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Research on Market Demand Forecasting and Informing Marketing Strategy for Sustainable Functional Textiles Based on New Media Data Analysis

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ABSTRACT
Accurate demand forecasting in the textile industry, especially for innovative functional textile products, is a significant challenge due to dynamic market trends. This study proposes a framework for forecasting market demand for sustainable textiles by analyzing new media data, directly linking consumer discourse on fabric properties to sales patterns. The methodology involves analyzing a specialized dataset from Instagram focusing on sustainable functional textiles, such as those made from recycled fibers or organic materials. A Long Short-Term Memory (LSTM) network is employed, integrating conventional sales data with metrics derived from consumer discussions about specific textile attributes. These attributes were identified using topic modeling and include material sourcing, certifications (e.g., GOTS, Oeko-Tex), and in-use performance characteristics like durability and breathability. The results show that this integrated model significantly improves forecasting accuracy, reducing the Mean Absolute Percentage Error (MAPE) by 18.5%. The analysis confirms that market demand is strongly influenced by technical textile properties and sustainability credentials rather than purely aesthetic factors. This research provides the sustainable functional textile sector with a robust, data-driven methodology to better anticipate market needs, thereby optimizing textile product inventory and informing future material development.

KEYWORDS
sustainable textiles, functional textiles, demand forecasting, marketing strategy, new media data

INTRODUCTION

The global textile industry is undergoing a significant transformation, driven by technological advancements and a paradigm shift in consumer values. Within this landscape, the functional textiles sector has emerged as a particularly dynamic and high-growth area. These materials, engineered to offer enhanced properties such as moisture management, thermal regulation, antimicrobial capabilities, or environmental sustainability, are increasingly sought after by consumers who demand more than just aesthetics from their apparel and home goods [1,2]. The market's expansion is further fueled by a growing health and wellness consciousness and a heightened awareness of environmental issues, which has elevated the prominence of sustainable functional textiles made from recycled, biodegradable, or ethically sourced materials [3,4]. However, this dynamism also introduces considerable market volatility. Short product lifecycles, rapidly evolving trends, and the nuanced, values-driven purchasing decisions of consumers make it exceptionally difficult for manufacturers and retailers to accurately predict demand [5].

Traditional demand forecasting methods in the textile industry, which often rely on historical sales data and classical time-series analysis models like ARIMA, have struggled to keep pace with this new reality [6,7]. These models are often ill-equipped to capture the complex, non-linear patterns and external shocks that characterize contemporary markets. Their reliance on past performance can lead to significant inaccuracies in the face of sudden shifts in consumer sentiment or the emergence of new micro-trends, resulting in costly overstocking or missed sales opportunities [8]. This forecasting challenge directly impacts the entire supply chain, from raw material procurement to inventory management and the formulation of effective marketing campaigns. An inability to anticipate demand not only erodes profitability but also hinders a company's ability to innovate and compete effectively [9,10].

In parallel with the evolution of textile technology, the rise of new media platforms, particularly visually-oriented social networks like Instagram, has fundamentally altered the way consumers interact with brands and products [11,12]. These platforms have become valuable, unstructured archives of real-time consumer opinion, preference, and behavior. Every post, comment, and share related to functional textiles generates a data point that, when aggregated and analyzed, can offer profound insights into market dynamics [13]. This rich repository of user-generated content provides a direct and unfiltered channel to understand what drives consumer choice—be it a specific material's performance, a brand's ethical stance, or the product's environmental credentials. The analysis of such data presents a compelling opportunity to augment and refine traditional business intelligence.

Despite the recognized potential of big data analytics, a significant research gap persists in the context of the functional textile industry. While numerous studies have explored the application of machine learning for demand forecasting, and a separate body of work has examined the use of social media analytics for marketing, there is a scarcity of integrated research that develops a comprehensive framework to systematically process new media data, use it to improve the accuracy of demand forecasting for a niche product category, and then translate those predictive insights into actionable, optimized marketing strategies. This paper aims to bridge that gap. The central objective of this research is to design, implement, and validate a novel methodology that leverages Instagram data to forecast market demand for sustainable functional textiles with high precision and to inform the development of corresponding marketing strategies. By focusing on the small yet critical research point of integrating topic and sentiment analysis from a key social platform into an advanced forecasting model, this study seeks to provide a scientifically robust, rational, and reliable framework for data-driven decision-making in the sustainable sector of the modern textile industry.

