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Artificial Intelligence Adoption in the Apparel Supply Chain in Sri Lanka: Strategies for Small and Medium-Sized Enterprises

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A B S T R A C T

Artificial Intelligence (AI) is rapidly transforming supply chain operations across industries, driving efficiency, cost reduction, and sustainability improvements. In Sri Lanka, large-scale apparel companies have successfully integrated AI into their supply chain processes, but small and medium-sized enterprises (SMEs) face significant challenges in adopting AI. This study focused on identifying these challenges, particularly key financial, technological, and organizational barriers. Data were collected through surveys using a two-phase, mixed-methods approach. In the first phase, data were collected from 156 respondents across 50 SMEs through open-ended qualitative questions to explore the barriers hindering AI adoption. Thematic analysis helped identify 15 key barriers, which were then used to design a second survey. This survey assessed current AI applications, perceived benefits in large-scale companies, and expert-proposed strategies for overcoming SME barriers. This survey was completed by 280 professionals from 12 large-scale apparel companies. Analytical techniques, including descriptive statistics, thematic coding, and graphical representation through bar charts, Pareto analysis, and bell curve modeling, were employed to analyze the data. Findings indicated that technologies like Predictive Analytics, Robotic Process Automation (RPA), and the Internet of Things (IoT) are widely used, particularly in applications such as inventory management, product design, and demand forecasting. These technologies provide significant benefits in terms of efficiency and cost reduction, while the study also revealed key barriers for SMEs, such as high initial investment costs, ongoing maintenance costs, limited technical expertise, and resistance to change. Based on these results, a strategic framework comprising 30 practical strategies was developed to guide SMEs in overcoming these barriers and integrating AI technologies effectively into their supply chain operations. This framework was subsequently validated by 328 industry experts. The framework is feasible, clear, and relevant for resource-constrained SMEs seeking to adopt AI in their supply chains.

Keywords: AI Adoption Barriers, Apparel Supply Chain, Artificial Intelligence, SMEs, Strategic Framework

1. Introduction

Artificial Intelligence (AI) is becoming a transformative force across global industries, with a particularly strong impact on supply chain management (SCM). In the apparel industry, AI technologies are reshaping supply chain operations by enhancing efficiency, supporting sustainability goals, and enabling faster, data-driven decision-making (Ali & Yousef, 2022). Globally, AI has been applied to address challenges in demand forecasting, quality control, inventory optimization, and supplier coordination. These areas are critical for maintaining competitiveness in a fast-changing market environment (Chaimae Zouhri et al., 2023).

In Sri Lanka, the apparel industry plays a vital role in the national economy by contributing significantly to export earnings and employment. Large-scale apparel companies in the country have begun adopting AI to optimize supply chain processes, improve responsiveness to market changes, and align with international standards in efficiency and sustainability. These companies have benefited from access to investment capital, digital infrastructure, and a skilled workforce, allowing them to integrate AI effectively and gain a competitive edge (Chamathka Madushanka et al., 2023).

Although existing literature has extensively explored the advantages of AI in large enterprises and developed countries, there is a notable lack of research focusing on the barriers experienced by small and medium-sized enterprises (SMEs) in developing economies such as Sri Lanka.

This research addresses this critical gap by examining the barriers to AI adoption faced by Sri Lankan apparel SMEs and by exploring how best practices from large-scale companies can inform strategies suitable for smaller firms. The study is guided by the following research questions:

- **RQ1:** What are the current applications of AI in large-scale apparel companies in Sri Lanka?
- **RQ2:** What benefits have these companies experienced from AI adoption?
- **RQ3:** What financial, technological, and organizational barriers prevent SMEs from adopting AI?
- **RQ4:** What strategies can be implemented to support SMEs in overcoming these challenges and integrating AI into their supply chain operations?

This study aims to fill a gap in current research by exploring the key financial, technological, and organizational barriers faced by Sri Lankan SMEs in adopting AI. To achieve this, data were collected through surveys involving both SMEs and large-scale apparel companies. By referencing best practices and successful AI integration strategies from large-scale companies, this research proposes a practical framework with actionable strategies that help SMEs overcome their barriers to AI adoption, not only in Sri Lanka but also in similar developing economies.

2. Literature Review

The adoption of AI in supply chain management (SCM) has emerged as a transformative development within the apparel industry. As global fashion supply chains become increasingly complex and fast-paced, AI technologies offer strategic solutions to enhance sustainability, improve operational processes, and strengthen supplier management. This section synthesizes recent research findings to provide a broader understanding of AI's role in the apparel sector, with emphasis on its applications, benefits, and the key barriers to adoption.

2.1 AI and Sustainability in Apparel Supply Chains

Sustainability is now a central focus in the apparel industry due to growing environmental concerns, consumer expectations, and regulatory pressures. AI technologies are playing a vital role in promoting sustainable practices. Studies show that AI enables more efficient use of resources by improving demand forecasting, thereby helping companies reduce overproduction and manage inventory more effectively (Ali & Yousef, 2022). Accurate forecasting helps avoid excess stock and reduces waste, which is often a result of traditional forecasting errors (Guo et al., 2023).

In addition, AI supports circular economy initiatives by identifying recyclable or reusable materials in production. Tools such as computer vision and machine learning can automate sorting processes and enhance textile recycling. AI also enables real-time monitoring of energy and water usage, allowing for adjustments that reduce the environmental impact of manufacturing processes.

2.2 Improving Operational Efficiency with AI

AI is also widely recognized for its ability to improve operational efficiency in the apparel supply chain. Traditional processes such as forecasting, production scheduling, and inventory control often suffer from inefficiencies and delays. AI helps streamline these functions through automation and advanced data analytics.

Machine learning algorithms are used to analyze large volumes of sales and market data to predict demand, optimize production timelines, and improve inventory control (Komal Dhiwar, 2024). Computer vision technologies are applied in quality control systems to detect fabric defects during the manufacturing process, ensuring higher product quality and fewer reworks (Nair & Trivedi, 2024). Natural Language Processing (NLP) automates supplier communications and order handling, reducing the time and effort involved in managing procurement workflows (Liang et al., 2019). Robotics and automated warehousing systems are also becoming more common, allowing apparel companies to reduce manual labor and speed up order fulfillment.

These technologies collectively reduce costs, minimize lead times, and enhance the responsiveness of supply chains. This is particularly important in the apparel industry, where product life cycles are short, and consumer trends change rapidly.

