Artificial Intelligence-Enabled in Clothing Supply Chains:
Research Context and Motivation Perspectives

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The IAFOR International Conference on Arts & Humanities in Hawaii 2024
Official Conference Proceedings

Abstract
As artificial intelligence (AI) continues to drive technological advancements today, it profoundly influences economic and social development. Publication of research on AI integrated with multiple disciplines, such as creative computing, art, innovation management, finance, etc., reveals the boost of academic attention. In this context, research on AI in the fashion industry provides insights for industrial practitioners, such as stakeholders in clothing supply chains (CSCs). However, limited research has reviewed AI in CSCs, especially from a context perspective. This paper aims to identify the macro context of AI in CSCs using descriptive and coding analysis to address two research questions: What is the publication status of AI in CSCs has been published today? 2) What are the research contexts and motivations? 37 papers on AI in CSCs from 2005 to 2023 were obtained from the Scopus database. First, we analysed the publication status using a descriptive analysis. Second, we coded the research context to reveal their research context by six dimensions: 1) policy support, 2) awareness of sustainability, 3) consumer behaviours, 4) technology capabilities, 5) global market uncertainty, and 6) labour-intensive market shift. Findings suggested that global marketing uncertainty and consumer behaviour shifts are the two main motivations of their studies. On the other hand, the pressure on the labour-intensive market shifts from China to Southeast Asia, driving technological innovation in this uncertain market environment. Although the research sample has been limited so far, this shortage of research on AI in CSCs informed scholars' and policymakers' future research agenda.

Keywords: AI, CSCs, Context Perspectives, Motivation Perspectives

1. Introduction

The traditional fashion industry has experienced a revolution forced by economic, technological, and environmental factors. This has further influenced all stakeholders or participants in the CSC processes. The SCOR model (vision 12) provides the three vital configurations in the processes of supply chains: customer interactions, physical material transactions, and market interactions (APICS, 2017). Based on this model identified, would technology, such as AI, change these configurations in the future? Unfortunately, CSCs have yet to be applied entirely to be automated; thus, this barrier led to low-cost and labour-intensive manufacturing (Pal & Jayarathne, 2022). Correspondingly, the Asian market, including China, Bangladesh, and Vietnam, is still labour-intensive, with many raw materials and apparel manufacturers.

In this context, enthusiastic debates on AI-driven or AI-enabled CSCs are growing in the age of AI. Can AI enable CSCs to overcome this obstacle and challenge? Our research selected 37 published papers regarding AI in CSCs from Scopus databases from 2005 to 2023 to identify what and how they were debated. Following this aim, two research questions were identified: 1) What is the publication status of AI in CSCs has been published today? 2) What are the research contexts and motivations?

The outline of our research follows the theoretical background in section 2, focusing on two theoretical lenses: first, the life cycle of CSCs based on a framework for presenting the supply chain evolution, and second, AI in human decision-making in supply chain management (SCM). In section 3, we introduced our research methodology. Section 4 analysed the 37 selected papers using descriptive analysis and coding analysis. Section 5 discussed their research context and motivation integrated with the CSCs lifecycle framework.

2. Literature Review

2.1 Lifecycle of CSCs

There is extensive literature on the lifecycle of clothing but little research on the lifecycle of CSCs. The processes of CSCs are established from the product lifecycle. It was first proposed by Levitt (1965) in a Harvard Business Review article, which refers to a period that begins with the launch of a product into the market until it is finally withdrawn. In this definition, the life cycle of clothing ranges from material sourcing, design, sample making, order, production, and logistics (Figure 1). Similar to the general concept of supply chain, CSCs are processes of delivery from suppliers to customers and from upstream to downstream, where tangible and intangible activities are involved (Larson & Rogers, 1998; Mentzer et al., 2001). Previous literature emphasised the roles of collaborations between different stakeholders in the lifecycle of CSCs. For example, Cicculo et al. (2023) state that collaboration is central in CSCs, forced by joint initiatives with multiple supply chain stakeholders. As we initially presented, managing this complex process covering a whole spectrum of activities requires complex tradeoffs in that different entities in the chain may have conflicting objectives (Kempf et al., 2011). Therefore, the entire system and coordinate decisions should be prioritised (Kempf et al., 2011).

