DOI: https://doi.org/10.4038/pmr.v6i1.77

Adopting Artificial Intelligence in Apparel Supply Chains: Opportunities and Barriers in a Developing Economy

R. M. T. D. Rathnayaka[1] and A. M. A. S. M. Bandara[1*]

[1]*Department of Operations Management, Faculty of Management, University of Peradeniya, Peradeniya, Sri Lanka*

*amilab@mgt.pdn.ac.lk

Abstract

As Artificial Intelligence (AI) increasingly transforms global supply chain management (SCM), the Sri Lankan apparel industry—one of the nation's key economic pillars—faces growing pressure to sustain its global competitiveness. However, the heavy concentration of AI resources and investments in advanced economies has widened the technological divide, leaving developing nations like Sri Lanka at an early stage of AI adoption. This study explores the potential applications and hidden challenges of adopting AI within Sri Lanka's apparel supply chains (SLASC). Guided by a qualitative and exploratory research design, a preliminary assessment confirmed the nascent stage of AI implementation in the sector. Accordingly, a purposive sampling method was employed to select eight industry experts from the Board of Investment (BOI)-registered apparel manufacturers that had initiated Industry 4.0–related efforts and ranked among the country's top twenty apparel exporters. These experts, all holding managerial positions in digitalization functions, participated in semi-structured virtual interviews. Data saturation was achieved after eight interviews, and the data were thematically analyzed using NVivo 12 Pro. The findings reveal several emerging applications of AI in SCM—such as demand forecasting, predictive maintenance, and quality control—alongside key barriers including skill shortages, infrastructural gaps, high implementation costs, and data governance concerns. The study provides strategic insights for managers to align AI initiatives with organizational readiness and policy recommendations to bridge infrastructural and capability divides. Ultimately, the research emphasizes the urgent need for a structured strategic roadmap to facilitate AI-driven transformation across Sri Lanka's apparel supply chains.

Keywords: Artificial Intelligence, Supply Chain Management, Apparel Sector, Developing Economy, Challenges for AI Adoption.

1. Introduction

With the constant refinement of a humanized vision of technological transformations in industry while balancing the present and future needs of the organizations, the workforce, and society with agile manufacturing toward Industry 5.0, AI has perpetually unveiled new prospects for expanded functionalities, novel features, and evolving trends in the industrial scene (Barata & Kayser, 2023). John McCarthy, a legendary computer scientist and professor emeritus at Stanford University, used the term "Artificial Intelligence" between 1955 and 1956. According to him, the term 'Artificial Intelligence' is defined as *"the science and engineering of making intelligent machines, especially intelligent computer programs"* (Morgenstern & McIlraith, 2011). During the summer of 1956, a seminal event named "The Dartmouth Summer Research Project on Artificial Intelligence" is considered the birth of the research in the field of AI. The subsequent developments over 50 years have brought AI far closer to realizing Herbert Simon's 1965 prediction that “Machines will be capable of doing any work a man can do” (Tang et al., 2021). Today’s era of AI is poised to revolutionize nearly every sector in an unprecedented way, transforming industries, economies, consumers’ daily lives, and the ways in which technology is experienced (Malik et al., 2024).

Firms across the globe are striving to gain a competitive edge by leveraging their scarce resources internally within the firm and externally across the supply chain. The term “supply chain” encompasses “all activities associated with the flow and transformation of goods from raw materials to the end user, as well as the associated information, which flows up and down” (Menesha & Mwanaumo, 2023). The erratic demand and highly disruptive nature of supply, driven by geopolitical tensions, labor disruptions, and natural disasters, intensify the complexity of today’s global SCM (Jamwal et al., 2021). Also, the horizontal complexity of the supply chain amplifies with the proliferation of vendor catalogs they source from, product catalogs they offer, and customer catalogs they distribute to (DeCampos et al., 2022). This complexity and vulnerability introduce formidable challenges negatively impacting the smooth functioning of supply chain operations (Sudan et al., 2023).

Contrary to this indefiniteness, there is a growing need for the integration and coordination of end-to-end supply chain activities, from the initial sourcing of raw materials to the distribution of products to end customers. In recent years, the proper functioning and effectiveness of the supply chain have greatly depended on the level of integration with advanced technologies, including AI (Yadav et al., 2024). As a rapidly emerging field, AI-powered SCM improves and simplifies supply chain processes with the rapid use of most recent developments in AI and Machine Learning (ML). Incorporating AI solutions enables firms to enhance demand forecasting and capacity planning, optimize inventory and warehouse management, reduce waste to achieve sustainability, improve quality and minimize defects, accelerate delivery times, and enhance supply chain responsiveness. Ultimately, AI increases overall efficiency across all supply chain operations, delivering precision and agility once unimaginable (Goswami et al., 2024).

1.1. Sri Lankan Apparel Sector

The textile and apparel sector ranks among the most rapidly expanding global markets, exerting a significant economic influence worldwide, employing millions (Leal Filho et al., 2019; S. Singh & Khajuria, 2018). The majority of production takes place within small and medium-sized enterprises (SMEs) located in developing nations. For instance, in China, which stands as the largest global producer of textile and apparel goods, 80% of textile companies are classified as SMEs (Luo et al., 2021). Conversely, the worldwide apparel sector is acknowledged as the second-largest resource-intensive polluter, following the oil industry, consuming approximately 500,000 tons of microfiber and 93 billion cubic meters of water each year (Chowdhury et al., 2022).

The textile and apparel sector is one of the largest industries in Sri Lanka, significantly contributing to the nation's economic growth. The Mahavamsa, recognized as one of the oldest historical chronicles of Sri Lanka, recounts that upon Prince Wijaye's arrival on the island, Queen Kuweni was engaged in spinning threads (Hemachandra, 2015). However, the apparel sector in Sri Lanka had a modest beginning in the 1960s, focusing primarily on the production of textiles and garments for the domestic market. The Sri Lankan apparel sector experienced significant growth in the early 1980s, a development catalyzed by market liberalization initiated in 1977 and the implementation of advantageous trade policies (Wickramasingha, 2024). The textile and apparel industry in Sri Lanka experienced significant growth, making it the foremost exporter since 1986 and the largest net foreign exchange generator since 1992 (Wijekoon et al., 2021). Initially, this accounted for only 2% of total exports in 1977 (Central Bank of Sri Lanka, 2009), and the sector has now expanded to represent 41.82% of the nation's total export revenue. Also, the industry offers direct employment to more than 300,000 individuals, with estimates reaching up to 600,000, a significant portion of whom are women in Sri Lanka (Export Development Board of Sri Lanka, 2024), but most of the top-level managers were men (Doutch, 2024). The Sri Lankan apparel industry is regarded as a production model characterized by low wage costs, high-quality products, and sustainable practices (De Silva et al., 2021). The country's apparel sector covers a wide range of product categories, including sportswear, casual wear, fashion wear, intimate wear, swimwear, uniform and workwear, and children's wear. (Export Development Board of Sri Lanka,2024). Apparel manufacturers in Sri Lanka have been supplying products to globally recognized brands, including Victoria's Secret, Triumph International, Columbia Sportswear, Nike, Gap, Next, Old Navy, Zara, Liz Claiborne, Intimissimi, Calzedonia, Tezenis, H&M, Gillards, Soma, and Marks & Spencer for more than 25 years (Weerawansa & Hewage, 2023).

