to tackle the bullwhip effect from an AI perspective and so far, have neglected to outline a research agenda. In other words, the trigger for our study was the observation that current AI literature in supply chain seems to be focusing on quantitative modeling, thus highlighting the need for a comprehensive and structured management perspective that can guide supply chain and logistics scholars and managers to expand their understanding of the future scope of research how AI can smoothen the bullwhip effect.

In an attempt to addressing this topic, we develop the Bullwhip-Smoothing-Framework (BSF) based on key management tasks and functions to analyze the bullwhip phenomenon in the supply chain from AI perspective. We argue that it provides a wealth of opportunities for supply chain management scholars to advance knowledge in this critical area, better understand processes and disseminate knowledge between academic and managers. It needs to be emphasized that this paper neither presents and addresses the analytical and modeling perspective, nor discusses specific forecast techniques. Rather, this review of the literature focuses on the management perspective, asking the research question: *"How can AI smoothen the bullwhip effect in the supply chain?"*

With AI and its link to the bullwhip effect still in its infancy, this paper conducts a systematic literature review to provide an overview about the research published to date. Hence, this paper's contribution is threefold. First, we review the scope and characteristics of the bullwhip effect and AI and discuss its implications to date. In doing so, we propose the new BSF framework that is based on key management pillars that can help to analyze the bullwhip phenomenon in the supply chain from an AI perspective. Third, we use key management pillars of the framework to provide an integrated perspective of AI and the bullwhip effect and to highlight future research directions that will result in further debate and investigation into this important but neglected area of study. By proposing a new framework using a structured management approach that examines the link between AI and the bullwhip phenomena, this study offers scholars and managers a foundation for the advancement of theorizing how to smoothen the bullwhip effect along the supply chain.

The remainder of this paper is organized as follows: The next chapter describes the scope and characteristics of AI and the bullwhip effect and outlines the key management pillars of the proposed framework. This is followed by a description of the methodology we used for our systematic literature review. Next, the main findings of the literature review are presented by summarizing the literature on AI and the bullwhip effect. Finally, a research agenda is proposed based on the current gaps in the literature and we provide directions for future research.

2. AI and the bullwhip effect: scope and characteristics

The following section defines the scope of study by highlighting the key elements of the bullwhip effect, discussing the capabilities of AI and presenting the key management pillars that contribute to our BSF framework. According to Durach *et al.* (2017), a framework reveals the scope of the systematic literature review by specifying the unit of analysis, the study context and the definition of the constructs used. Our BSF framework can be used as a tool to analyze the bullwhip effect and its implications in the supply chain and uses AI as a construct to extract meaning and highlight future research opportunities. We firstly highlight the elements of the bullwhip effect in the next section, followed by the key management pillars that are most relevant to manage the bullwhip effect and an outline of relevant AI capabilities.

2.1 Bullwhip effect

The main argument behind the bullwhip effect is that the information between supply chain layers is only available to few selected participants and restricted to members further up and down the supply chain (Lee *et al.*, 1997a). As a consequence, companies have thus no data about the actual consumer demand which results in distorted information by the companies' own forecasts and transactions and a lack of coordination along the supply chain (O'Donnell *et al.*, 2006). This results in an amplified change of demand (e.g. when variances of orders may be larger than sales), which causes multiple problems along the supply chain, such as an increase in inventory costs, manufacturing costs, replenishment times and/or transportation costs (Wiedenmann and Größler, 2019).

To categorize the bullwhip effect, Lee *et al.* (1997a) identified four main causes: *Demand forecast, order batching, rationing and shortage gaming* and *price variations*. Concerning *demand forecast,* companies usually base their orders on data from previous orders received by their customers, not on the actual demand. The fact that most companies are untrusting and are not willing to share information leads to various forecast methods within the supply chain, potentially causing a bullwhip effect either by using wrong data or imperfect forecast techniques. With regard to *order batching*, companies may order a larger quantity of a product to reduce transportation costs or to receive a discount for larger quantities. Although this benefits the company, it may cause problems along the supply chain as the order is not based on actual consumer demand, leading to a distortion of the "true" demand.

Rationing and shortage gaming can also cause a bullwhip effect, as manufactures may ration their product when demand exceeds supply, leading to an exaggeration of orders. However, the exaggeration of orders may result in lower demand and cancellation of orders, which leaves manufacturers with excess inventory and uncertainty of demand, although consumer demand is unchanged. *Price variations* may also cause a bullwhip effect: for example, sales promotions usually result in large spikes in demand in consumer demand and may lead to distortions downstream and upstream in the supply chain due to inefficiencies such as excessive inventory, overtime costs, missed production schedules, poor customer service and/or quality problems.

2.2 Management pillars for AI

The scope of the bullwhip effect comprises the typical structure of distribution logistics, i.e. we focus on the flow between (1) the retailer, (2) the wholesaler or the distribution center and (3) the manufacturer (see Figure 1). In a typical structure, information often flows upstream only between two consecutive members of the supply chain; however, our framework argues that AI is a tool that can be used to improve the information flow between all relevant members, further supporting an integrative approach.

