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Research Article

The Influence of Social Network on Forecasting in Fashion Industry

Michal Koren[1]*, Adaya Monsonego[2] and Rotem Biton[2]

[1]*School of Industrial Engineering and Management, Shenkar–Engineering. Design. Art, Ramat-Gan, Israel*

[2]*Industrial and Information Systems Engineering, Bar Ilan University, Ramat-Gan, Israel*

***Corresponding author:** Michal Koren, Shenkar-Engineering. Design. Art, School of Industrial Engineering and Management, Anne Frank 12, Ramat Gan 5252626, Israel.

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Abstract

The fashion industry is a significant contributor to environmental degradation, with its rapid turnover of trends leading to substantial waste. This underscores the necessity for precise forecasting methods to optimize production, procurement, lead time management, and inventory control. Traditionally, fashion forecasting relied on statistical analyses and retail sales data. However, the rise of social media has significantly influenced fashion preferences, trends, and consumer behavior, yet few forecasting models effectively integrate social media data. This paper introduces a forecasting model that leverages social media data from TikTok, Facebook, and Instagram, considering the distinct engagement metrics and demographic segments of each platform. By analyzing data from these social networks and incorporating operational parameters, the model aims to provide more accurate sales forecasts. The integration of diverse data sources is expected to enhance the predictive accuracy, offering a robust approach to demand forecasting in the fashion industry. Further support for the precision and reliability of predictions derived from social network data comes from the anticipated growth in social media usage.

Keywords: Forecasting; Demand; Fashion; Social network

Introduction

The fashion industry, recognized as one of the most environmentally detrimental sectors globally, operates at an accelerated pace, with fashion retailers planning collections up to three seasons in advance. This relentless turnover of trends leads to substantial waste, highlighting the imperative for precise forecasting [1]. underscores the importance and complexity of fashion forecasting, which is vital for optimizing production processes, procurement planning, lead time management, and inventory control. In the ever-evolving fashion landscape, keeping up with trends is crucial, but it comes with significant environmental consequences, especially in the textile manufacturing sector. Reports reveal an alarming $400 billion worth of clothing wasted annually [2]. Moreover, in 2021 the Impacts from the fashion industry comprise over 92 million tons of waste produced per year and 79 trillion liters of water consumed [3]. This waste issue is compounded by the harmful chemicals used in production, notably dyes, which pose additional environmental risks. The fast-paced nature of the fashion industry exacerbates these challenges. With trends constantly changing, garments are quickly discarded, leading to a buildup of waste. When these garments end up in landfills or are incinerated, they release significant amounts of CO_2 into the atmosphere [4,5], exacerbating climate change. Given the environmental concerns previously discussed, accurately predicting future demand becomes paramount in the fashion industry. By forecasting production needs, brands can effectively reduce clothing waste and improve resource management efficiency [6].

Demand forecasting is a cornerstone of fashion operations, enabling retailers to offer the right products at the right time, enhancing profitability, and operational flexibility (Ren et al., 2019). Moreover, predicting trends is essential for brands to stay aligned with evolving consumer preferences, optimizing inventory, and driving sales while fostering brand loyalty. Building upon the urgency of accurate demand forecasting, numerous models have been proposed to address this challenge within the fashion industry. These models typically leverage traditional statistical approaches along with machine learning methods [7].

Forecasting in the fashion industry is both important and challenging due to uncertain product demand and short product life cycles. Accurate forecasting is crucial for optimizing production, procurement planning, lead times, and inventory management in fashion. However, forecasting faces significant challenges due to the brief lifespan of products and unpredictable demand fluctuations [1,8]. Various methods have been developed over time to predict demand for fashion products. Regression models, clustering, different types of neural networks, fuzzy methods, and survey-based methods have all been utilized [9]. Artificial intelligence has emerged as a significant tool in recent years, particularly in forecasting. Additionally, new methods such as statistically significant clickstream tracking on non-transactional websites and leveraging Google Trends have become available for [10].

One popular data source for fashion trend analysis is the purchase record on either online or offline retailing platform. However, purchase records reflect people's buying decisions which are influenced by many factors such as retailers' promotions, which hardly reveal real fashion preferences of users, neither the real fashion trends [11,12]. In the realm of contemporary fashion analysis, our attention is drawn to predicting trends through the lens of social media. Social media prediction has emerged as a pivotal tool, capturing the interest of researchers and practitioners alike. Today, social media serves as a global platform for communication, connection, and interaction, generating vast amounts of Big Data at an unprecedented rate [13]. This wealth of data presents business owners with an invaluable resource to leverage for strategic decision-making.

