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A Review of Fast Fashion Demand Forecasting Methods

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Abstract

Fast-fashion retail operates in an environment characterized by short product life cycles, high demand volatility, and rapidly changing consumer preferences. Accurate demand forecasting is therefore essential for reducing inventory risk and improving supply chain responsiveness. This paper provides a comprehensive review of demand forecasting methods applied in fast fashion. The objective of this review is to analyse the existing traditional forecasting approaches, machine learning techniques, and hybrid forecasting systems. Different specific models were chosen based on the three categories, such as ARIMA, Regression-based for traditional models, LSTM, social media-driven methods for artificial intelligence-based models and hybrid models which combined elements of both traditional and AI-based. The paper concludes that no single method dominates across all fast-fashion forecasting; however, different types of models are used based on specific characteristics. Hybrid methods are considered more promising than traditional forecasting methods due to the reviewed literature showing overall best performance.

Keywords

fast fashion, demand forecasting, machine learning, retail analytics, supply chain management

1. Introduction

"Demand forecasting" refers to the process of predicting future consumer demand using historical data and relevant factors. In supply chain management, demand forecast has become important in supporting the key decision-making and operational decisions like product inventory allocation, logistics management and further product production planning [1]. This is particularly important in fast fashion, where products have a specific seasonal nature, with spring and summer considered one stage and autumn and winter the other [2].

The review, therefore, examines fast-fashion demand forecasting from its interconnected perspectives. Firstly, it is important to consider why demand forecasting is especially difficult in fast fashion, where demand is volatile, product life cycles are short and limited data is available on past sales information [2]. Additionally, it evaluates how traditional statistical methods, AI-based methods and hybrid forecasting methods respond to these characteristics of fast fashion. Moreover, it aims to identify limitations in the existing literature and discuss future research directions, particularly the need for forecasting models that can support new product forecasting and inform practical inventory and replenishment decisions.

2. Theoretical Background

In fast fashion, demand forecasting is closely linked with theories such as inventory management, supply chain responsiveness, and product life cycle [3]. It is essential for retailers to understand and accurately forecast customer demand to manage stock levels precisely. If demand is overestimated, the company may face excess inventory storage costs, markdowns, and waste. If underestimation happens, the company may eventually experience stockouts, lost sales, and lower customer satisfaction [4]. Hence, it shows how important an accurate forecast is for inventory decision-making.

The newsvendor model, which originates in inventory theory and focuses on products over a single selling period, shows that unsold stock loses value after the season ends [5]. This is important in fast fashion because clothing items follow trends and have short selling windows. This model highlights the trade-off between the cost of overage, which occurs when inventory remains unsold, and the cost of underage, which occurs when demand exceeds available stock and potential sales are lost [6]. Showing how accurate demand forecasting supports more effective inventory decisions by reducing uncertainty and helping retailers balance the risk of over- or understock.

Another theory relevant to fast fashion demand forecasting is the short product life-cycle theory [7]. This explains how, in fast fashion, products often have limited historical sales data. Many items are trend-based and sold fast only for a short period. Creating a “cold-start” problem in which retailers must forecast demand without prior sales data for the exact product [8]. Hence, forecasting relies on similar past products, product attributes, prices, promotions, and external factors, all of which need to be considered.

Several theoretical debates are also relevant to demand forecasting in fast fashion. For instance, some researchers argue that fast replenishment can reduce the need for highly accurate initial forecasts[9]. However, other studies suggest that forecasting and responsiveness are complementary because response systems still depend on the accuracy of early demand signals to guide replenishment decisions [10]. Additionally, researchers found concerns with the role of human judgement compared with algorithmic forecasting. Statistical and AI-based models can process large datasets and identify demand patterns, but human buyers may have additional preferences based on promotions. Competitors or emerging trends. On the other hand, human judgments are criticized for being unstructured, which can introduce bias and reduce forecast accuracy[11]. Hence, it is important to consider how human input should be used to support rather than be replaced by an algorithmic forecast entirely [11].

3. Literature Review of Forecasting methods in fashion retailing

Fast fashion demand forecasting has developed from traditional statistical models to artificial intelligence-based and hybrid forecasting systems. Existing studies show how forecasting in fashion retail is difficult due to fashion demand being highly volatile, short life cycles and sales being influenced by trends, customer taste, promotions, and weather[7].

3.1 Traditional forecasting methods

Traditional methods mainly rely on time-series models and regression-based methods, such as exponential smoothing, ARIMA, Bayesian methods, and panel-data approaches, which assume that future demand patterns can be derived from past observations, especially when data are relatively stable [12]. Their main strengths are simplicity, transparency, relatively low computational requirements and ease of implementation.

ARIMA is a time-series forecasting method [13]. It predicts future demand by using past sales values and past forecasting errors. In Fast fashion, ARIMA models are often considered limited due to short product lifecycles. For instance, Aburto & Weber [14], applied ARIMA models to demand forecasting in the Chilean retail sector, finding good performance for stable product categories but deteriorating accuracy for highly seasonal or trend-sensitive items.