Drawing from this integrative approach (Kurniawan *et al.*, 2017; Lee *et al.*, 1997b) and in addition to the previous discussed causes, the following three distinct but interrelated key management pillars form a crucial part of our BSF framework.

First, collaboration between members of the supply chain is a key pillar to smoothen the bullwhip effect, mainly referring to the *willingness* among supply chain members to share data. Studies show collaboration along the supply chain is of mutually benefit as aligns supply and demand and can significantly improve performance (Herold *et al.*, 2021b). The fundamental aspect of collaboration can be attributed to information sharing (Barratt, 2004), and although today's technology and technological standards would allow a "seamless" supply chain, exchanging data between members along the supply chain is still challenging (Bailey and Francis, 2008; Herold *et al.*, 2021c; Mikl *et al.*, 2021). Often, intermediation leads to information asymmetry and constitutes a non-value adding activity (Roeck *et al.*, 2020) and the lack of trust between members in the supply chain also results in increasing costs and limited efficiency (Panahifar *et al.*, 2018). As such, technological advancements and the use of

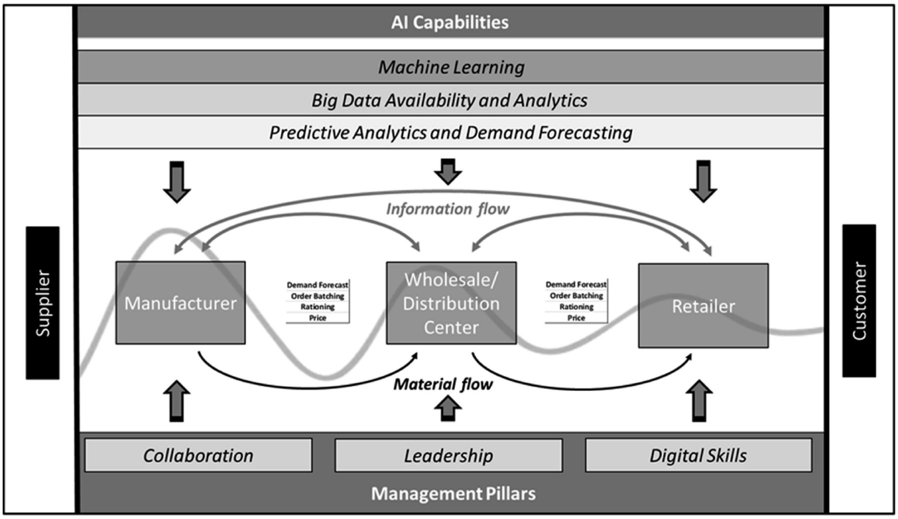


Figure 1.
The BSF

AI to anonymize data (e.g. federated machine learning) may present a potential solution to tackle the information sharing and trust challenges.

Second, leadership can also be considered one of the key pillars to smoothen the bullwhip effect by using AI. This happens mainly through commitment and execution, both referring to the *ability* of the organization to invest in relevant resources to drive AI as well as to the *willingness* to commit to potentially time- and cost-intensive adaption processes (Hsu *et al.*, 2019; Mikl *et al.*, 2020). However, AI applications often rely on augmentation, i.e. "humans collaborate closely with machines to perform a task" (Raisch and Krakowski, 2021, p. 193), which includes resource-intensive repetitive tasks of human-machine learning. As a consequence of the human involvement and its associated human biases, every initiated augmentation can be regarded as a new learning effort which may end up as a failure. Organizations can react to these failures either by stopping AI applications due to internal pressures; however, they may also further commit to invest in AI applications and continuing failures until the AI application provides value (Sabherwal and Jeyaraj, 2015). As such, it is not clear whether companies and their managers are willing to provide a long-term investment of resources to implement AI applications.

Third, digital skills are considered to be one of the key pillars in AI, mainly referring to the *ability* to share, process and manage data (Petropoulos, 2018). However, it seems that companies face problems to find rightly skilled labor and often companies and their managers drive automation in the organization to remain competitive, thereby potentially losing the human skills to change and adapt technological processes (Endsley and Kiris, 1995). Studies show that the increasing automation within organizations not only lead to a loss of human expertise, but can also deskill staff and results in limited organizations' choices (Lindebaum *et al.*, 2020). As such, organizations may face a digital skills shortage when implementing AI applications along the supply chain.

2.3 Artificial intelligence capabilities

The common perception is that AI is one of the most prominent technologies that seem to have the ability to influence supply chain management and transform global supply chains (Raisch and Krakowski, 2021). Stemming originally from the field of computer science, AI comprises the development of systems that are capable to fulfill tasks that are associated with human intelligence (Brynjolfsson and Mcafee, 2017). The phenomenon of AI has been studied by numerous researchers over the last decades; however, technological advancements have only recently shown that AI started delivering its promised value in supply chain management (Min, 2010).