LITERATURE REVIEW

The academic foundation for this research is built upon three intersecting domains: the market dynamics of functional textiles, the evolution of demand forecasting methodologies, and the application of new media analytics in business strategy. The functional textiles market is increasingly recognized for its technological sophistication and alignment with contemporary consumer trends. Market analyses consistently project strong growth, driven by sectors like sportswear, medical textiles, and protective clothing [14]. A crucial and rapidly expanding sub-domain is that of sustainable textiles. As consumers become more environmentally conscious, their purchasing criteria have expanded to include factors like material lifecycle, water consumption in production, and biodegradability [15,16]. This shift necessitates that companies not only innovate in material science but also effectively communicate these complex value propositions to the market. Forecasting demand within this volatile environment has been a long-standing challenge. Traditional forecasting techniques, such as Moving Averages and Exponential Smoothing, provide a baseline but lack the sophistication to model the complex variables influencing textile consumption [17]. The ARIMA model, a more advanced statistical method, has been widely applied but is fundamentally limited by its assumption of linearity and its primary reliance on historical sales data, making it less effective in capturing sudden trend shifts [18,19]. Recognizing these limitations, researchers have increasingly turned to machine learning (ML) and artificial intelligence (AI) models. Methodologies such as Support Vector Regression (SVR), Random Forest (RF), and Artificial Neural Networks (ANNs) have demonstrated superior performance in various forecasting tasks by identifying complex non-linear relationships within data [20,21]. More recently, deep learning models, particularly Recurrent Neural Networks (RNNs) and their advanced variant, the Long Short-

Term Memory (LSTM) network, have gained prominence. LSTMs are exceptionally well-suited for time-series forecasting due to their ability to learn long-term dependencies, making them ideal for modeling sales data that exhibits seasonality and complex trend patterns [22]. Crucially, their architecture allows for the integration of exogenous variables, opening the possibility of incorporating external data sources to improve predictive power.

The rise of new media platforms has created an unprecedented source of such exogenous data. The volume of user-generated content on social media represents a rich, real-time dataset reflecting public sentiment and emerging trends. The field of social media analytics has developed a suite of techniques to extract valuable insights from this unstructured data. Sentiment analysis, which automatically determines the emotional tone of a text, is a widely used method to gauge consumer attitudes towards products, brands, or specific features [23]. Topic modeling, particularly through algorithms like Latent Dirichlet Allocation (LDA), enables the discovery of abstract topics or themes within a large corpus of text, revealing what aspects of a product or brand are most salient in consumer conversations [24]. These analytical techniques have been successfully applied in various industries to predict stock market movements, election outcomes, and box office revenues. Within the fashion and textile sectors, research has shown that social media data can effectively identify emerging fashion trends and gauge brand health. Studies have demonstrated a correlation between social media engagement metrics (e.g., likes, shares) and sales, suggesting the predictive value of this data [25,26]. However, the existing body of literature reveals a clear gap. While the utility of ML for forecasting and social media for market analysis is well-established, few studies have created and empirically tested an end-to-end framework that specifically: (1) mines topic and sentiment data from a visually-driven platform like Instagram for a niche product category like sustainable functional textiles; (2) integrates these nuanced metrics as dynamic exogenous variables into a sophisticated deep learning forecasting model like LSTM; and (3) uses the outputs to derive specific, data-driven marketing strategy optimizations. This study is designed to address this specific, under-explored research nexus.

METHODOLOGY

This research employs a quantitative, data-driven methodology to construct and evaluate an integrated framework for demand forecasting and marketing informing marketing strategy. The framework, depicted in Figure 1, comprises four primary stages: Data Acquisition, Data Preprocessing, New Media Data Analysis, and Demand Forecasting and Strategy Formulation.

