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Influence of data analytics in business decision making in the Sri Lankan apparel industry

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Abstract

This research examines the influence of data analytics on decision-making within the apparel industry. Due to increasing market competition and rapidly evolving customer trends and demands, the adoption of data analytics has become imperative for apparel businesses seeking to maintain a competitive edge. The purpose of this study is to assess the current state of data analytics adoption in Sri Lanka's apparel sector and to provide recommendations for enhancing its application in strategic and operational decision-making. Employing a qualitative approach, the research is based on face-to-face, semi-structured interviews with eight professionals working across various apparel companies. Key thematic findings include the use of data analytics in demand forecasting and inventory management, the extent and manner of its adoption within businesses, and its impact on organisational decision-making culture. Furthermore, the study proposes practical recommendations and best practices to support the efficient utilisation of data analytics in the Sri Lankan apparel industry. These insights demonstrate how data analytics can be leveraged to create competitive advantage and optimise business operations in the sector.

Keywords: Apparel Industry, Business Decision Making, Data Analytics

1. Introduction

1.1 Background of the study

Traditionally, decision-making in the apparel industry relied heavily on creative intuition, key insights, trend forecasts and historical sales data (Lima, 2020). However, the advent of data analytics has fundamentally transformed how decisions are approached within the sector (Marr, 2015). The industry is now evolving rapidly due to the influence of digital technologies and shifting consumer preferences, necessitating the use of data analytics to forecast market dynamics and support long-term improvements in business performance (Rosario & Dias, 2023).

Data analytics is applied across multiple functions in apparel, including collection planning and design, inventory management, trend forecasting, consumer targeting, sales forecasting, data-driven decision-making and personalisation (Samarakoon & Liyanage, 2022). By leveraging data from sources such as online shopping carts, point-of-sale systems, and consumer surveys, apparel firms analyse consumer behaviour and tailor promotions based on previous consumer interests (Oh, 2020). This analytical capability enables businesses to evaluate past performance and model future scenarios, leading to more informed decisions regarding design, production, inventory, distribution and promotions (Hickins, 2023). As a result, companies gain a competitive edge through increased sales, improved profit margins and enhanced customer satisfaction (Samarakoon & Liyanage, 2022).

1.2 Research Problem

Much of the current research on data analytics focuses on its generalised applications, leaving significant gaps in understanding its specific implementation within the apparel industry, particularly in areas such as fashion forecasting and trend identification. This study aims to address this gap by providing a detailed analysis of the current state of data analytics in the Sri Lankan apparel sector and its impact on decision-making. From a practical standpoint, the research offers actionable recommendations for apparel manufacturers, supply chain managers and industry stakeholders in Sri Lanka on how to enhance operational efficiency and competitive advantage through the adoption of data-driven decision-making processes.

1.3 Research Aim

The research aim is to understand how data analytics can be used to improve decision making in the Sri Lankan Apparel Industry.

1.4 Research Objectives

- To understand how data analytics is being used in business decision making in the apparel industry.
- To investigate to what extent data analytics is being used in decision making in the Sri Lankan apparel industry.
- To make recommendations on how data analytics can be used effectively in the Sri Lankan apparel industry.

1.5 Significance

This study aims to provide insights and findings that help apparel businesses optimise operations, reduce waste and better meet consumer demand by evaluating the impact of data analytics on decision-making processes.

From an academic perspective, this research contributes to the Sri Lankan apparel industry by elucidating the benefits of data analytics and identifying pathways for companies to improve through its adoption. Practically, this study aims to demonstrate how the effective use of data analytics can enhance demand forecasting and inventory management practices, offering actionable benefits to the industry.

2. Methodology

2.1 Research Design

2.1.1 Research Approach

This study employs an inductive research approach, which aligns appropriately with the qualitative data collection method used. Through this approach, patterns and themes are allowed to emerge organically from the interview data (Azungah, 2018). Rather than relying on or testing pre-existing hypotheses, the inductive method enables the researcher to develop theoretical insights grounded in the participants' lived experiences and perspectives (Monsen et al., 2009). This is particularly beneficial for exploring how data analytics influences decision-making processes within the apparel industry, as it facilitates a deeper, context-sensitive understanding.