The main difference of AI applications to former IT application is the role of decision-making in organizations (Shrestha *et al.*, 2019). While making decisions in computing has been a core aspect throughout its history, “AI is fundamentally about making decisions autonomously” (Berente *et al.*, 2021, p. 1437). In other words, AI involves automating decision-making through exhibiting “goal directed” intelligence (Russell, 2022) with current applications achieving a high performance that humans are not capable of achieving (Pournader *et al.*, 2021). In fact, AI as tool to enhance productivity or improve efficiency has generated a momentum in both in industry and academia, which is not only proven by the investments from tech-companies such as Meta, Microsoft or Amazon (Markoff and Lohr, 2016), but mainly because today’s AI technology is based on three specific, but interrelated capabilities that can create a competitive advantage along the supply chain, namely (1) the development of machine learning and deep learning, (2) the ability to analyze big datasets to “train” algorithms and (3) using predictive analytics for accurate demand forecasting.

First, machine learning tries to mimic the human way of thinking and examines pathways how to translate knowledge directly from data in order to solve problems (Nayal *et al.*, 2021). In combination with deep learning, which extends machine learning by neural networks, analytics use multiple layers of interplay between algorithms that feed and process numerous data flows simultaneously to produce more accurate insights (Carbonneau *et al.*, 2008). Second, scholars found that there is an interdependence between AI and big data sets, arguing that big data has empowered AI, but in turn, AI need to maintain a constant income stream of big data sets to make correlative predictions (O’Leary, 2013). These data sets provide, e.g. data from multiple sources to forecast the material flows and the consumer demand along the supply chain (Wang *et al.*, 2016). Third, as a consequence of the first two capabilities, AI has the ability to predicative forecasting by using numerous layers of algorithms to better understand the past, resulting in a more accurate forecast of initially distorted information along the supply chain to potentially reduce the bullwhip effect (Riahi *et al.*, 2021; Seyedan and Mafakheri, 2020).

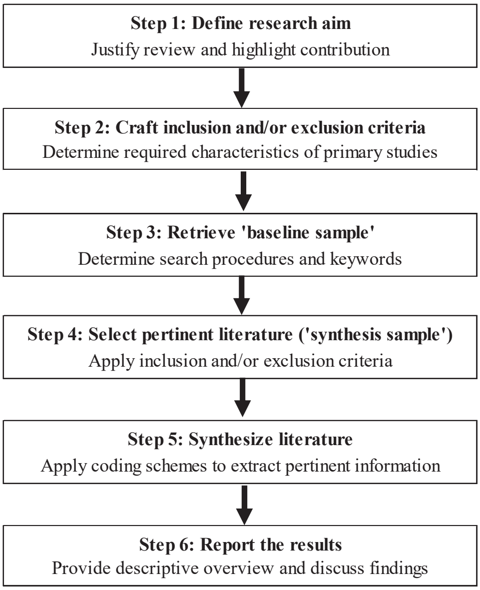
However, although interest in AI has led to broader presence and scholarly discourse within academia, research using AI to examine supply chains is still limited, in particular with regard to the bullwhip effect. The next section presents the research design, which will help us to better understand how AI can be used in the supply chain to smoothen the bullwhip effect.

3. Methodology

This study follows the systematic literature review approach developed by Durach *et al.* (2017). According to Tranfield *et al.* (2003), systematic literature reviews offer high-quality knowledge by using repeatable, transparent and rigorous processes that synthesize scientific evidence. To avoid research bias, our review comprises two databases and involves three researchers from different countries. Following Durach *et al.* (2017), a six-step procedure is applied (see Figure 2) and is outlined below.

3.1 Define research aim

As the aim of this paper is to identify how AI can smoothen the bullwhip effect in the supply chain, we use our proposed BSF framework to analyze and synthesize existing supply chain management literature in order to highlight avenues for future research for supply chain management scholars.



Source(s): Adapted from Durach *et al.* (2017)

Figure 2.
Steps for conducting a systematic literature review

3.2 Craft inclusion and/or exclusion criteria

We adopted a rigorous methodological approach by developing a list of inclusion criteria that was agreed upon by all authors (see Table 1). We decided not to limit the search to specific journals (Briner *et al.*, 2009) and research methods (Durach *et al.*, 2017). However, our search focused on peer-reviewed articles because peer-reviewed articles are regarded to be of higher quality than non-peer-reviewed articles (see Light and Pillemer, 1984). In addition, we selected only articles from 2011 to February 2022, since 2011 was the year in which Industry 4.0 was introduced (Yang and Gu, 2021). We need to emphasize that our review refers to content related to *management* literature regarding the bullwhip effect and AI. However, as AI can be regarded as an extremely fragmented field (Pournader *et al.*, 2021), we extended our search to

Table 1.
Inclusion criteria

Inclusion criteria	Rationale
Peer-reviewed articles	Published peer-reviewed articles increase the quality of the manuscript (Denyer and Tranfield, 2009) and enhance the quality control (Light and Pillemer, 1984)
Selection of papers published 2011 to Feb-2022	The year 2011 was selected as a starting point due to the introduction of Industry 4.0 (Yang and Gu, 2021)
Summary must address a management aspect (as identified in the framework) within the context of AI and/or bullwhip	The aim of the review is to analyze and synthesize the different features of AI and the bullwhip effect to improve conceptual clarity and understanding
Different type of article considered (e.g. empirical, conceptual)	The focus of the study is to evaluate and synthesize the various topics approaches to the concept of AI and the bullwhip effect
Article must be written in English	English is the dominant research language in the field of SCM, AI and management

technological adoptions and innovations within the supply chains to reduce the bullwhip effect. Consequently, articles had to demonstrate a relevant and narrow focus how management can use AI and related technologies to smoothen the bullwhip effect according to our key management pillars identified in our framework. Peer-reviewed articles that did not fulfill these criteria were excluded.