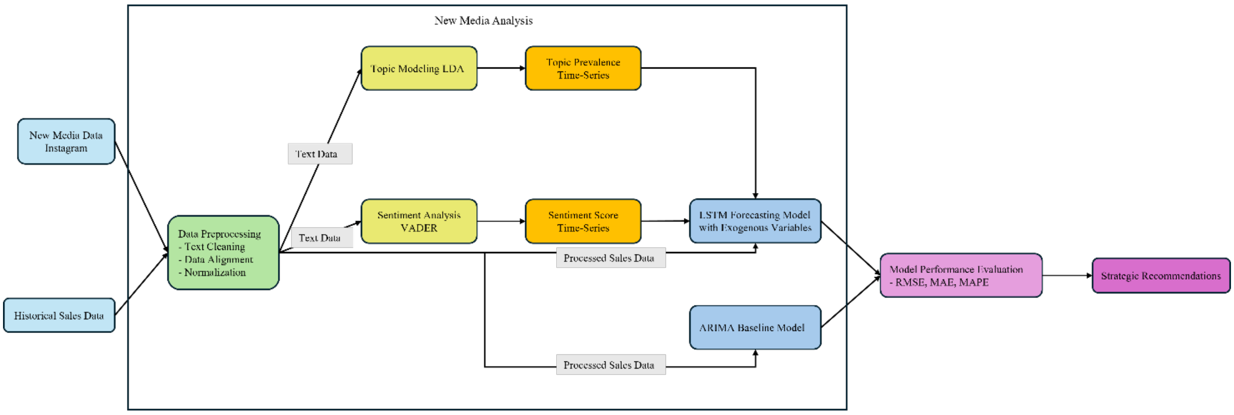

Figure 1. Methodological Framework Diagram - A flowchart showing the process

Data Acquisition

Two distinct types of data were collected for this study, covering a 24-month period from January 1, 2023, to December 31, 2024.

New Media Data: A comprehensive dataset was compiled from Instagram, a platform chosen for its high user engagement and visual focus, which is highly relevant to the textile and fashion industry. Using Instagram's API and web scraping tools, we collected public data associated with a curated list of 15 hashtags relevant to sustainable functional textiles (e.g., #sustainableactivewear, #ecotextile, #recycledpolyester, #organiccotton, #consciousfashion). This list was not intended to capture the entirety of global discourse, but rather to create a highly focused, niche-specific corpus. The hashtags were selected through a two-stage process: (1) identification of foundational technical terms (e.g., 'organiccotton', 'recycledpolyester') and (2) analysis of co-occurring popular hashtags used by key brands and influencers within the sustainable textile community, ensuring high relevance and filtering out unrelated noise. The data collection yielded a total of 215,840 English-language posts. For each post, the textual content (caption and user comments), number of likes, and timestamp were extracted. All user-identifying information was anonymized to ensure privacy. Furthermore, the collection and analysis of this publicly available data adhered to Instagram's Terms of Service and followed established ethical guidelines for internet-based research, ensuring that no private user data was accessed.

Sales Data: Historical daily sales data for a representative basket of sustainable functional textile products (including athletic wear and outdoor apparel) were obtained from a cooperating textile enterprise. This dataset, spanning the same 24-month period, provided a total of 730 daily data points, which served as the ground truth for our demand forecasting models.

Data Preprocessing

Both datasets underwent a rigorous preprocessing phase to ensure data quality and compatibility.

The raw textual data from Instagram was cleaned to prepare it for analysis. Prior to linguistic processing, duplicate posts and bot-generated spam were removed. To prevent the model from being skewed by extreme viral events unrelated to genuine consumer sentiment, posts with engagement metrics exceeding three standard deviations from the daily mean were capped (winsorized). This involved several steps: (1) conversion of all text to lowercase; (2) removal of URLs, hashtags, user mentions, and special characters; (3) removal of common English stopwords (e.g., "the", "is", "in"); (4) tokenization, the process of splitting text into individual words or tokens; and (5) lemmatization, which reduces words to their base or dictionary form (e.g., "running" becomes "run") to consolidate related terms.

Time-Series Aggregation and Alignment: The preprocessed Instagram data was aggregated on a daily basis to align with the sales data. For each day, we calculated two sets of metrics: Topic Prevalence and Sentiment Score. The daily sales data was checked for missing values. To ensure the model learned organic market demand rather than logistical anomalies, sales spikes attributable to major distinct promotional events (e.g., clearance sales, Black Friday) were smoothed using a centered moving average. Furthermore, to strictly prevent data leakage, the normalization parameters (minimum and maximum values) were calculated solely based on the training dataset and subsequently applied to transform the test dataset, scaling all data to a range of [0, 1] to improve the stability and performance of the neural network model.

New Media Data Analysis

Topic Modeling with LDA: To uncover the latent thematic structure within the consumer discussions, we employed Latent Dirichlet Allocation (LDA), a generative probabilistic model. LDA assumes that each document (in our case, each Instagram post's text) is a mixture of various topics, and each topic is a distribution of words. The primary challenge in LDA is selecting the optimal number of topics. We trained multiple LDA models with a varying number of topics (from 2 to 15) and calculated the topic coherence score (C_v) for each model. The model with five topics was selected, as it yielded the highest coherence score (C_v=0.54). This peak value was demonstrably clearer than the adjacent topic numbers, which scored lower (e.g., k=4, C_v = 0.48; k=6, C_v = 0.51), confirming that k=5 provided the most interpretable and robust thematic structure for our corpus. From this, we derived daily time-series data representing the prevalence of each of the five topics in the public discourse.