2.1.2 Research Strategy

This research employs an interview-based qualitative strategy, which enables the researcher to explore respondents' experiences and perspectives regarding data analytics within their organisational context (Wedawatta, Ingirige & Amaratunga, 2011). This approach allows for meaningful engagement with participants, facilitating a deeper understanding of how data analytics is utilised and its influence on business decision-making.

2.1.3 Research Choice

This study uses an exclusively qualitative research method. This choice aligns well with the inductive research approach adopted in this study. By concentrating on a single methodological framework, the researcher can allocate greater time and resources to ensure a more precise and higher-quality data collection process, thereby enhancing the significance and depth of the findings (Wesel, Boeije & Alisic, 2015).

2.2 Population and sampling

The study targets professionals in Colombo with knowledge and experience in data analytics and business decision-making, ensuring the collection of rich and relevant data from diverse perspectives across varying organisational levels (Spector, 2019). A sample of eight participants, comprising both managers and team members, will be selected using a non-probability purposive sampling method.

This sampling approach enables the researcher to efficiently identify and recruit suitable participants, which is particularly advantageous given the specialised nature of the topic and the limited sample size (Link, 2018).

2.3 Data collection tools

The primary data collection tool in this study is the semi-structured interview, which offers the researcher the flexibility to explore unexpected themes and insights that emerge during conversations with participants (Nazar & Hasan, 2024).

2.4 Data analysis

Thematic analysis was used to analyse the data collected through the interviews.

3. Analysis and Findings

3.1 Participants' Background

The participants background details are given in Table 1.

Table 1. Participants' Background

Respondent	Designation	Work Experience
A	Product Performance Manager	5 years
B	Supply Chain Manager	3 years
C	Marketing Manager	5 ½ years
D	E-commerce Manager	1 year
E	Product Development Manager	4 years
F	Manager	5 years
G	Operations Manager	2 ½ years
H	Manager	1 ½ years

3.2 Implementation and Adoption of Data Analytics

3.2.1 How do companies implement data analytics in their operations?

The implementation of data analytics in the apparel industry depends on its broad integration across business units and centralised infrastructure. Most respondents reported integrating data analytics into sales, marketing, supply chain, manufacturing and e-commerce operations through centralised data warehouses. These warehouses consolidate data from e-commerce platforms, physical stores and supply chain systems. While this approach enables comprehensive insights, it also heightens vulnerability to data breaches and system failures (Vahn, 2014).

As Respondent E noted: "*We have implemented data analytics in sales, marketing and supply chain departments. Also, we use a centralised data warehouse to collect information from our e-commerce platform, physical stores and supply chain systems*."

More advanced implementations include IoT sensors in factories for real-time production monitoring. For example, Respondent E mentioned using IoT sensors in their facilities to gather real-time data on production efficiency and quality control. This technological integration enables apparel companies to respond more effectively to demand fluctuations and production issues, thereby reducing waste and improving overall operational efficiency (Mounika & Sowmya, 2016).

3.2.2 Important factors for successful adoption of data analytics in the apparel industry

The successful adoption of data analytics hinges on leadership support, adequate capital investment and an enabling organisational culture.

Respondent B articulated this interdependence clearly, stating: "*Strong leadership support, investment in appropriate tools and talent and a culture that supports the use of analytics are necessary for successful adoption*."

The majority of respondents provided similar responses, reinforcing the view that adoption success is highly sensitive to top management's attitudes, commitment and expertise. Moreover, the requirement for appropriate tools and talent demands substantial capital investment, while building a data-driven culture across the organisation proves essential for implementation (Needham, 2023). This organisational transformation ultimately yields long-term benefits, including enhanced adaptability and innovation within the apparel sector.

3.2.3 Benefits of data analytics on business performance

Data analytics delivers substantial performance improvements across multiple operational and strategic dimensions. Approximately 80% of respondents reported significant gains in areas including enhanced inventory control, improved profit margins, waste reduction and deeper customer insights, enabling more targeted product development and marketing strategies.

As Respondent E explained: "*Data analytics has helped us to develop even more customer-centric products, which gave us higher sell-through rates and customer satisfaction scores*."