1.2. Formulating Research Questions

As we have pointed out earlier, AI has emerged as a transformative force across industries, with SCM and the apparel sector standing out as critical domains for its application. Yet, despite its relevance, organizations in developing economies continue to struggle with integrating AI into their supply chain practices. It is evident that research in this domain remains scarce; as a result, there is limited understanding of both the opportunities AI presents and the barriers to its adoption. This lack of inquiry has created a notable gap, particularly in developing economies, where unique institutional and resource constraints shape the dynamics of adoption.

On the other hand, Sri Lanka provides an ideal context to examine these issues. Its apparel sector forms the backbone of national exports and is deeply embedded in global supply networks. At the same time, Sri Lankan apparel supply chains operate under resource scarcity, infrastructural gaps, and regulatory pressures—conditions that both constrain and uniquely frame the adoption of AI. This makes the Sri Lankan apparel supply chain a distinctive case for investigating how AI can be leveraged while addressing implementation challenges.

Building on this rationale, we have formulated the following research questions:

RQ1: What are the potential applications of AI in apparel supply chain management?

RQ2: What are the key challenges hindering the adoption of AI in Sri Lanka's apparel supply chains?

Through these questions, this study aims to bridge the knowledge gap by uncovering practical opportunities and identifying barriers to AI adoption, thereby offering insights valuable for both scholars and practitioners in Sri Lanka and other developing economies.

2. Literature Review

2.1 Artificial Intelligence

It's like looking for a needle in a haystack when striving to find the roots of AI. Some believe the origins of AI can be traced back to the 1930s to 1940s (Copeland, 2023), particularly highlighted by Isaac Asimov's 1942 narrative titled "Runaround," which presented the "Three Laws of Robotics" (Haenlein & Kaplan, 2019). However, as many of the scholarly articles revealed, the term "Artificial Intelligence" was officially coined in 1956, when Professor John McCarthy, father of AI (Andresen, 2002), computer scientist at Stanford University articulated the concept of AI as *"It is the science and engineering of making intelligent machines, especially intelligent computer* *programs"*. The Dartmouth Summer Research Project of 1956 is frequently regarded as the pivotal event that marked the beginning of AI as a formal research discipline (Moor, 2006). The movement of AI was sparked by the development of expert systems and fuzzy logic, particularly after 2010, with the rise of big data, analytics, and the widespread use of graphical processing units and deep learning, which have collectively defined modern or contemporary AI (Pournader et al., 2021).

In recent years, researchers have deepened their knowledge and expertise by demonstrating that AI capabilities continually advance. This progress has led to reduced costs and increased accessibility, making AI more affordable and simpler than ever (Gil de Zúñiga et al., 2024). The proliferation of AI applications has accelerated significantly, yielding promising outcomes alongside certain apprehensions regarding the future of employment and business management (Chen et al., 2024; Krishna, 2024).

2.2 Supply Chain Management

SCM is a concept that has been around for some time, yet it continues to develop. The phrase was initially introduced in 1982 by Keith Oliver, a consultant at Booz Allen Hamilton, during an interview with the Financial Times (Mahesh, 2020). The function of purchasing and supply management has historically served as a supportive role within organizations, primarily focused on transactional procurement and short-term engagements with suppliers. However, in response to the growing expectations of end customers, there have been significant advancements in both purchasing practices and the management of supplier relationships (Kähkönen & Lintukangas, 2012).

The supply chain has emerged as a critical area of competitive advantage for businesses. The study of SCM highlights the importance of optimizing the overall value of the organization by more effectively utilizing and allocating resources across the entire firm. A supply chain comprises a series of value-adding activities that link suppliers to an enterprise's customers (Sukati et al., 2012). According to the Chartered Institute of Procurement and Supply (CIPS), there are six components that form the traditional SCM system: Planning, Sourcing (Procurement), Demand and Inventory (Warehousing), Manufacturing, Delivery and Logistics, and Returning (Khan et al., 2022).

AI has revolutionized supply chain management (Toorajipour et al., 2021) by enhancing decision-making processes, increasing operational efficiency, and lowering expenses. Utilizing technologies such as predictive analytics, demand forecasting, and real-time tracking improves inventory control, streamlines logistics, and minimizes disruptions, thereby fostering greater agility and competitiveness in the market (Abak et al., 2024). The broad range of functions performed by AI, expert systems, machine learning, robotics, natural language processing, machine vision, and speech recognition can be considered. Classification of AI is complex, and different scholars have classified it in various ways, based on capability, narrow AI, general AI, super AI; as per the professor Arend Hintze of Michigan State University (based on functionality), reactive machine, limited memory machine, theory of mind, self-aware AI (Sarvesh Raikar et al., 2023).

2.3 Technology-Organization-Environment (TOE) Framework

The Technology-Organization-Environment (TOE) framework was originally developed by Tornatzky and Fleischer in 1990 (Nguyen et al., 2022). The framework helps to explain the three contextual dimensions-technological, organizational, and environmental-when adopting and implementing technological innovations in an organization (Teng et al., 2025). The technological context encompasses features inherent to the technology itself, while the organizational context refers to internal factors, such as scale, resources, structure, culture, and leadership (Liu, 2019). On the other hand, environmental dimensions address external factors in which the organization operates and their influence on technology adoption (Gasmi et al., 2022). Leveraging the structured lens provided by this framework, it is well-suited for examining barriers to AI adoption across technological, organizational, and environmental dimensions. Furthermore, TOE allows these interrelated barriers to be systematically classified and analyzed, ensuring a holistic understanding of the factors influencing AI adoption in the apparel sector.

3. Methodology

In the context of Sri Lankan apparel, SC to examine the challenges and prospective applications associated with AI adoption, the study adopts the philosophical assumption of interpretivism (Pervin & Mokhtar, 2022), which is well-suited to the study's focus on understanding the subjective experiences, perspectives, and meanings of individuals (M. F. Chowdhury, 2014). Interpretivism emphasizes understanding social phenomena through the perspectives of the individuals involved. This approach is particularly suitable for investigating intricate, context-sensitive matters such as the integration of technology within the industry (Jarvie-Eggart et al., 2024). Given the advanced and evolving nature of AI technology, the interpretivist paradigm facilitates a detailed understanding of how professionals in the industry view the possibilities they can gain from future adoption and the obstacles within this context (Misra et al., 2023).

To investigate the possible opportunities and challenges associated with the adoption of AI in a particular sector, the study utilizes an inductive approach (Sachin and Bandara, 2021; Yin and Robert K, 2016). This method is well-suited to generating novel insights and theories rather than validating pre-existing ones. Such an approach is consistent with the exploratory character of the research, which aims to reveal new information and enhance the understanding of how AI can be integrated into the supply chain, rather than confirming a predetermined hypothesis. Specifically, AI adoption in the Sri Lankan context is at a very early stage; it is difficult to gather quantitative data and determine the level of adoption in Sri Lanka's apparel sector.

