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Investigation of Social Media Metrics With Respect to Demand Modeling for Promotional Products

Yvonne Badulescu[1] | Fernan Cañas[2] | Ari-Pekka Hameri[3] | Naoufel Cheikhrouhou[1]

[1]Geneva School of Business Administration, University of Applied Sciences Western Switzerland, HES-SO, Geneva, Switzerland | [2]Facultad de Ingeniería, Escuela de Ingeniería Industrial, Universidad de Costa Rica, San Pedro de Montes de Oca, San José, Costa Rica | [3]Faculty of Business and Economics, University of Lausanne, Lausanne, Switzerland

Correspondence: Yvonne Badulescu (yvonne.badulescu@hesge.ch)

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ABSTRACT

Social media (SM) has revolutionized the way companies connect with customers, enabling more personalized marketing strategies and enhancing engagement. With platforms like Facebook offering detailed user data, businesses can create more targeted advertising campaigns. This paper proposes an approach to categorizing SM variables based on their SM marketing objectives with respect to the demand modeling for promotional products, which is particularly challenging due to limited historical data. A taxonomy is developed of the Facebook marketing metrics that drive consumer behavior with respect to product demand. Moreover, the study explores how the SM marketing metrics groups impact short-term demand modeling for promotional products in an analysis of a real case study and finds that paid Facebook metrics, which are generated from paid advertising efforts on the platform, are the best predictors of demand for their promotional products.

1 | Introduction

Social media (SM) has made it possible for companies to connect directly with their customers and develop tailored marketing initiatives based on the actions of their followers. SM analytics and their driving impact on sales is a novel area that has been linked to short-term demand planning improvements (Verma and Yadav 2021). Determining the demand for promotional products is increasingly challenging as selling periods are becoming shorter and with the lack of historical demand information. Therefore, companies are searching for other sources of information to provide insights on potential sales. Accordingly, many companies own SM accounts for a direct line of contact with their customers, to improve their reaction time to customer feedback, and develop audience-relevant marketing initiatives. In particular, Facebook is one of the most utilized platforms for company advertising. With over 3 billion active users, it offers businesses an opportunity to reach a vast audience (Facebook MAU Worldwide 2023). Companies of all sizes invest in Facebook advertising because it provides detailed targeting options, allowing brands to focus on specific demographics, interests, and behaviors. Facebook's advertising tools also offer measurable outcomes, such as tracking impressions, clicks, conversions, and return on investment (ROI), making it an essential platform for both organic and paid marketing efforts. This availability of big SM data and the investment into promoting online awareness, engagement, and user sentiment has motivated academic and industrial research on understanding and developing how to use SM data for operational planning, particularly demand modeling. The influence of SM marketing extends across various industries, enhancing brand equity and increasing customer purchase intentions. By utilizing features like videos and images, brands can enhance consumer engagement, further increasing demand. Despite the growing recognition of SM's role in influencing consumer behavior, limited research has explored the direct connection between SM-specific marketing metrics and their effectiveness in demand forecasting, especially for promotional products.

While the importance of incorporating SM data into demand modeling is increasingly recognized, there has been little focus on understanding how different SM metrics linked to marketing objectives contribute to forecasting accuracy. This study aims to address this gap by proposing an approach to identify key SM marketing metric groups and SM variables from the literature, categorize them, and evaluate their effectiveness in modeling demand for promotional products. By examining these groups across different time lags, the study aims to provide a more comprehensive understanding of how SM activities influence product demand over time, offering practical insights for improving demand forecasts. The objective of this paper proposes a framework that aids the categorization of SM marketing metrics in the context of demand forecasting, particularly for promotional items with limited historical data. By focusing on distinct SM metric groups, this paper seeks to determine their respective contributions to modeling demand and provide actionable insights for businesses looking to improve their promotional planning and forecasting processes using SM data. This paper is divided into six sections: Section 2 reviews the state of the art in forecasting with SM. Section 3 proposes a methodology to categorize SM marketing metrics into groups to use in forecasting product demand, and Section 4 consists of the identification and categorization of relevant groups of Facebook SM marketing metrics from the literature as a demonstration of the methodology. The approach is demonstrated in a case of a real company that launches two new promotional products every year for Father's Day which is described in Section 5 and discussed in Section 6. Section 6 also includes the managerial impact of this approach in the case study company. Section 7 concludes the paper and identifies the future research work.

2 | SM Data and Sentiment in Demand Modeling

SM data can provide valuable insights into market trends, customer needs, and product demand (Huang et al. 2020). Dwivedi et al. (2021) highlight that SM's interactive nature allows brands to create personalized marketing campaigns, enhancing consumer engagement and brand visibility, which ultimately drives product demand. This view is supported by Shareef et al. (2019), who emphasize that consumer-generated advertisements on SM networks foster trust and authenticity, making them more effective in influencing demand. Ramanathan et al. (2017) further illustrate that consumer reviews and interactions on SM significantly impact retail operations and product demand by increasing credibility and facilitating a feedback loop that strengthens customer perceptions. In the airline industry, Seo and Park (2018) demonstrate that SM marketing activities enhance brand equity, leading to increased customer purchase intentions. Similarly, Liu et al. (2021) show that luxury brands that actively engage on SM see a rise in product demand, as positive interactions amplify brand awareness. These findings align with Alalwan (2018), who emphasizes that SM advertising's interactive features like videos and images are pivotal in enhancing consumer engagement and driving purchase intentions, highlighting the need for businesses to utilize these elements effectively.

The combination of SM data and sentiment analysis has been used to forecast product sales in a variety of industries, including automotive, fashion, and personal and electronic goods. In their study, Pai and Liu (2018) demonstrate that utilizing sentiment derived from Twitter data and stock market values with deseasonalized sentiment scores of tweets, stock market values, and past vehicle sales, results in the lowest forecast error for future vehicle sales. Fan et al. (2017) improved the forecast performance of multiple generations of automobiles by incorporating sentiment analysis from online reviews into the Norton–Bass model. In fact, sentiment deduced from SM information has been shown to improve the accuracy of forecasting models (Cui et al. 2018; Lee et al. 2019). The COVID-19 pandemic has resulted in an increase in consumer use of SM platforms for product identification, evaluation, and purchase, as well as the expression of opinions and reviews about such products (Mason et al. 2021). There are several studies that look at how SM data and sentiment can be used to generate predictions using a variety of techniques, such as the Bass diffusion model (Fan et al. 2017; Iftikhar and Khan 2020; Zhang et al. 2020), regression models (Asur and Huberman 2010; Bollen et al. 2011; Lassen et al. 2014; Pai and Liu 2018), and machine learning models (Arias et al. 2013; Cui et al. 2018; Hou et al. 2017). SM information is considered a valuable input into the short-term forecast (Hou et al. 2017; Lau et al. 2018) and for decision-making (See-To and Ngai 2018); however it is not always the case for user sentiment. While some articles find that sentiment improves short-term forecast accuracy, several find other exogenous variables that are better predictors (Chong et al. 2016; Singh et al. 2021). Malandri et al. (2018) examine the ability of SM sentiment analysis to reveal insights into business and social phenomena, particularly in predicting stock prices and asset allocation. By constructing a sentiment time series to measure polarity, Xing et al. (2019) have integrated sentiment analysis into their model for predicting stock price volatility, which incorporates sentiment data from StockTwits, a financial SM platform. Bollen et al. (2011) examined the sentiment of public Twitter to forecast the Dow Jones movement for the next day. Sentiment analysis of SM posts and comments can reveal intimate language patterns, which offer valuable insights into the strength of social connections and interactions within SM marketing strategies (Gilbert and Karahalios 2009). The lexicon-based method, in particular, has proven effective in categorizing SM comments into positive, neutral, or negative sentiment polarities (De Choudhury et al. 2014; Karabulut 2013). He et al. (2013) demonstrated that using lexicon-based sentiment analysis on SM networks helps identify brand awareness themes, providing insights into customer opinions and competitive positioning.