In April 2024, there were 5.44 billion internet users worldwide, which amounted to 67.1 percent of the global population. Of this total, 5.07 billion, or 62.6 percent of the world's population, were social media users (Statista; https://www.statista.com/). Each social network exhibits a predominant demographic group. For example, until recently, Facebook had dominated the social media landscape among America's youth, but it is no longer the most popular online platform among teens [14]. TikTok is now one of the most popular social media platforms among teenagers [15].

Social media serves as a dynamic platform where individuals globally showcase their daily activities, including their fashion preferences and opinions, offering an invaluable resource for researching fashion trends [12]. Furthermore, the extensive and diverse data available on social media, spanning a significant duration, facilitates comprehensive and sophisticated analysis of fashion trends on a large scale to explore trending information and frequently searched terms from social media data for decision making (see for example, [16] and [17]).

Social network is one of the favorite means for a modern society to perform social interactions and exchange information via the Internet. It allows people to share their contents without boundaries. People communicate and express their comments, likes and interests via social network as it provides a fast and easy way to share [18]. When individuals freely express their opinions on various subjects, utilizing this data can enhance the accuracy of predictions. Social networks play a crucial role for a significant portion of the population, making them a valuable source of insight for predictive analysis. Social media has become deeply ingrained in daily life, emerging as a pivotal platform for the dissemination and monitoring of fashion trends. The ease and accessibility of purchasing through social media have established it as a critical tool that warrants comprehensive utilization. Historically, the fashion industry's forecasting methodologies were predominantly based on statistical analyses and retail sales data [19].

However, in recent years, social media has exerted considerable influence on fashion preferences, trends, and consumer purchasing behavior. Despite this, there is a notable scarcity of forecasting models that effectively integrate social media data. In addition, it is imperative to account for the differential weighting of each social network, as each platform has its own popularity, and engages distinct demographic segments. This differentiation is crucial since the audience composition varies across networks, influencing the engagement metrics and their relevance to sales forecasts. it highlights the key factor of social media app of TikTok for example, as it is the fasted growing app at world level [20], it is essential to consider. The significance of social media data has been correctly proven in many studies [13,21] have shown a vast variety of fields such as finance, marketing, and sociopolitical field which have used social media data for prediction [22].

Materials and Methods

This paper proposes a forecasting model that leverages social media data to achieve more accurate and optimal predictions in the fashion industry. The objective of our research is to leverage data harvested from social media to forecast trends in the fashion industry. By incorporating data from social networks, our model aims to achieve highly accurate predictions, capitalizing on the extensive and diverse opinions expressed by users within these platforms. This research contributes by leveraging the easily accessible social media data to forecast fashion trends. Platforms like TikTok, Facebook, and Instagram provide real-time insights into consumer preferences, allowing for precise demand forecasting. By utilizing this data, fashion retailers can better align production with market trends, reducing waste and improving inventory management.

The objective of the model is to provide a sales forecast for a fashion item by analyzing social media engagement data. We assume one fashion item available in a retail store. For the item, two datasets are collected: (1) operational data (such as item color) and (2) data from various social networks (such as number of likes), with greater weight given to the item we are interested in forecasting. We focus on three primary social networks: TikTok, Facebook, and Instagram. Additionally, the model will consider the primary social network associated with the target demographic of each item. For instance, items targeting teenagers will assign greater weight to engagement metrics from TikTok, as it is a predominant platform for this age group. The weights different is important for us because each social network has its own audience and popularity (Table 1).

Table 1: The setting notations and parameters are used in the model.

Symbol	Remarks
x_{ijkp}	$The\ item \mid i \in item\ index, j \in type(shirt, pants, etc.), k \in color,$ $p \in population\ which\ the\ item\ belongs\ to$
IC_i	$Item\ code\ for\ item\ i$
$Q_{oi}(IC_i)$	$Average\ sales\ for\ item\ i\ with\ item\ code\ ICi$ $Item\ code\ for\ item\ i$
$N = \{T, F, I\}$	$Set\ of\ social\ networks - Tiktok, Facebook, Instagram$
$F = \{L_{Ni}, C_{Ni}, S_{Ni}\}$	$Number\ of\ likes, comments\ and\ shares$ $in\ social\ network\ N\ and\ item\ i(vector\ of\ counts)$
$W_e = \{W_l, W_c, W_s\}$	$Vector\ of\ weights\ for\ likes, comments, shares$
$W_n = \{W_t, W_f, W_i\}$	$Vector\ of\ weights\ for\ TikTok, Facebook, Instagram$
Q_s	$The\ weighted\ engagement\ score$
$K_i(t)$	$The\ amout\ of\ sales\ for\ item\ i\ in\ t\ days$