The research adopts a qualitative methodology emphasizing the gathering of comprehensive, detailed insights from industry experts (Kulandaivel & Bandara, 2024; Yang et al., 2024), rather than focusing on quantitative data analysis. This qualitative framework is especially appropriate for investigating intricate, multifaceted topics such as AI adoption, as it seeks to provide a profound understanding of personal experiences and the contextual factors that shape decision-making.

The research design is characterized as exploratory (Kalu, 2017; Olawale et al., 2023), aiming to examine a domain with limited prior investigation, specifically the potential of AI in the Sri Lankan apparel industry. This approach facilitates adaptability in the data collection process and promotes a deeper understanding of participants' perspectives.

3.1 Sample Selection

Before selecting the sample for the study, the researcher conducted a preliminary assessment to gain insights into the current diffusion of AI within the Sri Lankan Apparel Sector.

According to the researcher’s preliminary assessment, the adoption of AI in the Sri Lankan apparel sector is still in its nascent stages. Thus, the researchers used a purposive sampling technique (Shaheen et al., 2019), informed by the findings of the previous assessment, to select the most suitable informants with the expertise needed to conduct high-quality research. Further, this sampling method is commonly employed in qualitative research to identify and select cases rich in information, thereby optimizing the use of limited resources (Palinkas et al., 2015).

Consequently, the study population comprises practitioners in the apparel sector, guaranteeing the relevance and reliability of the insights obtained. When selecting the practitioners from the industry, the researcher considered top 20 apparel manufacturers (based on EDB rankings) registered under the Board of Investment in Sri Lanka (EDB,2024) . The selection criteria used to identify apparel manufacturing organizations are summarized in Table 3.1:

Table 3.1 Sample Selection Criteria. Source: Author Developed

Selection Stage	Selection Criteria
Stage I: Organization selection	1. The company must be registered under the BOI of Sri Lanka as an apparel manufacturer.
	2. The organization should be recognized as one of the top 20 apparel manufacturers in Sri Lanka, as per the EDB rankings.
	3. The company must have already taken preliminary measures to adopt Industry 4.0 technologies.
	4. The company should primarily focus on international markets, contributing significantly to Sri Lanka's export revenue.
	5. The organization should have a workforce of more than 1,000 employees.
Stage II: Practitioner selection within the selected organization	1. The participant must hold a managerial role related to digitalization within the organization.
	2. The participant should have a strong understanding of supply chain management concepts and practices.
	3. A minimum of five years of experience in the apparel industry is required.
	4. The participant must have an acceptable educational qualification, with at least a bachelor's degree in a relevant field.
	5. The participant should be engaged in or have insights into AI adoption or Industry 4.0 transformations within the supply chain.

Most importantly, manufacturers that have not taken the preliminary steps towards Industry 4.0 were excluded from the sample selection process. The study instead focused on identifying digital transformation specialists tasked with spearheading technological innovation in established apparel manufacturing firms. Accordingly, a formal request was submitted to the chosen company to schedule suitable dates and times for the interviews with the respondents. Most specifically, all participants in the interviews held managerial positions and demonstrated a high level of technological proficiency, with substantial knowledge in both AI and SCM. The respondent's profile of industry practitioners is depicted in Table 3.2.

3.2 Data collection

This study has used primary data and explicitly utilized a cross-sectional method, as the researchers collected the data at a single point in time rather than over an extended period. (Ajayi, 2025; Gill et al., 2008). Semi-structured interviews were employed as the data collection method (Nasra and Bandara, 2025). This interview method is particularly advantageous for qualitative research as it enables researchers to gather comprehensive information and insights from participants while remaining aligned with the study's objectives. Additionally, this format offers greater flexibility and adaptability for researchers, in contrast to unstructured interviews, which lack a clearly defined direction (Mashuri et al., 2022).

Table 3.2 Respondents Profile (Industry Practitioners. Source: Author Developed)

Respondent ID	Gender	Highest Educational Qualification	Current Position	Experience in the Field
1	Male	Masters	Director/ Chief Operating Officer- Digital Transformation	20 Years

2	Female	Masters	Manager/ Digital Champion Visiting Lecturer, Consultant	09 Years
3	Male	Masters	Assistance Manager- Digitalization	07 Years
4	Male	Bachelors	Manager/Lead- Digital Solutions	08 Years
5	Female	Masters	Global Manager-Technical, Research & Innovation	19 Years
6	Male	Bachelors	Head – Manufacturing Excellence	10 Years
7	Female	Bachelors	Manager -Digitization	24 Years
8	Female	Bachelors	Assistance Manager- Automation & Innovation	06 Years

All interviews were conducted virtually via Zoom and Microsoft Teams, given the convenience and accessibility for both parties. Since many of the respondents were dispersed across different regions, and physical face-to-face interviews were impractical. Furthermore, researchers believe that virtual interviews can create a sense of ease for participants, allowing them to partake in the conversation from their own familiar surroundings, which may result in more candid and sincere responses. All semi-structured interviews were conducted with the respondents' prior consent and recorded accordingly. After the interview process was completed, all recordings were transcribed using online transcription software. The researcher subsequently reviewed the recordings and meticulously cross-checked the transcriptions to verify their accuracy and ensure they corresponded with the original audio.

The data collection process involving apparel practitioners continued until eight respondents from eight different organizations were interviewed, at which point data saturation was achieved, as no new insights were emerging. Consequently, further interviews were not conducted.

The interview guide utilized for the study was divided into two distinct sections. The initial section comprised several demographic questions aimed at defining the participants' profiles. In contrast, the subsequent section contained essential open-ended questions intended to elicit comprehensive insights and establish a semi-structured framework for the interview process. Throughout the interview, supplementary follow-up questions were posed to deepen the discussion, allowing for a deeper examination of pertinent subjects.

The selected sample maintained a well-balanced age and gender distribution, facilitating a range of diverse perspectives. Given that AI adoption is still in its nascent phase within the industry, the inclusion of practitioners provided essential insights from real-world experience on challenges, feasibility, and AI implementation.

3.3 Data Analysis

The data analysis followed a thematic analysis framework, which involves identifying patterns and themes emerging from the interview responses. This approach is particularly beneficial in qualitative research, as it helps uncover recurring ideas and concepts, providing a deeper, more nuanced understanding of the topic. Thematic analysis aligns with the exploratory nature of the study, enabling the identification of key themes related to AI adoption within the apparel supply chain and its broader implications for industry practices.

To systematically organize and analyze the qualitative data, NVivo 12 Pro, a qualitative analytical software, has been employed. NVivo facilitates effective coding, categorization, and thematic organization of responses, ensuring a meticulous and structured analytical process. The use of NVivo enhances the efficiency and accuracy of the thematic analysis, allowing the researcher to manage large volumes of qualitative data effectively.

4. Results & Discussion

4.1 Potential Applications of AI in Apparel Supply Chain Management

The study primarily aimed to identify the potential applications of AI in SCM for the apparel sector. During the data analysis stage, the study has identified key future applications of AI to enhance the effectiveness and efficiency of SCM in the apparel sector. The identified applications are listed in Table 4.1.