Kim et al. (2015) propose a new method to enhance the accuracy of traditional demand forecasting models for medicine sales by incorporating SM activity data, using a time series VARX model with SM topic trends as exogenous variables. Cui et al. (2018) demonstrate the efficacy of improving the forecasting accuracy of a short-term demand forecast for an online fashion retailer by incorporating Facebook data and sentiment into their modeling process, which employs linear regression, random forest (RF), and support vector machines (SVM) techniques. Similarly, See-To and Ngai (2018) found that incorporating customer review sentiment into a fast-fashion e-commerce platform's short-term forecast leads to an improved model fit to actual sales. Badulescu et al. (2024) propose an approach to judgmentally adjust statistical demand forecasts for new products using SM information based on the four event-based factor approach and find that judgmental forecasting with SM improves forecast accuracy. Komtesse af Rosenborg et al. (2017) employ a multiple linear regression model to investigate the relationship between Facebook engagement and a retailer's financial performance, specifically using the number of posts, comments, and likes on the retailer's Facebook page as indicators of engagement. Mukkamala et al. (2014) introduce an integrated modeling approach that uses Fuzzy set theory to analyze large-scale social data focusing on posts made on H&M's Facebook page. Vatrapu et al. (2016) present an extension to this approach by introducing social set analysis as a method of integrating SM data with organizational data. In their study, Lassen et al. (2014) develop a linear regression prediction model that forecasts quarterly iPhone sales figures from Apple's annual report using various Twitter metrics such as Tweet likes, shares, and sentiment from comments. Similarly, Boldt et al. (2016) use a simple linear regression model that leverages data from Facebook to accurately predict Nike's quarterly sales. Evaluating movies via online user reviews on SM platforms improves the accuracy of predicting box office revenues (Dellarocas et al. 2007). To forecast box office movie revenues, Asur and Huberman (2010) use a simple linear regression model based on the tweet rate as a predictor variable in the model. Arias et al. (2013) report an unexpected finding in their study: the sentiment of tweets from Twitter does not improve the predictive accuracy of box office movie sales; however, they find that the volume of tweets has a statistically significant relationship with box office sales, particularly at lags greater than 2 days. Divakaran et al. (2017) used partial least squares structural equation modeling to demonstrate the potential of pre-release community buzz as a predictor of postrelease movie sales.

The literature review presented in Table 1 provides an overview of research studies using SM and online information for predictive purposes, particularly in forecasting sales and demand across various industries. The dependent variables range from book sales (Chevalier and Mayzlin 2006) to retail product sales (Badulescu et al. 2024), with data sources spanning from online reviews to Twitter and Facebook metrics. These studies primarily employ regression models, neural networks, and SVM as forecasting methods, often integrating sentiment analysis as a critical explanatory variable, as seen in the work of Asur and Huberman (2010), Chong et al. (2016, 2017), and Duan et al. (2008). However, while many of these studies utilize sentiment as a key metric, few integrate broader sets of SM metrics such as engagement or content-based variables. Moreover, despite the acknowledgment of the importance of including SM information in demand modeling, previous research has not focused on the type of SM metrics they took into consideration with respect to the marketing objectives. The key gap in this literature is the absence of standardized approaches for integrating comprehensive SM data, such as platform-specific variables or time-lagged impacts on demand. This gap is significant because understanding how these specific metrics interact can offer deeper insights into consumer behavior and purchasing patterns, which are crucial for making more accurate and responsive demand forecasts. Furthermore, as SM data evolves rapidly in real time, different types of metrics may have varying lead times in influencing consumer behavior and consequently, demand. Modeling the demand at various time lags enables a better understanding of the temporal relationships between SM activities and actual demand. Therefore, the objective of this paper is to propose an approach to identify SM marketing metric groups pertinent in demand modeling, categorize the SM variables in each group, and model the demand using the different SM marketing metric groups at different lags.

3 | Methodology for Modeling Demand With SM Marketing Metrics Groups

This section outlines the systematic approach used for categorizing SM variables into distinct marketing metric groups to model product demand. The methodology is designed to structure the process of identifying, categorizing, and evaluating how SM marketing metrics can be used to forecast demand for promotional products, particularly where historical data may be limited. The approach proposed to categorize SM variables into SM marketing metric groups is to firstly develop a taxonomy of SM variables and SM marketing metric groups, where categories are defined based on empirical research, followed by judgment-based categorization, in which the SM variables are manually categorized into the identified metric groups. This hybrid method combines theoretical guidance from a comprehensive literature review with expert judgment to systematically group SM variables based on their relevance to marketing objectives. The process is represented in Figure 1 and detailed in the following steps:

3.1 | Identification of an Exhaustive List of Platform-Specific SM Variables and SM Marketing Metrics Groups

The first step in the process involves a detailed literature review to identify preexisting frameworks, theories, and classifications of SM metrics used in demand forecasting, marketing, and consumer behavior research. This method ensures that the groups align with established theoretical foundations and are relevant to the predictive modeling process (Nickerson et al. 2013). The goal is to create an exhaustive list of distinct SM marketing metrics groups, which are defined based on their characteristics. The literature review serves as the basis for defining the marketing objective groups that SM variables should fall into. These theoretical groupings provide the structure within which specific SM platform variables are classified. Following the identification of marketing metrics groups, a detailed list of platform-specific SM variables is compiled from an analysis of the SM platform and literature. Each variable is defined in terms of its functionality on the platform with respect to its marketing objective. The review ensures that all potential variables are considered, and no relevant SM platform data point is overlooked.

TABLE 1 | Overview of the state of the research concerning using SM and Online information for predictive purposes.

Reference	Dependent variable	Data source	Explanatory variables	Forecasting method	Sentiment
Chevalier and Mayzlin 2006	Book sales	Online reviews	Individual book characteristics and user review data	Simple linear regression	x
Duan et al. 2008	Box office movie sales	Online reviews	Movie features and critic reviews	Log-linear dynamic model	
Asur and Huberman 2010	Box office movie sales	Twitter	Tweets	Simple linear regression	x
Archak et al. 2011	Digital cameras and camcorders	Online reviews	Product features and text from reviews	Consumer choice model	x
Arias et al. 2013	Stock market and box office sales	Twitter	Tweets, sentiment index	SVM	x
Lassen et al. 2014	iPhone sales revenue	Twitter	Tweet quantity, quality, sentiment	Simple linear regression	x
Chern et al. 2014	Retail cosmetics sales	Online reviews	Sentiment polarity	Regression model	x
Kim et al. 2015	Medicine sales	Google search words and fine dust air particles concentration	Topic trends and fine dust air particles concentration	VARX	
Boldt et al. 2016	Nike sales revenue	Facebook	Google trends, Facebook likes	Simple and multiple linear regression	
Chong et al. 2016, 2017	Electronic products sales	Reviews from Amazon.com	Sentiment polarity, product features, customer rating	Neural network	x
Hou et al. 2017	Electronic products sales	Reviews from Amazon.com	Sentiment polarity, product features, customer rating	Neural network	x
Fan et al. 2017	Multigenerational automobile sales	Online reviews	Online ratings, sentiment index	Bass Model with Naïve Bayes for sentiment	x
Lau et al. 2018	Large dataset of fast-moving goods	Amazon and Chinese e-commerce	Product aspects, sentiment polarity	Parallel coevolutionary extreme learning machine (PELM) model	x
Komtesse af Rosenborg et al. 2017	H&M quarterly sales	Facebook	Style icons, designer collections data, post, comments, likes	Social set analysis and Winter's method	
See-To and Ngai 2018	Online fashion retailer sales	Customer reviews	Number of positive and negative tags, cumulative review sentiment	OLS regression model	x