2.3 AI in Supplier Selection and Supply Chain Resilience

Supplier management is a critical function in supply chain operations. AI adds value to this process by analyzing real-time performance data and risk factors. Instead of relying solely on historical performance, companies can use AI to evaluate suppliers based on reliability, responsiveness, geopolitical factors, and economic indicators (Liang et al., 2019).

This data-driven approach supports more resilient sourcing strategies. Predictive models can identify potential supply disruptions and recommend alternative sourcing options. AI also assists in monitoring supplier performance across criteria such as cost, delivery timelines, and product quality, helping firms make better procurement decisions and improve supply chain flexibility.

2.4 Challenges and Barriers to AI Adoption

Despite its benefits, the adoption of AI in the apparel supply chain faces several challenges. One of the most significant barriers is the high cost of implementing AI systems. SMEs often lack the financial capacity to invest in AI technologies (Chamathka Madushanka et al., 2023). Limited access to skilled personnel and low digital literacy within SMEs also restrict their ability to adapt and manage these systems effectively.

Another common issue is the difficulty of integrating AI tools with existing business systems. Many SMEs operate using outdated or manual systems that are incompatible with new technologies. Data privacy and cybersecurity concerns further complicate the adoption of AI, especially when sensitive customer or supplier data is involved (Ramos et al., 2023).

These barriers are particularly relevant in developing countries, where infrastructure and training opportunities are often lacking. As a result, SMEs are frequently left behind in the digital transformation process.

2.5 Research Gaps and Future Directions

Although research highlights successful AI adoption in large apparel companies, there is a notable lack of empirical studies addressing the unique constraints and adoption pathways for SMEs. This gap calls for a more focused investigation into scalable, affordable, and practical AI strategies tailored to SMEs in developing contexts like Sri Lanka.

3. Research Objectives

The primary objective of this study is to investigate the barriers and opportunities associated with AI adoption in the apparel supply chain, specifically among SMEs in Sri Lanka. While large apparel companies have successfully implemented AI technologies to enhance their operations, SMEs face significant constraints. This research aims to understand these limitations and propose strategic solutions based on successful practices observed in large-scale enterprises.

The specific objectives of the study are as follows:

- **RO1**: To identify the current applications of AI in large-scale apparel companies in Sri Lanka.
- **RO2**: To assess the perceived benefits of AI adoption among large-scale apparel enterprises.
- **RO3**: To examine the financial, technological, and organizational challenges SMEs face in adopting AI.
- **RO4**: To propose a validated framework of practical strategies that can be used to overcome the identified financial, technological, and organizational barriers faced by SMEs in adopting AI technologies.

The study contributes to developing inclusive digital transformation strategies for developing economies through these objectives. It seeks to empower SMEs by equipping them with the knowledge and tools necessary for leveraging AI to achieve long-term growth and competitiveness in the global apparel market.

4. Methodology

This study employed a two-phase, mixed-methods approach to investigate AI adoption in the apparel supply chain in Sri Lanka, specifically focusing on SMEs. The methodology was designed to address four research objectives (RO1 to RO4), using sequential data collection and analysis phases.

4.1 Survey Development – Phase 1

The first survey was developed to address RO3. It involved the design of a qualitative questionnaire consisting of open-ended questions. These questions were designed to explore the financial, technological, and organizational barriers faced by SMEs in adopting AI.

4.2 Data Collection – Phase 1 (RO3)

The initial round of data collection was conducted among 156 respondents from 50 SMEs. Participants included SME owners, managers, engineers, technical staff, and consultants. They were asked to respond to open-ended questions, each targeting one of the following areas:

1. Financial Barriers
2. Technological Barriers
3. Organizational Barriers

Respondents were encouraged to list all the barriers they experience in each category. As a result, the dataset captured a rich range of insights from across SME operations.

4.3 Data Preparation – Phase 1

Collected responses from SMEs were cleaned by removing incomplete or invalid entries to ensure data accuracy. This step prepared the qualitative dataset for analysis.

4.4 Data Analysis – Phase 1

- **Tools Used:** ATLAS.ti, Excel
- **Technique:** Thematic Analysis, Graphical Representation

The cleaned SME responses concerning financial, technological, and organizational barriers were analyzed using thematic analysis in ATLAS.ti. This process involved open coding, grouping, and frequency counting to identify recurring patterns in the data. Similar responses were clustered and categorized into 15 barrier themes, with five themes identified under each category. These themes formed the foundation for the second phase of the study and directly informed the design of the follow-up survey distributed to large-scale apparel companies.

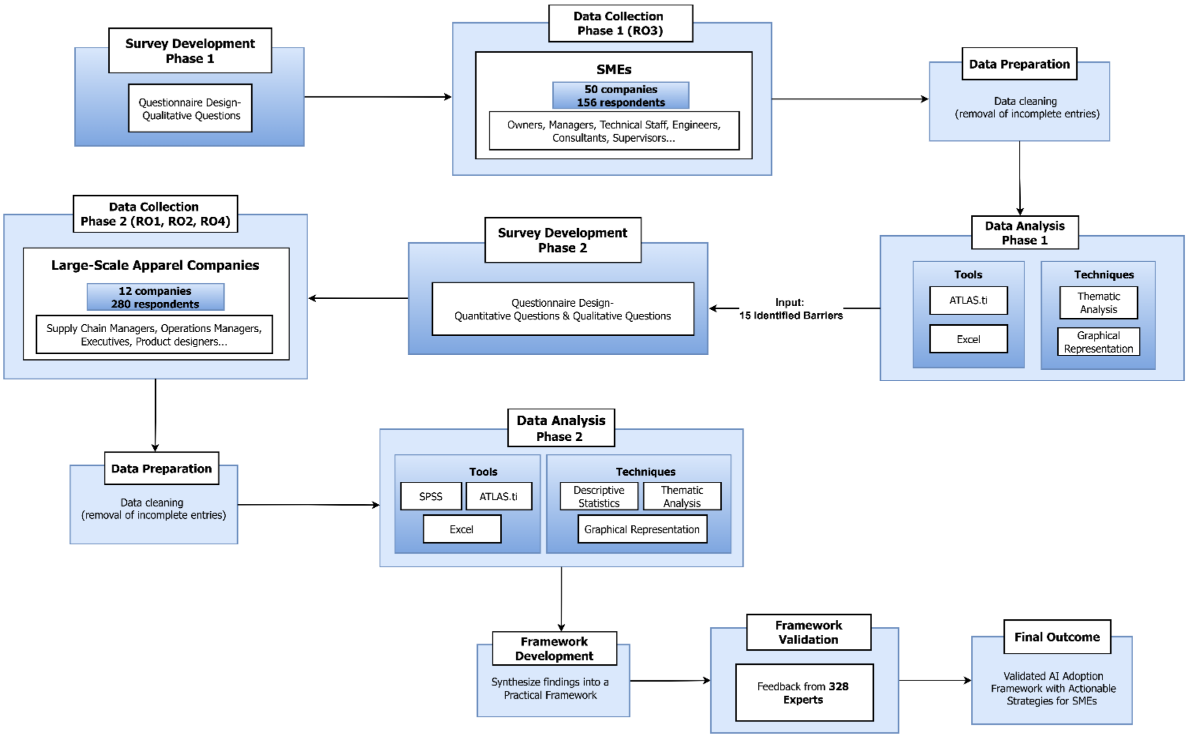

Fig. 1 – Methodology

4.5 Survey Development – Phase 2

Based on the 15 barrier themes identified in Phase 1, a second survey was developed targeting large-scale apparel companies. This survey included both quantitative and qualitative questions. It was designed to gather data related to:

- Current AI applications (RO1)
- Perceived benefits of AI (RO2)
- Strategic responses to overcome the identified SME barriers (RO4)

4.6 Data Collection – Phase 2 (RO1, RO2, RO4)

The second round of data collection involved 280 respondents from 12 large-scale apparel companies in Sri Lanka. Participants included supply chain managers, operations managers, executives, and product designers, all of whom had prior experience with AI implementation in their respective organizations.

- **RO1:** Participants were asked to indicate the supply chain functions where AI technologies were currently applied. The areas assessed included inventory management, product design, demand forecasting, supplier selection, quality control, and logistics and distribution.
- **RO2:** Respondents rated 6 key benefit dimensions using a 5-point Likert scale. The benefit dimensions included efficiency, cost reduction, inventory optimization, quality control, customer satisfaction, and sustainability.
- **RO4:** Building on the 15 barrier themes identified in Phase 1, participants were asked open-ended questions to suggest actionable strategies that could support SMEs in overcoming these barriers.

4.7 Data Preparation – Phase 2

The dataset obtained from large-scale companies was cleaned to eliminate incomplete or low-quality responses, ensuring the integrity of the final dataset for analysis.

4.8 Data Analysis – Phase 2

- **Tools Used**: SPSS, ATLAS.ti, Excel
- **Techniques**: Descriptive Statistics, Thematic Analysis, Graphical Representation

The data collected in Phase 2 were analyzed using a combination of quantitative and qualitative techniques tailored to address each of the research objectives.

- **RO1:** Quantitative responses related to AI applications were analyzed using descriptive statistics. Frequencies and distribution patterns were computed to determine the most commonly adopted AI use cases across supply chain functions. The results were visualized using bar charts highlighting functional areas with high and low AI integration.
- **RO2:** Likert-scale ratings on six key benefit dimensions were analyzed using descriptive statistics to calculate mean values and standard deviations. The results were visualized using bar charts to display the average scores across each benefit.

To gain deeper insight into the distribution and variability of responses, the ratings were further modeled using the Normal Distribution (Gaussian) formula:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

- $f(x)$: Probability density (y-axis value)
- μ: Mean (average rating)
- σ: Standard deviation
- x: Rating value (1 to 5)

This allowed for the creation of bell curve graphs, which illustrated how tightly or widely the responses were spread around the mean. These visualizations helped assess both the central tendency and the consistency of expert perceptions regarding AI-driven improvements in supply chain performance.

- **RO4:** Qualitative responses regarding strategic recommendations were analyzed using thematic coding in ATLAS.ti. Similar responses were grouped based on similarity, resulting in strategy themes for each of the 15 previously identified barriers. For each barrier, the two most frequently cited strategies were selected based on coding frequency. This final set of 30 strategies formed the foundation for developing the strategic AI adoption framework tailored for SMEs in the apparel sector.

4.9 Framework Development

Findings from both phases were synthesized to create a Strategic AI Adoption Framework for SMEs. For each of the 15 barriers, two high-frequency and practical strategies from large-scale experts were inserted. The framework was visually structured by barrier categories - financial, technological, and organizational- and was designed to be realistic, simple to interpret, and implementable by resource-constrained SMEs in the apparel sector.

4.10 Framework Validation

To ensure the reliability, clarity, and practical relevance of the proposed framework, a structured validation process was carried out involving 328 industry experts from both SMEs and large-scale apparel companies within Sri Lanka's apparel sector.

The evaluation was conducted via a structured online form, which ensured standardized responses and ease of data collection. Experts were presented with the finalized AI Adoption Framework in both visual and tabular formats. They were asked to evaluate the framework based on the following three key criteria, using a 5-point Likert scale (1 = Very Low, 5 = Very High):

- Feasibility for SME environments
- Clarity and ease of understanding
- Relevance to real-world operational challenges

All 328 responses were compiled and analyzed. For each criterion, a frequency distribution was calculated and visualized using bell curve graphs based on the normal distribution model.

4.11 Final Outcome

The final outcome of this process was a validated AI adoption framework. It includes actionable strategies SMEs can use to adopt AI technologies in their supply chain operations.

5. Results and Discussion

5.1 AI Adoption in Large-Scale Apparel Companies (RO1)

The survey revealed the key application areas where AI technologies are actively used. These findings are visualized in **Fig. 2**.