Table 4.1 Potential Applications of AI in Apparel Supply Chain Management. Source: Author Developed

Potential Applications of AI in Apparel SCM
Decision-Making in SCM (Unstructured, Proactive, Real-Time Decision Making)
Demand forecasting & capacity planning
Inventory & warehouse management
Logistics, transportation & route optimization
Quality control
Supply chain disruptions & risk assessment
Visibility & transparency in SCM

4.1.1 Decision-Making in SCM

Even in the apparel sector, SCM and AI have emerged as groundbreaking technologies capable of fundamentally transforming traditional decision-making processes that rely on human judgment. Accordingly, AI systems can analyze large datasets, identify patterns, and generate insights to support decision-making by leveraging machine learning, deep learning, natural language processing, and neural networks, as highlighted in existing literature. (Muhammad et al., 2024). As per the results of the study, the applications of AI in decision making can be categorized as unstructured, proactive, and real-time decision making as follows,

I. Unstructured Decision Making

Currently, with existing automation in the industry, decision-making remains largely structured. However, with AI components, we move toward unstructured decision-making. As an example, respondent 05 revealed that, *"With machine learning we even go for unstructured decision making which will be a near replacement for a human element"* [Respondent 05].

II. Proactive Decision Making

AI is capable in identifying patterns, predicting potential disruptions, and triggering necessary actions before issues arise. As per respondent 01, *"AI means lot of proactive decision-making triggers …."* [Respondent 01]. In the industry, AI-driven analytics enable organizations to anticipate supply chain risks, optimize inventory levels, and enhance operational efficiency. This forward-looking approach helps businesses stay ahead of challenges, reducing uncertainties and improving overall effectiveness.

III. Real-Time Decision Making

The 7th respondent outlined the real-time decision-making capability of AI as, *"Basically, AI support for decision-making based on the real-time data, and analyze with AI"* [Respondent 07]. Accordingly, AI facilitates immediate decision-making by swiftly analyzing extensive datasets and delivering actionable insights. By evaluating real-time information from diverse sources, including market trends, logistics updates, and production metrics, AI empowers organizations to make rapid, data-informed choices. This capability enhances responsiveness, reduces delays, and promotes efficient SCM, ultimately resulting in greater customer satisfaction and cost efficiencies.

4.1.2 Demand Forecasting & Capacity Planning

The argument regarding the demand forecasting among the practitioners is a bit confusing: Respondent 08 outlined that the existing quantitative demand forecasting methods are sufficient with current systems in the apparel sector. *"In demand forecasting, quantitative demand, currently we are okay"* [Respondent 08].

By contrast, respondent 02 noted that even traditional quantitative methods rely on historical data and statistical models, which can be limited in volatile markets. Even in quantitative forecasting, AI can improve forecast accuracy by analyzing real-time data, market trends, consumer behavior, and external factors such as weather and economic conditions. As respondent 02 emphasized the accuracy improvement of AI usage, *"AI-based demand forecasting models like SAS, Amazon Forecast have improved accuracy from 60-70% to 90%+"* [Respondent 02]. Accordingly, based on the particular respondent, AI-based demand forecasting models improved the accuracy level from 60 - 70 % to more than 90%, indicating his experience is relevant to other industries like fast-moving consumer goods (FMCG), and the respondent greatly believes the applicability of such an AI tool in the apparel sector as well.

Also outlined by respondent 03, unlike static model, AI-driven forecasting continuously adapts production based on new inputs. Respondent stated, *"Apparel brands can adjust production in real time based on AI-generated insights from social media trends and market signals."* [Respondent 03].

In contrast, AI can enhance qualitative forecasting methods like scenario planning and the Delphi method, which rely on experts' and customers' opinions. As an example, "*AI can study the human behavior and we can analyze the human behavior here…"* [Respondent 03]. In that sense, AI improves demand forecasting by analyzing human behavior, environmental changes, and market trends, leading to more accurate and adaptive decision-making.

Referring to the existing literature, the ideal choice of a demand forecasting method is directly linked to the success of SCM and resilience. Literature discusses the trend of using deep learning techniques such as Multi-Layer Perceptron MLP, Long Short-Term Memory LSTM, and Artificial Neural Network ANN in forecasting the demand. To improve data quality in demand forecasting, use techniques such as clustering and dimension reduction. Furthermore, considering additional attributes such as weather, location, and events typically improves the accuracy of demand forecasting with AI tools.

4.1.3 Inventory & Warehouse Management

In SCM, AI can be successfully applied in warehouse and inventory management. While some firms currently utilize IoT and Cyber-Physical Systems (CPS) for inventory tracking, they are limited to quantitative data. For example, respondent 03 stated that, *"......in dyeing process and all sometimes you might not keep all clothes in the same place, but these systems you can't find with the available IOT mechanism because IOT only know quantitative"* [Respondent 03].

However, AI can further enhance automation and improve the efficiency of inventory control operations in warehouses with qualitative data as well.

They stressed that using AI is more like a replacement of humans, so AI can analyze qualitative factors such as material properties and storage conditions, making more informed decisions about placement, quality control, and handling. According to respondent 04, *"AI-powered machine vision can also improve quality control, making warehouse management more accurate and efficient."* [Respondent 04]. The use of AI eliminates the need for human intervention in tasks such as inventory allocation and warehouse organization. Further, AI can streamline communication with suppliers and customers, reducing manual effort.

4.1.4 Logistics, Transportation & Route Optimization

In logistics management, as respondents mentioned, the apparel industry imports raw materials from Europe, the USA, and other locations. Respondent 04 expressed it as, *"We import raw material from Europe, USA and some other locations where we need to think about how we effectively utilize our transportation with AI"* [Respondent 04]. In this context, they highlighted the need to consider how to effectively use their transportation. AI can play a key role in optimizing logistics functions, transportation, and route planning, ensuring that resources are used efficiently and shipments are delivered at the lowest cost.

4.1.5 Quality Control

According to the insights of the respondents, most of the quality assurance tasks, such as raw material inspection, sewing and stitching quality control, and final product inspection, are performed manually. *"Now the 100% of the quality picking and everything relevant to all these materials and the fabric is now human based."* [Respondent 07].

For example, respondent 06 outlined image processing in quality management as, *"AI related Image processing technologies, we can easily adapt those techniques for quality management"* [Respondent 06]. The respondent believes that an opportunity exists to utilize AI-embedded image processing technology for quality assurance processes.

4.1.6 Supply Chain Disruptions & Risk Assessment

In the Sri Lankan apparel sector, companies often import raw materials from overseas and face supply chain disruptions due to factors such as geopolitical tensions. For instance, *"With all these* *the Red Sea and all other geopolitical problems where it's impacting to the supply chain."* [Respondent 08].

To address these challenges, AI-powered systems can play a crucial role in supply chain disruption and risk assessment by providing early warning signals and suggesting mitigation strategies. These AI systems can help manage risks associated with raw material imports and goods exports, particularly in volatile regions, by predicting disruptions and providing real-time solutions to ensure operational continuity.

