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Judgmental adjustment of demand forecasting models using social media data and sentiment analysis within industry 5.0 ecosystems

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ABSTRACT

Industry 5.0 ecosystems focus on a human-centric approach to operations and supply chain management by integrating stakeholders, advanced technologies, and processes. While incorporating social media (SM) information into demand forecasting can significantly improve accuracy, it also brings about several challenges. This paper proposes an approach to leverage Big Data originating from SM networks combined with human judgment to build demand forecasts for new products. The structured methodology is demonstrated to improve forecast accuracy in a real case of a F&B company while providing several insights into the challenges and opportunities of integrating advanced information technology into the demand forecasting process. The main challenges include effectively categorising the impact factors of SM on demand forecasting, translating insights from SM into actionable decisions, and ensuring the accuracy and reliability of the data obtained from SM networks. Future studies should involve collaborative expert input and validating the approach across various companies and industries.

1. Introduction

Industry 5.0 (I5.0) ecosystems involve an interconnected network of stakeholders, advanced technology, and integrated processes to create a human-centric approach to operations and supply chain management (SCM) (Sindhvani et al., 2024). The demand forecasting process is a critical element in operations and SCM, and integrating I5.0 advanced technologies, such as real-time consumer insights and Big Data analytics, into this process offers multiple opportunities for improved forecasting but also poses potential challenges while using these technologies. Forecasting demand for a new product or service is a major challenge for any company, whether to predict the success of a new product, optimise its production, inventory and logistics, or capacity planning and allocation. This is due to limited historical data associated with the new product, uncertain market response from consumers regarding the adoption of the new product, and changes in consumer behaviour due to external factors and events (Saunders et al., 2024). Therefore, companies heavily rely on social media (SM) networks for information exchange with their consumers regarding their new products and services, as well as improving online customer journeys and engagement (Dwivedi et al., 2021). Wehrle et al., 2022) show how

effectively using SM to co-create knowledge with employees and customers, along with developing dynamic capabilities, can significantly improve a company's performance in developing new products. With several billion users every day, SM networks have given marketing a new dimension to gauge the opinions and sentiments of actual and potential consumers towards their newly launched products to inform their marketing decisions (Hicham & Karim, 2023). User-generated content on SM networks often contains product reviews and sentiments towards the company, making it a valuable source of information for demand forecasting. In fact, the consumers perception of the company's ability to rapidly adapt to feedback and customer needs on SM networks, increases their willingness to purchase the company's products (Bozkurt et al., 2023). Moreover, customers seek information on SM networks which influence their decisions before making a purchase as well as sharing their product reviews after a purchase (Lin & Wang, 2023; Xie & Lee, 2015). The quality of the relationships between consumers and companies due to marketing activities on SM networks is indirectly linked to increased purchase intentions of SM users (Wibowo et al., 2021). Hu et al. (2019) highlight the importance of SM analytics in generating actionable insights for strategic business decisions, such as product positioning and customer relationship management (CRM). Actually,

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effective SM CRM is essential to ensure improved marketing performance (Luo et al., 2024). SM networks provide accurate, real-time information on the customer journey which has been shown to improve demand forecast model accuracy, providing information directly from the consumers and the social network of customers (Onofrei et al., 2022; Xu et al., 2016). Moreover, research has shown that the more customers engage with a company on SM networks, the more likely they are to visit the company more often, demonstrating increased loyalty as well as profitability (Rishika et al., 2013).

There are various forecasting approaches for new products: (1) Statistical approaches that consist of time-series models, regression models, and diffusion models like the Bass model (Mas-Machuca et al., 2014); Bayesian models which incorporate prior information about parameters into the modelling process and update them based on observed data to make probabilistic predictions about future events (Lei et al., 2023); (2) Forecasting based on judgmental approaches including Delphi studies, judgmental adjustment of statistical models, and Analytical Hierarchical Process (AHP) (Swaminathan & Venkitasubramony, 2023); (3) Data-driven methods including artificial intelligence (AI) with supervised and unsupervised machine learning (ML) (Elalem et al., 2022), as well as agent-based modelling (ABM) techniques (Petroopoulos et al., 2022); (4) Market studies consisting of customer surveys and market analysis (Hanaysha, 2022); and finally a hybrid combination of one or more of these approaches. Since the advent of social networks, few articles have considered social media information (SMI) to improve the accuracy of demand forecasting models for new products, however no papers have yet looked at a human-centric approach to new product forecasting which leverages IS.0 technologies such as real-time SM data analytics. Potential reasons could be due to limited understanding of SM dynamics regarding how to leverage SMI for forecasting purposes (Fildes et al., 2022) pushing practitioners to favour quantitative methods, as well as potential concerns regarding subjective biases present due to the unstructured nature of human judgment (Petroopoulos et al., 2022), in particular in the context of highly dynamic SM networks. Nevertheless, the incorporation of a well-structured judgmental adjustment approach has been shown to improve demand forecast accuracy (Alvarado-Valencia et al., 2017; Brau et al., 2023) by minimising cognitive biases of experts, such as contextual and motivation biases (Petroopoulos et al., 2022). Integrating expert judgment into forecasting models based on information coming from advanced data analytics in the IS.0 ecosystem can be challenging, and experts may introduce biases, therefore subjective adjustments must be made objectively. Consequently, a key challenge in utilising insights from SM to in the forecasting process for new products includes the difficulty in translating these insights into real-time decisions. This is due to the complexity of interpreting SM signals, such as in the case of a rapid increase in positive or negative comments. Moreover, the use of SMI in demand forecasting must be treated carefully as SM posts must be connected to the product in question in order to analyse the direct relationship (Fildes et al., 2022).

Therefore, the motivation for this study is to explore a human-centric approach for refining demand forecasting models for new products by interpreting advanced data analytics from SM networks within the IS.0 ecosystem. The research question is: How effectively can expert insights from social networks be utilised to adjust demand forecasting models, particularly in the context of new products? The objectives are to develop a framework for a forecast adjustment approach for the classification of the SMI and sentiment variables into four adjustment factors: transient, transferred, quantum jump, and trend change. The proposed approach is then tested and validated using a real case study from the Food & Beverage (F&B) industry which deals with new products for special yearly events. Unlike prior research that has primarily focused on incorporating SMI into forecasting models for new products either as exogenous variables in statistical approaches or using solely ML approaches, this study proposes a systematic judgmental forecasting methodology to reflect the direct influence of SM variables in the

demand forecast of new products, offering a structured approach to judgmental adjustment based on SMI and sentiment.

The following section presents the review of the literature on new product forecasting with data from SM platforms, and on judgmental adjustment of forecasts. Section 3 presents the four-phase methodology that identifies SMI into four impact factors with which to judgmentally adjust new product demand forecasting. The approach is validated using a case study in Section 4 and the results are discussed. Section 5 presents the theoretical and managerial implication of the study and Section 6 presents the conclusions to this research and highlights the future research directions.

2. Literature review

2.1. Forecasting with data from social networks

Recently, the use of online data for demand forecasting has surged due to the increasing availability of big data and the advent of advanced tools like ML for predictive analysis and sentiment analysis (Fildes et al., 2022). Moreover, research has shown the extensive influence of positive “word of mouth” on SM on organisations and other individuals (Grover et al., 2022). Increases in sales volume has been observed to be statistically significant when promoting products via social network campaigns (Dolega et al., 2021). Integrating SM into a Susceptible–Exposed–Infectious–Recovered (SEIR) model has also been shown to improve COVID-19 infections forecasting (Bae et al., 2021). On the other hand, Schaer et al. (2019) dispute the reported performances of the forecasting approaches in the literature using SMI when compared to a naive forecasting approach, and recommend caution be used in forecast accuracy evaluation methods. Similarly, Bauer et al. (2023) illustrate the dangers of human interpretation in explainable AI within the domain of real estate price forecasting. Their research highlights how information provided by AI can shape users’ perceptions and prioritisation of data, potentially reinforcing biases and leading to sub-optimal decisions. Nevertheless, it is essential to quickly understand and respond to customers’ needs, and SM platforms offer valuable insights that can help businesses sense these requirements in real-time (Wehrle et al., 2022).

The following studies incorporate SMI into their analyses for statistical and ML models for demand forecast modelling for products with limited historical data and uncertain demand. Badulescu et al. (2023) employ multi-criteria decision-making models to analyse the relationships between SM and sales variables for new product forecasting and find that the number of followers as well as comments on SM networks are the most critical influencers for sales according to expert judgment. Rousidis et al. (2020) find a prevalence of single-source social networks, primarily Twitter, with regression algorithms widely used, particularly in finance, for accurate predictions. Brand trust has been shown to have a mediating effect on the consumer’s purchasing decision (Hanaysha, 2022). Kitsios et al. (2022) explore the elements impacting SM users’ trust in travel-related data from SMI, highlighting the significance of perceived enjoyment and value as crucial influencers. Ampountolas and Legg (2021) introduces a framework based on a combined ARIMA and ML approach using Segmented boosting methods (XGBoost) and sentiment analysis of unstructured SMI from Twitter to predict hotel demand with greater precision. He et al. (2016) underscore the predictive power of negative sentiment from social network posts in company stock price prediction, emphasising variable selection and data source. Furthermore, Xie et al. (2020) demonstrate how SM discussions can predict changes in Bitcoin prices and find that less connected SM networks are better at forecasting next-day returns in the Bitcoin market. Boldt et al. (2016) discuss using Facebook page data for Nike sales prediction, highlighting the need to differentiate products with varying purchasing behaviours. Lassen et al. (2014) devise a linear regression model forecasting iPhone sales via Twitter metrics like Likes, Shares, and sentiment. Cui et al. (2018) compare linear regression, SVM, and RF in sales

forecasting for a fashion brand using SMI, with RF showing superior performance. [Giri et al. \(2019\)](#) investigate the impact of Twitter on garment sales by collecting and analysing tweets and sales data, finding a correlation between consumer tweets and apparel sales and proposing a SM based fuzzy time series model that outperforms traditional forecasting methods. [Fu and Fisher \(2023\)](#) propose a SKU-level forecasting method in the fashion industry using Lasso regression, support vector machine (SVM), and random forest models, with the random forest model demonstrating the lowest mean absolute deviation, while highlighting the importance of mitigating biases and noise in SMI for improved accuracy. [Hu et al. \(2020\)](#) develop a deep forest prediction model leveraging customer feedback on products from the e-commerce website Alibaba for to forecast various electronic products with positive results. While numerous studies have demonstrated the potential for enhanced forecast accuracy through the inclusion of SMI, there is a noticeable absence of research exploring the specific influence of SM variables on product-specific forecasting ([Boone et al., 2019](#)). Moreover, the articles mentioned above concentrate on established products already in the market. Despite the unpredictability inherent in industries like tourism and fashion, which are heavily influenced by external factors, practitioners can still leverage historical sales data to develop statistical and ML techniques for analysis.

On the other hand, new product forecasting presents several unique characteristics compared to forecasting existing products such as limited historical information, uncertain demand due to factors such as novelty and lack of market awareness, and rapidly changing consumer preferences. In this context, statistical approaches such as the Bass diffusion model is commonly used when considering SMI in new product forecasting. [Zhang et al. \(2022\)](#) propose a SM-based method, integrated with the Bass model, to forecast upcoming movie box office earnings, leveraging online reviews from microblogs and extracting sentiment, consumer behaviour, and audience attention metrics, demonstrating superior performance compared to traditional models and prior research. [Dellarocas et al. \(2007\)](#) integrate magazine forum data into four prediction models to forecast movie revenues based on the Bass diffusion model. [Zhang et al. \(2022b\)](#) introduce a novel product forecasting method that utilises online reviews and search engine data, incorporating sentiment analysis, demonstrated through a case study on monthly automobile sales forecasts. [Fan et al. \(2017\)](#) integrate sales history and online reviews of automobiles into a Norton/Bass model, innovating sentiment analysis through social network sentiment with positive results. [Iftikhar and Khan \(2020\)](#) develop a framework for forecasting new fashion products based on the Bass Emotion model developed by [Fan et al. \(2017\)](#) to include sentiment polarity retrieved from SMI and tested it on products from an apparel retail company. Bass diffusion models excel in predicting adoption patterns for durable consumer goods, however, their effectiveness diminishes when confronted with products subject to fluctuating seasonal demand or situations where distinguishing between initial and repeat purchases is difficult ([Mas-Machuca et al., 2014](#)). Additionally, a significant limitation of the Bass diffusion model arises from its reliance on historical data and the complexity involved in estimating its parameters which poses a challenge when applying the model to entirely new products, where uncertainties surrounding market acceptance and adoption are prevalent ([Elalem et al., 2022](#)).