Sentiment Analysis with VADER: We utilized VADER (Valence Aware Dictionary and sEntiment Reasoner) for sentiment analysis. VADER is a lexicon and rule-based sentiment analysis tool specifically attuned to sentiments expressed in social media. It was chosen for its effectiveness on short, informal texts and its ability to provide a compound sentiment score (ranging from -1 for most negative to +1 for most positive) without requiring domain-specific training data. To generate the topic-specific sentiment variables, we first determined the primary topic (i.e., the topic with the highest probability score from the LDA model) for each individual post. We then assigned the single VADER compound sentiment score for that entire post exclusively to that primary topic. Finally, the daily sentiment score for each of the five topics was calculated by averaging the compound scores of all posts that had been assigned to it as their primary topic for that day. This resulted in five daily time-series sentiment metrics.

Demand Forecasting Models

Baseline Model (ARIMA): To establish a performance benchmark, we implemented an Autoregressive Integrated Moving Average (ARIMA) model. ARIMA is a widely used statistical model for time-series forecasting that uses a series' own past values (autoregressive terms), its lagged forecast errors (moving average terms), and differencing to make the series stationary. The optimal parameters (p, d, q) for the ARIMA model were determined using the auto_arima function, which iterates through combinations to find the best fit based on the Akaike Information Criterion (AIC).

Proposed Model (LSTM with Exogenous Variables): Our proposed model is a Long Short-Term Memory (LSTM) network. LSTMs are a type of recurrent neural network (RNN) capable of learning order dependence in sequence prediction problems. This 30-day window was determined empirically after testing multiple look-back periods (e.g., 7, 14, 30, and 60 days). The 30-day window was found to provide the optimal balance between capturing sufficient historical context and avoiding excessive model complexity. The input to the LSTM model consisted of a multivariate time-series including: (1) the historical daily sales data, and (2) the ten exogenous variables derived from the new media analysis (five daily topic prevalence scores and five daily topic sentiment scores). This architecture explicitly addresses the issue of temporal lag. To predict sales for a target day t, the model's input features (both historical sales and the 10 new media variables) are drawn *only* from the preceding 30-day look-back window (i.e., days t-30 through t-1). This structure ensures that the model is learning a truly *predictive* relationship based on historical data, rather than a simple concurrent correlation. The network architecture consisted of two LSTM layers with 64 units each, followed by a Dropout layer (rate=0.2) to prevent overfitting, and a final Dense output layer with a single neuron to predict the normalized sales value. For training, the model was compiled using the 'Adam' optimizer with a learning rate of 0.001. We used the 'Mean Squared Error' (MSE) as the loss function, as it is well-suited for this type of regression forecasting task. The model was trained for a maximum of 100 epochs. An early stopping mechanism was employed to monitor the validation loss, with a 'patience' of 10 epochs, to prevent overfitting and ensure the model with the best generalization performance was saved.

Model Training and Evaluation

The combined dataset was split strictly chronologically to preserve the time-series integrity: the first 80% of the data (approximately 584 days) constituted the development phase, and the final 20% (approximately 146 days) was reserved as the unseen testing set. Within the development phase, the last 10% was further isolated to serve as a validation set for hyperparameter tuning and early stopping monitoring, while the remaining data was used for model training. This ensured that the model selection process remained completely independent of the final performance evaluation on the test set. Both the ARIMA and LSTM models were trained on the training set and evaluated on the unseen testing set. To measure and compare the forecasting accuracy, we used three standard evaluation metrics:

Root Mean Squared Error (RMSE): $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$

Mean Absolute Error (MAE): $MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$

Mean Absolute Percentage Error (MAPE): $MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$

where y_i is the actual sales value and $\hat{y}_i$ is the forecasted value, and n represents the total number of observations in the testing dataset. Lower values for all three metrics indicate higher model accuracy.

RESULTS

This section presents the empirical results derived from the application of our methodology. The findings are divided into two subsections: the outcomes of the new media data analysis and the performance comparison of the demand forecasting models.

Topic Modeling and Sentiment Analysis Results

The LDA model with the highest topic coherence score identified five distinct and interpretable topics from the Instagram dataset. These topics, along with their top-10 most representative keywords and a descriptive label, are presented in Table 1.