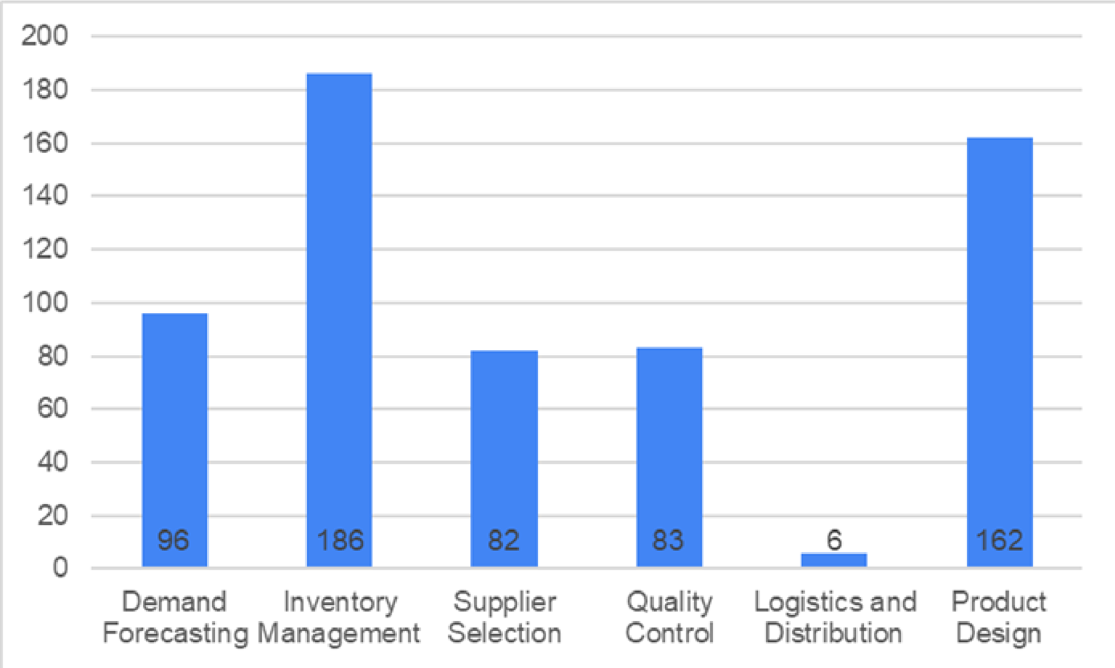

Fig. 2 – Current applications of AI in the supply chain

The applications include:

- **Inventory Management (186 responses):** AI is used for stock optimization, automated replenishment, and warehouse efficiency.
- **Product Design (162 responses):** AI-driven design tools help forecast trends, personalize products, and reduce design-to-market time.
- **Demand Forecasting (96 responses):** AI tools analyze historical sales and market trends to improve prediction accuracy.
- **Supplier Selection (82 responses):** AI systems evaluate real-time performance data for selecting and managing suppliers.
- **Quality Control (83 responses):** Computer vision is commonly used to detect defects, improve consistency, and reduce human error.
- **Logistics and Distribution (6 responses):** Adoption is lowest in this area, possibly due to external dependencies or lack of integrated infrastructure.

These results suggest that upstream supply chain functions (e.g., planning, production) benefit the most from AI, while downstream activities like logistics remain underutilized.

To support these applications, apparel companies deploy a variety of AI technologies. **Fig. 3** shows the frequency of usage of each key technology reported.

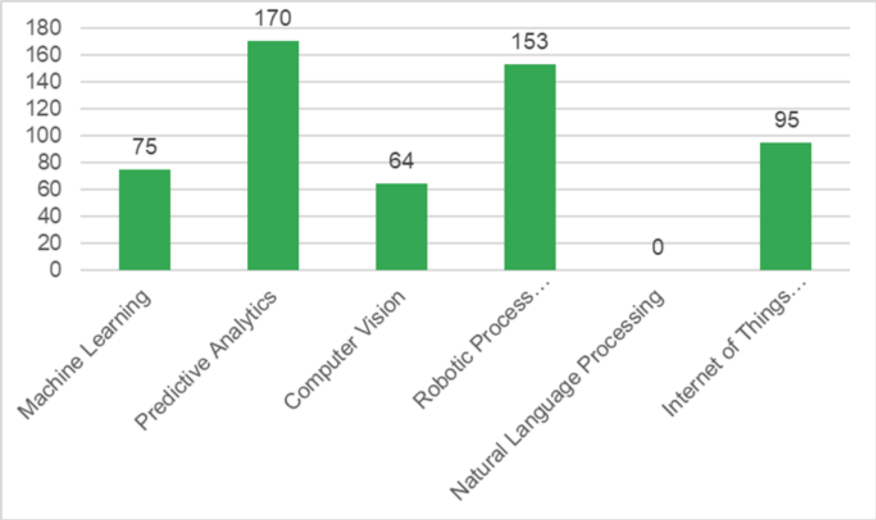

Fig. 3 – AI technologies used in the supply chain

The results show that:

- **Predictive Analytics** received the highest number of responses, indicating widespread adoption.
- **Robotic Process Automation (RPA)** and **Internet of Things (IoT)** followed closely in terms of usage.
- **Machine Learning** and **Computer Vision** were moderately adopted.
- **Natural Language Processing (NLP)** was the least reported among the listed technologies.

A Pareto analysis was performed to better understand the significance of each AI technology. This is shown in **Fig. 4**, which illustrates that a few technologies contribute to the majority of AI use cases.

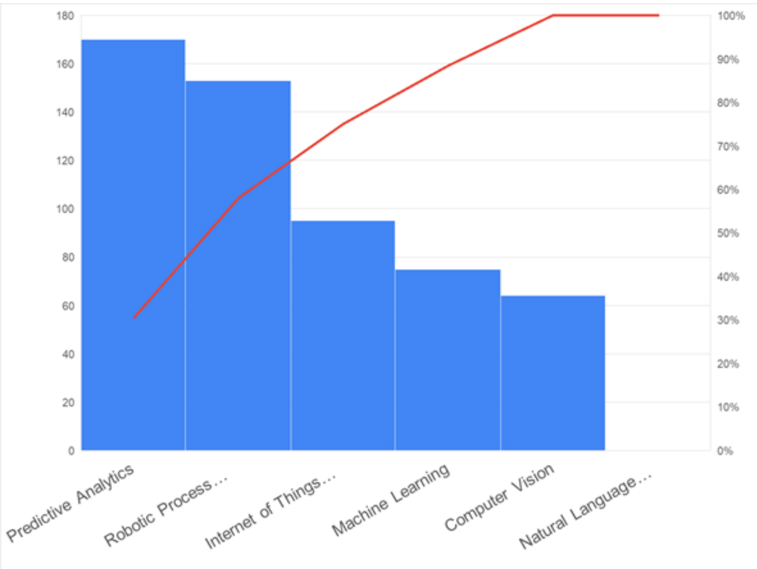

Fig. 4 – Pareto analysis of AI technologies used

- Predictive Analytics accounts for approximately 50–60% of reported AI usage.
- By including RPA and IoT, the cumulative contribution reaches around 80–90%, confirming the Pareto Principle: most outcomes result from a few critical contributors.
- Technologies like Machine Learning and Computer Vision offer additional support but are less dominant.
- NLP remains in early adoption phases, with potential future expansion.

Perceived Benefits of AI Adoption (RO2)

The bar chart in **Fig. 5** presents the mean ratings for each benefit based on responses from large-scale apparel companies.