3.3 Retrieve "baseline sample"

In the third step, potentially relevant articles were compiled a "baseline sample". Two databases were selected for the literature search to reduce bias: EBSCO Business Source Complete and the Scopus database. Both databases represent large repositories of management and business articles (see Sandberg and Aarikka-Stenroos, 2014) and offer a wide range of research with high impact within the business research community. The search string based on the research aim and the inclusion criteria was validated by a team of three academics who specialized in AI and supply chain management. After the validation of the initial search string, incremental keywords and associated synonyms were developed to cover all relevant topics.

Similar to other systematic literature reviews, we searched first for supply chain management articles in both databases entering the keyword "bullwhip" in combination with "artificial intelligence", "technology" or "innovation" (see Table 2). The search string was amended for each database based on respective search guidelines and entered into the search field. To ensure that the selection covered all relevant scientific manuscripts dealing with the AI and/or the bullwhip effect, we additionally conducted citation searches and manually added missing papers to the pool of articles. The search was conducted in February 2022.

3.4 Select pertinent literature

The fourth step comprised "synthesizing" the sample, i.e. we included relevant publications while at the same time excluding irrelevant ones (Durach *et al.*, 2017). In the initial search we identified 458 articles from EBSCO and 295 articles from Scopus. Redundant articles were eliminated by two authors who subsequently examined the abstracts based on the inclusion criteria. Abstracts were analyzed independently blindly by the two researchers for validity purposes. This procedure reduced the articles for the subsequent analysis to 112. Following (Durach *et al.*, 2017), the two researchers split and read the full manuscripts as a next step to assess true relevance. This step identified 43 additional articles through cross-referencing, but at the same time, the sample was refined by excluding manuscripts that did not address relevant AI topics. This resulted in a final sample of 97 articles. The process of article selection is shown in Figure 3.

3.5 Synthesize literature

This final sample of 97 articles was subsequently synthesized with the goal of providing a consolidated overview of articles that address how the bullwhip effect can be smoothed by AI. In addition, the content of the manuscripts will be categorized using our BSF framework

Construct	Original search string	Databases
AI/bullwhip/ management	(AB ("bullwhip")) AND (AB ("artificial intelligence") OR AB ("SCM") OR AB ("supply chain") OR AB ("technology") OR AB ("skills")) AND NOT AB ("leadership") OR AB ("collaboration")	Business Source Complete Scopus

Note(s): AB = Abstract

Table 2. Keywords and search string

and, in particular, the key management pillars identified above. We followed the interpretive synthesis approach from Rousseau *et al.* (2008) using themes by the authors as well as open coding schemes. As a result, nine critical sub-topics were identified within the three major management pillars in the 97 articles. Each sub-topic represents a unique characteristic identified in the key management pillars. Each of these themes represents a unique characteristic or dimension within the management pillars. Thus, the mapping of articles to the key management pillars and sub-topics provides a solid basis for identifying gaps and suggestions for future research.

3.6 Report the results

This step provides the results of all selected studies, their relationship to each other and, according to Denyer and Tranfield (2009), "what is known and not known" (p. 672). As such, the analysis can be regarded as an "informed interpretation" (Rousseau *et al.*, 2008) of the scientific findings in relation to the research objective and the gaps identified during the review procedure. The next section presents these findings on the current state of the art and explains how AI can smoothen the bullwhip effect.

4. Results

In presenting our study results, we first provide a snapshot of the 97 papers from our review based on the three identified key management pillars *collaboration, leadership* and *digital skills* and its nine identified sub-topics (Table 3). Given the extremely fragmented dimensions of AI and its interaction with other areas such as human resource management, contemporary supply chain issues, leadership characteristics and even broader organizational change, the findings will focus on how AI can smoothen the bullwhip effect. The following section includes sub-consequently the most significant findings under each of the pillars and sub-topics.

4.1 Collaboration

Collaboration with members and along the supply chain is commonly seen as the key aspect to smoothen the bullwhip effect in current literature with 53% of all papers (51 out of 97). We found that collaboration can play a pivotal role in order to reduce the bullwhip effect through a cluster of three topics comprising (1) the importance of quality information sharing and trust, (2) use of other technologies for planning and operations and (3) use of forecasting/predictive models.