On the other hand, to maximise profit, the strategy of virtual integration has become a vital tool in the lifecycle of CSCs. It refers to using technology to connect participants, including employees, suppliers, customers, and partners, allowing for better collaboration, more efficient processes, and faster decision-making (Ojha et al., 2023). Based on this definition, it can be seen as a "decentralised" strategy in the lifecycle of CSCs, where several independent enterprises will carry out value-creation activities with each core competence through technology adoptions and knowledge or information sharing.

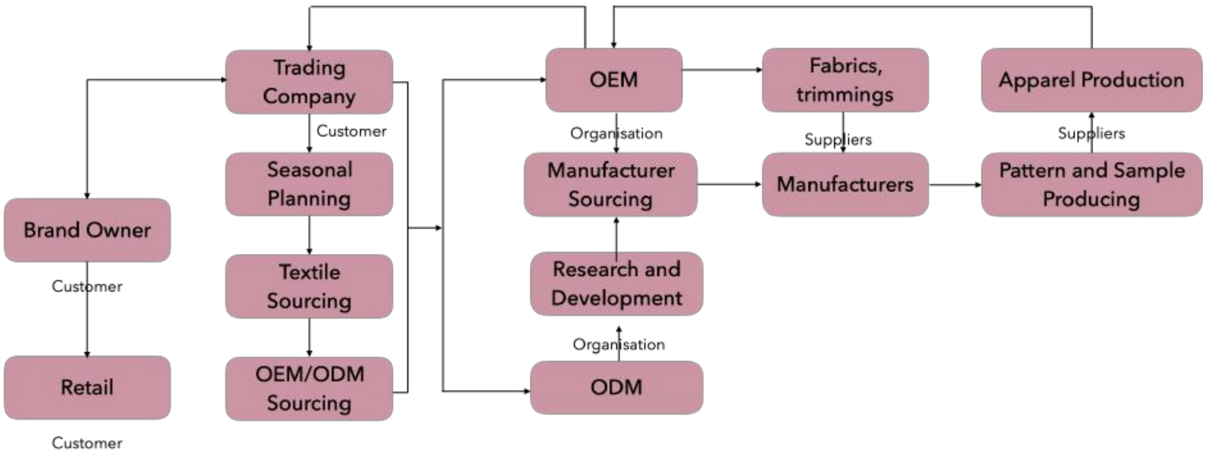

Figure 1. Clothing Supply Chain Process (Source: Author)

2.2 AI in Human Decision-Making in SCM

As section 2.1 provided, virtual integrations highlight that technology can be better used for collaborations and decision-making in CSCs. This section draws on the theoretical lens of AI in human decision-making in SCM. The thinking process has a crucial role in decision-making, where decision-makers make choices by "identifying a decision, gathering information, and assessing alternative resolutions in this process" (Panpatte & Takale, 2019, p. 3). AI technology is today mainly adopted in supporting decision-makers in making appropriate decisions and taking appropriate actions to tackle challenging situations in a chain (Zamani et al., 2023). Literature has highlighted numerous ways to use AI techniques to manage SCM information better. For example, AI with chat robots, such as Chat GPT, can address the inaccuracy and postponements of information and classify potential stakeholders, thereby making optimal decisions and promoting the dynamics of supply chains (Rathor, 2023). Belhadi et al. (2022, p.4488) proposed that "human thinking" is one of the AI technologies in SCM, based on the heterogeneous techniques in the field of AI. However, Efstratiadis (2023) states that although artificial neural networks (ANN) and deep learning (DL) based on patterns and predictions in data trained by AI systems are often used for generating predictions, they are not original. Therefore, AI is not an original thinker but supports idea creation in SCM.

The previous two theoretical lenses have provided an understanding of CSC's configuration, participants, strategy, and AI support fields of decision-making. While previous studies have provided valuable contributions to AI in SCM, no such highlights exist from research context and motivation perspectives in the CSC field. Two main rationales are employing these perspectives. First, the context perspective emphasises the significance of a social environment in knowledge creation (Nonaka, 1998). Second, the motivation perspective promotes rationality by researchers' capturing and generating knowledge (Choo et al., 2007). Therefore, to fill this gap, our research offers room for the state quo of current AI research on CSCs, mainly in the research contexts and motivations to synthesise the gaps in knowledge creation, thereby informing a future research agenda.