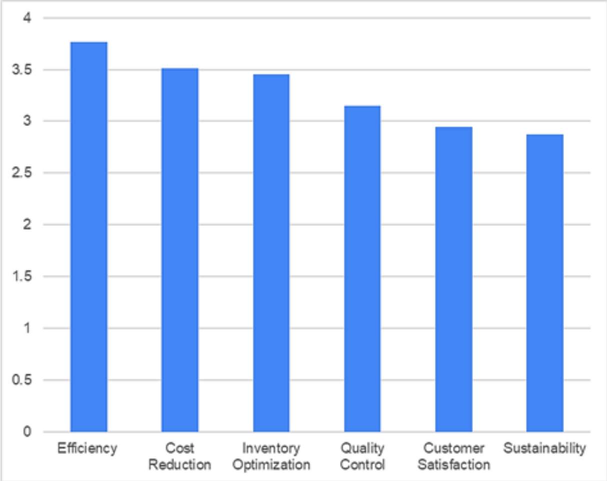

Fig. 5 – Perceived benefits of AI adoption in supply chain improvement

The results indicate the following:

- **Efficiency (Mean = 3.76)** was the most highly rated benefit, indicating a strong perception that AI enhances process speed and resource utilization.
- **Cost Reduction (3.51)** and **Inventory Optimization (3.45)** also received high average scores, suggesting that AI contributes to economic and operational efficiency.
- **Quality Control (3.15)** showed moderate perceived benefit, reflecting improvements in consistency and defect reduction.
- **Customer Satisfaction (2.94)** and **Sustainability (2.88)** received the lowest ratings, though still above the neutral midpoint, indicating that these areas are more variable and context-dependent.

To better understand the variability in responses, a probability density distribution of each benefit rating is shown in **Fig. 6**.

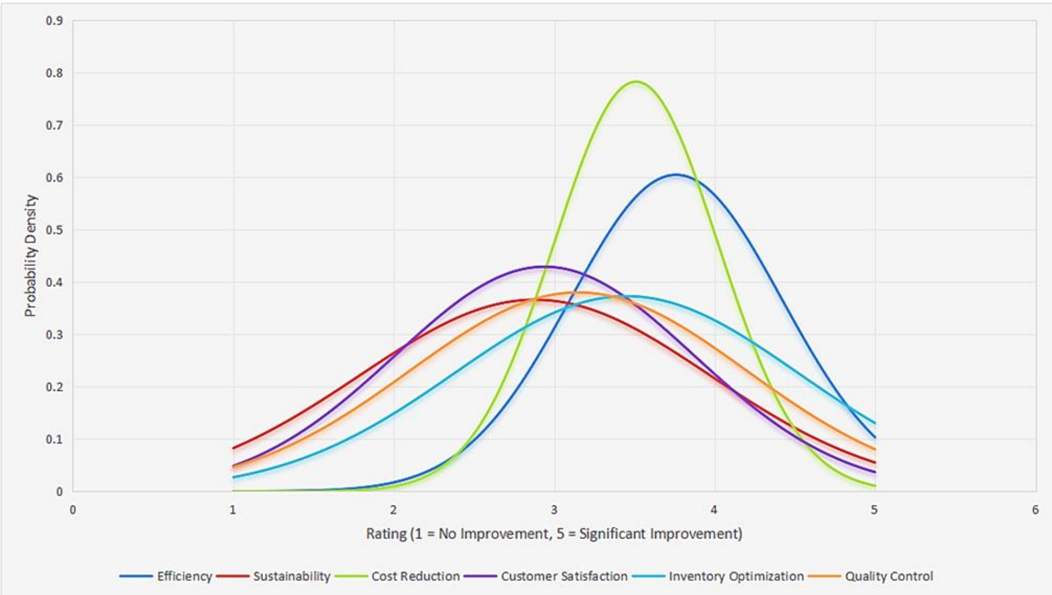

Fig. 6 – Distribution of ratings for perceived benefits

The chart shows that:

- Efficiency and Cost Reduction curves are tall and narrow, showing high consensus and strong agreement across companies.
- Inventory Optimization and Quality Control show wider curves, indicating generally positive but more varied experiences.
- Customer Satisfaction and Sustainability have flatter curves, reflecting diverse or uncertain experiences, with some firms seeing improvement and others not.

The Y-axis in this graph represents probability density, not the number of responses. The height of each curve shows how tightly responses are clustered around the mean. A higher peak implies more consistent views, while a flatter curve indicates broader disagreement or variation in experience.

Table 1 - Descriptive Statistics and Interpretations of AI Benefits

Aspect	Mean	SD	Chart Curve Description	Interpretation
Efficiency	3.76	0.66	Tall, narrow, far right	Consistently high ratings; most agree AI improved efficiency
Cost Reduction	3.51	0.51	Sharp peak, slightly left of efficiency	Very positive and even more consistent than efficiency
Inventory Optimization	3.45	1.07	Wider curve around 3.5	High average but more varied responses
Quality Control	3.15	1.05	Lower, wider peak centered near 3.1	Moderate improvement; mixed opinions
Customer Satisfaction	2.94	0.93	Flatter and closer to center	Neutral to moderate; responses were divided
Sustainability	2.88	1.09	Flattest and furthest left	Lowest average with most disagreement across responses

While sustainability had the lowest overall average rating, further analysis shows that specific environmental benefits are being achieved. These are visualized in **Fig. 7**.

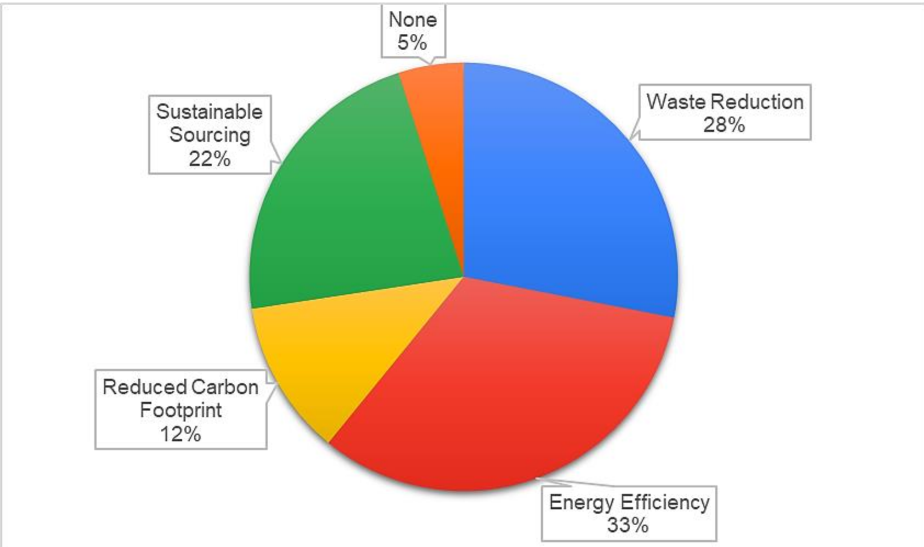

Fig. 7 – Sustainability benefits of AI adoption

According to the data:

- **Energy Efficiency (33%)** and **Waste Reduction (28%)** are the most frequently recognized sustainability improvements.
- **Sustainable Sourcing (22%)** and **Reduced Carbon Footprint (12%)** are also notable outcomes.
- Only **5%** of respondents indicated they observed no sustainability benefit.