With 16% of all papers (16 out of 97), a strong focus is placed on the sharing of quality and transparent data and information along the supply chain. Most of the papers see joint decisions from sharing as a competitive advantage (Jain *et al.*, 2021); however, Büyüközkan and Göçer (2018) argue that often information about supply chains operations is held locally, which undermines effective and efficient collaboration among members along the supply chain. As a response, Soosay and Hyland (2015) emphasize that members along the supply chain have to establish an appropriate level of trust and integrate supply chain

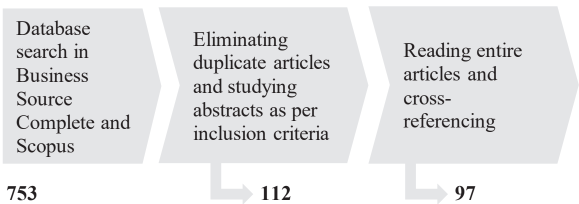


Figure 3.
Article selection process

Key pillar	Topic	Authors
Collaboration	*Information sharing and trust*	Dai *et al.* (2016), Jain *et al.* (2021), Soosay and Hyland (2015), De Almeida *et al.* (2017), Singh and Teng (2016), Ghode *et al.* (2021), Xue *et al.* (2021), Ran *et al.* (2020), Badraoui *et al.* (2020), Costantino *et al.* (2014), Jeong and Hong (2019), Rodrigues *et al.* (2015), Jiang (2019), Jiang and Ke (2019), Rached *et al.* (2016) and Büyüközkan and Göçer (2018)
	Technologies for planning and operations	Hill *et al.* (2018), Yuan and Zhu (2016), Qin *et al.* (2017), Tian (2016), Pournader *et al.* (2021), Prakash and Pandey (2014), Preil and Krapp (2022), Raisch and Krakowski (2021), Wiedenmann and Größler (2019), Baryannis *et al.* (2019), Sharma *et al.* (2022), Toorajipour *et al.* (2021), Min (2010), Dash *et al.* (2019), Klumpp (2018), Dhamija and Bag (2020) and Dubey *et al.* (2020)
	Use of Forecasting/Predictive Models	Ilie-Zudor *et al.* (2015), He *et al.* (2017), Gunasekaran *et al.* (2017), Lee *et al.* (2019), Seyedan and Mafakheri (2020), Souza (2014), Waller and Fawcett (2013), Brynjolfsson and Mcafee (2017), Rahwan *et al.* (2019), Jaipuria and Mahapatra (2014), Prakash and Pandey (2014), Pournader *et al.* (2021), (Helo and Hao, 2021), Kiefer *et al.* (2019), Singh and Challa (2016), Wiedenmann and Größler (2019), Balan *et al.* (2007), Moghadam and Zarandi (2022), Poornikoo and Qureshi (2019) and Aggarwal and Davè (2018)
Leadership	*Top-level commitment and AI strategy execution*	Fountaine *et al.* (2019), Bakker and Budde (2012), Stone *et al.* (2020), Baryannis *et al.* (2019), Brock and Von Wangenheim (2019), Duan *et al.* (2019), Berente *et al.* (2021), Davenport (2018), Wang *et al.* (2016), Henke *et al.* (2018), Smith and Green (2018) and Wijayati *et al.* (2022)
	Implementation of a centralized budget	Beltagui *et al.* (2020), Frick *et al.* (2021) and Kruhse-Lehtonen and Hofmann (2020)
	Establishment of quick wins	Belhadi *et al.* (2021), Lichtenthaler (2019), Campion *et al.* (2020), Polak *et al.* (2020) and Kankanhalli *et al.* (2019)
Digital skills	*Human–machine interaction for decision-making*	Binns (2020), Arslan *et al.* (2021), Ashta and Herrmann (2021), Hanelt *et al.* (2021), Bankins (2021), Jarrahi (2018), Keding and Meissner (2021), de Fine Licht and de Fine Licht (2020), Felzmann *et al.* (2020), Sjödin *et al.* (2021), De Cremer (2019) and Tambe *et al.* (2019)
	War for talent/digital skills shortage	Chamorro-Premuzic *et al.* (2019), Karacay (2018), Lutz (2019), Istomina *et al.* (2020), Wang and Ha-Brookshire (2018), Pillai and Sivathanu (2020) and Klett and Wang (2013)
	Targeted upskilling	Black and van Esch (2021), Ng (2016), Jaiswal *et al.* (2021), Foroughi (2020), Frankiewicz and Chamorro-Premuzic (2020), Elliott (2018), Vallor (2015) and Budhwar *et al.* (2022)

Table 3.
Topics by author

processes to achieve performance improvements through collaboration. Scholars claim that the transfer of sensitive data by a central actor requires a high degree of trust in its discretion as well as sense of responsibility and competence (Singh and Teng, 2016); however, by "chaining" the immutable transaction history as well as the decentralized control function of the network, blockchain is considered a technology that could promote security, transparency and collaboration in the supply chain (Dobrovnik *et al.*, 2018; Ghode *et al.*, 2021; Hribernik *et al.*, 2020; Kummer *et al.*, 2020).

Apart from classical collaboration concepts such as Collaborative Planning, Forecast and Replenishment (CPFR), Just-in-Time or Just-in-Sequence, collaboration is also distinguished between planning support and management support (Hill *et al.*, 2018). While planning support (e.g. CPFR) focuses on aspects of intensive partnership-based planning and coordination, management support focuses on operational aspects such as the organization of cross-company data transfer. Moreover, some studies also highlight technologies that can help to overcome collaboration issues between members of the supply chain (Yuan and Zhu, 2016). For example, the trend to use sensor technology for monitoring and data collection is regarded as a potential solution as well as radio frequency identification (RFID) provides also an opportunity to capture current and product-related data (Bottani *et al.*, 2010).