Sales Forecast

This following equation was used to estimate the sales of an item i over time t by combining its average sales with a weighted score of social media engagement.

$$K_i(t) = Q_s(IC_i).\mathrm{Q}_{oi}(IC_i) \quad (1)$$

Weighted Engagement

This score will be a weighted sum of the likes, comments, and shares from the relevant social networks and the

social network's weight, calculated using equation 2.

$$Q_s(IC_i) = (W_i.L_{Ti} + W_c.C_{Ti} + W_s.\mathrm{S}_{Ti}).W_t + (W_l.L_{Fi} + W_c.C_{Fi} + W_s.\mathrm{S}_{Fi}).\mathrm{W}_f + (W_l.L_{Ii} + W_c.C_{Ii} + W_s.\mathrm{S}_{Ii}).\mathrm{W}_i \quad (2)$$

This structured approach allows for a comprehensive analysis of social media engagement data to forecast sales effectively.

Algorithm Sales forecast

The sales forecast was carried out by the following Algorithm in Visual Studio Code[1] environment.

Input: *All parameters required for both engagement and operational scores.*

Output: *Weighted engagement score* (Qs) *and the sales forecast* (K).

function *calculateWeightedEngagementScore*

$$\begin{pmatrix} IC_I, W_l, W_s, L_{Ti}, C_{Ti}, S_{Ti}, \\ L_{Fi}, \mathrm{C}_{Fi}, S_{Fi}, \mathrm{L}_{Ii}, C_{Ii}, S_{Ii}, W_t, W_f, W_I \end{pmatrix}$$

$TiktokSum = (W_l.L_{Ti}. + \mathrm{W}_c.\mathrm{C}_{Ti} + W_s.S_{Ti}).W_t$

$FacebookSum = (W_l.L_{Fi}. + \mathrm{W}_c.\mathrm{C}_{Fi} + W_s.S_{Fi}).W_f$

$InstagramSum = (W_l.L_{Ii}. + \mathrm{W}_c.\mathrm{C}_{Ii} + W_s.S_{Ii}).W_i$

$Q_s = TiktokSum + FacebookSum + InstagramSum$

return Q_s

end function

function *calculateSalesForecast*

$$\begin{pmatrix} IC_I, W_l, W_c, \mathrm{W}_s, L_{Ti}, C_{Ti}, S_{Ti}, \mathrm{L}_{Fi} \\ \mathrm{C}_{Fi}, S_{Fi}, \mathrm{L}_{Ii}, C_{Ii}, S_{Ii}, W_t, W_f, W_I, \mathrm{Q}_{oi} \end{pmatrix}$$

[1] https://code.visualstudio.com/

$Q_s = calculateWeightedEngagementScore$

$$\begin{pmatrix} IC_I, W_l, W_c, W_s, L_{Ti}, C_{Ti}, S_{Ti}, L_{Fi} \\ , C_{Fi}, S_{Fi}, L_{Ii}, C_{Ii}, S_{Ii}, W_t, W_f, W_I \end{pmatrix}$$

$K = Q_s \cdot Q_{oi}$

return K

end function

The algorithm comprises two functions: 'calculate Weighted Engagement Score' and 'calculate Sales Forecast'. The 'calculate Weighted Engagement Score' function computes the weighted engagement score (Q_s) by integrating engagement metrics from TikTok, Facebook, and Instagram. It uses weights for likes, comments, and shares, alongside platform-specific engagement data, to calculate a network-specific weighted sum, which is then aggregated to yield Q_s.

The 'calculate Sales Forecast' function uses Q_s from the previous function and multiplies it by the average sales for the item (Q_{oi}) to forecast future sales (K). This method combines social media engagement data with operational metrics to provide a comprehensive sales prediction.

Determining the weights of social networks

In the model equations, determining the weighted influence of social networks and their user engagements is a critical factor. In this subsection, we describe the process for determining the weights assigned to different social networks and different engagements in our forecasting model.