These results highlight that while sustainability may have the lowest average overall rating, AI adoption is also contributing meaningfully to sustainability goals, a priority area in the global apparel industry.

Barriers Faced by SMEs in AI Adoption (RO3)

Five key themes identified for each category are presented below, along with their coding frequency. These frequencies represent the number of respondents who mentioned the respective issue.

5.2 Financial Barriers

The most frequently cited financial barrier was high initial investment costs, mentioned by 140 participants. This reflects widespread concern over the capital-intensive nature of AI adoption. Other notable themes included limited funding access (110) and ongoing maintenance costs (95), indicating that both upfront and recurring costs are significant challenges. ROI uncertainty and seasonal revenue patterns further highlight the financial unpredictability SMEs face when planning tech investments.

Table 2 - Themes and frequencies of financial barriers to AI adoption among SMEs

Theme	Frequency
High initial investment costs	140

Limited access to funding	110
Ongoing maintenance/operational costs	95
Uncertain return on investment (ROI)	89
Seasonal cash gaps	62

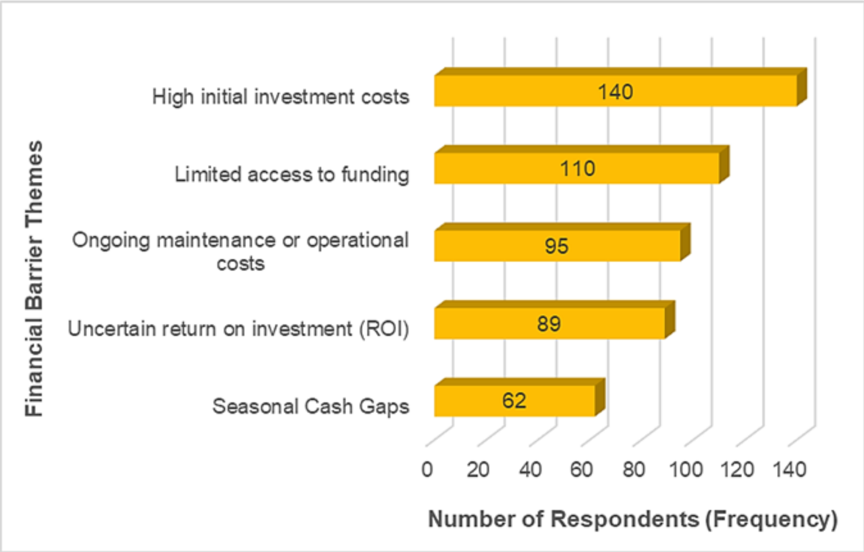

Fig. 8 – Financial barriers to AI for SMEs

5.3 Technological Barriers

Responses to technological challenges frequently pointed to a lack of technical expertise (119 mentions), suggesting SMEs often lack the internal capacity to deploy and manage AI systems. Data unavailability (98) and inadequate infrastructure (84) were also prominent, indicating gaps in digital readiness. Issues related to integration and security suggest operational and compliance concerns when embedding AI into existing workflows.

Table 3 - Themes and frequencies of technological barriers to AI adoption among SMEs

Theme	Frequency
Lack of technical expertise	119
Data unavailability or poor quality	98
Inadequate IT infrastructure	84
Integration with existing systems	79
Security and privacy concerns	61

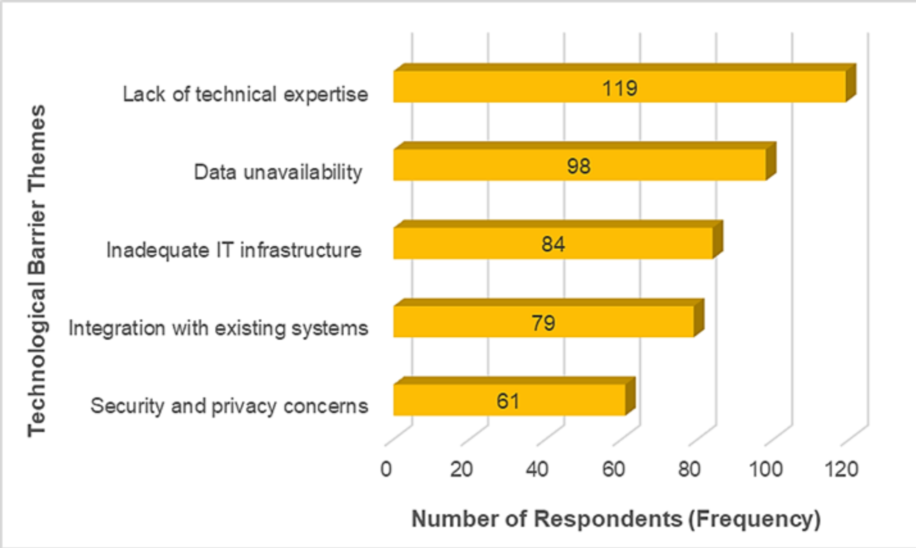

Fig. 9 – Technological barriers to AI for SMEs

5.4 Organizational Barriers

Organizationally, resistance to change (92) was the most cited challenge, indicating cultural hesitancy and inertia in many SMEs. Training gaps (85) and a lack of awareness about AI's benefits (79) show that many SMEs do not currently prioritize AI capability-building. These are reinforced by the mention of limited leadership support (70), which points to the need for executive-level commitment in driving digital transformation.