However, there are fundamental limitations of traditional methods in forecasting, as these methods depend heavily on historical sales patterns, while fashion products have short selling windows and limited historical data[15]. Often, for new fashion items, there may be no previous sales record for the exact product, which makes traditional forecasting methods difficult [2].

Regression-based models predict demand using explanatory variables such as price, promotions, seasonality, colour, and others. Their main advantage over different traditional forecasting methods is that they can be used for new products with no sales history. With the introduction of considering eternal explanatory variables, the model improved forecast accuracy by 12% compared to ARIMA models [10].

Moreover, life cycle models and analogous forecasting are also traditional forecasting methods that involve identifying the best-selling items from the previous season in a given category and using their characteristics as templates for forecasting new introductions [16]. However, these models still have limited ability to capture complex and nonlinear demand patterns, especially trends and rapid changes [10].

Therefore, traditional methods are considered fundamental baseline tools. Due to their advantages of simplicity, speed and interpretability. However, there are also limits such as low performance under high volatility, short-lifecycle products and nonlinear consumer behaviour [12].

Overall, traditional forecasting methods differ primarily in their data requirements and suitable application contexts. ARIMA and other time-series models are most appropriate for established products with relatively stable demand and sufficient historical sales records, while regression is not. Based models are more suitable when demand is influenced by measurable dependent variables. Life cycle and analogous forecasting methods are comparatively more useful for new products. Across reviewed studies, traditional methods offer clear advantages in terms of simplicity, computational efficiency and managerial interpretability, but are less effective when demand is highly volatile, nonlinear or driven by sudden changes in consumer preference.

3.2 Artificial Intelligence Forecasting Methods

With the introduction of different new technologies, it has catalysed widespread adoption of AI-based methods in fashion demand forecasting[2]. Decision trees, random forests, artificial neural networks, and support vector machines are the primary AI tools used for demand forecasting in fashion, where forecasting went beyond learning mappings to demand output without requiring explicit model specification [17][5].

Artificial neural networks were the early AI methods applied to fashion demand forecasting. The model could incorporate different indicators, such as economic or social indicators, such as consumer price index, temperature and indicators that could affect sales[18]. These models primarily improved in capturing non-linear regression models.

Moreover, another model that improved forecasting was the Long Short-Term Memory networks[19]. Additionally, LSTM with a “forget gate” could allow retailers to gather information, preserve relevant historical signals, but at the same time reset and discard irrelevant historical signals [20]. Furthermore, Abbasimehr et al. [21] suggested how LSTM could capture fluctuating patterns and rapid changes, which could be attractive for fashion retailers due to fashion products having short life cycles.

A distinctive feature of AI-based fashion forecasting compared to traditional models is the ability to collect and identify different social media signals, search trends, online reviews and influencer engagement as indicators for consumer demand [22]. For example, Silva et al. [22] demonstrate that the relevance of Google Trends could improve the modelling of fashion search behaviour. Moreover, adding social media variables produced statistically significant improvements in daily sales forecasts [23] This was very helpful, showing how fashion trends are highly influenced by social media [22].

Overall, the three approaches are complementary rather than interchangeable. Because ANN models are more suitable for relatively stable products with rich structured data; LSTM models are better adapted to trend-sensitive products with observable short-term sales sequences; and social media-driven methods are particularly valuable for new or viral products whose demand is shaped by rapidly emerging online attention. In practice, the most appropriate model depends on whether demand is driven mainly by recurring product characteristics, recent sales momentum, or external social influence.

3.3 Hybrid Forecasting Methods

Hybrid forecasting methods combine traditional statistical models with AI models in order to perform with the strengths of both approaches. Recently, these methods have been considered to perform better because they could capture different parts of demand through more efficient methods. Statistical models, such as ARIMA, are useful for stable and structured patterns, while AI models such as LSTM are more suitable for capturing complex, nonlinear and rapidly changing patterns.

Various hybrid forecasting methods are commonly used to forecast demand in fast fashion. For instance, the ensemble method, which combines several different models. This model addresses the ideology that because different models make different errors, combining the models could be more accurate, as the models can limit the errors as few as possible and produce more stable predictions. For example, in the M5 accuracy competition, the largest systematic empirical evaluation of forecasting methods was a hybrid approach combining statistical and machine learning models [24].

Moreover, Zhang [25] introduced a sequential hybrid model which first uses ARIMA as a baseline to capture basic seasonal patterns through a linear approach. Then an AI model, such as an LSTM, is introduced to forecast more complex, non-linear aspects of demand that the statistical model cannot explain [25]. For big companies such as Zara and H&M, this is useful because they often need to forecast demand for short-term trends, such as one or two weeks ahead. Hence, this type of model could help capture expected seasonal demand while also adjusting to recent trend signals and product-specific demand changes.

Recent research also illustrated the practical relevance of combining traditional and AI-based forecasting methods in e-commerce inventory management. For example, Long Short-Term Memory (LSTM) networks were used to predict monthly inventory and to forecast daily sales across 350 product categories on a major e-commerce platform. This has been shown to provide a strong, data-driven basis for optimising warehouse resource planning and product category allocation [26].