Companies also cited measurable benefits such as substantial sales growth, cost reductions and increased return on marketing investment (ROI), all contributing to strengthened competitive positioning. For instance, Respondents C and D noted that marketing initiatives informed by analytics achieved higher website conversion rates and increased average order values, transforming both conventional retail operations and supply chain structures. By providing senior management with actionable insights and predictive capabilities, data analytics enhances organisational agility and competitive responsiveness (Neves & Bernardino, 2021).

Additionally, data analytics supports sustainability objectives by enabling companies to monitor and reduce water usage, carbon footprints and energy consumption across the supply chain. This analytical oversight fosters improved sustainability practices and contributes to waste minimisation (Karaosman, Perry, Brun & Morales-Alonso, 2020).

3.2.4 Challenges faced during the implementation of data analytics

Organisations encountered significant obstacles during the implementation of data analytics, primarily centred around data quality, cultural resistance and regulatory compliance. These barriers were consistently highlighted across interviews, revealing both technical and human factors that impede integration.

As Respondent A articulated: "*We had difficulties with some departments who were used to making decisions based on intuition rather than referring to data. Also, extracting data from older systems and ensuring data quality were challenging.*"

Approximately 70% of respondents reported similar difficulties, particularly concerning the integration of data from disparate legacy systems and the resource-intensive process of cleaning, validating and standardising data from multiple sources.

Cultural resistance was another prominent challenge, with three out of eight respondents noting opposition from staff accustomed to intuition-based decision-making. This resistance often stemmed from change aversion, concerns about job security and misconceptions regarding data-driven approaches. Employees who traditionally relied on experiential knowledge and intuition perceived data-oriented methods as undermining their expertise and authority (Choi, Hui, Liu, Ng & Yu, 2014).

Furthermore, 60% of respondents cited challenges related to the initial costs of adoption, the need for continuous employee training, and heightened data security concerns, particularly under stringent regulations such as the General Data Protection Regulation (GDPR) (Awan et al., 2021).

3.3 Data Analytics used in Demand Forecasting

3.3.1 How has data analytics improved the company's demand forecasting accuracy?

Data analytics has significantly enhanced forecasting accuracy across the apparel industry. The majority of organisations reported measurable improvements in demand forecasting accuracy, with gains ranging from 15% to 30%, although the extent of these improvements varied across different industry segments.

Respondent D highlighted this impact clearly: "*Our demand forecasting accuracy has improved by about 30%, which was important for managing our fast-moving inventory*."

Fast-fashion companies generally experienced the highest levels of improvement, driven by the need for rapid inventory turnover and responsiveness to short-term trends. In contrast, sustainable and luxury brands reported more moderate gains, reflecting differences in product lifecycle and market dynamics.

These quantitative improvements align with recent empirical studies. For instance, machine learning approaches have been shown to reduce forecast errors by up to 30% compared to traditional time series methods (Silva, Hassani & Madsen, 2019). The enhanced forecasting capability is particularly valuable for apparel retailers managing volatile inventories, as it helps address persistent challenges related to product seasonality, demand variability and extended restocking lead times (Sundararaman & Ramalingam, 2024).

3.3.2 Tools used for demand forecasting

Companies employ a range of sophisticated analytical techniques tailored to their operational capabilities and resource availability. The majority of respondents reported using advanced methods such as gradient boosting, neural networks, regression modelling and time series analysis. Implementing these complex techniques necessitates robust data collection and storage infrastructure, along with substantial investments in both technology and specialised human capital, particularly in training data scientists.

As Respondent C explained: "*We use time series analytical techniques and machine learning algorithms. Data from our CRM system is used to forecast customer purchase behaviour*."

Smaller firms, constrained by resources, tend to rely on more foundational statistical methods, such as moving averages and exponential smoothing, often combined with supervised machine learning for basic pattern recognition.

The application of machine learning and deep learning has markedly transformed demand forecasting within the apparel sector (Giri & Chen, 2022). Point-of-sale systems are instrumental in capturing real-time customer preferences and purchasing patterns, while the integration of CRM data and web analytics further refines short-term forecasting accuracy (Hoffmann, Joerb, Mai & Akbar, 2022).

3.3.3 Integrating external factors such as market trends and economic indicators into demand forecasting models

The integration of external data into analytical models provides significant competitive advantages, particularly in risk management and operational loss minimisation. Respondents highlighted the strategic value of incorporating diverse data sources beyond internal sales and inventory metrics.