3. Methodology

3.1 Data Sampling

In the data search process, we conducted two search phases through Scopus index databases (www.scopus.com), which is a significant search engine for searching scholarly sources (Pournader et al., 2021) (see Table 1). Step one is a keyword search, and step two is a search string employing Boolean operators (AND, OR, and NOT), allowing standardised search and free-text terms to be combined (Atkinson & Cipriani, 2018). Each was refined and searched using artificial AND intelligence AND apparel OR fashion OR clothing OR garment AND supply AND chain, and 67 hits were screened. Further, we added AI techniques, such as deep AND learning OR Machine AND learning OR Artificial AND neural AND networks, then obtained seven additional results. We excluded the duplicated samples and excluded book chapters and review papers. Finally, we obtained 37 hits based on the filtering criteria (see Table 2).

Table 1. Keywords-based Retrieval Criteria

Search Phase	Keyword and Search Strings
Step One-Keyword Search	artificial intelligence, clothing supply chain, garment supply chain, fashion supply chain, apparel supply chain
Step Two-Search String	artificial AND intelligence AND apparel OR fashion OR clothing OR garment AND supply AND chain, deep AND learning OR Machine AND learning OR Artificial AND neural AND networks,

Table 2. Final Selected Articles (n=37)

ID. No.	Journal Article (JA)/Conference Article (CA)	Title of Article	Author and Year
01	JA	A Bibliometric Survey of Fashion Analysis using Artificial Intelligence	(Wazarkar et al., 2020)
02	CA	Detailed Review of Artificial Intelligence Applied in the Fashion and Apparel Industry	(Giri et al., 2019b)
03	JA	A fully yarn integrated tag for tracking the international textile supply chain	(Kumar et al., 2016b)
04	CA	A global decision support system for garment manufacturing by using genetic algorithm	(Chen et al., 2005)
05	JA	A hybrid bi-objective optimization approach for joint determination of safety stock and safety time buffers in multi-item single-stage industrial supply chains	(Guo et al., 2015)
06	JA	A novel ensemble learning approach for corporate financial distress forecasting in fashion and textiles supply chains	(Xie et al., 2013b)
07	CA	Advances in AI-Based Garment Returns Prediction and Processing: A Conceptual Approach for an AI-Based Recommender System	(Gry et al., 2023b)
08	CA	AI based forecasting in fast fashion industry: A review	(Laaziz, 2020)
09	CA	An integrated QFD-TOPSIS methodology for supplier selection in SMEs	(Kumaraswamy et al., 2011)
10	JA	An RFID-based intelligent decision support system architecture for production monitoring and scheduling in a distributed manufacturing environment	(Z. X. Guo et al., 2015)

Table 2. Continued.

No.	Journal Article (JA)/Conference Article (CA)	Title of Article	Author and Year
11	CA	Artificial intelligence: Technology and application in apparel manufacturing	(Nayak et al., 2016)
12	JA	Challenges and Opportunities in Deep Learning Driven Fashion Design and Textiles Patterns Development	(Simian & Husac, 2023)
13	JA	Climate change adaptation and disaster risk reduction in the garment industry supply chain network	(Bag et al., 2023b)
14	CA	Coordinated optimization of production and delivery operations in apparel supply chains using a hybrid intelligent algorithm	(Guo et al., 2019)
15	JA	Customer models for artificial intelligence-based decision support in fashion online retail supply chains	(Pereira et al., 2022)
16	CA	Data mining dynamic hybrid model for logistic supplying chain: Assortment setting in fast fashion retail	(Fares et al., 2019)
17	CA	Design of Clothing Supply Chain Network Based on Stochastic Simulation	(Dai & Zheng, 2016)
18	CA	Digital intelligence as prerequisite of artificial intelligence's integration in the clothing industry 4.0	(Kampakaki & Papahristou, 2020)
19	JA	Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study	(Cubric, 2020)
20	JA	Evaluating supply chain resilience using supply chain management competencies in the garment industry: a post COVID analysis	(Islam et al., 2023)
21	CA	FBD_Bmodel Digital Platform: A Web-Based Application for Demand Driven Fashion Supply Chain	(Thomassey & Zeng, 2021)
22	CA	How adoption speed affects the evolution of fashion cycle	(Xing, 2018)
23	JA	Implementation of Digitalized Technologies for Fashion Industry 4.0: Opportunities and Challenges	(Akram et al., 2022)
24	CA	Implementation of the newsboy method for the sales forecasting of the apparel industry	(Sébastien & Pierre, 2005)
25	CA	Implementing IoT-adaptive fuzzy neural network model enabling service for supporting fashion retail	(Chan et al., 2020)
26	CA	Information Distortion in a Fast Fashion Supply Network: The Impact of Digitalization	(Turino et al., 2021)
27	JA	Integrating machine learning, modularity and supply chain integration for Branding 4.0	(Yan et al., 2022)
28	CA	Intelligent Enabling Fashion Supply Chain Management Innovation	(Li, 2020)
29	JA	Investments in digital technology advances in textiles	(Špiler et al., 2023)
30	CA	IoT data acquisition in fashion retail application: Fuzzy logic approach	(Chan et al., 2018)
31	CA	Leveraging object tracking infrastructures to manage product carbon footprints	(Dada et al., 2009)
32	JA	Linking marketing and supply chain models for improved business strategic decision support	(Laínez et al., 2010)
33	JA	Planned fashion obsolescence in the light of supply chain uncertainty	(Philip et al., 2020)