Hybrid methods differ from both traditional and AI-based models because they allocate different components of demand characteristics to the models that are most capable of forecasting them. They could use statistical methods to capture linear, seasonal, or structured demand patterns before applying AI models to the remaining nonlinear variation. This method can also be used across planning horizons, with statistical models supporting longer-term inventory decisions and AI models producing more responsive short-term sales forecasts. This makes hybrid models particularly relevant to fast-fashion retail, where predictable seasonal patterns coexist with sudden trend-driven changes. However, performance accuracy depends heavily on how different types of models are combined and whether their errors are complementary; therefore, complex forecasting methods entail high implementation complexity, computational cost, and maintenance requirements.

4. Discussion & Synthesis

The literature review suggests that no single forecasting method is universally superior for fast-fashion demand forecasting. Instead, different models address different stages and data [24]. For instance, traditional statistical methods such as ARIMA remain useful because they are simple and effective when demand patterns are stable. However, their usefulness is limited in fast fashion where demand is often irregular, trend-driven and affected by short product lifecycles [27].

Hence, traditional methods are best understood as useful baselines supporting stable demand planning, while remaining less appropriate as the only forecasting method for fast fashion products [27]. AI-based methods, instead, could offer potential in more complex forecasting environments. The findings show how machine learning could incorporate large numbers of explanatory variables such as product attributes, price, promotions, digital engagement and other important forecasting variables. For example, AI models could help predict demand for new items by learning from similar product and becoming more accurate as information accumulates [20].

Hence, a complex AI model may outperform a traditional method in a data-rich environment, but it may also overfit limited or noisy data and produce predictions that are difficult for managers to interpret. In smaller retail settings, or where data quality is poor, a simpler statistical or regression-based model may be more reliable and easier to implement. The choice of forecasting method should therefore reflect the retailer's data capabilities and decision-making needs rather than a general preference for more advanced technology. Hybrid and ensemble methods provide a practical union between traditional and machine learning approaches [25]. This makes hybrid models theoretically attractive in fast fashion. However, their apparent superiority should be interpreted cautiously. The reviewed studies frequently use different datasets, product categories, forecast horizons, and evaluation measures, which makes direct comparison difficult. It is therefore not possible to determine whether hybrid models perform better because of the model combination itself or because they were tested under more favourable conditions.

There are also important debate concerns in fast fashion forecasting. In practice, fashion buyers often adjust algorithmic forecasts using their own market knowledge. For example, some studies have shown how industries can improve forecasts when they have more information that is not included in the models, such as upcoming promotions, competitors' activities and early signals from their store chains[28]. While other studies have shown how additional adjustments from human knowledge could reduce accuracy due to the influence of bias or overconfidence [11].

Moreover, as mentioned in the literature, many fast fashion products are new and have no direct sales history, hence suffering from the cold-start problem [29]. Although the study suggests the regression model that focuses on characteristics such as colour, price, fabric style, and design features to forecast demand [10]. There are also other types of learning patterns across many similar products, and forecasting new products based on this knowledge may be helpful. However, small details can change the product overall, which may lead to differences in forecasting [29]. This makes it difficult to determine which method is most effective for cold-start demand forecasting in real fast-fashion contexts [8].

Additionally, there are several limitations in the existing literature. First, there is limited evidence using internal forecasting data from major fast fashion retailers such as Zara, H&M and Shein. Moreover, studies rarely compare traditional, AI-based, and hybrid models using the same dataset, product categories, forecast horizons, and evaluation measures. This lack of standardisation makes it difficult to determine whether differences in performance result from the models themselves or from differences in research design. Consequently, the current literature does not provide sufficient evidence to identify one method as consistently superior. Hence, future studies are needed in order to test different models with the same data specific to fast fashion retailers.

Table 1: Summary of the different models

Model type	Supporting advantages	Limitations	Overall interpretation
Traditional models	Simple, effective for stable demand, good for easy interpretations	Weak with volatile and limited data	Useful for a general baseline
AI models	Good for nonlinear patters, and can include multiple variables	Requires large amount of data, hard to interpretate, and understand.	Valuable with rich-data settings
Hybrid models	Combine statistical and AI models strengths	Hard to compare and evaluate whether it has errors,	Promising but not superior

5. Conclusion

The paper shows that the central difficulty of fast-fashion forecasting originates from limited data, a short product lifecycle, and the volatility of product variables that influence demand. The literature shows that traditional methods still remain competitive as a baseline, while hybrid models are considered to be most helpful in accurately forecasting demand. However, several research gaps have been identified: limited publicly available primary empirical research involving major fast-fashion retailers such as Zara and H&M that systematically compares the predictive accuracy of different forecasting models. This limitation may be partly attributable to the proprietary and commercially sensitive nature of their operational data. Moreover, it is important to address the cold-start problem for fast-fashion products with limited data. Addressing these gaps would substantially advance both the academic understanding of retail-side demand forecasting in fast fashion and the practical capability of retailers operating in this high-velocity, high-stakes environment.

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