Other statistical models have also been investigated when forecasting new products using SMI. [Asur and Huberman \(2010\)](#) reveal that a simple regression model incorporating frequency of tweets from Twitter outperforms market-based models for predicting movie demand. They also conclude that integrating the sentiment from tweets in their model enhances short-term forecast accuracy. [Lee et al. \(2019\)](#) investigate the use of SMI to forecast the demand for hyper-differentiated products both online and offline using predictive global sensitivity analysis to generate forecasting equations with a focus on DVD movies. [Parviero et al. \(2022\)](#) employ ABM to forecast new product adoption based on peer influence from social networks as well as external factors.

[Shen et al. \(2023\)](#) examine how SM exposure after fashion shows affects two sales approaches: 'See now buy later' (SNBL) which involves selling months after shows and 'See now buy now' (SNBN) which enables immediate post-show purchases. Using a two-period newsvendor model, they find that SNBN performs better than SNBL when demand feedback accuracy and holding costs are low, however, the effectiveness of SM exposure varies based on consumer valuation and product preference. [Table 1](#) provides the overview of the literature regarding forecasting approaches using SMI for existing and new products. Notably, judgmental approaches have not been considered in the literature despite their effectiveness in improving forecasting accuracy, and few articles focus on new product forecasting.

Forecasting products with short life-cycles, sensitivity to trend and seasonality, and consumer behaviour such as consumer electronics, fast moving consumer goods such as the F&B industry, automotive, and the fashion industry, is complex due to ever-evolving consumer preferences and rapidly changing trends, all of which contribute to high volatility and uncertainty in the market. Although these industries have warranted much research in short-term demand forecasting for new products due to the nature of their businesses, there has been very little research in qualitative methods that integrate human judgment and expertise ([Swaminathan & Venkitasubramony, 2023](#)) even though expert judgment is considered significant in forecasting these types of products ([Seifert et al., 2023](#)). While AI has infiltrated marketing decision-making processes ([Newell & Marabelli, 2015](#)) and demand forecasting models, judgment is still considered essential in understanding customer purchase intentions and behaviours ([Hicham & Karim, 2023](#)).

2.2. Judgmental forecast adjustment

Judgmental adjustment is a decision-making approach that enriches statistical forecasting models by incorporating contextual elements and expert knowledge in order to capture events that lie beyond the scope of historical data, such as supply chain disruptions or strikes ([Petropoulos et al., 2022](#)). [Marmier and Cheikhrouhou \(2010\)](#) introduce a structured method for judgmental adjustment based on impact factors and find that it enhances the accuracy of forecasting models. Moreover, a collaborative fuzzy forecast adjustment approach is developed by [Cheikhrouhou et al. \(2011\)](#) in order to minimise the biases and limitations that come with judgmental decision-making by replacing a single expert with a group of experts. [Maaß et al. \(2014\)](#) suggest that data mining can help improve forecasting accuracy, particularly when the data has low volatility and noise, and found that combining data mining with judgmental adjustment significantly improves short-term forecast accuracy. Expert knowledge from forecasters, sales teams, and marketing is crucial for refining demand forecasting techniques. [Petropoulos et al. \(2018\)](#) evaluate the accuracy of judgmentally selected forecasts compared to those recommended by software and find that a significant number of forecasting experts select different models to those recommended using software, and that judgmentally selected models perform as well as, if not better than, those selected by software. [Van den Broeke et al. \(2019\)](#) investigate the impact of two types of judgmental decision-making with a focus on positive or negative, and small or large adjustments. They find that, in scenarios where statistical forecasts remain unchanged over time, judgmental adjustments improve short-term forecast accuracy, especially close to the time of purchase and that larger adjustments are more impactful than smaller ones. [Fischer and Harvey \(1999\)](#) explore forecast accuracy in cases where experts combine forecasting models using hindsight information and show that judgmental adjustment outperforms average forecasts primarily due to forecast errors' communication to forecasters.

[Fildes et al. \(2009\)](#) evaluate methods for addressing bias adjustments in statistical and non-statistical forecasting approaches and uncover the limited effectiveness of positive adjustments compared to negative ones. The authors recommend structured approaches in judgmental

Table 1
Overview of new and existing product forecasting approaches using social media information (SMI).

Reference	Forecasting Approaches			Product Forecasted	SMI Source	New product?
	Data-driven methods (ML, ABM)	Judgmental	Statistical modes (time series, regression, Bass)			
Ampountolas and Legg (2021)	x		x	Hotel Occupancy	Twitter & SocialMention	no
Asur and Huberman (2010)			x	Box office revenue for movies	Twitter & sentiment	yes
Boldt et al. (2016)			x	Nike Sales Revenue	Facebook	no
Cui et al. (2018)	x		x	Fashion Apparel products	Facebook	no
Dellarocas et al. (2007)			x	Box office revenue for movies	Magazine forum data	yes
Fan et al. (2017)			x	Automobile sales	Online reviews & sentiment	yes
Fu and Fisher (2023)	x			Fashion Apparel products	Twitter and the Google Search Volume Index	no
Giri et al. (2019)			x	Fashion Apparel products	Twitter & sentiment	no
Hu et al. (2020)	x			Various product categories	Customer feedback on e-commerce website Alibaba	no
Iftikhar and Khan (2020)			x	Fashion Apparel products	Twitter and Facebook & sentiment	no
Kitsios et al. (2022)	x			Forecast traveller behaviour	Comments on hotel booking websites	no
Lassen et al. (2014)			x	iPhone sales revenue	Twitter & sentiment	no
Lee et al. (2019)			x	Online and Offline Movie Sales	Box Office Mojo; Movie reviews and an e-commerce platform	no
Parviero et al. (2022)	x			Adoption of a new product	Mobile phone network	yes
Shen et al. (2023)			x	Luxury Fashion products	Social media exposure	yes
Zhang et al. (2022a)			x	Box office revenue for movies	Online reviews from microblogs & sentiment	yes
Zhang et al. (2022b)			x	Automobile sales	Online reviews & Search traffic data & sentiment	yes

decision-making to mitigate optimism bias in forecast adjustment decisions. Duru and Yoshida (2009) assess judgmental forecasting’s effectiveness and applicability in the shipping industry using Delphi, expert-opinion, and ARIMA-based forecasts, and conclude that judgmental adjustments are valuable, particularly in response to intermittent events. Trapero et al. (2012) find that judgmental adjustments reduce forecasting errors when adjustment sizes are moderate for promotional products. The study also reveals a tendency towards optimism, wherein positive adjustments lead to greater errors than negative ones. De Baets and Harvey (2020) analyse forecasting decision support systems, revealing users’ ability to learn from past performance records for effective model-based forecast selection and adjustment.

In the context using information from SM networks for judgmental decision-making, SMI is being increasingly used as a decision support in strategic and operational decision-making, although the focus has mainly been to understand customer behaviours and market trends in order to inform marketing decisions (Yang et al., 2022). No articles have yet explored the use SMI as a decision support for judgmental business decisions regarding new product demand forecasting however this is expected to increase with the development of SMI collection methods (Hasani et al., 2023). This article seeks to address this gap in the literature by investigating the potential of judgmental adjustment of new product forecasts using SMI. Hence, the primary objective of this study is to address the following research question: How effectively can expert insights from social networks be utilised to adjust demand forecasting models, particularly in the context of new products?

3. Methodology adopted for the SMI-based judgmental adjustment of time-series demand forecasts

The methodology consists of four phases shown in Fig. 1 each with several steps, which are: Phase 1: Data Gathering and Structuring; Phase 2: Variable Selection and Analysis; Phase 3: Forecast Adjustment based

on SMI; and Phase 4: Methodology Validation.

3.1. Phase 1: data gathering and structuring

This phase consists of several steps. Firstly, the SMI is extracted from the social network, either by an API directly connected to the company account or using a web scraping tool (Python code for web scraping Facebook data in Appendix 1). The information extracted includes data related to the number of Followers (total, new, lost), Impressions (organic, paid, viral), number of Comments, Likes, Reactions and Shares (paid or organic), Post URL, number of Video Views (organic, paid, viral), Content consumptions, Reach (organic, paid, viral), and Total Page Views.

The second step in Phase 1 is to convert the unstructured data into structured information. This includes determining the sentiment of Comments left by users of the SM platform, as well as the number of positive, negative, and neutral comments. To perform sentiment analysis, a classifier is generated and trained using a language dataset that includes attributes of positive, negative, or neutral sentiments. The classifier is constructed employing a supervised ML technique, the SVM. The SVM classifier is employed to categorise comments sourced from SM as positive (+1), negative (-1), or neutral (0) sentiment. Then the sentiment scores are calculated and aggregated daily to derive the average daily sentiment.

The SVM, originally intended for addressing binary classification tasks, necessitates an adaptation when confronted with a multi-class classification problem, shown in this paper by the three sentiment categories (positive, neutral, and negative). In this approach, multiple binary SVM classifiers must be trained and then the results combined to create a multi-class sentiment classification.

For positive sentiment (class 1), the linear SVM classifier aims to find a decision boundary that best separates the positive class from the rest. The decision boundary for class 1 can be represented as:

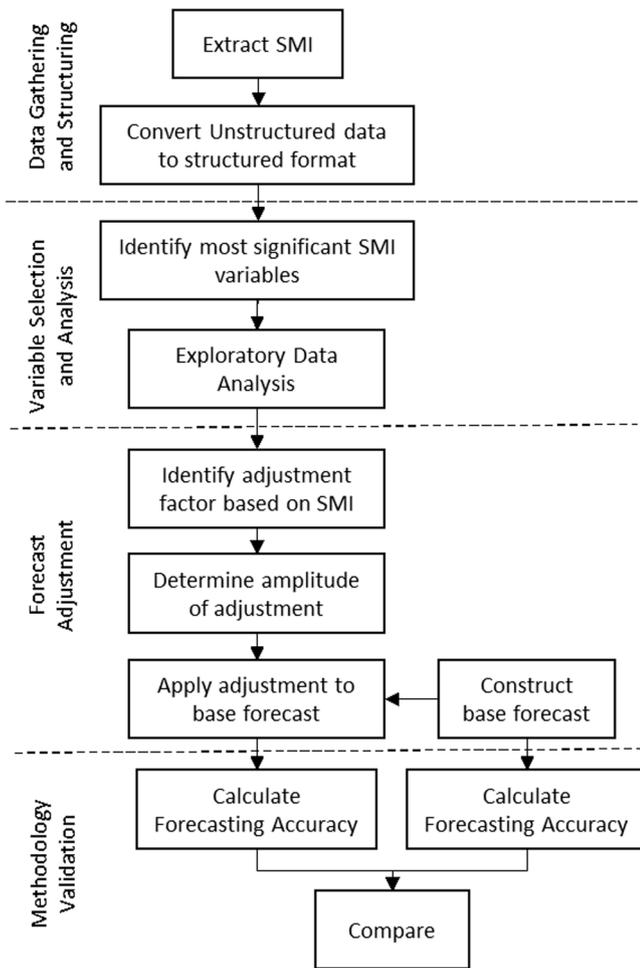


Fig. 1. Methodology for judgmental forecast adjustment using SMI.

$$\omega_1 \cdot x + b_1 = 0 \quad (1)$$

Where, ω_i represents the weight vector for class i , x represents the input features of the text data, and b_i represents the bias term for class i .

Similarly, for neutral sentiment (class 0) and negative sentiment (class -1), the decision boundaries can be respectively represented in Eqs. (2) and 3, respectively:

$$\omega_0 \cdot x + b_0 = 0 \quad (2)$$

$$\omega_{-1} \cdot x + b_{-1} = 0 \quad (3)$$

The linear SVM model assigns the class label based on which decision boundary the input falls on. For example:

- If Eq. (1), $\omega_1 \cdot x + b_1 > 0$, then the input is classified as positive (class 1),
- If Eq. (2), $\omega_0 \cdot x + b_0 > 0$, then the input is classified as neutral (class 0),
- If Eq. (3), $\omega_{-1} \cdot x + b_{-1} > 0$, then the input is classified as negative (class -1).

The SVM training process involves finding the optimal values for ω and b that maximise the margin between the decision boundary and the data points while minimising classification errors.