From an AI perspective, 17 studies mention AI or machine learning in the context of collaboration management, mainly in the context of predictive models or forecasting. For example, machine learning is also used in conjunction with predictive maintenance or predictive quality (Ilie-Zudor *et al.*, 2015). The main argument is that by using historical data, a system learns to evaluate current data in such a way that it can make a prediction about future developments (Gunasekaran *et al.*, 2017; Lee *et al.*, 2019). Furthermore, similar predictive models can also be used for forecasting along the entire supply chain (Seyedan and Mafakheri, 2020). The authors argue that with the help of machine learning, more precise statements can be made about inventory, orders, deliveries and demand. As a consequence, the utilization of warehouses and transport service providers can thus be estimated more accurately, leading to reduced costs and more efficiency.

4.2 Leadership

Our analysis revealed the importance of the leadership for a successful use of AI along the supply chain. However, we couldn't identify a study that particularly includes the bullwhip effect in their examinations. Nevertheless, we identified 19 papers (20% of all paper) that discuss the role of leadership in the context of AI, consisting of the three leadership topics (1) top-level commitment and AI strategy execution, (2) implementation of a centralized budget and (3) the establishment of quick wins. In general, leadership is seen as crucial as it up to management to make the key decisions about AI, to oversee AI projects, allocate resources, govern the organization and coordinate the members along the supply chain.

Studies show that companies still have problems to identify business or use case for AI in the organizations and often struggle to design interfaces and determine when and how machines and humans need to interact (Fountaine *et al.*, 2019). As a result of this uncertainty, companies may become disillusioned how to build AI applications and managers may be disappointed by the pace of progress (Bakker and Budde, 2012), leading to growing impatience and a potential stop of all AI activities. Scholars found that the use of AI along the supply chain can be regarded as a long-term investment for companies and top-level commitment and its associated determination and persistence are key factors for the implementation (Brock and Von Wangenheim, 2019; Duan *et al.*, 2019). In particular, the authors stress that a fully committed leadership, from the board over to C-suite to the senior managers, is required and managers need to be highly involved in all execution aspects of the company's AI strategy and data initiatives.

Companies need to be prepared to develop, test, and deploy the AI technologies internally and need to integrate AI in all of decision-making on all business levels from strategy to operations along the supply chain. Baryannis *et al.* (2019) argues that for AI to work, it needs to satisfy the two characteristics of *autonomously* deciding on a course of action that leads to success in supply chain-related objectives and do so under a *partially unknown* supply chain environment. Supply chain academics stress that the implementation of AI calls for commitment and execution to create an effective business environment for AI, instead of relying on IT specialists, coding and data scientists (Wang *et al.*, 2016).

For the implementation, leadership should be able consider where to deploy AI first. Belhadi *et al.* (2021) argues that using AI for marketing and sales is preferable as it results in quick wins, as does it with process optimization business cases. The main argument is here that cost savings opportunities are easier to justify than building new business opportunities for novel revenue streams, which in turn leads to quick(er) demonstration of AI benefits and to a subsequent further buy-in and commitment from management. In order to push AI applications, studies show that a centralization of budgets is useful as the separate organizations' units and functions are often not prepared to carry the expenses for the whole organizations' AI capability building. This leads not only to an integrated AI approach, but also frees up resources that might be needed for a scaling up (Beltagui *et al.*, 2020).

4.3 Digital skills

Our analysis reveals that digital skills or competencies are seen as a central factor for the successful digital transformation as well as for the exploitation of the potential of AI. In particular, literature about digital skills in a broader AI context comprised 27 papers with a cluster of three topics, where management needs to (1) define human–machine interaction for assisted decision-making, (2) address the war for talent, i.e. digital skills shortage and (3) offer targeted upskilling to shape the digital transformation.

However, as the topic of skills is strongly related to the human resources discipline, scholars discuss and highlight the implications for managers that need to be considered when using AI in the supply chain (Binns, 2020). For example, scholars stress that while it is essential to invest massively in digital education and skills, information literacy and critical thinking should be taught at the same time to prepare for tasks beyond the reach of machines (Ashta and Herrmann, 2021). Other scholars emphasize that although qualification programs and training courses should be "enriched" with AI content, the digital transformation and the use of AI will lead to demand for numerous new job profiles that cannot be clearly described at the moment (Hanelt *et al.*, 2021).

Another important aspect is the ethical aspect when using AI in the supply chain. According to Bankins (2021), managers need to acknowledge that AI should not lead to a conflict of "machines vs employees", but rather to identify pathways how these two can-coexist. Keding and Meissner (2021) show that the more technology is involved in the automation of decision-making processes, the more human judgment is needed; thus, humans and AI are needed to achieve "assisted decision-making." Other scholars go further and see the use of AI technologies to drive democratize decision-making and thus enable users to act in an informed way by providing transparency and linking people, information and knowledge (Sjödin *et al.*, 2021).