Table 2. Continued.

No.	Journal Article (JA)/Conference Article (CA)	Title of Article	Author and Year
34	CA	Redesign of Supply Chain in Fashion Industry based on Strategic Engineering	(Bruzzone et al., 2022)
35	CA	The decision support system applied in Agile Supply Chain	(Dragon, 2008)
36	JA	The role of artificial intelligence in shaping the future of Agile fashion industry	(Mohiuddin Babu et al., 2022b)
37	JA	Transformation of the innovative and sustainable supply chain with upcoming real-time fashion systems	(Lee, 2021)

3.2 Coding Process

We further identify the paper text employing a qualitative coding analysis using NVivo 12. We retrieved 37 articles into 84 nodes, grouping them into six dimensions to further summarise their research context, thereby segmenting their research motivations. Each node was named as a unique ID (see Table 3). For example, in the third article's first piece of policy-support context, we coded them as PS3-1 by parity of reasoning.

Table 3. Coded Nodes (N=84)

Dimension	Nodes of Texts
Policy support	PS 3-1, PS 4-1, PS 4-2, PS 5-1, PS 6-1, PS11-1, PS 29-1, PS32-1
Awareness of sustainability	AOS 2-1, AOS3-1, AOS13-1, AOS13-2, AOS13-3, AOS21-1, AOS23-1 AOS23-2, AOS 31-1, AOS 37-1, AOS 37-2
Consumer behaviors	CB 2-1, CB3-1, CB4-1, CB7-1, CB7-2, CB13-1, CB13-2, CB15-1, CB15-2, CB16-1, CB21-1, CB 22-1, CB 25-1, CB 25-2, CB 25-3, CB 25-4, CB26-1, CB27-1, CB27-2, CB27-3, CB28-1, CB 32-1, CB37-1
Technology capability	TC 1-1, TC6-1, TC8-1, TC9-1, TC10-1, TC 24-1, TC 27-1, TC28-1, TC 29-1, TC 30-1, TC 34-1, TC 35-1, TC 36-1, TC 36-2, TC 37-1
Global market uncertainty	GM3-1, GM3-2, GM3-3, GM3-4, GM4-1, GM4-2, GM7-1, GM10-1, GM12-1, GM12-2, GM15-1, GM17-1, GM18-1, GM19-1, GM20-1, GM21-1, GM23-1, GM 32-1, GM33-1, GM36-1, GM37-1, GM 37-2
Labor-intensive market shift	LMS4-1, LMS10-1, LMS11-1, LMS21-1, LMS 36-1

4. Results and Analysis

4.1 Publication Timeline

As shown in Figure 2, the number of articles reviewing AI in CSCs has increased yearly since 2018 and peaked in 2020. The number of publications significantly reduced after 2020. Among these, 20 studied are conference papers, and 17 studied published journal articles. This indicates that there was little empirical high-quality research on AI in CSCs between 2005 and 2017, and after 2017, journal papers on this field started growing gradually. Therefore, it tricks us into exploring their research motivations behind that. Table 3 suggests a broad range of publication outlets, showing study titles on AI in CSCs.