Table 4 - Themes and frequencies of organizational barriers to AI adoption among SMEs

Theme	Frequency
Resistance to change	92
Insufficient staff training & development	85
Lack of understanding of AI benefits	79
Lack of skilled workforce	75
Limited leadership support	70

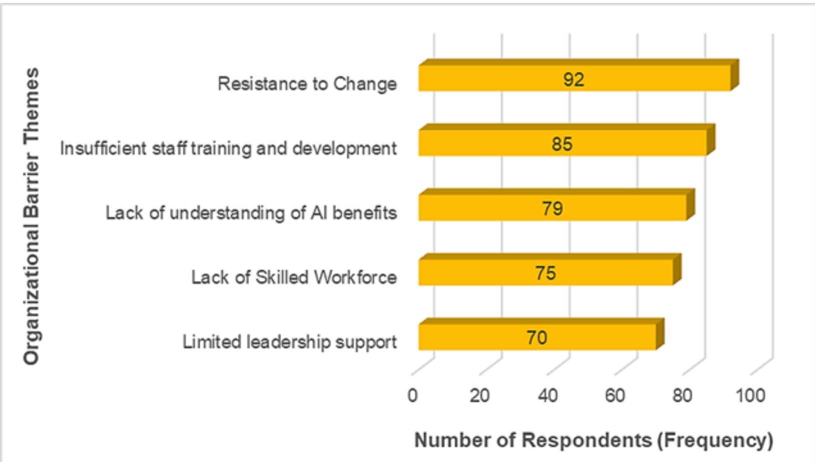

Fig. 10 – Organizational barriers to AI for SMEs

Strategic Framework Development and Validation (RO4) Strategy Selection

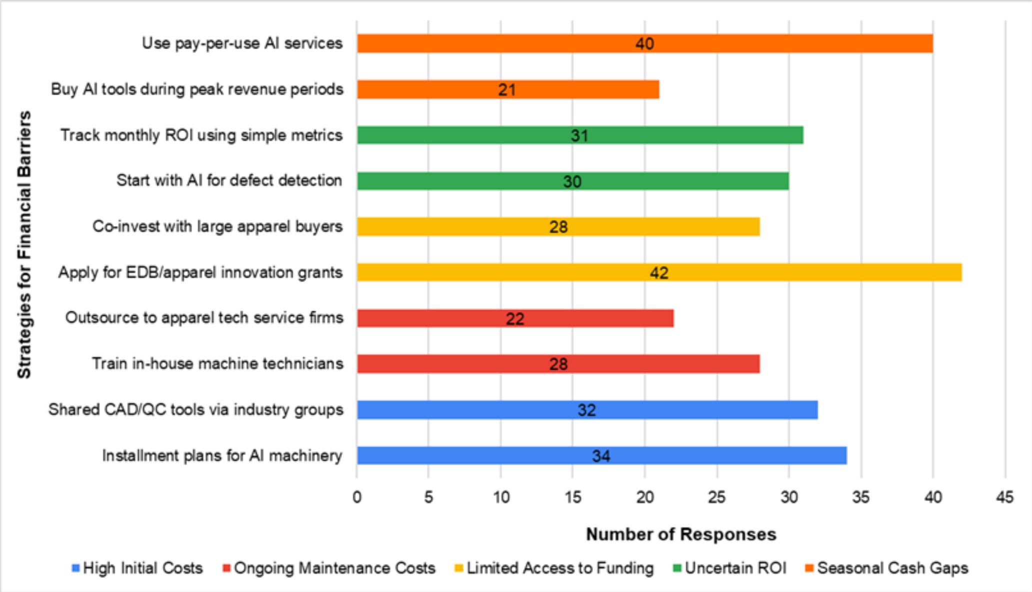

Fig. 11 – Two selected strategies for each financial barrier

Fig. 12 – Two selected strategies for each technological barrier

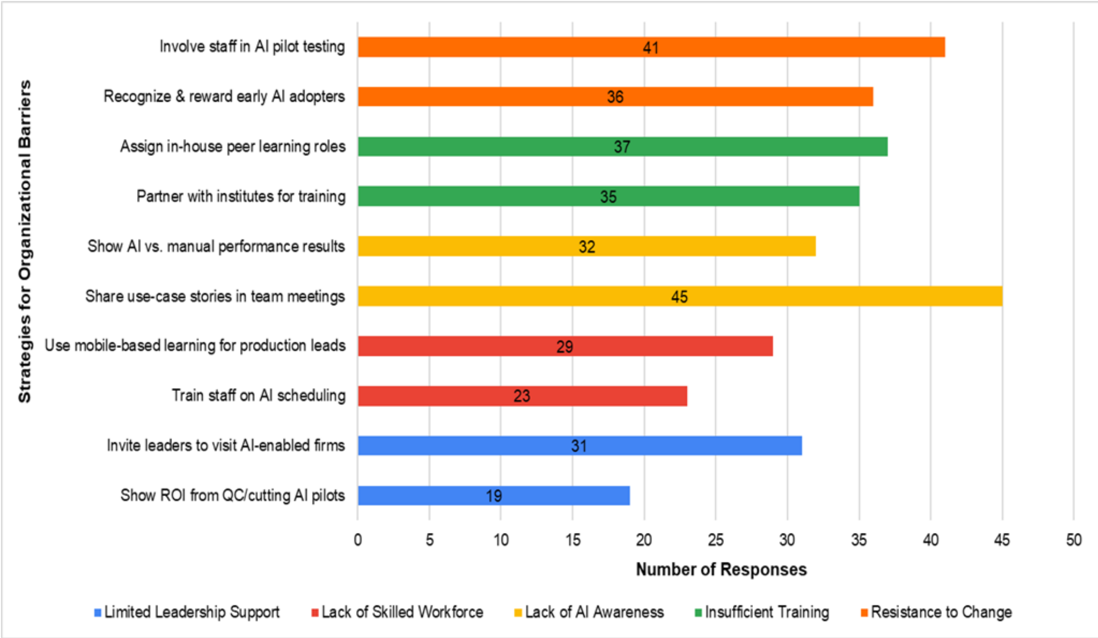

Fig. 13 – Two selected strategies for each organizational barrier

Final Framework Presentation

The selected 30 strategies across the 15 barriers were organized into a comprehensive framework and presented visually in Figure 14. Each segment of the framework addresses a specific barrier and includes the two most relevant, validated strategies to address it.