(Continues)

TABLE 1 | (Continued)

Reference	Dependent variable	Data source	Explanatory variables	Forecasting method	Sentiment
Cui et al. 2018	Online fashion retailer sales	Facebook	Volume and valance of posts, and sentiment	Linear regression, random forest, SVM	x
Pai and Liu 2018	Vehicle sales	Twitter and stock market	Sentiment scores of Tweets	Naïve, ETS, ARMIA, SARMINA, neural networks, multivariate regression models	x
Papanagnou and Matthews-Amune 2018	Pain medicine	YouTube videos web, search index data	Product features, weekly google index, weekly keyword index, minutes per viewer	VARX	
Lee et al. 2019	Box office and DVD sales	Online reviews (Amazon and IMBD)	Number of reviews, cumulative customer ratings, #people who read reviews, helpfulness of reviews	Structural equation modeling with predictive global sensitivity analysis	
Zhang et al. 2020	Automobile product sales	Online reviews and Search traffic data	e-Word-of-mouth index, product attributes, sentiment	Bass model	x
Singh et al. 2021	Car sales	Negative online reviews	Sentiment, product features	Dynamic panel data model	x
Badulescu et al. 2024	Product sales	Facebook	social media metrics, sentiment	Judgmental adjustment + SVM	x
This paper	**Promotional product sales**	**Facebook**	**Groups of SM marketing metrics**	**SVM**	**x**

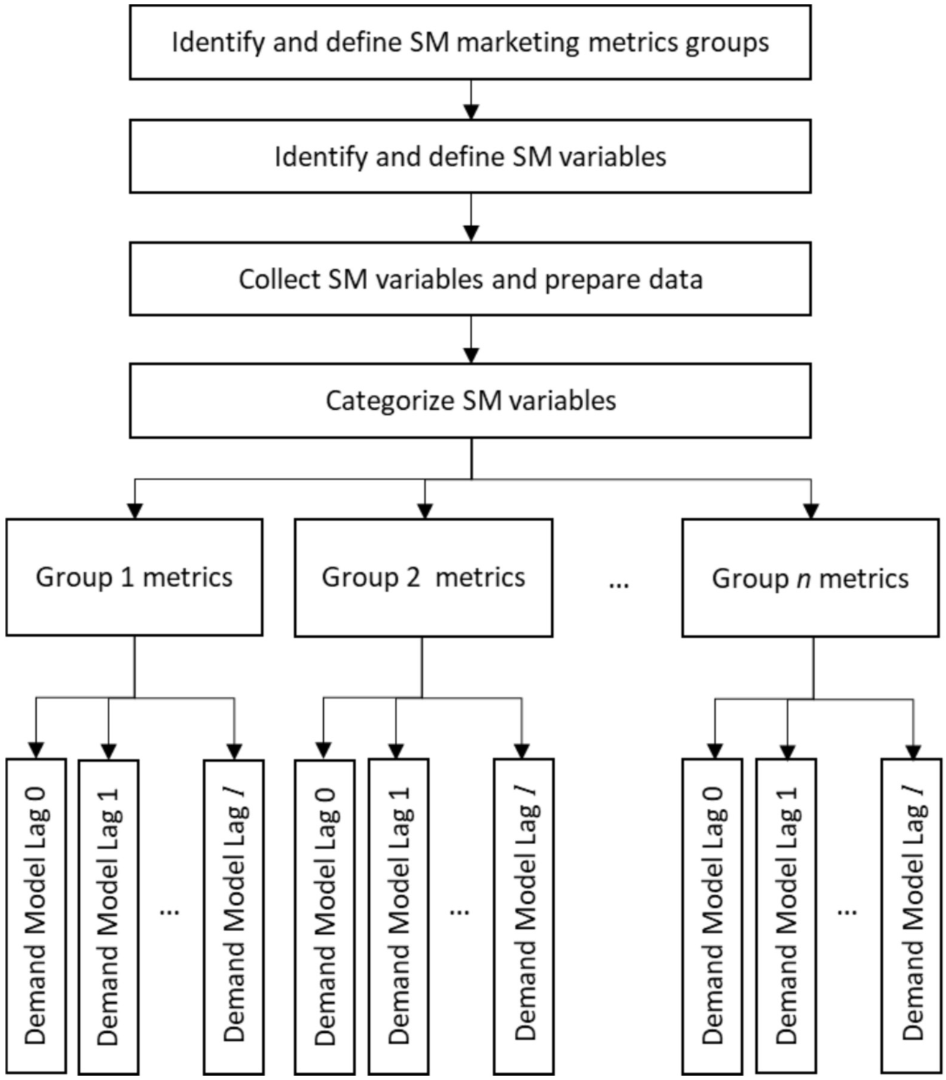

FIGURE 1 | Framework for categorizing SM variables for demand modeling across time lags (0 to l).

3.2 | Data Preparation

Before building the demand forecasting model, a crucial step is preparing the data for analysis. The raw data from the collected SM metrics must be processed to ensure compatibility and accuracy for forecasting.

3.2.1 | Data Cleaning

The first step in preparation involves handling any missing values, outliers, or inconsistent data points in SM datasets. This ensures the data is ready for accurate modeling without skewing the results.

3.2.2 | Time Alignment

The SM Metrics and Sales Data must be aligned temporally to enable time-lagged analysis. For example, the desired forecasting period may cover a promotional period of several days or weeks, while the SM data may be collected continuously over several months. Ensuring both datasets are matched based on the same time periods is critical.

3.2.3 | Lag Creation

To capture the influence of timing, data preparation includes creating lagged versions of the SM metrics. Define the number of period lags (l) to model. For each metric, lagged variables are created to represent the impact of SM activity from 1 to l periods prior to the demand period. This allows for the analysis of both immediate and delayed effects of SM activity on product demand.

3.3 | Categorization of SM Variables Into SM Marketing Metrics Groups

After establishing the classification framework, judgment-based categorization is applied to assign individual SM variables to the predefined groups. This approach requires expert interpretation and alignment of variables with the theoretical definitions provided in the literature. Unlike purely automated classification techniques like clustering or factor analysis, this method allows for a nuanced understanding of how each variable functions in a marketing context, as a specific SM variable could be interpreted as belonging to more than one metric group. This step is critical because it allows for flexibility and adaptability in categorizing SM variables that may exhibit overlapping characteristics. This categorization step relies on the definitions from the literature review and is aimed at simplifying the modeling process by grouping variables with similar characteristics.