As Respondent D stated: "*We integrate data on sporting events, fitness trends, and even weather forecasts into our models. For example, we can predict spikes in demand for certain products during major sporting events*."

Similarly, Respondent H emphasized the role of digital and social influence: "*We rely on social media data and influencer trends to anticipate demand because a single viral post or influencer partnership can create a significant impact on our business*."

The majority of respondents reported incorporating social media trends, weather data, and economic indicators into their forecasting frameworks. Social media analytics enables apparel firms to assess consumer sentiment, identify emerging trends and predict demand for specific styles more responsively (Liu & Deng, 2022).

Different market segments adopt tailored approaches:

1. Luxury brands analyse trends among high-net-worth individuals and fashion week data.
2. Children's fashion brands consider demographic indicators such as birth rates and trending media content.
3. Sustainable brands focus on sustainability trends and shifting consumer attitudes toward eco-friendly products.

These tailored strategies help address unique forecasting challenges, especially for new fashion items lacking historical sales data (Giri & Chen, 2022).

Despite the adoption of advanced analytics, several respondents, notably A, D and F reported persistent difficulties in forecasting demand for new products. These challenges stem from rapidly shifting consumer preferences, market volatility and supply chain unpredictability, which are often exacerbated by external shocks such as political instability or pandemics.

Even sophisticated forecasting models can be disrupted by unforeseen externalities, as demonstrated during the COVID-19 pandemic (Haciibrahimoglu, 2022). Effective decision-making in such contexts requires balancing data-driven insights with managerial judgment and industry experience to navigate complex and uncertain market conditions (Arruda & Madhavji, 2017).

The increasing use of advanced AI and machine learning techniques raises important questions regarding data privacy and the ethical use of customer information. As analytics grow more intrusive tracking social media behaviour, location data, and personal preferences, companies must navigate evolving regulatory landscapes and maintain consumer trust while leveraging data for competitive advantage (Li, 2023).

3.4 Data Analytics used in Inventory Management

3.4.1 Key performance indicators used to track data analytics

Companies monitor inventory performance through comprehensive data-driven KPI frameworks. Most respondents indicated that they systematically track key performance indicators (KPIs) using analytics tools, with the most frequently mentioned metrics being inventory turnover ratio, sell-through rate, days of supply and gross margin return on inventory investment (GMROI). These tools enable organisations to analyse inventory data to determine optimal stock levels that balance holding costs against the risk of stockouts.

Respondent F noted a growing emphasis on sustainability-oriented metrics, stating: "*Key KPIs include material utilisation rate, recycled material percentage and carbon footprint per unit of inventory*."

By continuously monitoring these KPIs, organisations can identify inefficiencies in their inventory management systems earlier, leading to more responsive and adaptive decision-making in reaction to market changes. GMROI, for instance, provides insight into how effectively firms balance inventory turnover with profitability, supporting more informed and economically optimal inventory investment decisions (Vahn, 2014).

Additionally, respondents B and F highlighted that sustainable apparel brands increasingly integrate environmental indicators into their performance measurements. This includes tracking metrics such as material utilisation rates and carbon footprints associated with inventory, underscoring the growing importance of sustainability in operational assessments (Esrar, Zolfaghariania & Yu, 2023).

3.4.2 How was data analytics used to prevent stockouts or overstock situations?

Data analytics enable proactive inventory optimisation that enhances customer satisfaction and competitive positioning. Moreover, 80% of respondents identified avoiding stockouts or overstock conditions as a common application, resulting in improved customer satisfaction, greater customer loyalty and shifts in industry power dynamics. Through demand forecasting, companies decrease stock amounts and carrying costs, thereby increasing profitability. In addition, 60% of respondents applied predictive analytics to identify demand and supply changes, consistent with big data analytics usage, especially machine learning algorithms analysing sales historical records, social media sentiments and weather patterns for improved stock management (Beer, 2017).

Respondent C said, *"We use predictive analytics to forecast demand for specific styles and sizes. This helps us produce the right quantities and reduce excess inventory, which has been important for maintaining our brand's exclusivity."*

Some respondents used real-time information for responsive demand management across distribution centres and shops, including distributed inventory models and increased supplier responsiveness pressure.