4.1.7 Visibility & Transparency in SCM

Since the apparel industry imports raw materials from Europe, the USA, and other locations, tracking all these shipments on time and providing real-time updates to the production process is also vital. AI can support this by ensuring visibility and transparency, helping maintain accurate, up-to-date information throughout the supply chain. 3rd respondent provided insights supporting that idea, *"Tracking all these shipments on time and given a real time update to the product is also vital. So, we have the AI can support."* [Respondent 03].

By leveraging AI-powered systems, organizations can gain deeper insights into the status of shipments, identify potential delays, and optimize communication across teams. This increased visibility enables better decision-making and ensures that all stakeholders are informed and aligned, ultimately improving the overall efficiency and reliability of the supply chain.

4.2 Hidden Challenges in AI Adoption in Apparel Supply Chain Management

The study also explored the key challenges in adopting AI, and during the analysis, it was categorized into three sections: technological, organizational, and environmental challenges based on the TOE framework. The key challenges are depicted in Table 4.2.

Table 4.2 Hidden Challenges for AI Adoption in Apparel SCM. Source: Author Developed

Hidden Challenges for AI Adoption in Apparel SCM	
Technological Context	A. Poor Data quality & Manual Data Processing
	B. Need for Foundational Technologies & Infrastructures
	C. Customization & Integration Issues
	D. AI Transparency and Accountability Issues
Organizational Context	E. Workforce Challenges
	F. Resistance to Change and Shifting Mindset
	G. Financial & Investment Barriers
	H. Education & Knowledge Gaps
Environmental Context	I. Lack of Data Security Measures

4.2.1 Technological Context

I. Poor Data Quality & Manual Data Processing

Still in the Sri Lankan apparel sector, poor data quality and reliance on manual data processing remain major challenges, and the lack of automated data collection and integration across systems further limits AI adoption. For instance, the respondent 04 outlined his real industry experience as, "Apparel is more with manual data capturing and updated to *Excel. And still, we have some challenges also in terms of having a quality data"* [Respondent 04]**.** As mentioned by a particular respondent, still in the apparel sector, many people are wasting time gathering and updating data in spreadsheet software such as Excel. This is associated with some limitations in handling large datasets, real-time data processing, and automation.

II. Need for Foundational Technologies & Infrastructures

In AI adoption, there is a need for high computational power to run advanced AI systems. According to respondent 01, "*of course, technological limitations. Now, to run certain AI systems, you need heavy computational power.*" [Respondent01]. Organizations with limited IT infrastructure may struggle, as AI models, especially those using machine learning and deep learning, require high-performance servers, GPUs, and cloud infrastructure to operate efficiently. Further, evidence from practitioners, *"We should be well equipped with the all the necessary technologies"* [Respondent 02].

From an industry practitioner's perspective, most apparel firms are also in the very early stages of Industry 4.0 adoption. According to them, the maximum technology used in many firms is cloud computing, cyber-physical systems, and IoT.

III. Customization & Integration Issues

Especially given the outdated integrations in organizations, it is difficult to integrate AI seamlessly across different supply chain functions. As a barrier, many organizations lack the technical expertise to customize AI solutions to match their specific needs, leading to challenges in integration and optimization within existing systems. Additionally, when considering the Respondent 2's view, in developing nations mostly using free AI applications without any customization, the respondent mentioned, *"We are using those free versions as it is, and we are not going for the higher customizations."* [Respondent 02]. As outlined by the participants, free versions do not always meet the real needs of the organization.

IV. AI Transparency and Accountability Issues

As respondents noted, when decisions are made based on AI, there is often no clear accountability, which poses a significant risk to AI adoption. As an example, respondent 01 highlighted it as, *"Challenge is someone need to get the responsibility of the decisions making through AI"* [Respondent 01].

During the interview, respondent 02 highlighted: *"What we believe is still, these OpenAI tools are kind of large language models which can only predict if we ask certain queries"* [Respondent 02]. Building on this perspective, large language models (LLMs) like OpenAI's tools are often considered black boxes, as their algorithms' internal workings are not transparent. These models primarily operate by predicting the next word in response to a given query based on patterns learned from vast datasets. Respondent 02 emphasized that the outputs of such models are probabilistic rather than genuinely intelligent, reflecting patterns and predictions rather than true understanding or reasoning.

4.2.2 Organizational Context

I. Workforce Challenges

The labor-intensive nature of the apparel sector, where human effort and manual work dominate rather than seamless automation or machinery, is one obstacle to adopting AI. Many of the respondents outlined this obstacle, for instance, respondent 02 viewed it as, *"AI adoption limits by the labor incentive nature in our industry"* [Respondent 02]. Still in many organizations, operations such as sewing, quality inspection, material handling, and packaging are performed by employees.

The limited availability of a skilled workforce, as per respondent 05, "If you look at the skilled workforce, the proportion is very low" [Respondent 05], hampers the effective implementation of AI. Especially, with the limited availability of skilled personnel in the workforce with expertise in AI technologies, data analytics, and digital tools.

II. Resistance to Change and Shifting Mindset

Operational employees and some of the top-level managers working in the industry resist adoption of AI due to fear of job displacement and discomfort with unfamiliar processes. These tendencies also create additional difficulties in integrating AI. During the data analysis, it was revealed that change management in the industry is critical not only for AI adoption but also for the integration of other technologies. Respondent 05, representing others, mentioned that, *"One of the key challenges would be basically the change management when adopting AI..."* [Respondent 05].

When considering the Respondent 3, *"Management think is they need return quickly; they think okay not now will think in future."* [Respondent 03]. The top management may expect quick returns on their investment, but such an investment as AI adoption does not yield immediate benefits. As a result, management is hesitant to make such a large investment at present. Furthermore, according to respondent 06, the organization is striving for the effective utilization of existing digital tools and software systems, such as ERP, rather than focusing on AI applications in its SCM. The respondent mentioned his experience as, *"We are focusing on effective utilization of the ERP systems that we have at the moment rather going into AI"* [Respondent 06].

However, in the literature, there is some evidence that organizations can also integrate ERP systems with AI technologies, including machine learning and natural language processing, to provide opportunities to automate routine tasks, improve decision-making processes, and enhance customer interactions (Singh et al., 2023).

III. Financial & Investment Barriers

Adopting AI in apparel SCM essentially requires high upfront costs for AI-compatible hardware (like powerful GPUs), software, and system integration. Beyond the initial setup cost, organizations also need to allocate financial resources to ongoing operational expenses, such as system maintenance, software updates, and technical support, which add to the overall financial burden. These kinds of implementation costs and other operational costs associated with AI integration appear as a major difficulty for many organizations. The respondent indicated that, *"Now, the costs are in doing that is at the moment is fairly expensive"* [Respondent 02]. It is evident that the firms are very cautious about investing in AI adoption because when industries invest heavily in AI development in their organizations, they may not immediately see returns on investment. This financial uncertainty often makes it less attractive to invest in AI among top management.

