Towards Explainable Artificial Intelligence (XAI) in Supply Chain Management: A Typology and Research Agenda

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Abstract.
The potential for artificial intelligence (AI) to drive digital supply chain transformation today is beyond question. However, its full potential to address more complex supply chain management (SCM) problems is still unclear partly due to AI's black-box problem both in practice and in literature. This paper attempts to highlight the significance of explainable AI (XAI) in SCM and shades light on SCM areas where AI's black-box problem remains problematic. The goal of this integrative literature review paper is to provide new insight into the status of XAI as a solution to AI's black-box problem in SCM where AI techniques have made rapid in-roads. The AI techniques in SCM literature and the significance of XAI in SCM are contrasted. We present an integrative research typology for XAI in SCM to better align how SCM literature has conceived AI deployment in SCM this far. The typology should help us understand the gap between what we know about AI deployment in practice, AI maturity in SCM, and the extent of XAI in SCM.

Keywords: Artificial intelligence, explainable AI, supply chain management, supply chains, integrative literature review

1 Introduction

Supply chains today have increasingly become more information-intensive due to the gradual shift from physical assets management (e.g., inventory, warehouses, transport equipment) to data and information management [1,2]. As a result, the adoption of artificial intelligence (AI) in supply chain management (SCM) has become one of the most important applications for digital supply chain transformation in the last 10 years [3,4]. [2, 22] show that AI has the potential to improve SCM through better inventory forecasting, sourcing optimization, asset maintenance, targeted marketing, and better customer experience. [3] cite several examples where AI applications have enhanced supply chain performance including in warehouse automation, demand planning, supplier performance management, transport optimization, predictive risk management etc. [1] predict that AI will become one of the biggest contributors to the digitalization of SCM with a demonstrable impact on cost reduction, revenue, and market growth.

Yet despite the potential for AI, SCM literature has not fully conceptualized the complexity and risks of AIs black-box which has arguably limited AIs adoption in even more complex SCM tasks [1, 23]. The application cases of AI in SCM presented in [2, 3, 4] including in demand forecasting, logistics, transport, supplier selection, order-fulfillment, vehicle routing, etc. shows an operational and tactical orientation of AI in SCM. The literature presents limited application cases for more strategic SC processes such as supply chain design, supply chain innovation, strategic sourcing, supply network optimization, etc. This may partly explain AIs low adoption for more complex SCM activities [24]. In the information systems (IS) research, AIs black-box problem has long been associated with the reluctance by users to trust and accept outcomes from algorithms and opaque AI systems [5,6]. Because SCM decisions have a disruptive impact on firm performance, it is important therefore SC decision markers understand how AI models work, or how AI systems arrive at their decisions [7, 22]. Model comprehensibility and interpretability are critical to AI's ability to solve complex SC problems in the short term as well as for the long-term adoption of AI in complex industrial and SCM processes [3, 22].

Human-machine trust, AI model interpretability, and comprehensibility are well-known characteristics of explainable AI (XAI) [5,6,7]. The concept XAI is fundamentally about how AI models *must* become more interpretable to humans: to enable humans to understand how AI systems arrive at a specific decision and why a specific action or output should be trusted [6,7]. XAI is about AI models and systems being understandable, fair, trustworthy, and transparent [5]. Distrust and lack of transparency lead to aversion and decision-making overrides. In SCM this will translate into the reluctance to implement digital SCM which's been touted as a definitive enabler of competitive advantage, better end-to-end SC visibility, better collaboration, advanced decision making, accelerated innovation, and enhanced SC responsiveness [8].

So, this paper examines the view that the potential for AI and its maturity in SCM will be limited by the nuances of the black-box problem in AI. This problem increases exponentially as AI systems become even more complex – from basic algorithms, fuzzy sets, and machine learning to very complex deep learning and convolutional neural networks [9]. The proposed solution, therefore, is to conceptualize the AI application areas in SCM and examine the extent of XAI in those areas currently under-researched. Therefore, the paper answers the research question (RQ): *how significant is XAI in SCM, and where in the application of AI in SCM will black-box risks of AI emerge?* Through a synthesis of few studies on this topic, the paper contributes to a better understanding of XAI in SCM by identifying the weaknesses of XAI in SCM literature.