3.4 | Modeling Demand With SM Marketing Metrics Groups

The SM marketing groups serve as the set of explanatory variables used to model demand for promotional products. Selecting the appropriate model to forecast demand depends on both the characteristics of the SM data and the relationships with the product demand. The demand is modeled using the SM marketing groups at the various lags defined in the previous step. By incorporating these time lags, it becomes possible to analyze how immediate versus delayed SM actions influence consumer behavior and product demand. This iterative approach can be represented through a recursive forecasting model with lagged variables. In general, the demand $D(t)$ at time t can be modeled as a function of different SM metrics $SM_i(t-l)$, where l represents the lag. Therefore, the general modeling framework that allows for various types of relationships between $D(t)$ and SM can be represented by

$$\mathrm{D(t)} = \mathrm{f}\big(\mathrm{SM_1(t), SM_1(t-1), \dots, SM_1(t-l), \dots, SM_m(t), SM_m(t-1), \dots, SM_m(t-l)}\big) + \epsilon_\mathrm{t}$$

where D(t) is the demand at time t $SM_i(t-l)$ represents the values of the i-th SM variable at $(t-l)$, where i ranges from 1 to m, accounting for a lag of l time periods. m is the number of distinct SM metrics group. f is an unknown function that related the demand to the lagged SM variable. ϵ_t is the error term at time t, capturing any unexplained variation in the model.

Finally, the demand models at each lag are evaluated to determine the most accurate SM marketing group for demand modeling.

4 | Facebook Marketing Metric Categorization

In this section the relevant Facebook marketing groups are identified through an extensive literature review, which provides the theoretical foundation for grouping SM variables based on their marketing objectives. Then, Facebook-specific SM variables are categorized according to these groups, with references to studies that have previously utilized these variables for demand forecasting.

4.1 | Overview of SM Marketing Metrics

Misirlis and Vlachopoulou (2018) conduct a comprehensive review of SM marketing research articles based, classifying them into key categories based on marketing objectives, such as brand awareness, engagement, customer research, e-WOM (electronic word-of-mouth) promotion, relationship management, and social CRM (customer relationship management). Their analysis highlights that engagement, consumer behavior research, and relationship marketing are the most prevalent categories, focusing on understanding customer impressions, behavior, and sentiment to optimize SM strategies for marketing and sales effectiveness. Peters et al. (2013) propose a more detailed framework for categorizing SM marketing metrics based on four key elements: motives (underlying drivers that motivate users to engage with SM), content (characteristics and nature of the information shared, such as quality, emotional tone, and volume), network structure (configuration of social connections and the organization of actors within the SM platform), and social roles and interactions (evolving positions and behaviors of users as they interact with content and other actors in the network). These elements reflect a deeper analysis of user behavior, and the nature of content shared on social networks. Marketing metrics like likes, shares, reach, impressions, paid media, comments, and sentiment can fit into multiple categories in Peters et al.'s (2013) framework; for instance, metrics such as comments and shares relate to both motives and network structure, while likes and sentiment align with content and social interactions. This overlap suggests that many metrics are multifaceted, requiring additional classification layers for more precise categorization. Building on this, Choi et al. (2020) focus on SM's role in business intelligence (BI), categorizing SM platforms into different groups based on how they are used for sentiment analysis, topic modeling, and other techniques to extract insights. They focus on the importance of data preprocessing and explores different analytical techniques such as sentiment analysis, topic modeling, and machine learning, which are commonly applied to derive intelligent information for business decision-making. Lemel (2021) emphasizes the importance of SM metrics for small businesses, focusing on their role in promoting products and building brand awareness cost-effectively. The paper proposes a four-step conceptual framework: setting marketing objectives, selecting platforms, creating content, and evaluating campaign effectiveness through appropriate metrics. While various metrics like likes, shares, and conversion rates are discussed, Lemel (2021) does not explicitly categorize them, instead highlighting the need for flexibility based on campaign goals and platform specifics, and points out inconsistencies in the literature regarding metrics like engagement and stresses that the most crucial metrics are those directly tied to campaign objectives. Michopoulou and Moisa (2019) explore how SM integrates into marketing strategies within the hospitality industry, categorizing its use into passive and active approaches. The passive approach views SM as a source of customer feedback and insight, while the active approach leverages it as a tool for communication, customer acquisition, retention, and sales stimulation. They also examine SM measurement, highlighting the differentiation between activity-based metrics (e.g., likes, followers, and shares) and result-based metrics (e.g., conversions). Panigrahi and Borah (2019) analyze SM metrics by grouping them into content types (photo, status, link, and video) and performance measures (likes, shares, comments, and interactions). They use these categories to evaluate SM activity and identify the most accurate classifiers for predicting content types. Minazzi (2015) proposes that companies should establish a systematic approach to handle data, including registering, selecting, interpreting, communicating, and learning from data, with a cross-departmental team responsible for these tasks to ensure a holistic perspective. The paper categorizes SM metrics into four groups based on Lovett's (2011) framework: foundational metrics (interaction, engagement, influence, advocacy, and impact), business value metrics (impact on revenues and customer satisfaction), outcome metrics (KPIs such as reach, share of voice, and conversion rates), and counting metrics (raw data like likes and followers). More specifically, Minazzi (2015) provides a detailed overview of the Facebook Insights tool which offers six main sections: Overview, Likes, Reach, Visits, Posts, and People, each providing specific metrics and insights. The Overview section offers a general performance summary, including metrics like total page likes, post reach, and engagement, now detailed into actions such as post clicks, likes, comments, and shares. The tool also differentiates between organic and paid likes and reach, offering businesses clarity on unpaid and ad-driven activities. Other sections such as Posts provide insights into when fans are online and the success of various post types, helping businesses optimize content distribution, and timing. The People section provides demographic details about fans, including age, gender, and location, while Visit data tracks user interactions with the page and external referrers. Yoon et al. (2018) categorize SM information and digital engagement on Facebook into key dimensions to evaluate its impact on business performance. They introduce two primary metrics: digital engagement volume (the total number of comments a company receives) and digital engagement valence (the sentiment or tone of these comments). The study finds that both metrics positively influence revenue, emphasizing the role of consumer interactions in shaping company performance. The authors suggest that digital engagement goes beyond simple interactions (like or share) and encompasses more complex, effort-intensive actions like commenting, which can provide deeper insights into consumer behavior and attitudes. Bonsón and Ratkai (2013) propose a set of metrics for evaluating corporate Facebook pages and categorize them into several dimensions: popularity (measured by likes), commitment (measured by comments), and virality (measured by shares), which together provide a comprehensive view of stakeholder engagement. They also assess stakeholders' mood by categorizing comments as positive, neutral, or negative to capture sentiment. Ángeles Oviedo-García et al. (2014) propose a metric for measuring Facebook customer engagement through bidirectional interactions between firms and users. They distinguish “stronger actions” (e.g., likes, comments, and shares) from “weaker actions” (e.g., viewing details), capturing different engagement intensities. Their “Ratio of Interest” quantifies user engagement per post, while the “Ratio of Effective Interest” considers the number of impressions, highlighting posts that achieve more interactions with fewer views. Incorporating reach, the metric evaluates visibility beyond direct fans, helping firms optimize content effectiveness and engagement strategies.