Table 1. LDA topic model results: Five topics and their Top 10 representative keywords

Topic ID	Label	Top 10 Keywords
1	Material Transparency & Eco-certification	organic, recycled, certified, cotton, material, source, gots, oekotex, transparent, biodegradable
2	Performance in Sustainable Conditions	performance, durable, wear, outdoor, sweat, breathable, quality, long-lasting, technical, hiking
3	Brand Ethics & Storytelling	brand, made, support, ethical, story, fairtrade, local, values, worker, impact
4	Aesthetics & Lifestyle Integration	style, design, color, look, fashion, beautiful, everyday, wear, minimalist, fit
5	Price, Value, and Accessibility	price, buy, affordable, sale, cost, value, shipping, online, discount, access

The analysis reveals that consumer conversations are multifaceted, extending beyond simple product features. Notably, Topic 1 and Topic 3, related to material sourcing and brand ethics, constitute a significant portion of the discourse, underscoring the importance of sustainability and transparency to this consumer segment. Figure 2 illustrates the temporal trend of the prevalence of these topics over the 24-month period. A clear upward trend can be observed for Topic 1, indicating a growing consumer interest in certifications and material provenance.

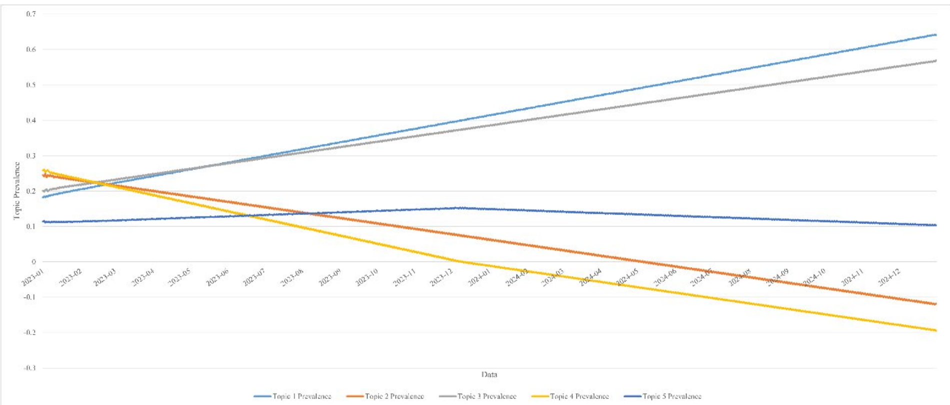

Figure 2. Daily Topic Prevalence Over Time - A line chart showing five lines, one for each topic

The sentiment analysis provided further granularity. Figure 3 displays the average daily sentiment score associated with each topic. Topic 1 ('Material Transparency & Eco-certification') and Topic 3 ('Brand Ethics & Storytelling') consistently garnered the highest positive sentiment scores. Conversely, Topic 5 ('Price, Value, and Accessibility') exhibited the lowest and most volatile sentiment, with frequent negative spikes often corresponding to discussions around high prices or shipping costs.