From a pure bullwhip perspective, no study specifically investigates digital skills regarding to the bullwhip effect, and only a handful of studies examine digital skills for AI and its implications along the supply chain. However, some studies that examine digital skills in and for AI, see the skill market situation rather as "dramatic" due to a potential digital skills gap (i.e. the gap between existing and required digital skills) that seems to be growing (Chamorro-Premuzic *et al.*, 2019). As a consequence, the "war for talent" – for digital talent – is supposed to intensify; thus, companies not only need to provide the right incentives to attract such talent, but need to invest in targeted upskilling to build further competencies, which will also help retain talent long term and subsequently shape the organization's digital transformation (e.g. Foroughi, 2020).

5. Identified gaps and directions for future research

In this study, we examined the academic literature on AI and the bullwhip effect from a management perspective, not only to provide a framework that characterizes the field and stimulates scholarly discussion, but also to provide explicit insights and concrete recommendations for an emerging research agenda. Overall, our literature review reveals that several topics related to AI and the bullwhip phenomenon from a management view are severely underrepresented. Therefore, we would like to suggest the following recommendations for future research.

5.1 Little attention has been given to how AI can smoothen the bullwhip effect in the supply chain from a management perspective

Although a number of papers have addressed AI and its impact on the bullwhip effect (data transfer, coordination, etc.), the management perspective and its processes and requirements to smoothen the bullwhip phenomenon have not been addressed properly in previous research. The lack of research in this area can be partially explained by the need for interdisciplinary research, as the field of AI and the bullwhip effect is not only extremely fragmented, but also interacts with other disciplines and areas such as human resource management, contemporary supply chain issues, leadership characteristics, or even broader organizational change. We believe that our BSF framework developed in this paper can provide a foundation for management-related directions of future research in two ways. First, our framework can provide the backbone for management analyses of supply chain processes in terms of the three key management pillars to identify success factors for management by acknowledging the idiosyncrasies of AI. Such analyses may also help to validate or further advance the framework as an appropriate management tool in supply chain management. Second, we encourage researchers to contribute with incremental concepts and frameworks on AI and the bullwhip effect, either developed from scratch or based on the various conceptual contributions from the information management and supply chain literature to date.

5.2 The link between AI applications and collaboration appears to be under-examined, in particular regarding the topic of trust between members along the supply chain

Although our review identified several important papers investigating collaboration along the supply chain in the context of a bullwhip effect, papers examining specifically AI to enhance collaboration efforts are still limited. The majority of these papers consist of literature reviews, which discuss only the potential of AI applications or only briefly touch the collaboration issue as part of a broader review. This is somewhat surprising, given that the collaborations are considered to be one of the key factors not only to reduce the bullwhip effect, but also as an area of improvements by AI and its applications. Moreover, the collaboration literature so far lacks also an examination of AI and its applications regarding the trust issue between supply chain members. Most of the articles we found present blockchain as a tool to decentralize the data, but fail to make clear recommendations how to specifically integrate and manage the trust issue with members – and often conflicting interests – along the supply chain. Furthermore, we also couldn’t identify any articles that discuss collaboration and the integration of digital start-ups that offering AI applications along the supply chain. Given that AI applications are increasingly created by start-ups, future research may not only examine the specifics of AI for collaboration along the supply chain, but also how digital start-ups offering AI solutions can reduce the bullwhip effect.

5.3 Ways how AI can influence collaboration efforts in practice to reduce the bullwhip effect have so far been neglected

We argue that the practical part how management can collaborate using AI along the supply chain has been heavily neglected. So far, the vast majority of papers examined for this study presenting or extending predictive models or specific forecast techniques are of theoretical nature. In particular, scholars use either the beer-game or other games to illustrate the implications of the bullwhip phenomenon, or they use experiments and complex modeling to demonstrate the effects on the supply chain. So far, concrete investigations how AI can smoothen the bullwhip effect from a practical management perspective is quite limited. Future research could, therefore, explore specific or interrelated management issue that can managers in the supply chain sphere to better understand how to overcome the challenges of AI and the bullwhip effect.

5.4 Specific leadership and digital skills that need to be built and to implement AI applications in the supply chain have only been partially explored

Our review suggests that the human resource-related issues regarding the digital transformation and the potential use of AI have been quite well researched. Interestingly, most of studies discuss the human–machine interaction and conclude that AI still needs humans to assist them in decision-making. Apart from these human resources research, only few studies mention the digital shortage and needed upskilling for a successful implementation of AI application. In particular, from a management perspective, there is lack of studies investigating what kind of specific skills are needed to implement AI, how organizational structures should be changed and how to address the digital skills gap. Hence, the challenge for future research in the area of digital skills it to find and develop realistic use cases and approaches within companies to identify specific leadership and skill demands.

6. Implications for theory and practice

6.1 Theoretical implications

Our paper employed a systematic literature review to examine how AI can smoothen the bullwhip effect. More specifically, our study is one of the first papers that specifically examine the link between AI and the bullwhip from a managerial perspective. As such, the paper extends the theory's propositions that the tasks and goals of a supply chain in implementing and using AI systems are better satisfied when the management involves collaboration among supply chain participants, strong leadership from the top as well as a focus on the development of digital skills. Our findings also respond to the call of Berente *et al.* (2021) to understand the "approaches to the communication, leadership, coordination, and control of AI soon" (p. 31).