4.2 | Identification of Facebook Marketing Metrics Groups for Demand Modeling

Based on the review, SM metrics for forecasting product demand can be categorized into the following groups:

1. Engagement metrics: These metrics capture the level and intensity of user interactions with a brand's content, including likes, shares, comments, video views, and other user actions. High engagement often indicates strong consumer interest and potential demand. Misirlis and Vlachopoulou (2018) and Ángeles Oviedo-García et al. (2014) highlight the importance of engagement as a consumer-centric marketing metric.
2. Sentiment metrics: Metrics that assess the tone and sentiment of consumer interactions (e.g., comments or reviews) provide insights into consumer attitudes toward a product. Yoon et al. (2018) emphasize that the valence of SM engagement (positive or negative sentiment) directly influences company performance.
3. Awareness metrics: These metrics measure the extent of content visibility and the number of users exposed to a brand's message. Minazzi (2015) and Ángeles Oviedo-García et al. (2014) include reach, impressions, and number of page followers in their frameworks, noting their relevance for assessing the potential impact of SM content on a larger audience.
4. Content type metrics: Panigrahi and Borah (2019) group SM activity based on content types (photo, status, link, and video) and associated performance measures like shares and interactions. By analyzing the effectiveness of various content formats, marketers can understand which types of posts generate the most interest.
5. Consumer behavior metrics: Metrics that track user actions beyond likes and comments, such as clicking on product links or engaging in discussions, provide deeper insights into consumer intent and behavior. Peters et al. (2013) and Choi et al. (2020) emphasize the value of monitoring user behaviors and network structures to predict consumer interest.
6. Demographic and audience metrics: Information about the audience's demographic profile, such as age, gender, and location, helps identify which segments are most engaged with the brand. Minazzi (2015) and Bonsón and Ratkai (2013) illustrate the importance of these metrics for targeted marketing efforts.

While the existing literature offers valuable frameworks for categorizing SM marketing metrics, a critical gap persists due to the lack of a widely accepted categorization, particularly in the context of demand modeling. Researchers like Misirlis and Vlachopoulou (2018) and Peters et al. (2013) suggest frameworks based on marketing objectives, content, and network structure. However, the overlap between categories, such as metrics like comments fitting under both engagement and network structure, points to inconsistencies in how metrics are classified. Moreover, these studies often focus on general marketing outcomes without explicitly addressing their role in forecasting demand, especially for promotional products where time lags and short-term demand predictions are crucial.

Furthermore, current frameworks may have overlooked other potential metric categories, especially related to newer forms of advertising. In fact, a group that has not been considered in the literature with respect to demand modeling is Paid Metrics, which are interactions and reach data obtained specifically through paid advertising efforts, such as paid likes, paid comments, paid shares, paid reach, and paid impressions. These metrics capture the additional audience exposure and engagement a brand gains through monetary investment on SM platforms. Paid metrics enable marketers to measure the ROI of their SM campaigns (Hoffman and Fodor 2010; Kaplan 2013; Michopoulou and Moisa 2019). They offer insights into how effective paid advertisements are in amplifying content, expanding reach beyond the organic audience, and driving user actions (Lemel 2021). Even though Kumar et al. (2020) considered advertising effectiveness in their demand-driven forecasting framework, they did not directly investigate the individual SM metrics themselves, such as engagement or sentiment, nor did they examine the role that Paid Metrics might play in understanding short-term consumer demand. Paid metrics also help distinguish the impact of organic engagement versus paid engagement, which is essential for understanding the genuine consumer interest and the role of monetary investment in driving demand (Yoon et al. 2018). Furthermore, in BI and demand forecasting, paid metrics serve as predictors of sales increase resulting from targeted advertising (Choi et al. 2020). They provide a direct link between advertising spend and consumer behavior, making it possible to adjust campaign strategies in real time based on performance outcomes. This approach aligns with the growing emphasis on performance marketing, where each dollar spent is closely monitored for effectiveness and impact (Misirlis and Vlachopoulou 2018). By analyzing how users interact with paid content compared to organic content, businesses can gain insights into audience behavior and better understand the motivations behind consumer actions. This understanding helps refine advertising approaches to align more closely with audience preferences (Peters et al. 2013). Therefore, an additional SM marketing group is proposed in this paper for consideration in demand modeling.

7. Paid metrics: Metrics which encompass all forms of user interactions and engagement that are directly influenced by monetary investments in SM advertising.

4.3 | Categorization of SM Marketing Metrics per Group

Focusing on the Facebook social network platform and the SM variables available to page owners, Table 2 categorizes and describes Facebook metrics, and cites in which articles they have been identified for demand modeling or forecasting purposes.

5 | The Case of Promotional Products for Father's Day

5.1 | Description of the Implementation Case and Data

A food and beverage company in a Spanish-speaking country serves as the subject of this case study that supplies B2C to its own restaurants and stores in commercial shopping malls (over 55 locations), and direct customer orders with fresh and frozen products, as well as B2B to supermarkets. The focus of this case study is on the new promotional products for an annual special event, Father's Day, occurring on the third Sunday of June each year. The raw data required for the process comes from two sources: the company's ERP system for sales and their Facebook page. The extracted data are cleaned and prepared for analysis using standard techniques.

The sales data consists of 118 datapoints for two products ranging over 3 years from May 31 to June 18, 2017, June 1 to 17, 2018, and May 30 to June 16, 2019. Father's Day is on the June 18, 2017, June 17, 2018 and June 16, 2019. The total sales of the two products were summed to obtain the total of Father's Day products over each period, thereby yielding 59 datapoints for these dates. The company brings out two new products every year that are on sale for 2–3 weeks before and including Father's Day, with 50% of total sales (product 1 + product two sales) occurring in the final 5 days of the promotion. They stop selling these promotional items the day after the event and all surplus inventory becomes obsolete. Figure 2 shows the total yearly sales of two promotional items for the 3 years on a timeline with Father's Day (FD) as the last sales date as each year it falls on a different date. The peak in 2019, at FD-5 (5 days before the event) is due to a special discount on that day.

The Facebook data retrieved from the company contains 19,307 datapoints from 23 explanatory variables from January 1, 2017 to July 1, 2019. The extract includes data for the following metrics: Page Likes, Page Unlikes, Total Followers, Likes, Comments, Shares, Content consumptions, Total page views, Total impressions, Paid impressions, Organic impressions, Viral impressions, Total video views, Organic video views, Paid video views, Paid reactions, Paid comments, Paid shares, Total Reach, Viral reach, Organic reach, Paid reach, and Paid media. The dates of the Facebook dataset were matched with the range of the sales dataset including a lag of up to 5 days between the datasets, that is from May 26 to June 18, 2017, May 27 to June 17, 2018, and May 25 to June 16, 2019. The data for Total Reach, Viral reach, Organic reach, Content consumptions, Total page views, and Paid media were not continuous over the desired period thereby excluding them from further analysis. Moreover, the Facebook daily comments over the same period were also extracted in excel format with 4152 user comments in 2017, 12,850 comments in 2018, and 6505 comments in 2019, excluding the comments from the page owner. Using the comments dataset, four additional metrics are added to the SM dataset: average daily sentiment, the weighted average daily sentiment, the number of positive comments per day, and the number of negative comments per day. This was done via a sentiment analysis performed by training an SVM classifier on the TASS dataset from the Spanish Society for Natural Language Processing dataset with attributed positive, negative, or neutral sentiments, which calculates the sentiment score per comment (positive which has a score of 1, negative, which has a score of −1, or neutral sentiment, which has a score of 0), which is aggregated daily to give the average daily sentiment. The weighted daily sentiment is also calculated, which is weighted by the number of Likes each comment receives.