The characteristics of SM comments data frequently encompass non-linear and complex patterns. To effectively handle this complexity, the SVM algorithms are specifically chosen for their capability to capture intricate non-linear relationships between the features (such as words

and the target variable (i.e., sentiment). Notably, SVM algorithms leverage kernel functions to map data into higher-dimensional spaces, allowing them to achieve high accuracy in tasks like sentiment analysis. This is especially crucial for evaluating sentiment in SM comments, given the often-substantial data volume and inherent sentiment ambiguity. Moreover, SVM proves resilient to the inherent noise in SM comments, which might include unstructured text elements like emojis, abbreviations, or misspellings (Arias et al., 2013; Ortigosa et al., 2014), thus making it an ideal choice for sentiment analysis tasks.

3.2. Phase 2: variable selection and analysis

This phase encompasses two critical steps, starting with the initial identification of the most important SMI variables related to product demand. Subsequently, an Exploratory Data Analysis (EDA) is conducted on the chosen variables. The objective is to ascertain the key SMI variables that significantly contribute to predicting potential associations between SM data and sales. To achieve this, the RF algorithm is employed. RF offers the advantage of comparing the importance of original variables against the importance of their randomised counterparts (Kursa et al., 2010). The utilisation of RF for variable selection is particularly advantageous due to its embedded nature, which results in high accuracy, interpretability, and improved generalisation. The percentage increase in Mean Squared Error (%incMSE) offers insights into the extent by which the accuracy of the RF model diminishes when a variable is excluded from a node split (Shi, 2022). This metric gauges the significance of each variable in contributing to the predictive power of the model.

The EDA includes the identification of significant events that could potentially impact the forecast such as product launches, promotional campaigns, public announcements, or any other occurrences that could generate heightened SM activity. Moreover, it is important to either align the timestamps of SM data and time-series forecast data or to introduce a 'lag' between them to represent the time between an SMI event and its impact on the demand. This ensures that SM activity is synchronised with the corresponding time intervals of the forecast to examine the timing of the identified events and their corresponding impact on both SM activity and the forecasted variable.

Furthermore, as part of the EDA, relationships and potential correlations between the SMI variables and historical sales figures of comparable products are identified which helps to expose any patterns or trends that might suggest a meaningful link between SM engagement and product demand. By analysing the historical sales data of analogous products together with SMI metrics, the EDA helps determine whether certain SM interactions coincide with spikes or declines in sales. This comprehensive exploration not only facilitates a holistic understanding of the dynamics between SM and product demand but also informs subsequent steps in constructing a robust forecasting model by aiding in selecting the appropriate SMI-based adjustment factors for each variable.

3.3. Phase 3: forecast adjustment

The forecast adjustment approach presented is inspired from the four event-based judgmental adjustment factors from Marmier and Cheikhrouhou (2010), which include transient factors, transferred impact factors, quantum jump factors, and trend change factors. These factors are shaped by causal variables that support experts to adjust the baseline forecasts. Firstly, the baseline demand forecast, $D_{Baseline}$ is initialised and represents the expected demand in the absence of any external influences. Estimating $D_{Baseline}$ for new products presents a challenge due to the lack of historical data, however, there are several viable approaches to tackle this issue. One method involves identifying analogous products within the portfolio or the market that share characteristics with the new product. By leveraging the historical demand data of these similar products, $D_{Baseline}$ can be estimated for the new item.

Alternatively, seeking input from experts such as product managers, industry specialists, and salespeople can provide valuable insights into the expected demand. Conducting thorough market research and surveys can also help in constructing a demand model that predicts $D_{Baseline}$ based on customer preferences and intentions. Simulation and modelling techniques, considering factors like market size and adoption rates using the Bass model, for example. Lastly, leveraging ML models trained on available data, including product attributes and market trends, can aid in predicting demand patterns.

In parallel, two steps of Phase 3 are to identify the type of adjustment factors pertaining to the selection SMI variables and to determine the size (magnitude) and direction (increase / decrease) of the adjustment. The adjustment factors are the following:

3.3.1. Transient factors

Within the framework of an SMI-based forecast adjustment approach, the transient factor serves to incorporate the impact of an event that disrupts the demand forecast, including events such as strikes, supply disruptions, or other transient events. Notably, once the event is over, its influence on the forecast dissipates entirely as seen in Fig. 2. On the other hand, identifying a transient factor in the context of SM's impact on a time-series forecast involves a comprehensive analysis of the SMI and its correlation with fluctuations in the forecasted variable, which are performed in Phases 1 and 2 of the methodology. Based on the events identification and correlation analyses performed as part of the EDA step in Phase 2, a transient factor is identified in the instance where an event leads to an increase or decrease in SM activity followed by a change in the forecast, during the period of the event, such as a special discount in a particular period. Moreover, it is important to monitor how the influence of SM activity on the forecast diminishes over time after the event. If the impact on the demand almost immediately fades after the event, it suggests a transient effect.

The size and direction of the adjustment quantity is derived by analysing historical data and the contextual judgment of the experts to estimate the extent of the impact of the event. For example, firstly, historical sales data for the product are gathered, including data from previous months without any special events and the average demand for those normal months is calculated. Then, the historical data is analysed to estimate the impact of the promotional campaign. Assuming in this example that, historically, similar campaigns have led to a 20% increase in sales during the campaign month, the adjustment quantity for the transient factor is calculated as the difference between the expected demand during the promotional month with the campaign (adjusted) and the average demand for normal months (baseline) as demonstrated in Eq. (4).

$$D_{Adjusted} = D_{Baseline} \times (1 + \% \text{ Increase due to campaign}) \quad (4)$$

Where $D_{Adjusted}$ is the adjusted demand, $D_{Baseline}$ is the initial forecast without any external factors or events influencing it, and $\% \text{ Increase due to campaign}$ is calculated based on historical data analysis or expert judgment.

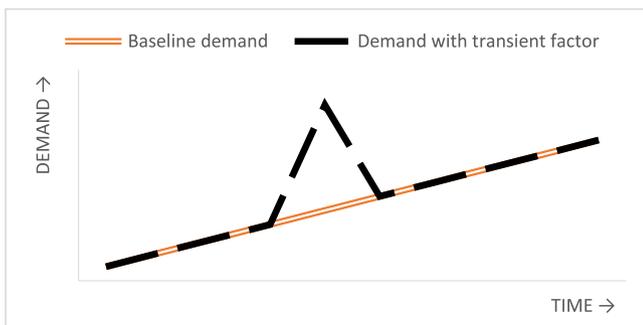


Fig. 2. Transient impact factor.

3.3.2. Quantum jump factor

In contrast to the transient factor, the quantum jump effect is characterised by its permanence after the event as seen in Fig. 3. This phenomenon arises when a company achieves a significant milestone, such as securing a major contract, successfully entering a new market, or establishing a new distribution network, resulting in a positive quantum jump. However, a quantum jump may also be negative in the case of a loss of a major customer or the introduction of a new competitor on the market. The quantum jump factor manifests when the consequences of a non-recurring event have an enduring impact. In instances where time-series models fail to inherently anticipate a quantum change, explicitly factoring in the sustained impact can prove beneficial for a certain duration. In the context of incorporating SMI into demand forecasts, identifying a quantum jump factor involves recognising significant and lasting shifts in demand that can be attributed to events or trends originating from SM. When observing a substantial and persistent change in SM users' sentiments, preferences, or behaviour on SM platforms, it may indicate the occurrence of a quantum jump effect.

For example, if there is a sudden increase in positive sentiment and discussions related to a new product on SM which "goes viral", and this sentiment shift aligns with a notable increase in actual product sales, it suggests the presence of a quantum jump factor. Similarly, if SM conversations consistently highlight a transformative event or development, such as the company successfully entering a new market, and this coincides with a sustained boost in demand for the product, it could indicate the influence of a quantum jump factor. Analysing the relationship between SM sentiment and corresponding changes in demand over time can help pinpoint instances where the impact of a social media-driven event or trend has led to a lasting adjustment in demand patterns.

$$IF_{QJ} = \tilde{D}_{expected} - \tilde{D}_{Baseline} \quad (5)$$

$$D_{Adjusted} = D_{Baseline} + IF_{QJ} \quad (6)$$

Where IF_{QJ} is the quantum jump impact factor, $\tilde{D}_{expected}$ is the expected average demand after the event pertaining to the quantum jump impact, and $\tilde{D}_{Baseline}$ is the average demand of the baseline forecast for the period.

3.3.3. Transferred impact factor

The transferred impact factor is characterised as an event's localised influence on specific time periods of the demand forecast without significantly altering the overall forecast for an extended period. This factor highlights situations where an event's impact is limited to a specific range of time, and its effects do not extend uniformly across the entire forecast horizon. Instead, the impact is "transferred" from one set of periods to another (Fig. 4).

One characteristic of the transferred impact factor is that it involves events that cause temporary shifts in demand or behaviour, but these shifts are confined to certain time periods. For example, a company announces a limited-time promotion on SM, leading to a sudden surge in

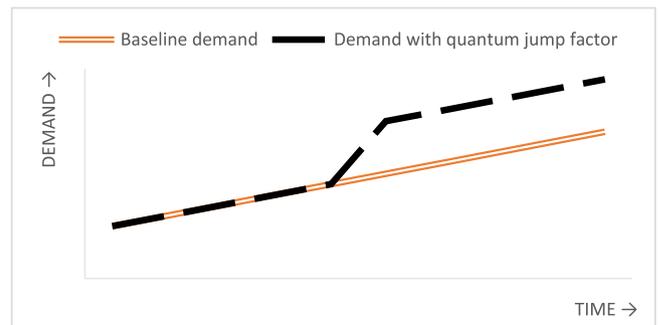


Fig. 3. Quantum jump impact factor.

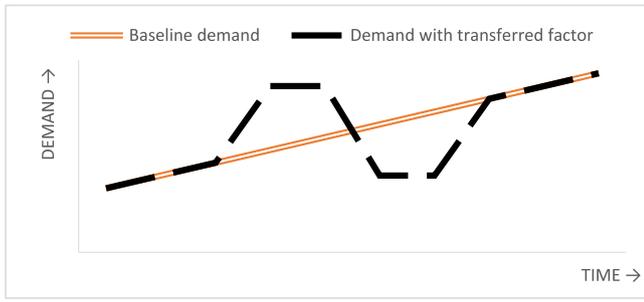


Fig. 4. Transferred impact factor.

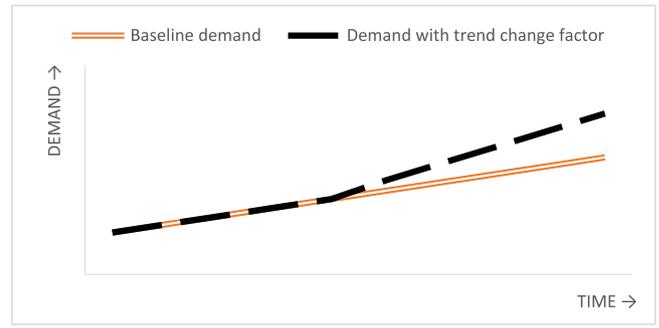


Fig. 5. Trend change impact factor.

interest and sales over a few weeks, however, after the promotional period ends, the demand returns to its regular pattern. In this case, the impact of the promotion is transferred from the promotional period to the time immediately following it, without causing a lasting change in overall forecasts. Another characteristic is that the impact of the event is isolated to specific periods while leaving the broader forecast unaffected. This factor often arises when events are pre-announced on SM and create a temporary fluctuation in demand that eventually balances out. It's common when dealing with short-term events that have a defined start and end date, and their effects can be attributed to the event itself rather than a systemic shift in the underlying demand pattern.

Detecting a transferred impact factor involves analysing the correlation between the event-triggering signal, such as SM engagement or promotional announcements, and the subsequent changes in demand within the designated time periods. If there's a noticeable increase in demand linked to the event's occurrence and subsequent decrease as the event concludes, without causing a persistent change in the overall forecast trend, it indicates the presence of a transferred impact factor.

In the case of a transferred impact factor, where an event affects demand in one set of periods, but the impact is felt in another set of periods, the adjustment quantity is calculated by redistributing the impact from the original set of periods to the affected periods as shown in Eqs. (7) and (8). This involves considering the timing and magnitude of the impact and transferring it accordingly.

$$D_{Adjusted}^t = D_{Baseline}^t - IF_{TF} \quad (7)$$

$$D_{Adjusted}^{t+l} = D_{Baseline}^{t+l} + IF_{TF} \quad (8)$$

Where IF_{TF} is the transferred impact factor, $D_{Adjusted}^t$ is the adjusted demand forecast in period t and $D_{Adjusted}^{t+l}$ is the adjusted demand forecast in period $t + l$, l is the positive or negative time difference between where the IF_{TF} is added or subtracted (depending on the direction of IF_{TF}). Similarly, the Baseline demand $D_{Baseline}$ is adjusted at both time t and time $t + l$ as in the equations.