So far, most managers and academics have rather overpraised the usage of AI systems, but neglected the challenges associated with the implementation of AI to smoothen the bullwhip effect or failed to appreciate the consequences from a management perspective. Thus, we examined existing literature and identified three interrelated key management pillars and provided insights into the specifics behind collaboration, leadership and digital skills. In other words, we shed light on the relationship between AI and the bullwhip phenomena, thereby analyzing its impacts on the business environment and expanding the different theoretical perspectives.

In addition, we present the BSF framework that can be used as a tool to analyze the bullwhip effect and its implications in the supply chain. The BSF start with the question what influences the bullwhip effect from an AI view, thereby presenting a context-aware approach how to manage the demand variability in the supply chain. As a result, our framework offers a foundation for the advancement of theorizing how to smoothen the bullwhip effect with AI by providing a structural management approach.

As its core, it assumes that AI provides a powerful tool to smoothen then bullwhip phenomena depending on the extent how the three key management pillars and their inherent challenges can be overcome. However, we need to point out that there is difference between *smoothing* and *eliminating* the bullwhip effect: although AI has the capability to greatly influence demand variability along the supply chain, the bullwhip effect will still represent a significant future management challenge for supply chain managers and scholars.

6.2 Practical implications

AI has had a dramatic impact on organizations in recent years. Initial AI applications were rather used as tools for complex calculations and automation, but the current application of AI is seen as transformative tool to enhance the productivity for organizations and individuals. However, so far, the productivity promise of AI applications is often not fulfilled, in particular along the supply chain with regard to the bullwhip effect. Our results reveal and identify the reasons behind these unfulfilled promises and present the key pillars and their challenges that need to be addressed to smoothen the bullwhip phenomena. In particular, this study emphasizes the pressing need for managers to further develop AI in their organizations and to deal with the inherent management challenges in the organization and along the supply chain.

Our paper offers interesting insights into the practical implications for smoothing the bullwhip effect by using AI systems that are supported by strong collaboration, leadership and digital skills. With AI rapidly becoming a preferred tool to enhance the organizations' ambitions, it is important that managers are aware of the opportunities and the challenges associated with the implementation of AI along the supply chain. Thus, managers are urged to look at how AI can influence the supply chain collaboration, in particular with regards to trust and the use of forecasting/predictive models to smoothen the bullwhip effect. Our findings also revealed that not only collaboration is a crucial element, but also that "softer" factors such as leadership and addressing the digital skills gap are necessary for successful AI systems.

Our framework also points to the need to find a balance between the performance of AI and its accountability. In particular, one the one hand, managers need to find a way to develop metrics and standards to quantify the performance, but, on the other hand, need also create ethical frameworks that provide transparency within and beyond their organizations. The inherent complexity behind the use of AI along the supply chain thus represents an ongoing challenge to address the demands from society and the market. Our framework and its structured management approach present a first step to analyze AI and its implications on the bullwhip effect along the supply chain.

7. Summary and conclusion

In this study, we set out to achieve three interrelated goals. First, we reviewed management literature specifically focused on how AI can help to smoothen the bullwhip effect in supply chain and discussed its implications to date. Second, we proposed the new BSF that is based on key management aspects and characteristic that can help to analyze the bullwhip phenomenon in the supply chain from an AI perspective. And third, we used the BSF as the backdrop to our systematic literature review on AI and the bullwhip effect to synthesize the research that has been published to date. By categorizing this research into key management pillars, we were also able to identify gaps and propose future research directions that will contribute to further debate and investigation into this important yet neglected field of study.

The identification of the scope and characteristics shows that AI and the bullwhip effect are defined by three core elements (Figure 1 above). First, the bullwhip effect can be categorized around four causes: demand forecast, order batching, rationing and shortage gaming as well as price variations. Second, the management of AI and the bullwhip effect are embedded around three pillars, comprising collaboration, leadership and digital skills. Based in these findings, we also provided a definition for the supply chain in the context of the bullwhip phenomenon. Third, the scope of AI is defined by the three types of capabilities, namely the exponential increase in computational power, the development of machine learning and deep learning and the ability to analyze big datasets to "train" these algorithms.

One central contribution of this paper is to shed light on the current state how management can use AI to smoothen the bullwhip effect. More specifically, by providing a structured management approach to examine the link between AI and the bullwhip phenomena, this study offers scholars and managers a foundation for the advancement of theorizing how to smoothen the bullwhip effect along the supply chain. Although the literature provided sufficient knowledge for a first definitional framework, our systematic review reveals that the AI and the bullwhip aspect from comprehensive management perspective to date have rather been neglected by academic scholars. In other words, research of AI and its implications on the bullwhip effect is in its infancy and provides plenty of opportunities for further research in each of the three key management pillars. Our study provides, therefore, a critical first step.

Even though AI is increasingly prominent topic among academics and managers, management literature dealing how to use AI in organizations with its operational and strategic horizons has yet to resonate in the minds of AI and supply chain scholars. We hope that both the gaps and challenges presented in this contribution will spark ideas, discussions and projects on how to fill this largely open canvas.

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