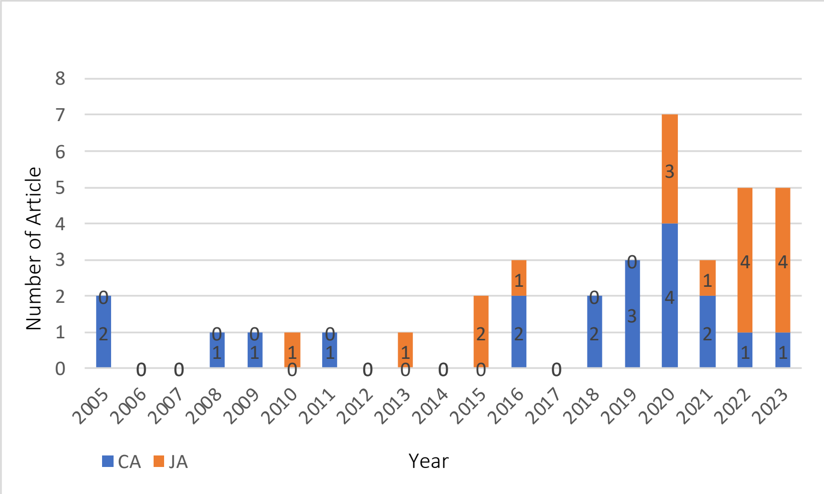

Figure 2. Timeline of Publication in Scopus as of 31/12/2023 (n=37)

4.2 Coding Analysis of Research Context

As seen in Table 4, the frequency of research contexts was depicted. The results show that six dimensions include 15 elements, which are policy regulations (7), AI ethics (1), eco-friendly (1), climate change (2), green production (8), consumer demands shift (4), consumer perception shift (11), consumer's decision-making shift (8), innovation development (3), lack of AI adoption (4), problem-solving (8), dynamic industry (15), pandemics (7), cheap labours (2), and agile manufacturing (3). For example, Giri et al. (2019) believe that the fashion and textile industry is dynamic, and even the consumers are dissatisfied with products with colours and materials and updating speed. Therefore, AI can be considered a predictor tool to forecast the market in this context (Kumar et al., 2016). These research motivations come from a dynamic scenario of the fashion industry and consumer behaviour. As Table 4 depicts, the most mentioned in their research is the dynamic industry in the global marketing dimension (17.86%), and the subsequent one is the consumer perception shift in the consumer behaviour dimension (13.10%).

Table 4. The Frequency of Research Context Dimensions

Dimensions	Elements of Dimensions	Coded Quantity	Percentage
Policy support	Policy regulations	7	8.33%
	AI ethics	1	1.19%
Awareness of	Eco-friendly	1	1.19%
Sustainability	Climate change	2	2.38%
	Green production	8	9.52%
Consumer behaviour	Consumer demands shift	4	4.76%
	Consumer perception shift	11	13.10%
	Consumers' decision-making shift	8	9.52%
Technology capability	Innovation development	3	3.57%
	Lack of AI adoption	4	4.76%
	Problem solving	8	9.52%
Global marketing	Dynamic industry	15	17.86%
uncertainty	Pandemics	7	8.33%
Labor-intensive	Cheaper labors	2	2.38%
	Agile manufacturing	3	3.57%

5. Discussions

5.1 The Publication Status of AI in CSCs

The above results and analysis suggested that transdisciplinary articles tend to come out in academia, and the focus on AI technology has attracted the attention of scholars in practical fields, such as CSCs. However, most conference papers have no attempts to publish their novel findings in high-quality journals. This shortage of paper publications reveals that AI's adoption in the processes of CSCs still needs to be explored. More importantly, AI knowledge sharing in organisations should be highlighted because clothing manufacturing has a lower threshold for talent ability. This leads to a low acceptance of technology used by employees, such as sewing makers and pattern cutters. Aware of these research gaps, the research on AI and CSCs could be more extensive.