3.3.4. Trend change factor

The trend change factor signifies a shift in the prevailing trend of the time series due a particular event such as a permanent change to the product selling price, that results in a noticeable fluctuation in total demand by a specific percentage (Fig. 5).

To account for such shifts, the trend change factor is adjusted using a ratio-based approach, which refers to the proportional change in demand due to the change in a particular event which has a permanent effect. Therefore, the baseline demand forecast is adjusted by multiplying the expected percentage change in demand due to the change in product price, shown in the following equation.

$$D_{Adjusted} = D_{Baseline} \times (1 + \% \text{ change in demand}) \quad (9)$$

For example, if a 10 % increase in price is expected to lead to a 5 % decrease in demand, the adjustment quantity would be computed based

on this ratio, that is:

$$D_{Adjusted} = D_{Baseline} \times (1 + (-0.05)) = 0.95 \times D_{Baseline} \quad (10)$$

Often, a price change is known in advance, allowing for the anticipation of an upcoming adjustment in the trend. Detecting a trend change factor involves monitoring changes in influencing variables and their potential impact on demand. In the context of SMI and its influence on time-series forecasts, identifying a trend change factor would entail observing significant shifts in SM engagement metrics coinciding with changes in the underlying demand pattern. If, for instance, an increase in SM activity consistently corresponds to a change in the overall demand trend for a specific product, it indicates the presence of a trend change factor driven by SM influences.

3.4. Phase 4: forecast evaluation

The final phase consists of a comprehensive evaluation of the forecast that has been subject to judgmental adjustments using SMI, in contrast to the baseline forecast. This pivotal step serves the purpose of assessing the effectiveness and utility of the proposed methodology. Specifically, its ability to enhance forecast accuracy for new products is analysed. The assessment of forecast accuracy is calculated using the Mean Absolute Percentage Error (MAPE) metric which is a widely adopted measure that gauges the average percentage deviation between predicted and actual values (Giri et al., 2019). MAPE is selected as it satisfies four out of the five basic criteria of measurement: validity, reliability, ease of interpretation, clarity of presentation and statistical evaluation support (Montaño Moreno et al., 2013). It aids in determining the extent to which the judgmental adjustments leveraging SMI contribute to improving forecast precision becomes quantifiable.

$$MAPE_{Adjusted} = \frac{1}{n} \sum_{t=1}^n \left| \frac{D_{Actual} - D_{Adjusted}}{D_{Actual}} \right| \times 100\% \quad (11)$$

$$MAPE_{Baseline} = \frac{1}{n} \sum_{t=1}^n \left| \frac{D_{Actual} - D_{Baseline}}{D_{Actual}} \right| \times 100\% \quad (12)$$

Where n represents the number of time periods and D_{Actual} denotes the actual value observed at time t .

This phase allows the validation of the value proposition of incorporating SMI-driven judgmental adjustments in the forecasting process, especially for scenarios where historical data is limited due to the novelty of the products. By quantifying the difference in forecast accuracy between the judgmentally adjusted forecast using SMI and the baseline forecast, organisations gain insights into the practical significance and benefits of this innovative methodology. This empirical validation, through the lens of MAPE, reinforces the potential of SMI-driven adjustments to improve forecasting accuracy of new product demand.

4. Case study results and discussion

4.1. Presentation of case

The F&B industry is chosen as the focus for a case study on forecasting new product demand due to its dynamic nature with short perishable product lifecycles and intense market competition. This industry experiences fluctuations in consumer demand driven by factors such as seasonality, changing dietary trends, and consumer preferences, therefore accurate forecasting is crucial for managing inventory levels, minimising waste and costs, and staying competitive in the market (Petropoulos et al., 2022). The case study analysed in this paper is a F&B company operating in a Latin American country which supplies its own restaurants and stores with fresh and frozen products, located in over 55 shopping centres and wholesale products to supermarkets. The analysis focuses on a new promotional product introduced each year for Father’s Day, which is celebrated on the third Sunday in June. The aim of this study is to develop a demand forecast and evaluate the use of SMI collected from the company’s Facebook page to determine whether they can improve forecast accuracy. The expert performing the judgmental adjustment is a demand planner.

Every year, the company puts on the market two new products which are on sale for 2–3 weeks before and including Father’s Day, which occurs on the third Sunday of June every year. However, the products and their components differ each year, which counts then for new short life-cycle products every time the product is launched on the market. Since the exact date of the Father’s Day changes every year, an additional variable is created, called “Countdown to FD” which initialises FD as Father’s Day, which counts backwards every day until the beginning of the selling period. For example, FD-1 is one day before FD, FD-2 is two days before FD, and so on. Fig. 6 shows the total yearly sales of two promotional items for three years Year 1, Year 2 and Year 3 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 Year 3, at FD-5 (5 days before the event) is due to a special discount on that day. 50 % of total sales occur 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.

The Facebook data retrieved from the company contains 19,307 datapoints from 23 explanatory variables from for 31 months January in Year 1 to July in Year 3. The extract includes data which is publicly visible such as number of Likes per post and Shares, as well as privately available data only accessible by the page owner such as, paid posts and advertisements. The SMI is a combination of quantitative data such as the number of Shares, Likes, and Followers, and qualitative data in the form of unstructured text which includes the content of comments left by

Facebook users on the company’s page.

4.2. Demand model initialisation

To determine the daily sentiment of comments on the Facebook posts, a classifier is trained using a training set of 80 % of the TASS dataset from the Spanish Society for Natural Language Processing and testing on 20 % of the data using SVM. An average of the classification accuracy of the test set results in 70 %. The SVM classifier is used to classify the Facebook comments for the implementation case into positive (+1), negative (−1) or neutral (0) sentiment and then calculate the sentiment score which are aggregated daily to give the average daily sentiment between −1 and +1. In addition to the average daily sentiment, the weighted daily sentiment is also calculated which is weighted by the number of Likes each comment receives.

The most significant variables are determined using the RF algorithm to calculate the %incMSE as in Fig. 7. The data required are the response variable (historical sales from Year 1 and 2) and the explanatory variables (SMI from Year 1 and 2). A lag is introduced between the response variable and explanatory variables as it is generally assumed that there is a short lag of time between the occurrence of a SM metric and the conversion into actual demand. As SMI has a very short turnover rate, it is expected that actions taken by users on SM may impact their short-term decision making such as purchasing the product they comment on. Therefore, building a model that can predict sales within a short time frame can provide the company with useful and timely information on which they can make operational decisions. The caveat to building models at different lags is that the most important variables must be determined at each lag, as they may change. Several lags are tested in the case study ranging from 0 to five days lag between the sales and SMI to identify the one with the best total correlation using the RF model. The model with the highest coefficient of determination (R^2) is the model with 4 days lag between the sales and SMI as seen in Table 2.

This analysis will then enable us to determine which variables are of greatest importance using a lag of 4 days between the response (sales) and explanatory variables (SMI). Through a process of comparison, the predictive capability of the RF model is assessed both before and after each explanatory variable is excluded, yielding the %incMSE. The %incMSE measures the change in model accuracy, assisting us in identifying the variables that have a significant impact on the model’s predictive ability. The first five variables are selected which include the Countdown to FD with the highest importance, meaning that excluding this variable from the model yields the largest error, implying a strong relationship between the day of the sale and its quantity. The following variables with %IncMSE between 4 and 5 % are the Paid Video Views,

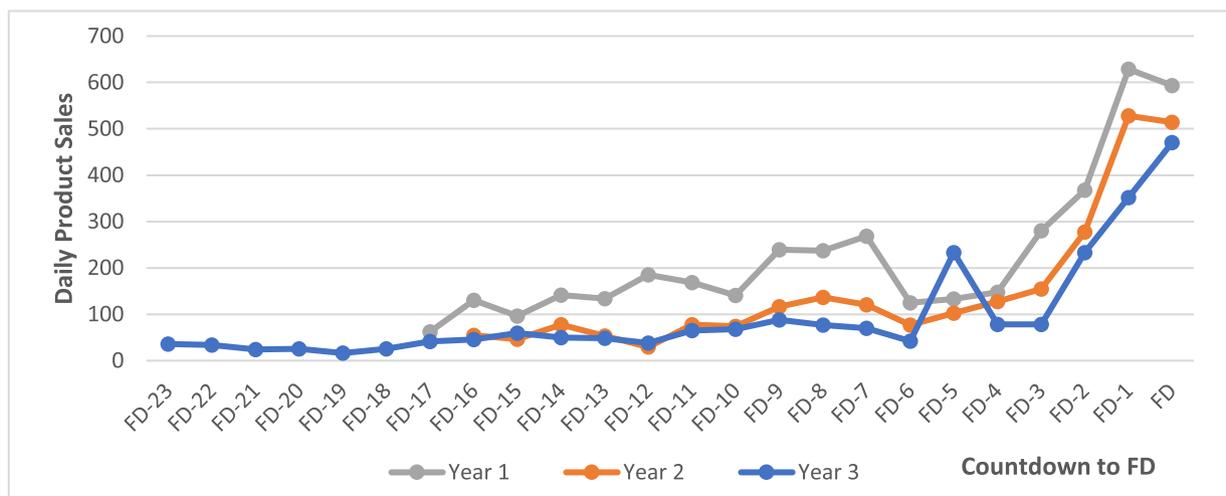


Fig. 6. Yearly sales for Father’s Day products.

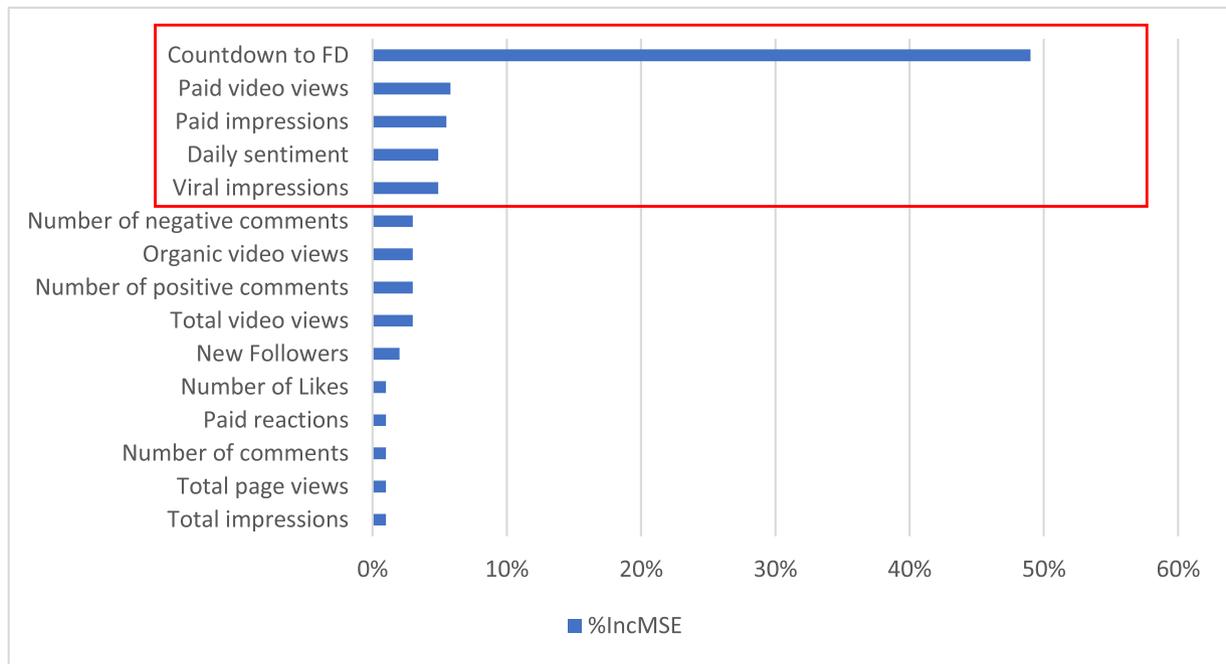


Fig. 7. Percentage Increase in Mean Squared Error (%IncMSE) based on RF approach.

Table 2

Coefficient of determination of RF models with 0–5 days lag between response and explanatory variables.