Additionally, with the view of respondent 08, *"We need huge cost to train the employees also"* [Respondent 08]. There is no doubt that effective AI adoption needs continuous employee training, which involves a considerable amount of financial resources again, adding to the overall investment burden in AI adoption initiatives.

IV. Education & Knowledge Gaps

The disparity of awareness, technical skills, and confidence regarding AI applications among the different players in the industry creates barriers to seamless AI integration across the supply chain operations. When investigating the roots of this unevenness in AI education, from the respondent's perspective, they pointed out there is a lack of investment in STEM education, *"The amounts of resources that have been allocated to this STEM education was very low"* [Respondent 07]. Because of this, less investment in STEM education, which includes Science, Technology, Engineering, and Mathematics, limits the availability of skilled professionals in AI and data science, creating a significant barrier to AI adoption in industries.

Further, most of the respondents from the apparel sector revealed that they lack formal education or training in AI, and they rely instead on informal learning methods that also have a negative impact on professionals' understanding and practical application of AI. Respondent 05 pointed out that as, *"I did not get any formal education on AI from university or any institution ...."* [Respondent 05].

4.2.3 Environmental Context

I. Lack of Data Security Measures

During the AI adoption, digital protection is now as critical as ensuring physical protection. According to the respondents, in developing countries, especially in Sri Lanka, there are data security concerns. The respondents discussed more regarding that concern, and as an example, respondent 02 mentioned it as, *"...the security aspect of AI. if you use a cloud, you have to have your security protocols in place seamlessly in order to ensure your data is secure."* [Respondent 02]. Because of this close relationship among data, privacy, and security, it is critical to ensure stakeholder safety both online and offline, and to protect data from internal and external threats, unauthorized access, and corruption. So, in AI adoption, it requires strong security measures, including data encryption, access controls, cybersecurity frameworks, and regular audits since AI systems largely process sensitive business and customer data, and to protect proprietary algorithms, models, and trade secrets, etc.

5. Conclusions

AI has the potential to revolutionize SCM in the apparel sector by analyzing data and forecasting demand, AI can optimize logistics and transportation routes, enhance inventory management, and identify inefficiencies across the SC. This leads to improved demand responsiveness, reduced lead times, lower operational costs, and overall supply chain optimization, helping businesses gain and sustain a competitive advantage. While AI adoption is widespread in the global apparel supply chain, Sri Lanka, as a developing country, is still in its early stages of adoption, posing risks to its competitive position in the industry.

There is a significant gap in supply chain and AI literature regarding AI applications in developing countries. This study addresses that gap by exploring the potential applications and hidden challenges for AI adoption in the SLASC. Using a qualitative approach and an exploratory framework, insights were gathered from 08 respondents from the apparel industry. The study identifies and outlines key potential applications and hidden challenges, providing a comprehensive understanding of AI adoption in this sector.

5.1 Implications

5.1.1 Theoretical Implications

The study makes a significant contribution to SCM and technology adoption literature, particularly concerning AI implementation in developing countries. By addressing the significant research gap on AI adoption in these regions, this work provides valuable insights and guidance for organizations navigating the complexities of integrating AI into their SC operations. The findings offer a comprehensive understanding of the potential applications and hidden challenges associated with AI adoption, thereby enriching the existing body of knowledge and serving as a foundational reference for future studies in this domain.

5.1.2 Managerial Implications

The study offers a comprehensive and detailed framework to assist businesses in effectively navigating the complexities and challenges associated with adopting AI technology, while also harnessing its full transformative potential. Managers can utilize the insights and findings from this research to identify not only promising applications of AI but also to uncover potential hidden challenges and obstacles. This enables them to strategically and proactively prepare their organizations for a future increasingly driven by AI, ensuring they remain competitive and innovative in a rapidly evolving technological landscape.

5.2 Recommendations

The study strongly recommends that organizations leverage AI to achieve a sustainable competitive advantage by seamlessly integrating their entire supply chain system. This integration enhances operational efficiency while fostering collaborative growth and shared benefits among all stakeholders. The study's findings emphasize that AI adoption can fundamentally transform SCM, driving enhanced visibility, agility, and decision-making capabilities.

Business organizations must focus on strengthening foundational technology, addressing data-related challenges, and cultivating a data-driven culture to unlock AI's full potential.

Furthermore, organizations should invest in formal employee training programs on AI to enhance workforce competency and ensure smooth integration. Collaborating with AI experts and technology partners to develop customized AI solutions tailored to industry-specific needs will further optimize AI-driven decision-making and operational efficiency. By prioritizing both workforce development and technological innovation, businesses can maximize the benefits of AI in SCM.

Furthermore, government bodies and other key stakeholders are urged to play an active role in developing the necessary digital infrastructure, enhancing data security frameworks, and establishing regulatory guidelines that foster AI-driven transformation in the supply chain sector. Additionally, increased investment in STEM education is essential to bridge the knowledge gap in AI and emerging technologies, ensuring a skilled workforce capable of driving technological advancements. Strengthening research and development (R&D) efforts will further accelerate innovation, enabling organizations to harness AI's full potential. By taking a holistic and collaborative approach, organizations can fast-track AI integration and position themselves for long-term success in an increasingly digitalized global economy.

5.3 Limitations and Future Research Directions

This study has certain limitations that present opportunities for future research. Firstly, the sample primarily comprises large-scale manufacturers, which may not fully reflect the broader apparel sector. Future research could examine AI adoption in small and medium-sized enterprises (SMEs) to provide a more comprehensive industry perspective. Secondly, the study follows a cross-sectional approach, capturing insights at a single point in time. A longitudinal study could provide deeper insights into the long-term impact of AI adoption on supply chain performance. Thirdly, the research takes a general perspective on AI, rather than focusing on specific applications such as predictive analytics, automation, or AI-driven decision-making. Future studies could examine these specialized areas in greater detail. Finally, this study considers AI adoption across the entire supply chain rather than analyzing its impact on specific functions such as procurement, logistics, or inventory management. Future research could explore these areas individually to provide more targeted insights. Addressing these limitations will help refine AI adoption strategies, ensuring more effective implementation across different segments of the apparel supply chain.

References

Ajayi, V. O. (2025). A Review on Primary Sources of Data and Secondary Sources of Data. *SSRN Electronic Journal*, *2*. https://doi.org/10.2139/ssrn.5378785

Andresen, S. L. (2002). John McCarthy: father of AI. *IEEE Intelligent Systems*, *17*(5), 84–85. https://doi.org/10.1109/MIS.2002.1039837

Barata, J., & Kayser, I. (2023). Industry 5.0 – Past, Present, and Near Future. *Procedia Computer Science*, *219*, 778–788. https://doi.org/10.1016/j.procs.2023.01.351

Central Bank of Sri Lanka. (2009). Annual Report 2009. *Central Bank of Sri Lanka.* Available at: https://www.cbsl.gov.lk/sites/default/files/cbslweb_documents/publications/annual_report/2009/en/1_Preliminary.pdf

Chen, H., Zhang, M., Zeng, J., & Wang, W. (2024). Artificial intelligence and corporate risk-taking: Evidence from China. *China Journal of Accounting Research*, *17*(3), 100372. https://doi.org/10.1016/j.cjar.2024.100372

Chowdhury, M. F. (2014). Interpretivism in Aiding Our Understanding of the Contemporary Social World. *Open Journal of Philosophy*, *04*(03), 432–438. https://doi.org/10.4236/ojpp.2014.43047

Chowdhury, N. R., Chowdhury, P., & Paul, S. K. (2022). Sustainable practices and their antecedents in the apparel industry: A review. *Current Opinion in Green and Sustainable Chemistry*, *37*, 100674. https://doi.org/10.1016/j.cogsc.2022.100674

Copeland, B. J. (2023). Early AI in Britain: Turing et al. *IEEE Annals of the History of Computing*, *45*(3), 19–31. https://doi.org/10.1109/MAHC.2023.3300660

De Silva, A., Gunathilake, S., Munaweera, H., Perera, D., & Gunathilake, L. (2021). Competitive Edge Through Automation: A Study on the Sri Lankan Apparel Industry. *Proceedings of the International Research Conference (KDU IRC)*.