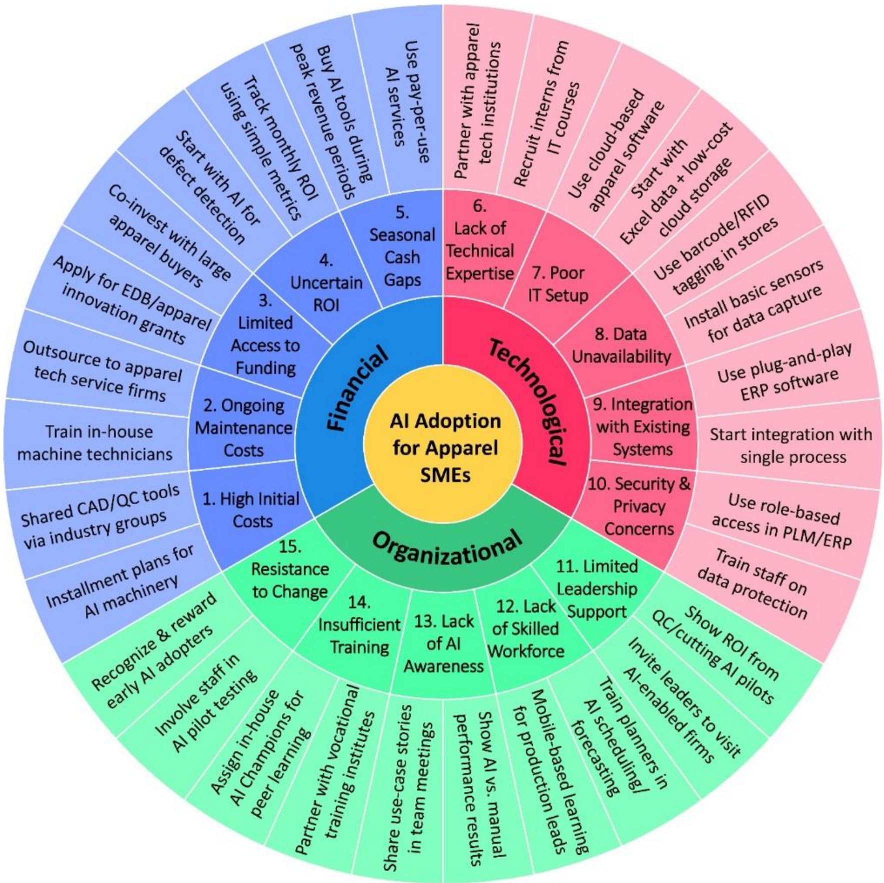

Fig. 14 – Strategic framework for AI adoption by apparel SMEs

Framework Validation

Figure 15 presents the bell curve distribution of expert ratings across the three validation criteria: feasibility, clarity, and relevance.

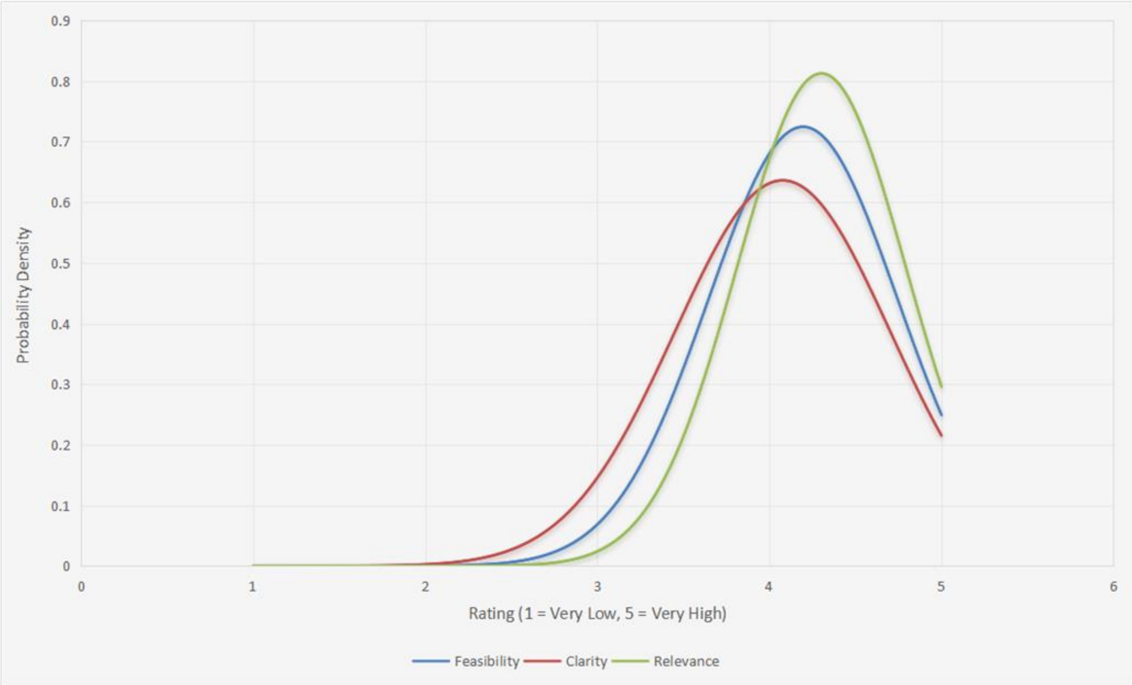

Fig. 15 – Bell curve distribution of expert ratings for framework validation criteria

The distribution curves show a strong central tendency around ratings **4 and 5**, indicating high agreement on the feasibility, clarity, and relevance of the framework.

- The Feasibility and Relevance curves are tall and narrow, suggesting high agreement and consistent positive evaluation.
- The Clarity curve, while still centered around high values, is slightly broader, indicating some variation in interpretation but still overall agreement.
- The height of each curve corresponds to the probability density, which reflects how concentrated the responses are around the average rating.

This visual pattern supports the conclusion that experts across various roles and company sizes strongly affirm the practical applicability, comprehensibility, and relevance of the framework.

The validation results confirm that the proposed framework is:

- **Feasible** for implementation by SMEs operating in resource-constrained environments
- **Clear** in its structure and easily understandable by industry professionals
- **Relevant** to the current and practical challenges faced by apparel SMEs in Sri Lanka

The bell curve distribution for each validation criterion revealed concentrated agreement, with minimal divergence toward lower ratings.

As a result, the framework is confirmed to be a validated, expert-reviewed tool that can support AI adoption in the apparel supply chains of SMEs in Sri Lanka. It may also serve as a foundational model for similar contexts in other developing economies.

6. Conclusion

This study explored the adoption of AI in Sri Lanka's apparel supply chain, with a specific focus on the barriers faced by SMEs. It identified 15 key financial, technological, and organizational challenges that hinder AI integration in these firms. Drawing on insights from large-scale apparel companies that have successfully implemented AI, the research developed a validated strategic framework consisting of 30 actionable strategies. These strategies are designed to be feasible, clear, and relevant, helping SMEs overcome barriers in resource-constrained environments.

Limitations and Future Research

Although the study provides valuable insights, its scope is limited to the apparel sector, and the findings may not be directly generalizable to other industries. Additionally, while the proposed framework was validated through expert evaluation, it has not yet been tested in real-world implementation. Future research could focus on assessing the practical impact of the framework through longitudinal studies involving SME adoption over time. Further studies in other manufacturing sectors would also help evaluate the adaptability and relevance of the framework across contexts. These future efforts can enhance understanding and support the broader, sustainable integration of AI in resource-constrained business environments.

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