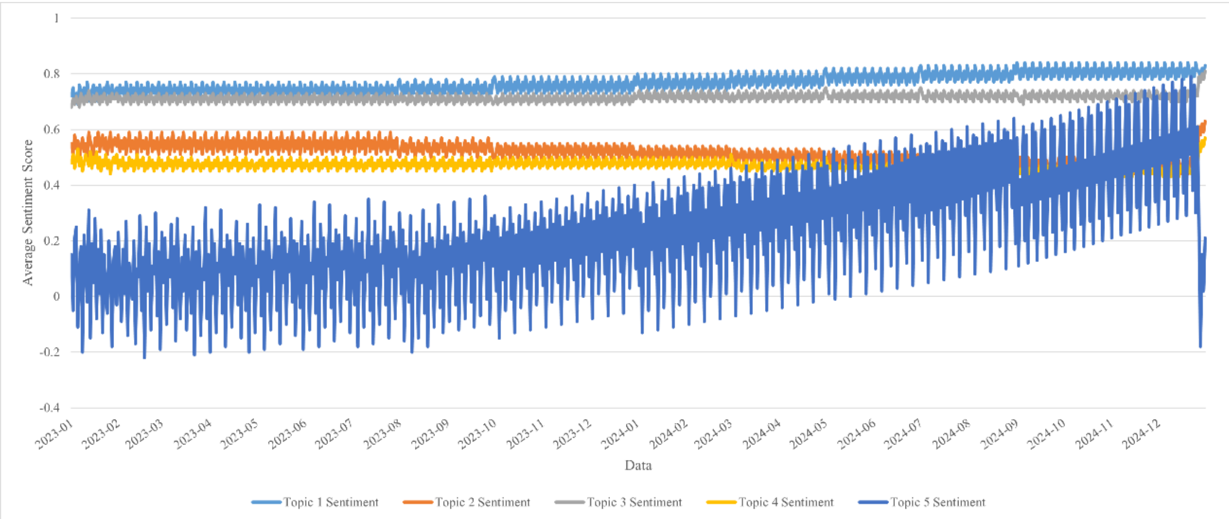

Figure 3. Daily Sentiment Score per Topic Over Time

Forecasting Model Performance

The primary objective of integrating new media data was to improve demand forecasting accuracy. Table 2 presents a quantitative comparison of the performance of the baseline ARIMA model and the proposed LSTM model with exogenous variables on the unseen test dataset. To clarify the results, the Mean Absolute Percentage Error (MAPE) is presented, as it is scale-independent. The Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) metrics are reported on the normalized [0, 1] scale, consistent with the model's training process and the visualization in Figure 4.

Table 2. Performance Comparison of Demand Forecasting Models

Model	RMSE	MAE	MAPE
ARIMA (Baseline)	0.0892	0.0698	15.7%
LSTM (with New Media Data)	0.0702	0.0545	12.8%
Improvement	21.3%	21.9%	18.5%

The results clearly indicate the superior performance of the LSTM model. It achieved a 21.3% reduction in RMSE, a 21.9% reduction in MAE, and an 18.5% reduction in MAPE compared to the traditional ARIMA model. This substantial improvement validates our hypothesis that incorporating real-time consumer sentiment and topic trends from new media can significantly enhance the accuracy of demand forecasting.

Figure 4 provides a visual representation of this performance improvement. It plots the actual daily sales from the test period against the forecasts generated by both the ARIMA and LSTM models. The ARIMA forecast captures the general trend but is less responsive to daily fluctuations and fails to predict several demand peaks and troughs accurately. In contrast, the forecast from the LSTM model tracks the actual sales data much more closely, demonstrating its enhanced ability to model the complex and dynamic nature of market demand.