5.2 Research Contexts and Motivations

The six dimensions and 15 elements provide a context focus. The high-frequency coded contexts indicate the focus on consumer behaviour shift within global market uncertainties. Disruptive technology, such as AI, has changed consumer behaviour, perceptions, and demands (Omoge et al., 2022; Verma et al., 2021). To optimise their satisfaction, scholars attempt to focus on AI's capability to predict consumer requirements that influence all participants in the processes of CSCs, e.g.TC6-1, TC 8-1. However, some authors argue that the current AI methods cannot be adopted individually because the individual forecasting method, such as ANN, has limited capability in describing bias characteristics (e.g. TC 6-1 by Xie et al., 2013). Thus, this inspires us to create hybrid AI capability-enabled CSCs. Some research is motivated by consumer pressure on green product requirements and AI's capability to predict environmental changes, e.g., AOS13-2 by (Bag et al., 2023). However, these studies have not empirically revealed how AI disrupts traditional configurations of CSCs from the stakeholders' feedback. Therefore, future research could be grounded in combinations of AI capabilities to predict customer and suppliers' green behaviours and build green manufacturing ecosystems.

Of the selected studies, some articles focus on global marketing uncertainty, including COVID-19, the post-pandemic global impact, and the dynamic fashion industry. The prevailing circumstances necessitate a heightened emphasis on addressing the dynamic capabilities of the supply chain, with a particular focus on enhancing supply chain resilience within a specified context, e.g., GM07-1, GM12-1, GM15-1, GM20-1, GM36-1, GM37-1, GM 37-2. In addition to the external uncertainty, the internal uncertain environment, such as labour turnover, also drives scholars to design clothing supply chain networks (Dai & Zheng, 2015).

Furthermore, AI has been practically implemented in recent years. Innovation development always needs a national strategy to support technology innovation and development from policies (Lundvall, 2007). Therefore, as AI has been recognised as a national strategy in many nations, such as China, the US, the UK, Japan, and the European Union (Qu & Kim, 2022), it is important to consider how policy context can play an active role in researching and developing AI in innovation for industries. The trend and characteristics of AI policy inclination may prove a country's innovation focus and development clusters. Some references mentioned the policy context, e.g. PS 3-1, PS 4-1, PS 4-2, PS 5-1, PS 6-1, PS11-1, PS 29-1, PS32-1.

Labour-intensive market shifts are often associated with a focus on environmental uncertainty, but among the selected articles, this element was pointed explicitly at a fashion context because clothing manufacturers are located in developing countries, such as China, Bangladesh and Vietnam. However, clothing manufacturing has not adopted AI and robots thoroughly or extensively. Therefore, facing these issues, AI-enabled agile manufacturing could respond quickly to customer needs and market changes (Mohiuddin Babu et al., 2022a).

6. Conclusions

This study includes a review of 37 literature published between 2005 and 2023 on AI adoption in CSCs from the Scopus database. Two research questions have been addressed. First, we excluded the review papers; thus, the quantity of empirical papers on AI in CSCs is limited. Among the selected papers, we identified six critical dimensions (policy support, awareness of sustainability, consumer behaviours, technology capability, global market uncertainty, labour-intensive market shift) of their research context by coding, which addresses our second research question on research motivations. The dimensions are categorised into 15 elements, contributing to a detailed scenario of their research context. However, this individual element is not separate, underscoring that their integration should be informed in a future agenda.

The shortage of research on AI in CSCs provides room for scholars to fill these gaps at large. Nevertheless, there are several limitations and challenges in this field. First, as mentioned, clothing manufacturing has not been automatically operated due to the talent shortage and lack of knowledge sharing. Second, since the global market environment is uncertain and the fashion industry is dynamic (Giri et al., 2019a), government policy for supporting AI development in CSCs should be considered as a focus. This support should be embodied in policies for value co-creation of all stakeholders in each configuration of CSCs. Third, consumer behaviour has changed dramatically during COVID-19, reflected in online purchasing and the high rate of clothing product return if consumers are dissatisfied with products (Gry et al., 2023a; Pang et al., 2022).

In summary, the literature review on AI-enabled CSCs from a context perspective is novel in a systematic literature review study. It grounded the research rationales in a detailed context coding analysis. This study contributes to informing scholars and policymakers on a future agenda.

Acknowledgements

Professor Eunyoung Kim proofread the outline of this research. Chen Qu conducted the research and wrote the paper.

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