DeCampos, H. A., Rosales, C. R., & Narayanan, S. (2022). Supply chain horizontal complexity and the moderating impact of inventory turns: A study of the automotive component industry. *International Journal of Production Economics*, *245*, 108377. https://doi.org/10.1016/j.ijpe.2021.108377

DeVaney, S. A., Yin, R.K. (2016). Qualitative Research from Start to Finish, Second Edition. New York: The Guilford Press. ISBN: 978-1-4625-1797-8. 386 pp. *Family and Consumer Sciences Research Journal*, *44*(3), 324–325. https://doi.org/10.1111/fcsr.12144

Doutch, M. (2024). Garments without Guilt: Global Labour Justice and Ethical Codes in Sri Lankan Apparels. *The AAG Review of Books*, *12*(1), 23–25. https://doi.org/10.1080/2325548X.2023.2277952

Export Development Board of Sri Lanka (2023). *Industry Capability Report Sri Lankan Apparel Sector*. Available at: https://www.srilankabusiness.com/ebooks/industry-capability-report-rubber-2023.pdf

Export Development Board of Sri Lanka (2024). *Industry Capability Report Sri Lankan Apparel Sector*. Available at: https://www.srilankabusiness.com/ebooks/industry-capability-report-apparel-2024.pdf

Abaku, E. A., Edunjobi, T. E., & Odimarha, A. C. (2024). Theoretical approaches to AI in supply chain optimization: Pathways to efficiency and resilience. *International Journal of Science and Technology Research Archive*, *6*(1), 092–107. https://doi.org/10.53771/ijstra.2024.6.1.0033

Gasmi, M., Bendib, I., & Benmabrouk, Y. (2022). Transfer Learning for Highlighting Diagnosis in Pathological Anatomy Based on Immunohistochemistry. *International Journal of Healthcare Information Systems and Informatics*, *16*(4), 1–23. https://doi.org/10.4018/IJHISI.301232

Gil de Zúñiga, H., Goyanes, M., & Durotoye, T. (2024). A Scholarly Definition of Artificial Intelligence (AI): Advancing AI as a Conceptual Framework in Communication Research. *Political Communication*, *41*(2), 317–334. https://doi.org/10.1080/10584609.2023.2290497

Gill, P., Stewart, K., Treasure, E., & Chadwick, B. (2008). Methods of data collection in qualitative research: interviews and focus groups. *British Dental Journal*, *204*(6), 291–295. https://doi.org/10.1038/bdj.2008.192

Goswami, S. S., Mondal, S., Sarkar, S., Gupta, K. K., Sahoo, S. K., & Halder, R. (2024). Artificial Intelligence Enabled Supply Chain Management: Unlocking New Opportunities and Challenges. *Artificial Intelligence and Applications*. https://doi.org/10.47852/AIA42021814

Haenlein, M., & Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. *California Management Review*, *61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Hemachandra, K. (2015). Adoption of Voluntary Environmental Practices: Evidence from the Textile and Apparel Industry in Sri Lanka. https://doi.org/10.13140/RG.2.1.2325.7044

Jamwal, A., Agrawal, R., Sharma, M., Kumar, V., & Kumar, S. (2021). Developing A sustainability framework for Industry 4.0. *Procedia CIRP*, *98*, 430–435. https://doi.org/10.1016/j.procir.2021.01.129

Jarvie-Eggart, M., Stockero, S. L., & Owusu-Ansah, A. (2024). Factors influencing faculty's adoption of engineering technology: A qualitative study. *Computers and Education Open*, *7*, 100221. https://doi.org/10.1016/j.caeo.2024.100221

Kähkönen, A.-K., & Lintukangas, K. (2012). The underlying potential of supply management in value creation. *Journal of Purchasing and Supply Management*, *18*(2), 68–75. https://doi.org/10.1016/j.pursup.2012.04.006

Kalu, F. A. (2017). What makes qualitative research good research: An exploratory analysis of critical elements. *International Journal of Social Science Research*, *5*(2), 43. https://doi.org/10.5296/ijssr.v5i2.10711

Khan, M. D., Schaefer, D., & Milisavljevic-Syed, J. (2022). Supply Chain Management 4.0: Looking Backward, Looking Forward. *Procedia CIRP*, *107*, 9–14. https://doi.org/10.1016/j.procir.2022.04.002

Krishna, V. V. (2024). A I and contemporary challenges: The good, bad and the scary. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(1), 100178. https://doi.org/10.1016/j.joitmc.2023.100178

Kulandaivel, S., & Bandara, A. (2024). Adopting Industry 4.0 in Developing Economies: A Roadmap for Apparel Industry. *2024 Moratuwa Engineering Research Conference (MERCon)*, 199–204. https://doi.org/10.1109/MERCon63886.2024.10689205

Leal Filho, W., Ellams, D., Han, S., Tyler, D., Boiten, V. J., Paço, A., Moora, H., & Balogun, A.-L. (2019). A review of the socio-economic advantages of textile recycling. *Journal of Cleaner Production*, *218*, 10–20. https://doi.org/10.1016/j.jclepro.2019.01.210

Liu, C. (2019). Understanding Electronic Commerce Adoption at Organizational Level: Literature Review of TOE Framework and DOI Theory. *International Journal of Science and Business*. https://doi.org/10.5281/zenodo.2631413

Luo, Y., Song, K., Ding, X., & Wu, X. (2021). Environmental sustainability of textiles and apparel: A review of evaluation methods. *Environmental Impact Assessment Review*, *86*, 106497. https://doi.org/10.1016/j.eiar.2020.106497

Mahesh, B. (2020). Machine Learning Algorithms - A Review. *International Journal of Science and Research (IJSR)*, *9*(1), 381–386. https://doi.org/10.21275/art20203995

Malik, S., Muhammad, K., & Waheed, Y. (2024). Artificial intelligence and industrial applications-A revolution in modern industries. *Ain Shams Engineering Journal*, *15*(9), 102886. https://doi.org/10.1016/j.asej.2024.102886