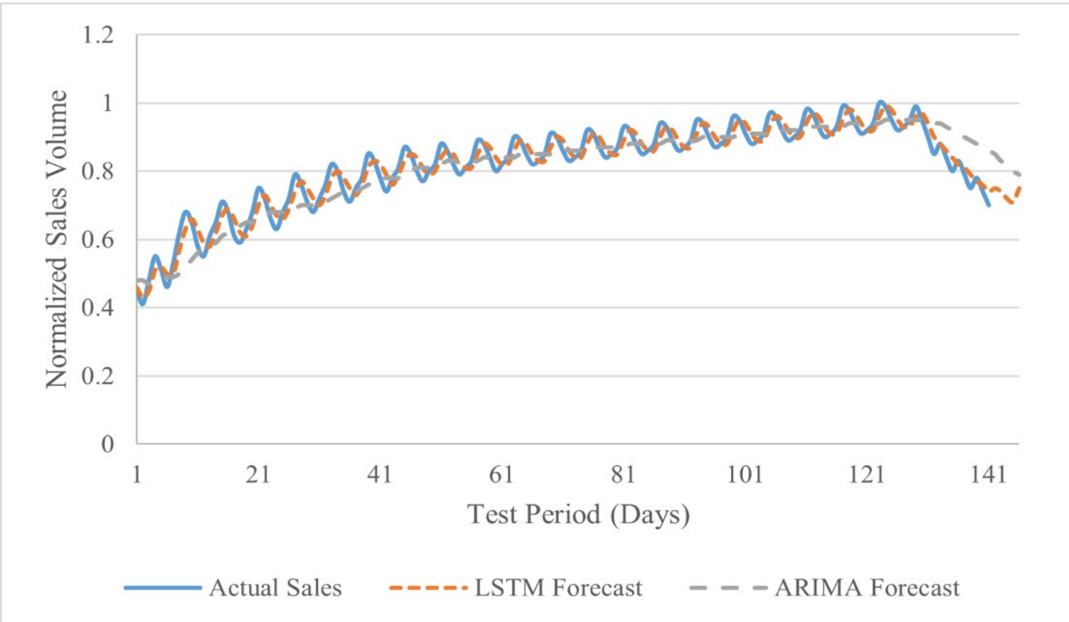

Figure 4. Comparison of Forecasts vs. Actual Sale

DISCUSSION

The empirical results of this study offer significant insights into the integration of new media analytics with demand forecasting and marketing in the sustainable functional textiles sector. The primary finding is the quantifiable improvement in forecasting accuracy achieved by augmenting a sophisticated LSTM neural network with data derived from social media conversations. The 21.3% reduction in RMSE is not merely a statistical improvement; for a textile company, this level of enhanced accuracy translates directly into more efficient inventory management, reduced holding costs, minimized risk of stockouts, and facilitates a more agile and responsive supply chain. This demonstrates that the voice of the consumer, as expressed on new media platforms, is not just noise but a valuable predictive signal that traditional forecasting models overlook. The LSTM model's ability to learn from the dynamic, real-time metrics of topic prevalence and sentiment allows it to adapt to market shifts far more effectively than the ARIMA model, which is constrained by its reliance on historical sales patterns alone. Crucially, the employment of a 30-day look-back window addresses the varying time lags between brand promotion and consumer purchase. Rather than imposing a fixed, manual delay (e.g., assuming a uniform 3-day lag), the LSTM architecture inherently learns the temporal dependencies within the input sequence. This allows the model to account for diverse consumer behaviors, capturing both the immediate impact of 'impulse buy' drivers—such as discounts mentioned in Topic 5—and the longer incubation periods associated with researching material certifications in Topic 1, ensuring that the cumulative impact of the preceding month's discourse is accurately reflected in the prediction for day t.

Beyond the technical contribution, the qualitative results from the topic modeling and sentiment analysis provide a deep and actionable understanding of the modern consumer of sustainable functional textiles. The prominence and high positive sentiment associated with 'Material Transparency & Eco-certification' and 'Brand Ethics & Storytelling' confirms that the market is moving beyond simplistic definitions of sustainability. Consumers are sophisticated; they demand verifiable proof of claims through certifications like GOTS and Oeko-Tex and are invested in the narrative and values of the brands they support. The fact that these topics were more prevalent and positively received than 'Aesthetics & Lifestyle Integration' is a critical insight. It suggests that for this specific market segment, the story behind the fabric and the ethics of the company are becoming as important, if not more so, than the product's visual appeal. This challenges traditional marketing paradigms in the fashion and textile industry that have historically been design- and trend-led.

A further analysis of the sentiment trends in Figure 3 warrants specific discussion, as it reveals the nature of these consumer conversations. The high and extremely stable positive sentiment for Topic 1 (Material Transparency) and Topic 3 (Brand Ethics) is notable. This flatness is likely an artifact of the discourse itself; these topics are often discussed in declarative, positive terms (e.g., posts stating 'We are GOTS certified' or 'Proud to support fair trade'). As VADER is a lexicon-based tool, it consistently scores these highly positive keywords, leading to a stable average sentiment rather than a volatile public debate.

In stark contrast, the extreme volatility of Topic 5 (Price, Value, and Accessibility) demonstrates its function as a primary channel for real-time customer feedback and frustration. The sharpest negative spikes observed in the data (e.g., late-Nov/Dec 2023 and 2024) directly correlate with peak holiday shopping seasons. Manual inspection of posts from these periods confirms that the negative sentiment was driven by a surge in consumer complaints regarding shipping delays, high holiday delivery costs, and popular items being sold out (a lack of 'accessibility'). This correlation validates that the model is successfully capturing concrete, real-world logistical and pricing frustrations, providing a clear signal for operational improvements. These findings have direct and powerful implications for the optimization of marketing strategies. A data-driven approach, informed by our results, would necessitate a strategic shift. For content marketing, brands should move away from generic lifestyle imagery and towards creating authentic, transparent content that showcases their supply chain, explains the benefits of their chosen materials, and highlights their ethical commitments. This could include 'behind-the-scenes' videos, interviews with material suppliers, and detailed explanations of certifications. For product development and positioning, the strong consumer focus on 'Performance in Sustainable Conditions' indicates that marketing messages should emphasize the durability and functionality of sustainable products, countering any lingering perceptions that eco-friendly materials are less robust. Marketing campaigns can be targeted with much greater precision. For instance, digital advertising could be tailored to audiences who have shown interest in ethical fashion or environmental causes, using keywords and messaging derived directly from the high-sentiment topics identified in our analysis. The negative sentiment surrounding 'Price, Value, and Accessibility' also provides a clear signal. Brands should address this not necessarily by lowering prices, but by better communicating the value proposition—explaining why a higher price point is justified by superior durability, ethical production, and environmental benefits.