Respondent A said, *"Our system provides real-time alerts in advance of stock-outs or overstock situations."*

This aligns with demand-driven supply network (DDSN) concepts in the apparel industry, using data analytics to align inventory with customer demand (Davis, 2016). Respondents C and G who work for luxury brands emphasised data analytics' role in sustaining exclusivity by producing appropriate product quantities. Alternatively, respondents B and F, who work for sustainable brands concentrated on reducing wastage and enhancing eco-friendly policies, demonstrating that sustainability has prominence in inventory handling and may become a competitive advantage for consumers and investors (Esrar, Zolfaghariania & Yu, 2023).

3.4.3 Improvements seen in inventory turnover and carrying costs after implementing data analytics

Organisations achieved substantial operational improvements following the implementation of data analytics. The majority of respondents reported enhancements in inventory management after adoption.

As Respondent E stated: "*Since implementing data analytics, we have reduced size-related returns by 30% and improved our overall inventory turnover by 25%.*"

Most respondents cited measurable gains, including carrying cost reductions of 15% to 40%, inventory turnover improvements of 20% to 35%, and reductions in end-of-season markdown inventory of up to 30%. These outcomes are likely to drive further investment in data analytics capabilities as companies seek to replicate such results. Sustainable brands reported significant improvements in material efficiency and the use of recycled materials, accelerating the industry's shift toward environmentally friendly practices. Luxury and children's apparel brands also demonstrated notable improvements in size-related metrics, with one children's brand reducing size-related returns by 30%. This may lead to revised sizing standards, lower return rates and increased customer satisfaction, particularly beneficial for the growing e-commerce sector.

Moreover, companies may be able to sustain higher prices for longer periods, influencing customer behaviour toward sales and discounts. This aligns with research on how data analytics informs assortment decisions in apparel production, especially concerning consumer preferences (Chen et al., 2016). As these improvements become more widely recognized, they could establish new industry benchmarks. Companies that fail to achieve similar efficiencies may struggle to remain competitive, potentially leading to market consolidation.

However, respondents B and G highlighted persistent challenges related to data quality, particularly when processing information from omnichannel inventory systems spanning physical stores, online platforms and warehouses. Issues such as high return and exchange rates, along with complex product hierarchies involving multiple sizes, colours, and styles, hindered real-time inventory updates. These shortcomings resulted in increased carrying costs due to overstocking across channels, difficulties in maintaining accurate inventory levels and lost sales from stockouts of popular items. Consequently, poor data quality undermines decision-making and operational accuracy, complicates the maintenance of sustainable practices, and risks damaging brand image through stockouts or order cancellations.

3.5 Data-Driven Decision Making in Apparel Industry

3.5.1 Impact of data analytics in decision-making processes

Data analytics has fundamentally transformed decision-making toward greater objectivity and efficiency. Most interviewees reported that data analytics made their decision-making more objective and efficient in product development, pricing strategies, marketing, sustainable sourcing and production methods. Decision Field Theory emphasises evaluating multiple factors and their probabilities for optimal decisions (Bhatia, 2017). Various business decisions have been made with data analytics assistance, such as seasonal clothing collection product mix determination, resulting in increased sales, improved average order values, enhanced customer satisfaction and recycling system technology investments, leading to waste and resource reduction (Cao, Duan & Li, 2015).

Respondent B stated, *"Data analytics helped us to make good decisions about sustainable material sourcing and production methods and whether to invest in a new recycling technology or not. The data we collected showed that it would reduce waste by 40%, which gave us a good sign to proceed."*

Balancing sustainability and production efficiency demonstrates Decision Field Theory's multi-attribute utility aspect, where companies use data to balance multiple attributes (Gallow, 2024). Applying data analytics to key decision-making factors increases industry financial performance, widening the gap between leaders and late adopters, relating to Rogers' five adopter categories, where early data analytics adopters gain competitive advantages while late majority and laggards will struggle to compete (Roelens, Baecke & Benoit, 2016).