The paper is organized as follows. The methods are presented in the next section; thereafter the results and discussion are presented. At the tail end of the paper is the conclusion and suggestions for future research.

2 Methods

We conducted an integrative literature review (ILR) following the approach of Torraco [10,11]. The goal of ILRs is to scour the literature of a specific topic to create preliminary conceptualizations and theoretical models as a basis for further theorizing [11].

We conducted a dummy search (on 24th January 2021) in google scholar (GS) using the search string **"**artificial intelligence in supply chain management**"** (with the search operators: **"**…**"**) and returned 174 results. Despite GS's wide source coverage, the lack of quality controls and clear indexing guidelines makes it problematic compared to other databases like Web of Science (WoS) and Scopus [12].

We retained the same search string and applied it to the Web of Science (WoS) and Scopus databases, which are extensive and renowned for high-quality bibliometric capabilities [9]. The search for articles from 2010 to date resulted in 137 hits for WoS and 101 hits for Scopus hence a total of 238 hits. We filtered the results for only English language and peer-reviewed published articles and controlled for phrases: "AI" and "SCM" in article keywords. This resulted in 50 hits for WoS and 36 articles for Scopus. We divided the 86 articles among the authors and read the abstracts individually, often iterating with each other on select articles to improve interrater reliability. After filtering out the duplicates, we ended up with a total of 18 articles for this review shown in **Table 1**: two articles [2,4] were cross listed.

Table 1. Search strings and results from in WoS and Scopus

Database	Search String	Articles for review
Web of science	TOPIC: (Artificial intelligence in supply chain management) Refined by: LANGUAGES: (ENGLISH) AND DOCUMENT TYPES: (ARTICLE) AND DOCUMENT TYPES: (ARTICLE) Timespan: 2010-2020. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI. **Total hits 137 (n=10)**	[2]*[4]*[13] [14] [15] [16] [17] [18] [19] [20]
Scopus	"Artificial intelligence in supply-chain-management" AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (EXACTKEYWORD , "Artificial Intelligence") OR LIMIT-TO (EXACTKEYWORD , "Supply Chain Management")). **Hits total hits 101 (n=08)**	[21] [22] [23] [24] [25] [26]

**Cross-listed in both WoS and Scopus*

3 Findings and discussion

Based on the studies reviewed, AI in SCM is a burgeoning research area. Most studies, mainly conceptual papers, report on the potential impact of AI techniques such as agent-based systems (ABS), genetic algorithms(GAs), expert systems (ES) deep learning (DL), multi-agent systems (MAS), artificial neural networks (ANNs), support vector machines (SVMs) in SCM processes including in demand planning and forecasting, supplier selection decisions, supplier performance assessment, make-or-buy decisions, order picking and CRM, SC network design, SC risk analysis, logistics workflow planning, and in transport network optimization [1, 2, 3, 4, 20, 24]. Only a couple of studies provide demonstrable use-cases of AI application in SCM. For example, [13] show the application of neural networks (NN) in SC forecasting, [19] demonstrate fuzzy logic (FL) and ML methods use in production planning, [22] apply AI in SC process optimization, [23] report on the use AI in inventory forecasting and fulfillment center optimization, and [25] show the use of ML in replenishment decision making.

Despite the exponential increase in computing power and availability of big data today than has ever been before [14], the big picture in the literature reveals a wait-and-see approach to the strategic adoption of AI within SCM. [21] show that early applications of AI are still predominantly operational than strategic. [22] demonstrate that AI adoption, especially ML, is still at the developmental stage because of the limited understanding of how ML tools can be applied to SCM processes, the low acceptance in company culture, and the inability to obtain suitable data. In some cases, the models are too complex, while some techniques such as DL make it even harder to understand the intrinsic knowledge emerging from a data set [17,19]. Complex AI models are meaningless unless they can be manually evaluated or are understood by the practitioners and thus applicable to practical SC problems [2,14]. This is exactly what XAI must address to enable ease of use for SCM decision-making, especially as AI systems learn and evolve into highly opaque architectures.