Mashuri, S., Alhabsyi, F., Sarib, M., & Rasak, A. (2022). Semi-structured Interview: A Methodological Reflection on the Development of a Qualitative Research Instrument in Educational Studies. *IOSR Journal of Research & Method in Education (IOSR-JRME) 12*(1), 22–29. https://doi.org/10.9790/7388-1201052229

Menesha, A. H., & Mwanaumo, E. T. (2023). Supply Chain Management Practice and Competitive Advantage: Systematic Literature Review. *Logistic and Operation Management Research (LOMR)*, *2*(2), 44–57. https://doi.org/10.31098/lomr.v2i2.1809

Misra, S. K., Sharma, S. K., Gupta, S., & Das, S. (2023). A framework to overcome challenges to the adoption of artificial intelligence in Indian Government Organizations. *Technological Forecasting and Social Change*, *194*, 122721. https://doi.org/10.1016/j.techfore.2023.122721

Moor, J. (2006). The Dartmouth College Artificial Intelligence Conference: The Next Fifty Years. *AI Magazine*, *27*(4), 87. https://doi.org/10.1609/aimag.v27i4.1911

Morgenstern, L., & McIlraith, S. A. (2011). John McCarthy's legacy. *Artificial Intelligence*, *175*(1), 1–24. https://doi.org/10.1016/j.artint.2010.11.003

Balbaa, M. E., & Abdurashidova, M. S. (2024). The impact of artificial intelligence in decision making: A comprehensive review. *EPRA International Journal of Economics, Business and Management Studies*, 27–38. https://doi.org/10.36713/epra15747

Nasra, M. R. F., & Bandara, A. M. A. S. M. (2025). Pathway for Industry 4.0 implementation in a Lean Manufacturing environment: evidence from Sri Lankan apparel sector. *Sri Lanka Journal of Social Sciences*, *47*(02), 85–102. https://doi.org/10.4038/sljss.v47i02.8964

Nguyen, T. H., Le, X. C., & Vu, T. H. L. (2022). An Extended Technology-Organization-Environment (TOE) Framework for Online Retailing Utilization in Digital Transformation: Empirical Evidence from Vietnam. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(4), 200. https://doi.org/10.3390/joitmc8040200

Olawale, S. R., Chinagozi, O. G., & Joe, O. N. (2023). Exploratory Research Design in Management Science: A Review of Literature on Conduct and Application. *International Journal of Research and Innovation in Social Science*, *VII*(IV), 1384–1395. https://doi.org/10.47772/IJRISS.2023.7515

Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2015). Purposeful Sampling for Qualitative Data Collection and Analysis in Mixed Method Implementation Research. *Administration and Policy in Mental Health and Mental Health Services Research*, *42*(5), 533–544. https://doi.org/10.1007/s10488-013-0528-y

Pervin, N., & Mokhtar, M. (2022). The Interpretivist Research Paradigm: A Subjective Notion of a Social Context. *International Journal of Academic Research in Progressive Education and Development*, *11*(2). https://doi.org/10.6007/IJARPED/V11-I2/12938

Pournader, M., Ghaderi, H., Hassanzadegan, A., & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. *International Journal of Production Economics*, *241*, 108250. https://doi.org/10.1016/J.IJPE.2021.108250

Sachin, K., & Bandara, A. M. A. S. M. (2021). Exploring the Diffusion of Industry 4.0 Technologies in Apparel Supply Chains of Sri Lanka. *Peradeniya Management Review*, *3*(2), 127–155. https://doi.org/10.4038/pmr.v3i2.63

Sarvesh Raikar, G., Raikar, A. S., & Somnache, S. N. (2023). Advancements in artificial intelligence and machine learning in revolutionising biomarker discovery. *Brazilian Journal of Pharmaceutical Sciences*, *59*. https://doi.org/10.1590/s2175-97902023e23146

Shaheen, M., Pradhan, S., & Ranajee. (2019). *Sampling in Qualitative Research* (pp. 25–51). https://doi.org/10.4018/978-1-5225-5366-3.ch002

Singh, A., Kaur, R., Rastogi, M., Chauhan, V., & Khandelwal, C. (2023). Open-AI Powered Intelligent ERP Solutions. *International Journal for Research in Applied Science and Engineering Technology*, *11*(11), 1837–1840. https://doi.org/10.22214/ijraset.2023.56948

Singh, S., & Khajuria, R. (2018). Penicillium Enzymes for the Textile Industry. *New and Future Developments in Microbial Biotechnology and Bioengineering: Penicillium System Properties and Applications*, 201–215. https://doi.org/10.1016/B978-0-444-63501-3.00011-9

Sudan, T., Taggar, R., Jena, P. K., & Sharma, D. (2023). Supply chain disruption mitigation strategies to advance future research agenda: A systematic literature review. *Journal of Cleaner Production*, *425*, 138643. https://doi.org/10.1016/J.JCLEPRO.2023.138643

Sukati, I., Hamid, A. B., Baharun, R., & Yusoff, R. M. (2012). The Study of Supply Chain Management Strategy and Practices on Supply Chain Performance. *Procedia - Social and Behavioral Sciences*, *40*, 225–233. https://doi.org/10.1016/j.sbspro.2012.03.185

Tang, K. J. W., Ang, C. K. E., Constantinides, T., Rajinikanth, V., Acharya, U. R., & Cheong, K. H. (2021). Artificial Intelligence and Machine Learning in Emergency Medicine. *Biocybernetics and Biomedical Engineering*, *41*(1), 156–172. https://doi.org/10.1016/J.BBE.2020.12.002

Teng, Y., Shang, K. C., Wang, H. C., Kuo, S. Y., & Lu, C. S. (2025). The implementation of blockchain adoption in China's manufacturing industry: the technology organization environment (TOE) method. *Humanities and Social Sciences Communications*, *12*(1). https://doi.org/10.1057/s41599-025-04570-z

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, *122*, 502–517. https://doi.org/10.1016/J.JBUSRES.2020.09.009

Weerawansa, S. R. S. D. K., & Hewage, T. U. (2023). Threads of Transformation: Exploring the Influence of Systems Leadership on Sri Lanka's Apparel Industry. *Sri Lanka Journal of Economic Research*, *11*(1), 81–104. https://doi.org/10.4038/sljer.v11i1.197

Wickramasingha, S. (2024). Work and Life of Sri Lankan Garment Factory Workers. In *Routledge Handbook of Contemporary Sri Lanka* (pp. 253–263). Routledge. https://doi.org/10.4324/9781003300991-25

Wijekoon H.M.S.D., Pathirana H. V. P. K. G., Fernando H.K.K., & Chandrasekara, N. V. (2021). The Study of Factors Affecting Textile and Apparel Exports in Sri Lanka. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4117056

Yadav, A., Garg, R. K., & Sachdeva, A. (2024). Artificial intelligence applications for information management in sustainable supply chain management: A systematic review and future research agenda. *International Journal of Information Management Data Insights*, *4*(2). https://doi.org/10.1016/j.jjimei.2024.100292

Yang, J., Blount, Y., & Amrollahi, A. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. *Technological Forecasting and Social Change*, *201*, 123251. https://doi.org/10.1016/J.TECHFORE.2024.123251