Data analytics could accelerate the apparel industry's sustainability shift as consumers demand greener practices. Higher customer satisfaction levels could generate customer loyalty and reduced acquisition costs, changing industry competitive structure. Data-utilising product development could lead to focused and effective product launches, though multiple firms using identical data sets may create uniform product portfolios. Additionally, improved data analytics-relying pricing decisions could result in improved profit margins, however, variable and individual pricing strategy usage could shift consumer expectations.

Furthermore, few respondents indicated a shift from intuition-based to data-driven decision-making and company benefits from data analytics implementation. This shift signifies that the apparel industry has established new technologies such as AI and IoT for quicker and better decisions across multiple steps, from designing clothes to selling them to customers (Chambers & Dinsmore, 2014).

Respondent A stated, *"Data analytics has changed the way we make decisions, now we make way more objective decisions and rely less on gut feelings and more on solid data. Recently, while planning our summer collection, we thought it would be better to use data analytics for figuring out the best mix of products and ended up seeing a 30% rise in sales compared to last year."*

The industry's shift toward data-driven decisions would mostly produce more accurate predictions and efficient strategies, as companies would face fewer errors from subjective judgments or outdated assumptions. Organisations could make decisions faster without waiting to check customer responses. Solid data-based decisions enable companies to minimise risk exposure and secure potentially more resilient performance, attracting more conservative investors to the sector.

3.5.2 Challenges faced in promoting a data-driven decision-making culture

Organisations encountered significant cultural and capability challenges during data-driven decision-making culture implementation. Most respondents faced challenges during implementation. Respondents C and F mentioned the balance between data and creativity, stating the challenge of using data analytics without losing creative aspects of designing clothes, including designing and maintaining unique shopping experiences. This focuses on balancing data-driven approaches and traditional creative processes, aligning with Rogers' Innovation Diffusion Theory's complexity attribute.

Respondent C mentioned, *"Definitely, data analytics helped our team to make better decisions on product development, pricing and marketing strategies, but we also depend on the creative intuition of our staff for design decisions."*

A lack of data literacy within organisational structures was reported by 70% of respondents. This gap is particularly significant given the growing emphasis on enhancing data knowledge at both individual and departmental levels. This issue aligns with the 'compatibility' aspect of Rogers' Diffusion of Innovation theory, as the adoption of data-driven decision-making must align with an organisation's existing values and past experiences (Lashgari, Sutton-Brady, Søilen, & Ulfvengren, 2018).

As Respondent A explained: "*It was challenging to make all departments understand and start trusting data. We are constantly working on improving data literacy in our organisation.*"

Consequently, companies struggle to hire personnel who can effectively balance analytical rigor with creative processes, as comfortable data literacy is not uniformly present across the organisation. The Technology Acceptance Model further elucidates why individuals adopt or resist new technologies, suggesting that successful implementation of data-driven decision-making requires substantial change management efforts (Saricam & Erdumlu, 2017).

Recurring challenges included how to apply data effectively while preserving brand personality, creative direction and demands for novelty. This tension appeared most pronounced in the luxury and children's wear segments.

A few respondents also highlighted difficulties in measuring the long-term impact of sustainability projects.

Respondent F noted: "*It is challenging to quantify the long-term benefits of our sustainability initiatives, while we can easily measure our immediate cost savings*."

Challenges in quantifying the effects of sustainability projects may slow the industry's overall progress, prompting increased investment in long-term data collection and analytical capabilities. This relates to Rogers' 'observability' attribute, as the benefits of some data-driven decisions are not immediately visible, potentially hindering adoption. This issue underscores the complexity of integrating economic, environmental and social goals into managerial decision-making, particularly for luxury fashion brands, and points to the need for more sophisticated data application across different market segments (Choi, 2018).

4. Conclusion

Data analytics has significantly transformed the Sri Lankan apparel industry by transitioning decision-making processes from traditional intuition-based approaches to more objective and evidence-based strategies. The findings indicate that the integration of predictive analytics and machine learning has enhanced demand forecasting accuracy by up to 30%, optimised inventory management through reduced carrying costs and supported sustainability goals by minimising waste.

Despite these advancements, the industry faces persistent challenges, including limited data literacy among staff, cultural resistance to change and issues with data quality across legacy systems. Ultimately, for Sri Lankan apparel manufacturers to maintain a competitive edge in the global market, they must strategically invest in comprehensive data literacy training, robust cloud-based infrastructure and advanced data quality management systems to fully leverage the potential of data analytics.