XAI must offer a suite of tools to help users understand how AI models work and interpret the recommendations which emerge from AI models [6,7]. With a slight exception of Zhang et al., [23], all the reviewed articles do not address the role of humans in the AI deployment in SCM processes. Humans and AI are complementary, both contributing cognitive and physical attributes to SCM tasks [23]. In addition, the symbiotic interface between users and AI technologies leads to the development of strong AI capabilities which creates significant business value [22,23]. Meske et al. [5] citing [27] offer a four-level continuum for explainability which AI models can be based on: Type I for trace and reasoning (how and why decisions were made), Type II for justification or support (to explain the reasoning behind a decision), Type III to explain the systems control behavior and problem-solving strategy, and Type IV to provide terminological detail. This framework for which the typology in **Figure 1** is based, suggests that the level of deep knowledge required for reasoning, audit and trace queries in AI systems tends to increase from Type I to Type IV. We map these into an XAI typology for SCM.

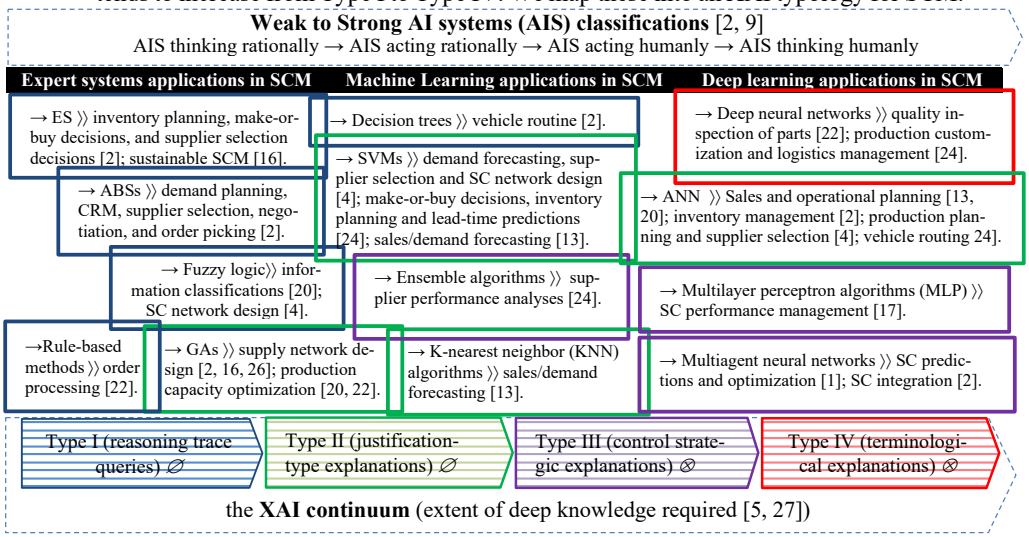

Fig. 1: *An XAI typology for SCM (∅ = represented; ⊗ = not well represented)*

4 Conclusion

In this paper, we set out to explain the significance of XAI in SCM and map where AI's black-box risks will likely emerge in the deployment of AI in SCM. We conclude that AI's potential even if significant in SCM is still limited by capacities of firms to uniquely add humans in the AI decisions loop. At the moment only Type I XAI and Type II XAI are well represented but mainly in operational SCM processes. In these processes', humans provide an external layer to monitor, audit, and validate the fidelity of AI decisions. As the literature shows in **Fig.1**, the visualized SC structure where AI is deployed, the human side of AI is only considered in "weak-to-moderate" AI systems, where SC processes are still operational. From this ILR and our typology, we can make the following observations:

- XAI is undeveloped and superficially addressed in the AI for SCM literature.
- The link between XAI and SC performance is evident but not well researched.
- AI adoption in SCM is fairly mature but XAI considerations are not researched yet.
- AI in some industries is advanced but deep SCM applications are still not well integrated in typical SCM processes which negatively impacts on XAI deployment.
- As AI systems become ubiquitous and complex, XAI will become a key enabler for digital SC performance.
- The future of AI deployment in SCM is the embedded co-development of AI systems with consideration of the humans e.g. users, regulators, etc. in the loop.
- It appears that true explainability in SCM (currently at Type I & Type II) is difficult to attain due to the gap between the SC skills and AIs rapid development.
- There is a need for the development of metatheories on XAI measures and indicators in SCM as well as to empirically test the XAI typology **(Fig.1)** with the existing AI maturity models in SCM

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