5.2 | Exploratory Data Analysis and Selection of the Model

The Pearson's correlation analysis was performed between SM variables and sales from Lag 0 (same day) to 5 (with sales correlated with SM variables from 5 days earlier). The correlation coefficients are presented in Table 3 with p-value < 0.05.

TABLE 2 | Categorization of Facebook metrics and descriptions.

Metrics group	Metrics description	References
Engagement metrics	—Likes: The number of users who have liked a post or the page, indicating approval or interest —Comments: The number of user responses on posts, providing feedback and engagement opportunities —Shares: The number of times a post has been shared by users, amplifying its reach and visibility —Post clicks: The number of clicks on a post, including link clicks, photo views, and other interactions	(Badulescu et al. 2024; Boldt et al. 2016; Cui et al. 2018; Komtesse af Rosenborg et al. 2017; Schaer et al. 2019)
Sentiment metrics	—Positive comments: user comments classified as positive, indicating favorable sentiment toward the content or brand —Negative comments: user comments classified as negative, reflecting dissatisfaction or negative sentiment —Neutral comments: comments that do not express a clear positive or negative sentiment, remaining neutral in tone	(Badulescu et al. 2024; Cui et al. 2018)
Awareness metrics	—PReach: The number of unique users who have seen the content, including organic and paid reach —Impressions: The total number of times the content is displayed, regardless of whether it was clicked. —Page views: The number of times the page has been viewed by users. —Page likes: The total count of users who have liked and followed the page over time —Page unlikes: The total count of users who have stopped following the page over time —Total followers: The number of new people who have followed the page during a given time period	(Badulescu et al. 2024)
Content type metrics	—Photo posts: Posts that contain images, often resulting in high engagement —Video posts: Posts that contain videos, which can increase engagement and viewing time —Link posts: Posts that contain links, driving traffic to other websites or content —Status updates: Text-only posts that communicate messages directly without multimedia	(Cui et al. 2018; Komtesse af Rosenborg et al. 2017)
Consumer behavior metrics	—Page visits: The number of visits to the page, reflecting interest levels —Link clicks: The number of clicks on links within posts, showing user engagement with external content —Post engagements: The total number of actions (likes, comments, and shares) on posts, indicating overall user interaction —Content consumptions: The number of times users clicked, watched, or otherwise interacted with the content	
Demographic and audience metrics	—Age: Distribution of the audience based on age groups, useful for targeted campaigns —Gender: Information on the gender breakdown of the audience, aiding in personalized content —Location: Geographical data showing where the audience is located, valuable for location-based marketing strategies —Language: Details on the languages spoken by the audience, helping to tailor communication	

(Continues)

TABLE 2 | (Continued)

Metrics group	Metrics description	References
Paid metrics	—Paid likes: The number of likes obtained through paid ads or sponsored content. —Paid reach: The number of unique users reached through paid advertising —Paid impressions: The total number of times paid content is displayed. —Paid comments: The number of comments generated specifically through paid campaigns. —Paid shares: The number of shares obtained as a result of paid advertising efforts.	(Badulescu et al. 2024)

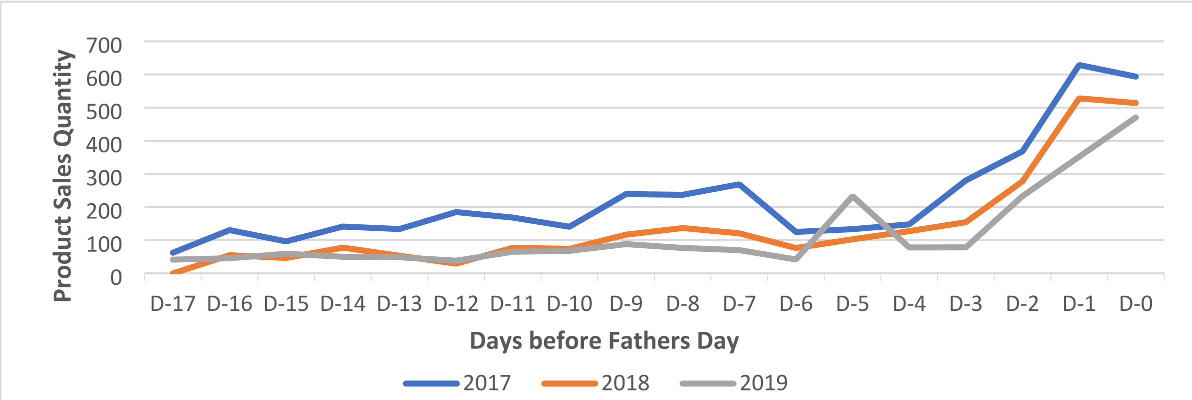

FIGURE 2 | Total daily sales for promotional Father's Day products.

The analysis of the correlation between SM variables and sales over various time lags reveals several key insights; organic video views show a consistently strong positive correlation with sales, particularly at Lag 0 (0.81), indicating that higher engagement with organic video content tends to coincide with immediate increases in sales, which decreases slightly over time but remains significant up to Lag 2. In contrast, Shares demonstrate a consistently negative correlation with sales, starting at −0.49 at Lag 0 and dropping to −0.74 by Lag 5, suggesting that while content is being shared, this engagement does not directly lead to sales. Paid impressions and Total impressions exhibit positive correlations, particularly at Lag 3 and Lag 4. Additionally, Paid interactions (such as paid shares and comments) consistently show negative correlations, particularly at later lags. The strong positive correlations between organic video views and sales across multiple time lags suggest that time-lagged relationships play a critical role in the relationship with sales, which can be modeled effectively with an autoregressive model or SVM with time-lagged variables. Additionally, the negative correlations observed between shares and sales point to the complexity of these relationships, reinforcing the need for a nonlinear model like SVM, which is better suited to manage such intricate interactions compared to linear models. Moreover, the positive correlations between paid impressions and total impressions with sales, especially with a delayed effect at Lags 3–5, further emphasize the need for a model that can account for the delayed influence of marketing metrics on sales. This complexity and the mixture of both positive and negative correlations suggest that a model capable of handling nonlinear relationships and multiple time lags, like SVM, would be ideal for this scenario.

5.3 | Categorization of SM Marketing Metrics

The Facebook variables are sorted into the four categories as shown in Table 4 as per the descriptions of the Facebook variables and the marketing metrics groups in Section 4.

6 | Results and Discussion

Several demand models are built with SVM at Lags 0 to Lag 5 shown in Table 5. The models are evaluated using various error measures: Total error, root mean squared error (RMSE) and mean absolute percentage error (MAPE). Total error highlights the overall difference between the forecast and actual sales, with lower values indicating better performance. RMSE, which penalizes larger errors more heavily, measures the variability and magnitude of errors, with lower RMSE values signaling better forecasts. MAPE, which expresses forecast error as a percentage, allows for comparison across different scales, and lower values indicate more accurate predictions.