5. Recommendations

Based on insights gained from this research, the following recommendations have been developed.

5.1 Developing Comprehensive Training Programs to Improve Data Literacy

The lack of data literacy creates significant barriers to effective data analytics implementation. Comprehensive training programmes should be developed to address this critical gap across all organisational levels. Data literacy represents a fundamental requirement for effective data analytics utilisation in apparel firms, depending heavily on training and development programs provided to employees (Morrow, 2023). These programs should cover key data concepts, analytical tools and interpretation techniques for data insights across different organisational functions (Guha & Kumar, 2018).

Enhanced data literacy increases employee confidence in using data for decision-making processes, resulting in better decisions at all organisational levels. For instance, retail managers who improve their sales data analysis abilities can make more appropriate stock and display choices based on customer preferences (Klidas & Hanegan, 2022). Furthermore, highly skilled data-literate employees can integrate new analytics tools and techniques across the business, driving digital transformation (D'Ignazio, 2017). Long-term advantages for data-literate organisations include improved efficiency, better customer insights and greater capacity to respond to environmental changes, ultimately increasing competitiveness in the constantly evolving apparel industry (Schmarzo, 2023).

5.2 Adopting Cloud-Based Analytics Solutions to Reduce Initial Investment Costs

The early-stage adoption cost difficulties can be addressed through cloud-based analytics solutions. Cloud-based analytics represents a cost-effective strategy for implementing data analytics in apparel firms, especially for small and medium enterprises (SMEs). These solutions grant access to analytical tools and storage equipment without requiring major hardware and software investments (Altaiar, Lee & Pena, 2019).

Organisations can easily scale their analytics capabilities up or down according to demand, paying only for resources actually used (Hadwer, 2022). For instance, a small clothing brand can apply cloud-based demand forecasting solutions to improve inventory management, gaining competitive advantages over massive retailers (Bass, 2018). Furthermore, cloud solutions provide access to recent analytical capabilities through consistent updates and maintenance (Zagni, 2023). Despite data migration costs, cloud-based solutions represent an appealing choice for apparel firms seeking to optimise data analytics utilisation without incurring significant additional IT costs and overheads (Kandi, 2023).

5.3 Applying Natural Language Processing (NLP) for Enhanced Demand Forecasting

The externality vulnerabilities affecting forecasting models can be mitigated through Natural Language Processing (NLP) implementation. NLP addresses demand forecasting difficulties for new products where customer preferences, market conditions and supply chain conditions constantly change. NLP enables real-time analysis of large textual data from social media, news articles and reports, allowing apparel firms to detect early signs of consumer sentiment shifts, emerging trends and supply chain disruptions before they materialise in the market (Just, 2024).

For instance, during the pandemic, NLP could have discovered earlier that the market gradually required more loungewear and athleisure products (Beysolow, 2018). Long-term NLP usage improves market trend forecasting accuracy, prevents overproduction, and optimises inventory (Rothman, 2024). Real-life applications include Zara, where NLP-derived insights helped them respond effectively to changing market demands and strategies (Sandra, 2024).

5.4 Implementing a Data Quality Management System with Advanced Analytics

The poor-quality data processing difficulties causing real-time inventory update challenges require multiple integrated approaches through a Data Quality Management System with Advanced Analytics. Automated data cleaning and standardisation tools should be deployed across the system to ensure consistency and reduce errors. Real-time data validation and Application Programming Interface (API)-driven integration help maintain accurate and synchronised inventory data (Kwon, Lee & Shin, 2014). Master Data Management develops a clear repository that simplifies complex product information, while analytical tools and machine learning categorise results and identify flaws (Rawat, 2023). Real-time insights are provided through centralised dashboards displaying data quality and inventory status (Needham, 2023).

Furthermore, blockchain technology preserves data integrity and offers complete transaction history records (Sarka, 2021). This approach enhances inventory data accuracy and reliability, facilitating effective inventory control and management, reducing carrying costs, and minimising stockout situations (Begley, 2017). Complex omnichannel operations of apparel firms can be managed effectively, solving key decision-making problems, increasing customer satisfaction, and improving overall business performance in the competitive retail environment (Strohmeier, Collet & Kabst, 2022).

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