	No Lag	Lag 1 day	Lag 2 days	Lag 3 days	Lag 4 days	Lag 5 days
R^2	0.54	0.842	0.73	0.728	0.853	0.06

which refers to the number of times promoted videos (advertised by the page owner / company) are viewed by Facebook users; the Paid Impressions, which refers to the number of times a promoted post (advertisement paid by the page owner / company) is viewed by anyone on Facebook; the Daily Sentiment which is the average sentiment per day of comments left by users on the company’s posts and page; and Viral impressions which refers to the number of times the page owner’s / Company’s posts are displayed as a results of it being shared by others.

To facilitate the expert’s decision-making process during adjustments, a comprehensive table containing Facebook data from Year 2 and Year 3 was provided, focusing on both absolute and relative values of the selected variables (Appendix 2). Moreover, additional support was provided to the expert by introducing predefined thresholds within the matrix: upper and lower limits signifying ranges whose change between Year 2 and Year 3 surpasses the -20% or $+20\%$ thresholds beyond which the expert’s consideration is deemed necessary. The matrix acts as a visual aid, effectively highlighting Facebook variables exhibiting variations exceeding specific thresholds. As can be seen from the Table in Appendix 2, the differences between the Paid and Viral impressions appear to decrease between Year 2 and Year 3, however the average daily sentiment from comments left on the Company’s posts increase in Year 3. The Paid Video Views are difficult to compare since the data is not continuous; there are some days in both Year 2 and Year 3 where there are zero Paid Video Views. This may be because the Company had decided to promote the videos on specific days, hence the ‘paid’ views.

The baseline forecast ($D_{Baseline}$) for Year 3 is initialised using exponential smoothing based on historical sales data from analogous products, which were associated with the same promotional event of Father’s Day in both Year 1 and Year 2. Exponential smoothing is a forecasting method that takes into account the historical sales data and emphasises recent observations while assigning decreasing weights to older ones

and considered a robust benchmark for time-series forecasting (Petro-poulos et al., 2022). Consequently, the smoothing parameter, α , is set to 0.1 indicating that recent data points (Year 2) have a larger impact than older data points (Year 1). The goal is to capture the underlying patterns and trends in the sales data over time, enabling the projection of future sales figures. Moreover, the Holt-Winter model and Linear Regression approaches were also performed to determine the $D_{Baseline}$ but under-performed in comparison to the exponential smoothing approach. The results can be seen in Appendix 3.

4.3. Judgmental adjustment based on SMI impact factors

The application of the four impact factors (transient, transferred, quantum jump and trend change) are considered with respect to the five identified variables (including the Countdown to FD). The expert was provided the information in an Excel tool pertaining to the values of the selected variables and their evolution between Years 2 and 3 (Appendix 2), as well as the actual sales (D_{Actual}) for Year 1 and 2, and the $D_{Baseline}$ for Year 3. The Excel tool and the adjustments made per variable by the expert are provided in Appendix 4 and described below. The expert explained the rationale behind the adjustments carried out:

- In terms of Paid Impressions, the expert mentioned that in Year 3, there is more a focus on paid advertising in the final week before Father’s Day, whereas in the previous year, the paid advertising focused more on the second week before Father’s Day. Therefore, the expert suggested that the Paid Impressions is reflected as a transferred impact factor in the forecast, half of the forecasted quantities from FD-12 to FD-6 (427 units) were transferred FD-5 to FD.
- There were no changes suggested for Paid Video Views due to the complexity of evaluating the differences between Year 2 and Year 3, as there are many zeros in both years. Therefore, this SMI was ignored in the adjustment process.
- The expert categorised the Viral Impressions as a negative quantum jump explaining that they observed a permanent decrease in the behaviour of Facebook users in sharing posts which are the source of Viral Impressions. The difference in Viral Impressions between Year 2 and 3 are -61% . Moreover, the fraction of Viral Impressions from Year 1 to Year 2 are -63% and the sales between Year 1 and 2

decreased by 66 % (from 3515 in Year 1 to 2335 in Year 2). Consequently, the expert leveraged this information to apply a similar ratio of 0.6 to determine the quantity of the Quantum Jump factor of -580 units dispersed over the forecasting period.

- The average Daily Sentiment is shown to increase in every period between Year 2 and Year 3 implying an overall higher customer satisfaction from Facebook users. The expert applied the average difference (37 %) as an increase in Trend over the full period. This resulted in an overall increase of 857 units from FD-12 to FD.
- The Countdown to FD, although not extracted from Facebook, is connected to the information conveyed in the posts made by the Company of their page. A marketing event on the Tuesday before Father’s Day (FD-5) was a special event which consisted of discounted products and free coffee in store. This event was classified as having a Transient impact factor which doubles the initially forecasted quantity for that day (+100 units). Moreover, the Saturday before Father’s Day (FD-1) consistently sells more than on day FD, therefore the expert added a transient factor in FD-1 to reflect this spike in demand the day before Father’s Day.

A summary of all the adjustments performed by the expert Are shown in Table 3.

The adjustments are applied to the Year 3 $D_{Baseline}$ for the period beginning at FD-12 to FD. Although, in Year 3 the sales started much earlier than Year 1 and 2, by almost a week, Year 2 only started the sales on FD-17. Including the four-day lag between the SMI and Sales limited the forecasting period in this example to 13 days from FD-12 to FD.

The variables associated with paid promotions, such as Paid Impressions, are the results of the company’s paid advertising activities on their Facebook page. The expert made an adjustment transferring quantities from the first week to the second week (details in Appendix 2) based on the comparative assessment of Paid Impressions between the previous year (Year 2) and the forecasted year (Year 3).

Moreover, Viral Impressions, indicative of the influence of user-generated content sharing on Facebook, show a declining trend from year to year. While the expert does not pinpoint the exact reasons for this decline, it raises questions about the perceived value of the shared content among the audience. Consequently, the expert reflects the declining trend in the $D_{Adjusted}$ categorised as a negative quantum jump factor showing a lasting shift in demand resulting from a sustained change in the behaviour of SM users when it comes to sharing posts. This observation highlights the critical need for generating compelling content for Father’s Day products, encouraging users to share it on SM. Such efforts could potentially elevate Viral Impressions and, consequently, boost product demand.

The final impact factor under consideration is the transient factor, with a particular focus on two key periods: FD-5 and FD-1. The adjustment pertaining to FD-5 is directly related to a unique marketing event that occurs on the Tuesday immediately preceding Father’s Day. It’s

worth noting that this event is exclusive to Year 3 and has not been observed in previous years, rendering it absent from the $D_{Baseline}$. This transient increase in demand on FD-5 is attributed to this specific event. Conversely, the adjustment for FD-1 is rooted in historical sales patterns in which sales figures on the Saturday of Father’s Day weekend surpass those on Sunday. However, it’s important to highlight that the D_{Actual} data for Year 3 contradicts this historical trend, with higher sales occurring on the Sunday of Father’s Day weekend compared to Saturday.

Both the $D_{Adjusted}$ and $D_{Baseline}$ for Year 3 are evaluated against the D_{Actual} using the MAPE to determine which forecasting approach performed better shown in Table 4.

The MAPE of the $D_{Adjusted}$ with adjustments made based on SMI, compared to the D_{Actual} in Year 3 is 43.9 %. The $D_{Baseline}$ compared to the D_{Actual} has a MAPE of 75.6 %. This demonstrates an improvement in forecast accuracy by 42 % (from a MAPE of 75.6 % to 43.9 %). Moreover, the absolute error between the total sum of quantities between the $D_{Baseline}$ of 2220 and the D_{Actual} (1892) is 17.3 %, and between the $D_{Adjusted}$ (1924) and the D_{Actual} is 1.7 %. In both cases of absolute error and the MAPE of the $D_{Adjusted}$ outperforms the $D_{Baseline}$.

5. Theoretical and managerial implications

5.1. Theoretical contributions to the literature

With regards to the contribution to Information Systems literature and IS.0 ecosystems, this study aligns with the literature on the adoption of advanced technologies in business processes, as highlighted by Sindhwani et al. (2024). By proposing a framework that leverages Big Data from SM networks combined with human judgment, the approach

Table 4
MAPE of the SMI adjusted forecast ($D_{Adjusted}$) and the baseline forecast ($D_{Baseline}$).

Day	D_{Actual}	$D_{Adjusted}$	$D_{Baseline}$
FD-12	38	21	82
FD-11	65	21	81
FD-10	68	27	105
FD-9	88	25	97
FD-8	77	39	152
FD-7	70	44	168
FD-6	42	44	170
FD-5	233	237	100
FD-4	78	146	112
FD-3	78	161	132
FD-2	233	205	190
FD-1	352	486	296
FD	470	468	535
Total	1892	1924	2220
<i>Absolute error</i>		1.7 %	17.3 %
MAPE		43.9 %	75.6 %

Table 3
Expert adjustment based on SMI-based impact factors.

	TRANSIENT FACTOR	QUANTUM FACTOR	TRANSFERRED IMPACT FACTOR	TREND CHANGE FACTOR	TOTAL ADJUSTMENT (UNITS)
FD-12	0	-50	-41	30	-60
FD-11	0	-50	-41	30	-60
FD-10	0	-64	-52	39	-78
FD-9	0	-59	-49	36	-72
FD-8	0	-92	-76	56	-112
FD-7	0	-103	-84	62	-125
FD-6	0	-104	-85	63	-126
FD-5	100	-61	61	37	137
FD-4	0	-68	61	41	34
FD-3	0	-80	61	49	29
FD-2	0	-116	61	70	15
FD-1	200	-181	61	110	190
FD	0	-326	61	198	-67
TOTAL	300	-1354	-62	821	-295

developed in this paper advances the understanding of how real-time consumer insights can be effectively utilised in demand forecasting, which has not been considered before this study. Moreover, it extends judgmental forecasting theory by incorporating SMI into new product demand forecasts, highlighting the value of structured judgmental forecasting and its impact on accuracy addressing a gap in the literature, as previous studies have primarily focused on quantitative methods or ML approaches (Petropoulos et al., 2022). The work presented in this paper is an important contribution to the literature on the use of judgmental adjustment to integrate SMI into demand forecasting models for new products. It adds to previous work in different manners: by proposing a structured forecast judgmental adjustment approach using four SMI-based impact factors, demonstrating the value of SMI-based judgmental adjustments in new F&B product forecasting based on a real-world case study, and providing a scalable methodology that can be applied in practice. Moreover, the results demonstrate the value of expert judgment in forecasting with SMI which is a novel and promising avenue in the research.

Previous research in Operations and Supply Chain Management proposing new product forecasting approaches using SMI use purely statistical approaches (see Table 1) either using linear regression (Asur & Huberman, 2010) or extended Bass models (Dellarocas et al., 2007; Fan et al., 2017; Zhang et al., 2022b, 2022a), except for Parviero et al. (2022) which employed ABM to determine demand dynamics in the short-term post-launch period and Shen et al. (2023) which consider the inventory implications of integrating SMI in a newsvendor problem. Bass diffusion models work best for durable consumer goods but may not be as effective for products with changing seasonal demand or when it's hard to tell initial from repeat purchases (Mas-Machuca et al., 2014). Moreover, a major drawback of the Bass diffusion model lies in its dependence on historical data and the estimation of its parameters, making it challenging to apply to entirely new products where market acceptance and adoption are uncertain (Elalem et al., 2022).

While expert judgment has been demonstrated to increase demand forecasting accuracy (Seifert et al., 2023), integrating SM data into this process has been relatively slow even though judgment is still heavily used in forecasting despite the advancements in AI methods and Big Data availability and analytics (Goodwin & Fildes, 2022). Therefore, it is essential to consider expert judgment of how SMI impacts forecasted demand. This study highlights the importance of balancing technological advancements in social big data analysis with human expertise and supports the development of an IS.0 ecosystem by emphasising the human-centric approach in the demand forecasting process (Maddikunta et al., 2022).

Moreover, this study contributes to the growing field of SM analytics by providing a novel approach to categorising and utilising SMI for demand forecasting complementing existing research on the strategic use of SM data in CRM and marketing performance (Luo et al., 2024), particularly with respect to the source of the SMI. In this paper, the case study company provided internal company data regarding the advertising spend on Facebook and the subsequent Paid variables on SM: Paid Impressions, Paid Reach, Paid Video Views, Paid Likes, Paid Shares and Paid Comments. The results reveal that for this case study, the Paid variables are within those of highest importance in the forecast. Other papers have only investigated publicly available SMI in forecasting new products (Asur & Huberman, 2010; Dellarocas et al., 2007; Fan et al., 2017; Zhang et al., 2022b, 2022a) with the exception of Cui et al. (2018) which received qualitative information from the company regarding advertising and product promotion of SM networks to avoid confusing effects with SMI, however the SMI obtained did not include the promotional information. Obtaining access to the internal SMI provides unique insights on the relationship between paid advertising on SM networks and historical sales of analogous products (Cui et al., 2018) for SM data-driven decision support for experts in the judgmental adjustment process.