The analysis of forecast performance across different SM metric groups reveals varying levels of accuracy across lags. For Lag 0, the best performing group is Sentiment, which has the lowest total error (−2%) and MAPE (93%), followed by Paid metrics, which show a total error of 25% and MAPE of 106%. Engagement and Awareness rank third and fourth, with Awareness having a high total error of 44%. At Lag 1, Paid metrics have the best predictive power, with a minimal total error of 4% and MAPE of 101%, closely followed by Engagement, which has the same total error but slightly worse MAPE (130%). Sentiment and Awareness follow, with Awareness showing a total error of 29%. For Lag 2, Paid metrics continue to perform best, with a total error of just 2%, while Sentiment and Engagement exhibit a total error of 33% and 13%, respectively. Awareness ranks last with a total error of 34%. In Lag 3, Paid metrics remain the top performer with a total error of 10%, while Engagement improves slightly with a 28% total error. Sentiment and Awareness show significant errors, with Awareness having the worst performance at 63% total error. At Lag 4, Engagement emerges as the best group, with a total error of 24%, followed by Paid metrics (37%). Sentiment and Awareness continue to perform poorly, with Awareness recording a total error of 59%. Finally, at Lag 5, Paid metrics perform the best once again, with a total error of 44%. Sentiment and Engagement follow with similar errors (58% and 53%, respectively), while Awareness underperforms significantly with a 116% total error. The ranking of forecast groups is summarized in Table 6:

TABLE 3 | Pearsons's correlation coefficient between sales at Lags 0–5 with SM variables (with p-value < 0.05).

Sales	SM variables	Pearson's correlation coefficient
Sales Lag 0	Organic.video.views	0.81
Sales Lag 0	Shares	−0.49
Sales Lag 1	Organic.video.views	0.63
Sales Lag 1	Paid.Post.shares	−0.54
Sales Lag 1	Shares	−0.59
Sales Lag 2	Organic.video.views	0.62
Sales Lag 2	Paid.Post.shares	−0.59
Sales Lag 2	Shares	−0.67
Sales Lag 3	Paid.impressions	0.70
Sales Lag 3	Total.impressions	0.66
Sales Lag 3	Paid.Post.shares	−0.51
Sales Lag 3	Shares	−0.62
Sales Lag 4	Paid.impressions	0.72
Sales Lag 4	Total.impressions	0.61
Sales Lag 4	Total.video.views	0.56
Sales Lag 4	Paid.video.views	0.56
Sales Lag 4	Paid.Post.comments	−0.50
Sales Lag 4	Paid.Post.shares	−0.56
Sales Lag 4	Shares	−0.67
Sales Lag 5	Total.video.views	0.56
Sales Lag 5	Paid.video.views	0.56
Sales Lag 5	Paid. impressions	0.55
Sales Lag 5	Paid.Post.comments	−0.53
Sales Lag 5	Paid.Post.shares	−0.67
Sales Lag 5	Shares	−0.74

The results presented in the demand modeling analysis show clear differences in how the various SM marketing metric groups contribute to demand forecasting accuracy. The strong performance of the Paid metrics across most lags can be attributed to their direct impact on consumer behavior. These metrics provide a more immediate and measurable impact on sales because they target specific audiences with intent to purchase (Hoffman and Fodor 2010). The alignment between paid marketing activities and short-term demand spikes is consistent with the findings of studies that demonstrate the effectiveness of targeted digital advertising in influencing consumer behavior (Misirlis and Vlachopoulou 2018). In contrast, Sentiment metrics, which performed best at Lag 0, likely reflect the immediate emotional reaction of consumers to promotional content. The initial strong correlation between sentiment and demand suggests that positive or negative consumer perceptions captured via comments or reviews have an immediate influence on purchase decisions, as for Yoon et al. (2018), who found that the valence of consumer feedback can significantly affect sales, especially in short-term forecasting. However, the decline in sentiment's predictive power at later lags might indicate that consumer emotions fluctuate quickly and are less reliable for long-term demand forecasting, as noted by Lee et al. (2019). Engagement metrics performed consistently, and particularly well at Lag 4, underscoring their

TABLE 4 | Categorization of Facebook metrics.

Awareness metrics	Engagement metrics	Paid metrics	Sentiment metrics
• Page likes • Page unlikes • Total followers • Total impressions • Organic impressions • Viral impressions • Total video views • Organic video views	• Likes • Comments • Shares	• Paid video views • Paid likes • Paid comments • Paid shares • Paid impressions	• Average daily Sentiment • Weighted average daily sentiment • Number of positive comments • Number of negative comments • Number of neutral comments

TABLE 5 | Demand modeled using SVM with SM marketing metrics groups.

	date	D-17	D-16	D-15	D-14	D-13	D-12	D-11	D-10	D-9	D-8	D-7	D-6	D-5	D-4	D-3	D − 2	D-1	D-0	Total	*Total error*	*RMSE*	*MAPE*
	2019 sales	41	46	59	50	49	38	65	68	88	77	70	42	233	78	78	233	352	470	**2138**			
Paid	**Lag0**	113	105	119	105	135	132	110	148	136	137	150	174	315	77	119	148	181	266	**2670**	*25%*	*93*	*106%*
	Lag1	155	114	115	95	112	98	93	126	123	105	135	115	147	246	78	94	149	129	**2229**	*4%*	*120*	*101%*
	Lag2	110	142	116	122	84	92	104	90	133	125	81	147	110	153	233	85	105	160	**2191**	*2%*	*122*	*103%*
	Lag3	130	148	105	158	166	83	95	110	91	171	160	69	169	122	146	185	116	120	**2344**	*10%*	*120*	*103%*
	Lag4	170	167	186	132	195	186	110	98	142	130	196	217	106	190	171	178	239	107	**2919**	*37%*	*137*	*163%*
	Lag5	156	185	163	186	157	191	187	129	127	164	153	186	189	133	196	171	178	238	**3088**	*44%*	*120*	*162%*
Sentiment	**Lag0**	115	126	98	97	116	113	130	108	148	102	119	120	133	108	113	108	111	137	**2102**	*-2%*	*116*	*93%*
	Lag1	176	125	134	118	115	132	121	145	127	165	130	139	133	149	111	136	132	135	**2423**	*13%*	*121*	*120%*
	Lag2	129	167	159	204	134	129	169	151	202	149	160	144	175	193	174	105	154	148	**2847**	*33%*	*131*	*151%*
	Lag3	199	150	168	185	234	152	150	201	175	223	185	148	185	207	232	193	133	168	**3288**	*54%*	*144*	*183%*
	Lag4	176	181	145	219	178	236	153	146	193	168	226	172	197	166	201	229	197	130	**3312**	*55%*	*143*	*184%*
	Lag5	205	188	161	175	238	162	180	193	180	177	156	203	172	233	171	192	182	212	**3380**	*58%*	*137*	*189%*
Awareness	**Lag0**	148	148	141	140	183	177	185	154	205	176	179	167	188	121	191	166	201	215	**3085**	*44%*	*119*	*156%*
	Lag1	119	138	143	107	104	169	157	172	142	213	155	163	140	206	111	178	148	185	**2751**	*29%*	*120*	*135%*
	Lag2	141	130	141	145	119	117	177	174	167	146	216	163	168	158	222	129	191	168	**2871**	*34%*	*123*	*143%*
	Lag3	211	180	157	169	173	155	153	219	214	212	177	242	198	213	182	262	144	233	**3494**	*63%*	*139*	*190%*
	Lag4	128	211	180	157	169	173	155	153	219	214	212	177	242	198	213	182	262	144	**3389**	*59%*	*136*	*175%*
	Lag5	235	222	263	271	269	266	268	279	279	259	273	239	277	235	246	278	233	235	**4628**	*116%*	*186*	*281%*
Engagement	**Lag0**	159	114	146	199	109	208	83	106	160	76	280	81	99	104	100	79	192	106	**2403**	*12%*	*136*	*129%*
	Lag1	164	138	90	140	202	78	202	55	97	171	52	251	53	74	101	105	64	180	**2217**	*4%*	*139*	*130%*
	Lag2	159	152	129	157	107	187	107	185	89	137	168	72	236	76	123	149	119	71	**2423**	*13%*	*133*	*119%*
	Lag3	163	180	155	175	124	155	131	206	120	131	185	104	242	108	142	164	144	104	**2734**	*28%*	*131*	*138%*
	Lag4	120	185	136	176	160	99	156	128	189	128	171	152	125	224	127	129	141	112	**2656**	*24%*	*135*	*142%*
	Lag5	217	162	181	130	213	202	125	175	196	209	188	171	121	182	252	189	190	174	**3278**	*53%*	*142*	*187%*

TABLE 6 | Ranking of SM marketing metrics groups, from best (1st) to worst (4th), based on their error measures.