We have decided to focus on six distinct age groups: 18-24, 25-34, 35-44, 45-54, 55-64, and 65+. This segmentation allows us to analyze and understand the varying engagement patterns and behaviors across different demographic cohorts. By categorizing our target audience into these specific age ranges, we can more accurately assess the influence of social networks and tailor our forecasting model to reflect the unique preferences and usage trends of each group. This approach ensures that our analysis and subsequent sales forecasts are grounded in a comprehensive understanding of demographic-specific social media engagement.

We focus on three primary social networks: TikTok, Facebook, and Instagram. These platforms exhibit varying levels of engagement across different age groups. Specifically, TikTok's largest age group is 18-24, constituting 36.2% of its user base. For Facebook, the largest age group is 25-34, comprising 29.9% of its users, while Instagram's largest age group is also 18-24, representing 30.8% of its users (Sprout Social; https://sproutsocial.com/). The number of monthly active users further highlights the platforms' reach: Facebook has 3.065 billion, Instagram has 2 billion, and TikTok has 1.7 billion active users (Khoros; https://khoros.com/).

Within the 18-24 age group, 61% of mobile internet users visited TikTok, 56% visited Instagram, and only 34% visited Facebook. For the 25-34 age group, Facebook is the most popular social media platform, with Instagram following closely. Beyond the age of 34, Facebook remains the predominant social media platform by a significant margin. These insights are crucial for our calculations, as they underscore the need to assign higher weights to the most relevant social networks based on the target demographic. For instance, when forecasting sales for a white t-shirt aimed at teenagers, we assign a higher weight to TikTok, given its greater popularity within this age group compared to Facebook and Instagram.

Results and Discussion

On social media platforms, likes, comments, and shares represent distinct levels of user engagement, each reflecting varying degrees of interaction with content. Facebook for example, gives different weight to different behaviors to determine what to show in user's screen. A share weights approximately as much as 2 comments, each of which has roughly equal weight to 7 likes [13]. A "like" is a relatively effortless action, typically performed with minimal thought, to express approval or appreciation for a post. While it indicates a positive response, it provides limited insight into the user's deeper sentiments or motivations. In contrast, a "comment" requires a more considered effort, involving users in articulating their opinions or reactions. Comments offer richer qualitative feedback and facilitate direct communication between users and content creators. "Shares" denote a more deliberate endorsement, as users actively disseminate content within their own network, suggesting that they find it valuable or relevant for broader distribution. This action not only extends the content's reach but also signifies a stronger level of engagement.

Given the varying significance of these interactions, it is crucial to assign different weights to each type of engagement in analytical models. Likes, being quick and easy to perform, may reflect superficial approval and thus warrant a lower weight compared to comments, which indicate more substantial user engagement. Shares, which involve actively promoting content, often represent the highest level of endorsement and should be assigned a higher weight to accurately capture their impact on content visibility and influence. Properly weighting these engagement metrics ensures a more nuanced and accurate analysis of social media interactions, thereby enhancing the reliability of models that depend on these data points.

While there is currently no empirical data available to validate the predictive accuracy of our model, we have outlined the anticipated outcomes based on its innovative integration of social network data and operational parameters.

Conclusions

With more than 5.17 billion users, social media is one of the most powerful forces in the world today. Consumers and businesses rely on it for connecting, researching, and communicating. And the impact is still growing- researchers indicates that more than 5.85 billion users are expected by 2027 (Exploding Topics; https://explodingtopics.com/). This anticipated increase in social media activity strengthens the argument that predictions derived from social network data will become increasingly precise and dependable. As more users engage with these platforms, the volume and richness of data available for analysis will expand, enhancing the accuracy and relevance of predictive models [13].

The advent of social media offers researchers a novel and abundant source of readily accessible data about individuals, society, and potentially the world at large. In particular, social media data captures the online behavior of users who communicate and interact on a wide range of issues and topics. In recent years, data harvested from social media has shown to be very popular with scholars interested in developing predictive models. The significance of social media data has been correctly proven in many studies [13,23,24] have shown a vast variety of fields such as finance, marketing, and sociopolitical field which have used social media data for prediction [25].

This combined strategy leverages real-time engagement metrics from prominent social media platforms alongside traditional operational data, a method that is not typically employed by organizations. Given this comprehensive and multifaceted data incorporation, we expect our model to provide more robust and reliable sales forecasts. By capturing the dynamic interplay between social media trends and operational factors, our model is poised to offer a more nuanced and accurate prediction of market demand, thereby presenting a significant advancement over conventional forecasting methods.

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Conflict of Interest

Authors declare no conflict of interest.

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