The implementation case demonstrates the value that SMI, in

particular daily sentiment and paid promotions have on forecasting demand for a new product as demonstrated in earlier studies by Cui et al. (2018), Fan et al. (2017), and Giri et al. (2019). These studies have highlighted the significance of incorporating SMI into forecasting models to capture consumer sentiment and promotional effects accurately, reflected by the improvement in forecast accuracy measures. However, what makes this current research a significant contribution is the study of a previously unexplored aspect: the role of SM in informing the decision-making process of forecasters when manually adjusting a statistical baseline forecast. By integrating insights from SM into the manual adjustment process, forecasters can make more informed decisions when building a demand forecast for a new product, resulting in improved forecast accuracy and better alignment with market trends and consumer behaviour.

The selection of the Latin American F&B company's promotional products for Father's Day provides a contextually relevant scenario for analysis due to the global shift towards more efficient F&B management for waste reduction (Petropoulos et al., 2022). The annual variability of Father's Day dates adds complexity to the demand pattern, making it an ideal scenario to evaluate the effectiveness of the proposed methodology in handling SKUs within a larger product family (Saunders et al., 2024). The focus on a relatively short promotional period aligns with the rapid turnover rate of SMI and its potential impact on short-term consumer behaviour (Dolega et al., 2021). The use of a diverse set of Facebook data, which includes quantitative metrics and qualitative user comments, demonstrates a comprehensive approach to capturing various facets of consumer engagement. The extraction of sentiment from unstructured textual data showcases the integration of ML techniques, enhancing the value of the collected information. Moreover, this paper is the first to provide real-world evidence within the F&B industry aligning with the Information Systems literature's emphasis on actionable insights and real-world applications (Hu et al., 2019). This methodology not only enriches the dataset but also demonstrates the innovation in leveraging advanced tools to transform unstructured data into actionable insights for decision-making.

5.2. Managerial implications

The focus of the case study was to determine how to effectively integrate expert judgment based on SMI into a new product demand forecasting model. A four-impact factor forecast adjustment approach is proposed which structures the decision-making process of the experts considering SMI. The results show that judgmental adjustment of a baseline demand forecast based on SMI improved the daily forecasted demand and decreased the MAPE and absolute error when compared to the actual sales. The product in the case study has a fixed selling period of 18 days and is sold in 26 restaurants as well as over 30 supermarkets, therefore sufficient stock is essential to satisfy the demand leading up to and including Father's Day. The short selling period is longer than the production lead-time of the products, therefore advanced production and holding the pre-produced quantity in stock is required. If the quantity of the pre-produced products is higher than the actual sales, the left-over products after Father's Day become obsolete incurring obsolescence costs as well as the costs associated with producing and storing unsold items. On the other hand, if the quantity of the products in stock is less than the demand during the selling period, a potential out-of-stock scenario could occur which has devastating effects not only on the lost sales revenue (opportunity cost) of a special promotional product that is specifically designed for Father's Day but also on the brand image (Khan & DePaoli, 2024). Judgment plays a crucial role in new product forecasting in order to ensure proper supply chain planning of production and inventory, particularly at the stock keeping unit (SKU) level within a product family (Saunders et al., 2024). Consequently, the F&B case study company forecasting expert recognised the value of judgmentally integrating SMI into the forecasting process for Father's Day and the potential positive impact on the supply chain planning associated with

the new product. By employing the structured methodology presented here, the case study company can improve the forecasting accuracy of their short-term demand forecasts for new Father's Day products. Integrating SM insights into their demand forecasting process can support the alignment of production and inventory management with SM-driven demand, thereby considering the risk of over- or under-stocking.

This study offers the opportunity to gain real-time insights into consumer sentiment and preferences through SM. With the knowledge of the direct link between paid variables (such as Paid Impressions) and product demand, the case study company are more informed when performing advertising budget allocation tasks. Moreover, by addressing the decline in Viral Impressions, the case study company can focus on creating more engaging posts that resonate with their followers. Monitoring the daily sentiment provides insight on customer satisfaction and sentiment and provide the opportunity to quickly identify and address potential concerns. These results and approach allow the company to adjust not only their demand forecast for new products but also obtain insight to adapt their marketing strategies based on evolving consumer sentiment.

Leveraging synergies between human and machine intelligence can significantly enhance the precision of industrial forecasts and execution (Sindhvani et al., 2022). In line with I5.0 principles, the approach presented in this paper exemplifies the human-machine collaboration for demand forecasting. The statistically derived baseline forecast, generated from historical quantitative data, acts as the machine element, providing an objective and data-driven baseline forecast. The 'human' element is represented by the qualitative insights from SM platforms which reveal emerging trends, customer sentiment towards products, and real-time reactions to marketing campaigns. This collaborative approach improves the understanding of new product demand, extending past the limitations of purely quantitative forecasting models (Petropoulos et al., 2022). It adheres to I5.0's focus on human-centricity by incorporating customer behaviour through SM analysis, ultimately leading to more robust and adaptable demand forecasts.

Commonly used production management software, such as ERP and MES systems, have traditionally lacked integration with SM analytics for demand forecasting, relying instead on manual data collection methods that are time-consuming, error-prone, and unsuitable for real-time needs (Cheikhrouhou et al., 2011b). Although advanced analytics has been integrated in I5.0 enterprise management systems for predictive analytics regarding maintenance and manufacturing (Maddikunta et al., 2022), there is still a gap for advanced analytics techniques in the context of demand forecasting with SMI highlighting a critical need for automatic data capture systems specifically tailored for demand forecasting. By incorporating SM analytics, these systems can provide more accurate, timely, and efficient predictions of consumer demand. Such integration would enable businesses to harness the vast amount of data generated on social media platforms, offering insights into consumer behaviour, market trends, and potential demand shifts. This advanced approach not only improves forecast accuracy but also enhances the responsiveness and adaptability of supply chain and production management, ultimately leading to better decision-making and increased competitiveness in the market.

6. Conclusion, limitations and future work

This paper investigates how an expert can effectively gain insights from social networks to adjust demand forecasts for new products within the context of I5.0 ecosystems. The methodology presented aligns with the human-centric approach of I5.0 by integrating advanced technologies and expert judgment, consequently improving the decision-making process. By replacing intuition, bias, and subjective judgments with a systematic methodology, the approach ensures more accurate and reliable forecasting as demonstrated in the implementation case. The results

show that including judgmental adjustments derived from SMI improves the accuracy of the demand forecast for the new products in the case study. The structured methodology, which categorises the SM impact factors as transient, quantum jump, transferred impact, and trend change, provides a robust framework for identifying and quantifying SM-driven adjustments.

There are several significant contributions to the field. Firstly, this research introduces an innovative hybrid approach that incorporates SMI into demand forecasting for new products, effectively filling a void in existing literature. The results also show that the adjustments should be a balanced response to the SMI and its analysis, between reacting too conservatively or aggressively which could incur an opportunity cost or increase the risk of obsolescence. Secondly, a better understanding of the dynamics between SM and demand by categorising the impact factors stemming from SM, contributing to the state of the art of social data-driven decision-making. This outcome underscores the potential of leveraging SMI as a valuable resource for demand forecasting, particularly for products with limited historical information. Moreover, this study extends judgmental forecasting theory and emphasises the human-centric approach of I5.0 in developing demand forecasts for products with little historical information which includes advanced data analytics from real-time SMI.

However, it's important to acknowledge certain limitations of the study. Relying on the insights of a single expert may not fully capture the range of human sensitivities and practices that influence forecasting judgments. To address this limitation, future studies could involve a broader pool of experts to enhance robustness and representativeness attributed to group decision-making, and the reduction of single expert bias (Cheikhrouhou et al., 2011a). Furthermore, the efficacy of this approach cannot be generalised to other products, companies and industries as the methodology was validated on one company. It is recommended to replicate this approach for new products in various companies and industries to understand its overall efficacy.

By addressing the challenges and opportunities of integrating SMI into demand forecasting, this study lays the groundwork for future research. Proposed future research avenues include collaborative expert input and validation across various industries, encouraging further exploration of the dynamic relationship between SM insights and demand forecasting in the context of new product launches. Moreover, research into alternative sources of SMI such as Google Analytics for companies with e-commerce websites could provide valuable information regarding user behaviour such as page views, time spent on certain product pages, and conversion data. Given the rapid growth of e-commerce sites (Hu et al., 2020; Lee et al., 2019), the proposed methodology in this paper could be extended to include valuable customer feedback regarding product reviews from e-commerce sites for new products. Moreover, a study of the impact of SMI on new product demand in online channels versus offline brick and mortar stores could be a future research avenue that could provide insights on the relevance and targeting of different SM advertising methods.

CRediT authorship contribution statement

Yvonne Badulescu: Writing – original draft, Methodology, Investigation, Conceptualization. **Fernan Cañas:** Writing – review & editing, Validation, Resources, Investigation, Data curation. **Naoufel Cheikhrouhou:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1. Webscraping code for Facebook posts in Python

Webscraping code for Facebook posts in Python

```
import pandas as pd
from facebook_scraper import get_posts

def scrape_facebook_posts(page_id, num_posts):
    urls = []
    for post in get_posts(page_id, pages=num_posts, start_date=start_date, end_date=end_date):
        urls.append(post['post_url'])
    return urls

# Specify the Facebook page ID and the number of posts to scrape
page_id = 'Facebook page ID'
start_date = '2023-07-01' # Date de début au format 'AAAA-MM-JJ'
end_date = '2023-07-10' # Date de fin au format 'AAAA-MM-JJ'
num_posts = 10

# Scrape the post URLs
post_urls = scrape_facebook_posts(page_id, num_posts)

# Print the scraped post URLs
for url in post_urls:
    print(url)
data = pd.DataFrame(post_urls, columns=['Post URL'])
data.to_excel('post_urls.xlsx', index=False)
```

Appendix 2. Social Media Information (SMI) per day before Father’s Day

Variables	Countdown to FD	FD-12	FD-11	FD-10	FD-9	FD-8	FD-7	FD-6	FD-5	FD-4	FD-3	FD-2	FD-1	FD
Paid impressions	Year 2	300,345	323,405	262,998	241,007	171,668	198,134	230,068	165,264	115,367	225,647	100,495	165,962	202,643
	Year 3	106,789	210,510	192,002	209,547	200,230	79,193	102,903	282,107	137,503	136,085	170,384	349,612	246,301
	Variation	-64 %	-35 %	-27 %	-13 %	17 %	-60 %	-55 %	71 %	19 %	-40 %	70 %	111 %	22 %
Viral impressions	Year 2	32,912	23,080	40,382	30,825	11,650	12,850	19,143	14,614	9171	10,143	5283	6858	55,079
	Year 3	2314	11,299	16,521	5976	5656	2774	2631	13,912	6985	4644	2403	2858	3228
	Variation	-93 %	-51 %	-59 %	-81 %	-51 %	-78 %	-86 %	-5 %	-24 %	-54 %	-55 %	-58 %	-94 %
Paid video views	Year 2	19,091	8969	0	0	0	17,530	12,776	4	0	0	0	0	31,831
	Year 3	0	0	0	6152	12	0	0	0	19,877	107	26,134	43,917	76
	Variation	-100 %	-100 %	0 %	0 %	0 %	-100 %	-100 %	-100 %	0 %	0 %	0 %	0 %	-100 %
Daily Sentiment	Year 2	0.4	0.431	0.401	0.425	0.467	0.174	0.342	0.418	0	0.214	0.227	0.515	0.524
	Year 3	0	0.562	0.463	0.512	0.313	0.5	0.465	0.508	0.8	0.35	0.366	0.542	0.518
	Variation	-100 %	30 %	15 %	20 %	-33 %	187 %	36 %	22 %	0 %	64 %	61 %	5 %	-1 %

Appendix 3. Baseline forecast calculation and comparison

The Linear regression equation is $y = -22.649x + 360.66$

The parameters for the multiplicative Holt-Winters model are: Alpha=0.2; Beta=0.1; Gamma=0.1.