	Rank of best to worst performing demand model			
Lag	**1st**	**2nd**	**3rd**	**4th**
Lag 0	Sentiment	Paid	Engagement	Awareness
Lag 1	Paid	Engagement	Sentiment	Awareness
Lag 2	Paid	Engagement	Sentiment	Awareness
Lag 3	Paid	Engagement	Sentiment	Awareness
Lag 4	Engagement	Paid	Sentiment	Awareness
Lag 5	Paid	Engagement	Sentiment	Awareness

importance in maintaining consumer interest and engagement over time. Engagement behaviors like likes, shares, and comments represent active consumer interactions with content and can signal higher intent to purchase but may not directly translate into immediate sales. This finding aligns with research that highlights the role of engagement in fostering brand loyalty and gradual purchase behavior (Komtesse af Rosenborg et al. 2017). Finally, the underperformance of Awareness metrics suggests that while the number of page followers and impressions provide visibility, they are not as tightly linked to short-term sales as more targeted or interactive metrics. Awareness metrics focus on exposure rather than active consumer responses, making them less effective in predicting immediate demand (Minazzi 2015). Cui et al. (2018) emphasize the importance of using more dynamic SM metrics, such as sentiment and engagement, for accurately predicting sales, rather than relying solely on simpler awareness-driven metrics like impressions or reach. While awareness metrics provide insight into consumer exposure, their predictive power for short-term demand is limited compared to more complex metrics. This aligns with our findings that Paid metrics and Sentiment consistently outperformed Awareness in forecasting demand, particularly over short time frames.

6.1 | Managerial Implications

The results of this study present important implications for improving the company's current demand planning process, particularly for promotional and special event items. Historically, demand planning for such products has been a collaborative effort involving Finance, Operations, Sales, Marketing, the General Manager, and Quality departments, integrating a top-down approach based on financial targets with a bottom-up approach using historical sales data of similar products from previous years. However, the current approach overlooks valuable SM data, particularly from Facebook, which could impact forecasting accuracy. This study demonstrates that incorporating Facebook metrics, particularly Paid metrics, can provide more precise and real-time insights into short-term demand. By integrating Paid metrics into the demand planning process, the company can better forecast the sales of promotional products, especially during special events like Father's Day. This shift enables management to move beyond traditional sales data and leverage the power of SM to improve demand forecasting accuracy.

A further managerial implication is the heightened importance of SM within the company's overall marketing strategy. The results underscore the effectiveness of Paid metrics in influencing product sales, supporting a data-driven allocation of resources toward SM advertising. Paid likes and paid shares, in particular, drive greater engagement, leading to more organic and viral impressions. This highlights a feedback loop where investment in paid advertising amplifies overall SM activity, further justifying the increased allocation of marketing resources to these channels. Additionally, understanding the impact of SM metrics allows the management to proactively trigger targeted marketing initiatives that respond to real-time customer behaviors and preferences observed on Facebook. This approach facilitates more dynamic and responsive marketing campaigns, enabling the company to adjust its efforts based on live data, ultimately improving the effectiveness of promotional activities and optimizing ROI in paid advertising.

7 | Conclusions

The aim of this paper is to introduce a framework that supports the classification of SM marketing metrics for demand forecasting, particularly in the context of promotional products with limited historical data. By categorizing SM metrics into distinct groups, the study explores the contribution of each group to demand modeling. This approach offers businesses practical insights, enabling them to enhance their promotional planning and forecasting processes by effectively leveraging SM data. Through this framework, companies can better anticipate consumer behavior and make more informed, data-driven decisions for future promotions.

The key findings of this study provide valuable insights into the use of SM metrics for demand modeling, particularly for promotional products. The proposed approach was demonstrated on a real-world case involving a food and beverage manufacturer and retailer that launches new promotional products annually for Father's Day. When evaluating the four identified metric groups (Paid, Awareness, Engagement, and Sentiment) at various time lags (ranging from 0 to 5 days), Paid metrics consistently demonstrated the strongest performance in demand modeling. This finding suggests that Paid metrics, which capture the direct results of targeted advertising efforts, are more effective in modeling product demand compared to the other groups. The precision and immediacy of paid advertising, especially during short-term promotional campaigns, likely contribute to this group's superior predictive power. In contrast, Awareness metrics were less influential in modeling demand, suggesting that these metrics are more relevant for gauging brand over the long-term rather than for short-term demand forecasting. Moreover, this approach provided a more accurate forecast compared to the company's traditional methods for the Father's Day promotional period. The company's leadership recognized the potential for improved accuracy in their demand planning processes by incorporating SM metrics, particularly Paid metrics, into their demand planning process.

The approach proposed in this paper has important implications for both research and industry practice. First, this study is the first to explore how groups of SM variables categorized by their marketing objectives can be employed to model demand. The implication of this novel approach is that it opens new avenues for understanding the relationship between SM marketing efforts and product demand. Furthermore, the analysis performed on Facebook variables led to the identification of a new category, "Paid metrics," within Facebook's SM metrics. Although prior research did not explicitly examine this group in the context of demand modeling, this study demonstrates that Paid metrics, such as paid likes, impressions, and shares, were the most effective predictors of demand in the case study. While the study focuses on one company and promotional period, the results highlight the significance of paid advertising efforts in modeling consumer behavior.

This study has several limitations that must be acknowledged. First, the findings are drawn from a single case study in the food and beverage industry during a specific promotional period, limiting their direct applicability to other sectors or campaigns. While paid metrics were identified as the most effective group for modeling demand in this context, it is important to note that the results might vary across different industries or promotional periods. Furthermore, the study focuses solely on Facebook data, which may not fully represent the dynamics of other SM platforms where user behaviors and engagement metrics could differ. Additionally, the analysis concentrated on short-term time lags (0–5 days), and a longer term investigation may reveal further insights. Despite these considerations, the framework and findings serve as a strong foundation for future research in the broader application of SM metrics in demand forecasting.

Future research could also investigate the effect of SM metrics for long-term demand forecasting, to provide insights into customer preferences and market trends and help companies make informed product promotion decisions. Moreover, a comparative analysis of SM platforms would examine the use of platform-specific metrics in demand modeling and evaluate SM advertising methods, which could help companies allocate resources across SM channels and determine the most important sales drivers. Future research should also examine the generalizability of the proposed modeling methodologies and variable choices across industries. In terms of demand modeling, real-time demand forecasting is another potential study area in which companies might make faster business choices by using streaming data from SM sites to track and respond to customer preferences and trends.

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Data Availability Statement

The data that support the findings of this study are openly available in Zenodo at 10.5281/zenodo.5808893, reference number 10.5281/zenodo.5808893.

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