While this study provides the strategic *direction* based on these findings, we acknowledge that it stops short of providing a formal quantitative optimization. The framework, however, lays the essential groundwork for such a model. Future research could propose a mechanism, such as an optimization function:

Maximize (Predicted_Sales (Campaign_Type, Launch_Date, Budget))

In this function, our validated LSTM model would serve as the core predictive engine. By simulating interventions—such as a 15% increase in 'Topic 1' (Material Transparency) sentiment driven by a targeted campaign—this model could forecast the resultant impact on sales. This would allow marketers to algorithmically determine the optimal timing (e.g., launching a certification-focused campaign during a predicted trough in Topic 1 sentiment to maximize lift) and resource allocation, moving from strategic insights to true data-driven optimization. This constitutes a critical next step for this research.

Nevertheless, it is important to acknowledge the limitations of this study. Our analysis was confined to a single new media platform, Instagram, and may not capture the full spectrum of consumer discourse occurring on other platforms like TikTok, Reddit, or specialized blogs. The data was also limited to English-language posts, which, combined with our highly specific 15-hashtag filter, resulted in a focused but relatively low-volume dataset. This specialized corpus is appropriate for our niche forecasting goal but is not representative of global consumer discourse and necessarily overlooks insights from non-English speaking markets. Furthermore, sentiment analysis tools, including VADER, can struggle to accurately interpret complex linguistic nuances such as sarcasm or irony. Furthermore, sentiment analysis tools, including VADER, can struggle to accurately interpret complex linguistic nuances such as sarcasm or irony. Additionally, our methodology assigned the entire sentiment score of a post exclusively to its primary topic (the topic with the highest probability). While this simplified approach effectively captured the dominant driver of consumer discourse, we acknowledge that it deviates from the multi-topic mixture assumption of LDA. This 'hard assignment' strategy may result in information loss regarding secondary themes within a post and theoretically bias the sentiment attribution by overlooking the nuances of multi-faceted consumer discussions. Finally, regarding the evaluation protocol, this study employed a single fixed-window segmentation (Training-Validation-Test) rather than a rolling-window (walk-forward) cross-validation. While this approach effectively demonstrates the model's viability, future research should adopt a rolling-window evaluation to further rigorously test the model's stability across different temporal market conditions. The sales data used was from a specific product category, and the generalizability of the model to other segments of the functional textiles market would require further validation. Future research could expand upon this framework by incorporating data from multiple social media sources and in multiple languages. More advanced natural language processing models, such as BERT or other transformer-based architectures, could be employed for more nuanced topic modeling and sentiment analysis. Additionally, future work could explore the integration of visual data—analyzing images and videos from posts—to capture trends in aesthetics and product usage, adding another rich layer of information to the forecasting model.

CONCLUSION

This research successfully designed and validated an integrated framework for forecasting market demand and informing marketing strategy for sustainable functional textiles by harnessing the power of new media data. We demonstrated that by systematically collecting, processing, and analyzing user-generated content from Instagram, it is possible to extract powerful predictive signals related to consumer interests and sentiment. The core contribution of this work lies in the empirical validation of an LSTM-based forecasting model that integrates these new media metrics as exogenous variables. The resulting model significantly outperformed a traditional ARIMA baseline, proving that social media discourse is a valuable resource for anticipating market dynamics in the volatile textile industry.

The study has provided not only a more accurate forecasting tool but also a strategic lens through which to understand the modern consumer. The identification of key value drivers, such as material transparency and brand ethics, offers clear, evidence-based guidance for textile companies seeking to align their products and messaging with market expectations. The proposed methodology provides a clear pathway for transforming unstructured social media chatter into structured, actionable business intelligence, enabling a shift from reactive to proactive decision-making. In an era where consumer preferences evolve at an unprecedented speed, the ability to listen to and learn from the market in real-time is a critical competitive advantage. This research provides a robust and replicable blueprint for achieving that advantage, marking a significant step towards a more data-driven and consumer-centric future for the sustainable functional textiles sector.

Author Contributions

Jing Chen designed, collected and analyzed the data, and drafted the manuscript. Jing Chen conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jing Chen participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Conflict of Interest

The author declares no conflict of interest.

Funding

This research received no external funding.

Availability of Data and Materials

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

Ethics Approval and Consent to Participate

This survey was conducted in compliance with Ethics Committee of Lishui vocational & technical college. Participants were informed of the study's purpose and data usage prior to participation, and responses were collected anonymously. No personally identifiable information was stored.

Acknowledgments

Not applicable.

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