Day	Actual Sales	Exponential Smoothing	Linear Regression	Holt Winters
FD-13	49	95	66	63
FD-12	38	82	89	36
FD-11	65	81	112	105
FD-10	68	105	134	108
FD-9	88	97	157	184
FD-8	77	152	179	240
FD-7	70	168	202	294
FD-6	42	170	225	148
FD-5	233	100	247	169
FD-4	78	112	270	196
FD-3	78	132	293	378
FD-2	233	190	315	535

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Day	Actual Sales	Exponential Smoothing	Linear Regression	Holt Winters
FD-1	352	296	338	961
FD	470	535	361	962
MAPE		75.56 %	125.78 %	143.78 %

Appendix 4. Judgmental adjustment tool

Sales & forecast	FD-12	FD-11	FD-10	FD-9	FD-8	FD-7	FD-6	FD-5	FD-4	FD-3	FD-2	FD-1	FD-0
Sales Year 1	185	168	141	239	237	269	125	133	148	281	368	629	594
Sales Year 2	29	77	74	117	137	121	77	103	127	154	278	528	514
Baseline Forecast Year 3	82	81	105	97	152	168	170	100	112	132	190	296	535
Adjusted forecast Year 3	21.2	21.1	27.3	25.2	39.4	43.8	44.2	237.3	145.9	161.3	205.4	486.0	467.6

JUDGEMENTAL ADJUSTEMENT															
Countdown to FD	Time to FD	FD-12	FD-11	FD-10	FD-9	FD-8	FD-7	FD-6	FD-5	FD-4	FD-3	FD-2	FD-1	FD	
		Transient (unit)	-	-	-	-	-	-	-	-	100	-	-	-	200
Transferred (unit)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
Paid impressions	Time to FD	FD-12	FD-11	FD-10	FD-9	FD-8	FD-7	FD-6	FD-5	FD-4	FD-3	FD-2	FD-1	FD	
	Transient (unit)	-	-	-	-	-	-	-	-	-	-	-	-	-	
	Quantum jump (unit)	-	-	-	-	-	-	-	-	-	-	-	-	-	
	Transferred (unit)	-41	-41	-52	-49	-76	-84	-85	61	61	61	61	61	61	
	Trend change (trend)	-	-	-	-	-	-	-	-	-	-	-	-	-	
Viral impressions	Time to FD	FD-12	FD-11	FD-10	FD-9	FD-8	FD-7	FD-6	FD-5	FD-4	FD-3	FD-2	FD-1	FD	
	Transient (unit)	-	-	-	-	-	-	-	-	-	-	-	-	-	
	Quantum jump (unit)	-50	-50	-64	-59	-92	-103	-104	-61	-68	-80	-116	-181	-326	
	Transferred (unit)	-	-	-	-	-	-	-	-	-	-	-	-	-	
	Trend change (trend)	-	-	-	-	-	-	-	-	-	-	-	-	-	
Paid video views	Time to FD	FD-12	FD-11	FD-10	FD-9	FD-8	FD-7	FD-6	FD-5	FD-4	FD-3	FD-2	FD-1	FD	
	Transient (unit)	-	-	-	-	-	-	-	-	-	-	-	-	-	
	Quantum jump (unit)	-	-	-	-	-	-	-	-	-	-	-	-	-	
	Transferred (unit)	-	-	-	-	-	-	-	-	-	-	-	-	-	
	Trend change (trend)	-	-	-	-	-	-	-	-	-	-	-	-	-	
Sentiment	Time to FD	FD-12	FD-11	FD-10	FD-9	FD-8	FD-7	FD-6	FD-5	FD-4	FD-3	FD-2	FD-1	FD	
	Transient (unit)	-	-	-	-	-	-	-	-	-	-	-	-	-	
	Quantum jump (unit)	-	-	-	-	-	-	-	-	-	-	-	-	-	
	Transferred (unit)	-	-	-	-	-	-	-	-	-	-	-	-	-	
	Trend change (trend)	37 %	37 %	37 %	37 %	37 %	37 %	37 %	37 %	37 %	37 %	37 %	37 %	37 %	

RECAP															
Variables		FD-12	FD-11	FD-10	FD-9	FD-8	FD-7	FD-6	FD-5	FD-4	FD-3	FD-2	FD-1	FD	
		Transient factor	-	-	-	-	-	-	-	-	100	-	-	-	200

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Quantum factor	-50	-50	-64	-59	-92	-103	-104	-61	-68	-80	-116	-181	-326
Transferred factor	-41	-41	-52	-49	-76	-84	-85	61	61	61	61	61	61
Trend change factor	30	30	39	36	56	62	63	37	41	49	70	110	198
Total adjustment	-60	-60	-78	-72	-112	-125	-126	137	34	29	15	190	-67

References

Alvarado-Valencia, J., Barrero, L. H., Önkal, D., & Dennerlein, J. T. (2017). Expertise, credibility of system forecasts and integration methods in judgmental demand forecasting. *International Journal of Forecasting*, 33, 298–313. <https://doi.org/10.1016/j.ijforecast.2015.12.010>

Ampountolas, A., & Legg, M. P. (2021). A segmented machine learning modeling approach of social media for predicting occupancy. *International Journal of Contemporary Hospitality Management*, 33, 2001–2021. <https://doi.org/10.1108/IJCHM-06-2020-0611>

Arias, M., Arratia, A., & Xuriguera, R. (2013). Forecasting with twitter data. *ACM Transactions on Intelligent Systems and Technology*, 5, 1–24. <https://doi.org/10.1145/2542182.2542190>

Asur, S., & Huberman, B. A. (2010). Predicting the future with social media. In *2010 IEEE/WIC/ACM international conference on web intelligence and intelligent agent technology. Presented at the 2010 IEEE/ACM international conference on web intelligence-intelligent agent technology (WI-IAT)* (pp. 492–499). IEEE. <https://doi.org/10.1109/WI-IAT.2010.63>

Badulescu, Y., Kassoul, K., & Cheikhrouhou, N. (2023). Associations between social media attributes for demand forecasting of new products. In *2023 9th international conference on control, decision and information technologies (CoDIT)*. Presented at the 2023 9th international conference on control, decision and information technologies (CoDIT) (pp. 01–06). <https://doi.org/10.1109/CoDIT58514.2023.10284267>

Bae, S., (Christine) Sung, E., & Kwon, O. (2021). Accounting for social media effects to improve the accuracy of infection models: Combatting the COVID-19 pandemic and infodemic. *European Journal of Information Systems*, 30, 342–355. <https://doi.org/10.1080/0960085X.2021.1890530>

Bauer, K., von Zahn, M., & Hinz, O. (2023). Expl(AI)ned: The impact of explainable artificial intelligence on users' information processing. *Information Systems Research*, 34, 1582–1602. <https://doi.org/10.1287/isre.2023.1199>

Boldt, L. C., Vinayagamoorthy, V., Winder, F., Schnittger, M., Ekran, M., Mukkamala, Raghava Rao, et al. (2016). Forecasting Nike's Sales using Facebook Data. In *2016 IEEE international conference on big data. Presented at the 2016 IEEE international conference on big data* (pp. 2447–2456). IEEE. <https://doi.org/10.1109/BigData.2016.7840881>

Boone, T., Ganeshan, R., Jain, A., & Sanders, N. R. (2019). Forecasting sales in the supply chain: Consumer analytics in the big data era. *International Journal of Forecasting*, 35, 170–180. <https://doi.org/10.1016/j.ijforecast.2018.09.003>

Bozkurt, S., Gligor, D., Locander, J., & Ahmad Rather, R. (2023). How social media self-efficacy and social anxiety affect customer purchasing from agile brands on social media. *Journal of Research in Interactive Marketing*, 17, 813–830. <https://doi.org/10.1108/JRIM-08-2022-0242>

Brau, R., Aloysius, J., & Siemsen, E. (2023). Demand planning for the digital supply chain: How to integrate human judgment and predictive analytics. *Journal of Operations Management joom*, 1257. <https://doi.org/10.1002/joom.1257>

Cheikhrouhou, N., Marmier, F., Ayadi, O., & Wieser, P. (2011a). A collaborative demand forecasting process with event-based fuzzy judgements. *Computers & Industrial Engineering*, 61, 409–421. <https://doi.org/10.1016/j.cie.2011.07.002>

Cheikhrouhou, N., Pouly, M., & Berthold, S. (2011b). Real-time collaborative information management in enterprises. In L. Canetta, C. Redaelli, & M. Flores (Eds.), *Digital factory for human-oriented production systems: The integration of international research projects* (pp. 125–146). Springer. https://doi.org/10.1007/978-1-84996-172-1_8

Cui, R., Gallino, S., Moreno, A., & Zhang, D. J. (2018). The operational value of social media information. *Production and Operations Management*, 27, 1749–1769. <https://doi.org/10.1111/poms.12707>

De Baets, S., & Harvey, N. (2020). Using judgment to select and adjust forecasts from statistical models. *European Journal of Operational Research*, 284, 882–895. <https://doi.org/10.1016/j.ejor.2020.01.028>

Dellarocas, C., Zhang, X.(Michael), & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing*, 21, 23–45. <https://doi.org/10.1002/dir.20087>

Dolega, L., Rowe, F., & Branagan, E. (2021). Going digital? The impact of social media marketing on retail website traffic, orders and sales. *Journal of Retailing and Consumer Services*, 60, Article 102501. <https://doi.org/10.1016/j.jretconser.2021.102501>

Duru, O., & Yoshida, S. (2009). Judgmental forecasting in the dry bulk shipping business: Statistical vs. judgmental approach. *The Asian Journal of Shipping and Logistics*, 25, 189–217. [https://doi.org/10.1016/S2092-5212\(09\)80002-3](https://doi.org/10.1016/S2092-5212(09)80002-3)

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., et al. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, 59, Article 102168. <https://doi.org/10.1016/j.ijinfomgt.2020.102168>

Elalem, Y. K., Maier, S., & Seifert, R. W. (2022). A machine learning-based framework for forecasting sales of new products with short life cycles using deep neural networks. *International Journal of Forecasting*. <https://doi.org/10.1016/j.ijforecast.2022.09.005>

Fan, Z.-P., Che, Y.-J., & Chen, Z.-Y. (2017). Product sales forecasting using online reviews and historical sales data: A method combining the Bass model and sentiment analysis. *Journal of Business Research*, 74, 90–100. <https://doi.org/10.1016/j.jbusres.2017.01.010>

Fildes, R., Goodwin, P., Lawrence, M., & Nikolopoulos, K. (2009). Effective forecasting and judgmental adjustments: An empirical evaluation and strategies for improvement in supply-chain planning. *International Journal of Forecasting*, 25, 3–23. <https://doi.org/10.1016/j.ijforecast.2008.11.010>

Fildes, R., Ma, S., & Kolassa, S. (2022). Retail forecasting: Research and practice. *International Journal of Forecasting, Special Issue: M5 competition*, 38, 1283–1318. <https://doi.org/10.1016/j.ijforecast.2019.06.004>

Fischer, I., & Harvey, N. (1999). Combining forecasts: What information do judges need to outperform the simple average? *International Journal of Forecasting*, 15, 227–246. [https://doi.org/10.1016/S0169-2070\(98\)00073-9](https://doi.org/10.1016/S0169-2070(98)00073-9)

Fu, Y., & Fisher, M. (2023). The value of social media data in fashion forecasting. *Manufacturing & Service Operations Management*, 25, 1136–1154. <https://doi.org/10.1287/msom.2023.1193>

Giri, C., Thomassey, S., & Zeng, X. (2019). Exploitation of social network data for forecasting garment sales. *International Journal of Computational Intelligence Systems*, 12, 1423. <https://doi.org/10.2991/ijcis.d.191109.001>

Goodwin, P., & Fildes, R. (2022). Forecasting with judgment. In S. Salhi, & J. Boylan (Eds.), *The Palgrave handbook of operations research* (pp. 541–572). Springer International Publishing. https://doi.org/10.1007/978-3-030-96935-6_16

Grover, P., Kar, A. K., & Dwivedi, Y. (2022). The evolution of social media influence - A literature review and research agenda. *International Journal of Information Management Data Insights*, 2, Article 100116. <https://doi.org/10.1016/j.ijimei.2022.100116>

Hanaysha, J. R. (2022). Impact of social media marketing features on consumer's purchase decision in the fast-food industry: Brand trust as a mediator. *International Journal of Information Management Data Insights*, 2, Article 100102. <https://doi.org/10.1016/j.ijimei.2022.100102>

Hasani, M., Angela Sihotang, E., Pratama, G., Kurniawan, A., & Utama, D. (2023). Systematic literature review of decision support system for social media. *Journal of Theoretical and Applied Information Technology*, 101, 1020–1028.

He, W., Guo, L., Shen, J., & Akula, V. (2016). Social media-based forecasting: A case study of tweets and stock prices in the financial services industry. *Journal of Organizational and End User Computing (JOEUC)*, 28, 74–91. <https://doi.org/10.4018/JOEUC.2016040105>

Hicham, N., & Karim, S. (2023). Machine learning applications for consumer behavior prediction. In M. Ben Ahmed, A. A. Boudhir, D. Santos, R. Dionisio, & N. Benaya (Eds.), *Innovations in smart cities applications volume 6, lecture notes in networks and systems* (pp. 666–675). Springer International Publishing. https://doi.org/10.1007/978-3-031-26852-6_62

Hu, X., Yang, Y., Chen, L., & Zhu, S. (2020). Research on a prediction model of online shopping behavior based on deep forest algorithm. In *2020 3rd international conference on artificial intelligence and big data (ICAIBD)*. Presented at the 2020 3rd international conference on artificial intelligence and big data (ICAIBD) (pp. 137–141). IEEE. <https://doi.org/10.1109/ICAIBD49809.2020.9137436>

Hu, Y., Xu, A., Hong, Y., Gal, D., Sinha, V., & Akkiraju, R. (2019). Generating business intelligence through social media analytics: Measuring brand personality with consumer-, employee-, and firm-generated content. *Journal of Management Information Systems*, 36, 893–930. <https://doi.org/10.1080/07421222.2019.1628908>

Iftikhar, R., & Khan, M. S. (2020). Social media big data analytics for demand forecasting: Development and case implementation of an innovative framework. *Journal of Global Information Management*, 28, 103–120. <https://doi.org/10.4018/JGIM.2020010106>

Khan, U., & DePaoli, A. (2024). Brand loyalty in the face of stockouts. *Journal of the Academy of Marketing Science*, 52, 44–74. <https://doi.org/10.1007/s11747-023-00924-8>

Kitsios, F., Mitsopoulou, E., Moustaka, E., & Kamariotou, M. (2022). User-Generated Content behavior and digital tourism services: A SEM-neural network model for information trust in social networking sites. *International Journal of Information*

- Management Data Insights, 2, Article 100056. <https://doi.org/10.1016/j.jjimei.2021.100056>
- Kursa, M. B., Jankowski, A., & Rudnicki, W. R. (2010). Boruta - A system for feature selection. *Fundamenta Informaticae*, 101, 271–285. <https://doi.org/10.3233/FI-2010-288>
- Lassen, N. B., Madsen, R., & Vatrapu, R. (2014). Predicting iPhone sales from iPhone tweets. In *2014 IEEE 18th international enterprise distributed object computing conference. Presented at the 2014 IEEE 18th international enterprise distributed object computing conference* (pp. 81–90). <https://doi.org/10.1109/EDOC.2014.20>
- Lee, C., Xu, X., Lin, C.-C., Lee, C., Xu, X., & Lin, C.-C. (2019). Using online user-generated reviews to predict offline box-office sales and online DVD store sales in the O2O Era. *Journal of theoretical and applied electronic commerce research*, 14, 68–83. <https://doi.org/10.4067/S0718-18762019000100106>
- Lei, D., Hu, H., Geng, D., Zhang, J., Qi, Y., Liu, S., et al. (2023). New product life cycle curve modeling and forecasting with product attributes and promotion: A Bayesian functional approach. *Production and Operations Management*, 32, 655–673. <https://doi.org/10.1111/poms.13892>
- Lin, X., & Wang, X. (2023). Towards a model of social commerce: Improving the effectiveness of e-commerce through leveraging social media tools based on consumers' dual roles. *European Journal of Information Systems*, 32, 782–799. <https://doi.org/10.1080/0960085X.2022.2057363>
- Luo, Z., Guo, J., Benitez, J., Scaringella, L., & Lin, J. (2024). How do organizations leverage social media to enhance marketing performance? Unveiling the power of social CRM capability and Guanxi. *Decision Support Systems*, 178, Article 114123. <https://doi.org/10.1016/j.dss.2023.114123>
- Maaß, D., Spruit, M., & de Waal, P. (2014). Improving short-term demand forecasting for short-lifecycle consumer products with data mining techniques. *Decision Analytics*, 1, 1–17. <https://doi.org/10.1186/2193-8636-1-4>
- Maddikunta, P. K. R., Pham, Q.-V., B. P., Deepa, N., Dev, K., Gadekallu, T. R., et al. (2022). Industry 5.0: A survey on enabling technologies and potential applications. *Journal of Industrial Information Integration*, 26, Article 100257. <https://doi.org/10.1016/j.jii.2021.100257>
- Marmier, F., & Cheikhrouhou, N. (2010). Structuring and integrating human knowledge in demand forecasting: A judgemental adjustment approach. *Production Planning & Control*, 21, 399–412. <https://doi.org/10.1080/09537280903454149>
- Mas-Machuca, M., Sainz, M., & Martinez-Costa, C. (2014). A review of forecasting models for new products. *Intangible Capital*, 10, 1–25. <https://doi.org/10.3926/ic.482>
- Montaño Moreno, J. J., Palmer Pol, A., Sesé Abad, A., & Cajal Blasco, B. (2013). Using the R-MAPE index as a resistant measure of forecast accuracy. *Psicothema*, 25, 500–506. <https://doi.org/10.7334/psicothema2013.23>
- Newell, S., & Marabelli, M. (2015). Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of 'datification'. *The Journal of Strategic Information Systems*, 24, 3–14. <https://doi.org/10.1016/j.jsis.2015.02.001>
- Onofrei, G., Filieri, R., & Kennedy, L. (2022). Social media interactions, purchase intention, and behavioural engagement: The mediating role of source and content factors. *Journal of Business Research*, 142, 100–112. <https://doi.org/10.1016/j.jbusres.2021.12.031>
- Ortigosa, A., Martín, J. M., & Carro, R. M. (2014). Sentiment analysis in Facebook and its application to e-learning. *Computers in Human Behavior*, 31, 527–541. <https://doi.org/10.1016/j.chb.2013.05.024>
- Parviero, R., Hellton, K. H., Haug, O., Engo-Monsen, K., Rognebakke, H., Canright, G., et al. (2022). An agent-based model with social interactions for scalable probabilistic prediction of performance of a new product. *International Journal of Information Management Data Insights*, 2, Article 100127. <https://doi.org/10.1016/j.jjimei.2022.100127>
- Petropoulos, F., Apiletti, D., Assimakopoulos, V., Babai, M. Z., Barrow, D. K., Ben Taieb, S., et al. (2022). Forecasting: Theory and practice. *International Journal of Forecasting*, 38, 705–871. <https://doi.org/10.1016/j.ijforecast.2021.11.001>
- Petropoulos, F., Kourentzes, N., Nikolopoulos, K., & Siemsen, E. (2018). Judgmental selection of forecasting models. *Journal of Operations Management*, 60, 34–46. <https://doi.org/10.1016/j.jom.2018.05.005>
- Rishika, R., Kumar, A., Janakiraman, R., & Bezawada, R. (2013). The effect of customers' social media participation on customer visit frequency and profitability: An empirical investigation. *Information Systems Research*, 24, 108–127.
- Rousidis, D., Koukaras, P., & Tjortjis, C. (2020). Social media prediction: A literature review. *Multimedia Tools and Applications*, 79, 6279–6311. <https://doi.org/10.1007/s11042-019-08291-9>
- Saunders, L. W., Merrick, J. R. W., Austry, C. W., & Holcomb, M. C. (2024). New product family demand planning: Addressing SKU-level spread bias. *Journal of Business Logistics*, 45, e12373. <https://doi.org/10.1111/jbl.12373>
- Schaer, O., Kourentzes, N., & Fildes, R. (2019). Demand forecasting with user-generated online information. *International Journal of Forecasting*, 35, 197–212. <https://doi.org/10.1016/j.ijforecast.2018.03.005>
- Seifert, M., Siemsen, E., Hadida, A. L., & Eisingerich, A. E. (2023). Effective judgmental forecasting in the context of fashion products (Reprint). In M. Seifert (Ed.), *Judgment in predictive analytics, International series in operations research & management science* (pp. 85–114). Springer International Publishing. https://doi.org/10.1007/978-3-031-30085-1_4
- Shen, B., Xu, X., & Yuan, Q. (2023). Demand learning through social media exposure in the luxury fashion industry: See now buy now versus see now buy later. *IEEE Transactions on Engineering Management*, 70, 1295–1311. <https://doi.org/10.1109/TEM.2020.3009742>
- Shi, J. (2022). Application of the model combining demand forecasting and inventory decision in feature based newsvendor problem. *Computers & Industrial Engineering*, 173, Article 108709. <https://doi.org/10.1016/j.cie.2022.108709>
- Sindhvani, R., Afridi, S., Kumar, A., Banaitis, A., Luthra, S., & Singh, P. L. (2022). Can industry 5.0 revolutionize the wave of resilience and social value creation? A multi-criteria framework to analyze enablers. *Technology in Society*, 68, Article 101887. <https://doi.org/10.1016/j.techsoc.2022.101887>
- Sindhvani, R., Behl, A., Singh, R., & Kumari, S. (2024). Can Industry 5.0 develop a resilient supply chain? An integrated decision-making approach by analyzing 15.0 CSFs. *Information Systems Frontiers*. <https://doi.org/10.1007/s10796-024-10486-x>
- Swaminathan, K., & Venkatasubramony, R. (2023). Demand forecasting for fashion products: A systematic review. *International Journal of Forecasting*. <https://doi.org/10.1016/j.ijforecast.2023.02.005>. S0169207023000134.
- Trapero, J. R., Kourentzes, N., & Fildes, R. (2012). Impact of information exchange on supplier forecasting performance. *Omega, Special Issue on Forecasting in Management Science*, 40, 738–747. <https://doi.org/10.1016/j.omega.2011.08.009>
- Van den Broeke, M., De Baets, S., Vereecke, A., Baecke, P., & Vanderheyden, K. (2019). Judgmental forecast adjustments over different time horizons. *Omega*, 87, 34–45. <https://doi.org/10.1016/j.omega.2018.09.008>
- Wehrle, M., Birkel, H., von der Gracht, H. A., & Hartmann, E. (2022). The impact of digitalization on the future of the PSM function managing purchasing and innovation in new product development – Evidence from a Delphi study. *Journal of Purchasing and Supply Management*, 28, Article 100732. <https://doi.org/10.1016/j.pursup.2021.100732>
- Wibowo, A., Chen, S.-C., Wiangin, U., Ma, Y., & Ruangkanjanases, A. (2021). Customer behavior as an outcome of social media marketing: The role of social media marketing activity and customer experience. *Sustainability*, 13, 189. <https://doi.org/10.3390/su13010189>
- Xie, K., & Lee, Y.-J. (2015). Social media and brand purchase: Quantifying the effects of exposures to earned and owned social media activities in a two-stage decision making model. *Journal of Management Information Systems*, 32, 204–238. <https://doi.org/10.1080/07421222.2015.1063297>
- Xie, P., Chen, H., & Hu, Y. J. (2020). Signal or noise in social media discussions: The role of network cohesion in predicting the bitcoin market. *Journal of Management Information Systems*, 37, 933–956. <https://doi.org/10.1080/07421222.2020.1831762>
- Xu, Z., Frankwick, G. L., & Ramirez, E. (2016). Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. *Journal of Business Research*, 69, 1562–1566. <https://doi.org/10.1016/j.jbusres.2015.10.017>
- Yang, J., Xiu, P., Sun, L., Ying, L., & Muthu, B. (2022). Social media data analytics for business decision making system to competitive analysis. *Information Processing & Management*, 59, Article 102751. <https://doi.org/10.1016/j.ipm.2021.102751>
- Zhang, C., Tian, Y.-X., & Fan, Z.-P. (2022a). Forecasting the box offices of movies coming soon using social media analysis: A method based on improved Bass models. *Expert Systems with Applications*, 191, Article 116241. <https://doi.org/10.1016/j.eswa.2021.116241>
- Zhang, C., Tian, Y.-X., & Fan, Z.-P. (2022b). Forecasting sales using online review and search engine data: A method based on PCA–DSFOA–BPNN. *International Journal of Forecasting*, 38, 1005–1024. <https://doi.org/10.1016/j.ijforecast.2021.07.010>