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ORIGINAL RESEARCH

Forecasting duty-free shopping demand with multisource data: a deep learning approach

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Abstract

Accurate forecasting of duty-free shopping demand plays a pivotal role in strategic and operational decision-making processes. Despite the extensive literature on sustainability, operations management, and consumer behavior in the context of duty-free shopping, there is a noticeable absence of an integrated end-to-end solution for precise demand forecasting. Furthermore, existing forecasting models often encounter limitations in effectively leveraging multi-source data as reliable indicators for duty-free shopping demand. To address these gaps, our study introduces a pioneering deep-learning architecture known as the Attention-Aided Interaction-Driven Long Short-Term Memory-Convolutional Neural Network Model (AI-LCM). Designed to capture intricate cross-correlations within multi-source data, encompassing search queries, COVID-19 impact, economic factors, and historical data; this model represents a significant methodological advancement. Rigorous evaluation against state-of-the-art benchmarks conducted on robust real-world datasets confirms the superior forecasting performance exhibited by our AI-LCM model. We elucidate the manifold implications for various stakeholders while illustrating the extensive applicability of our model and its potential to inform data-driven decision-making strategies.

Keywords Duty-free shopping · Demand forecasting · Deep learning · Cross-correlation · Time series · Multisource data

1 Introduction

Non-aviation business is vital to the economic viability of airports, constituting nearly half of all revenues (Fasone et al., 2016). As the core of the non-aviation business, duty-free shopping has become one of the most popular tourism activities among passengers (Han et al., 2018a,

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2018b). According to Statista (www.statista.com),[1] there has been a steady increase in the proportion of U.S. airport passengers visiting duty-free shops over time, reaching its highest point at 39% in 2021. The duty-free industry has become an important element of tourism infrastructure in many countries such as China and Korea. In Hainan province alone, duty-free sales reached \$7.38 billion in 2021, contributing to 35.76% of total tourism income according to Haikou Customs.[2]

The duty-free industry, however, has witnessed significant volatility in recent years. For instance, due to the COVID-19 pandemic, Dubai duty-free that usually competes with Incheon International Airport for the leading position in the industry, experienced a drastic 67% decline in 2020.[3] Forecasting can provide a systematic foundation for comprehending the factors that influence the volatility of the duty-free industry. It is crucial to obtain an accurate forecast of duty-free shopping demand to make well-informed investment and planning decisions (Birim et al., 2022). Precise forecasting of duty-free shopping demand enables governments to make informed policy and infrastructure development choices while organizations can establish appropriate inventory levels, price their products effectively, and determine future expansion or contraction strategies. Therefore, it is imperative to develop effective models for forecasting duty-free shopping demand to facilitate informed decision-making.

Duty-free shopping is a form of shopping tourism (Choi et al., 2017). Previous studies have examined the impact of search query data, economic indicators, and the COVID-19 pandemic on forecasting tourism demand. We contend that these factors can be utilized to forecast duty-free shopping demand. Our considerations are as follows. Firstly, with rapid technological advancements, tourists can utilize search engines to conduct keyword searches for information on the Internet. Search query data reflects tourists' interests in specific topics (Law et al., 2019; Li et al., 2020; Xie et al., 2021a, 2021b), making it for forecasting duty-free shopping demand. Secondly, economic growth significantly impacts shopping tourism (Aratuo & Etienne, 2019). Prior research has demonstrated correlations between various economic indicators and tourism demand (Song et al., 2019). Changes in tourism demand can affect duty-free shopping. Therefore, considering the impact of economic indicators when forecasting duty-free shopping demand would be advantageous. Lastly, the COVID-19 pandemic has had a profound effect on the tourism industry (Pham et al., 2021; Yang et al., 2021; Zhang et al., 2021). As airports worldwide have been devoid of travelers due to the pandemic's impact, duty-free shops have experienced substantial setbacks. Thus, incorporating the influence of the pandemic into forecasts for duty-free shopping demand would be beneficial.

Existing forecasting models, encompassing time-series model, econometric model, and machine learning algorithms, exhibit notable limitations. Primarily, these conventional approaches are inadequate in unraveling the intricate nonlinear dynamics inherent in multivariate time-series data. They often overlook both intra-modal and inter-modal cross-correlations among different variables types, resulting in a significant compromise to forecast accuracy. This research gap renders these models less effective for real-world applications and underscores a critical need for further investigation.

In the specific domain, the limitations of linear models become particularly evident as they fail to adequately capture the intricate nonlinear relationships that encompass multiple data sources, including search queries, economic metrics, and COVID-19 statistics. Recent studies have provided evidence supporting the nonlinearity in how search queries influence tourism

[1] https://www.statista.com/statistics/1270410/duty-free-shops-footfall-rate-us/.

[2] https://assets.kpmg/content/dam/kpmg/cn/pdf/en/2021/05/travel-retail-market-in-hainan-ftp.pdf.

[3] http://www.customs.gov.cn/haikou_customs/index/index.html.

shopping (Hu et al., 2023; Xie et al., 2021a, 2021b). Therefore, our research aims to contribute to the existing literature by employing a nonlinear methodology to comprehensively analyze the nuanced interplay among these diverse data sources.

The primary contributions of our research are as follows. Firstly, in contrast to previous studies that primarily focused on investigating factors influencing duty-free shopping, this study concentrates on the prediction of duty-free shopping demand using publicly available data. Specifically, we utilize search query data, the number of COVID-19 cases, and economic indicators to forecast future months' duty-free shopping demand. Secondly, this research makes a significant contribution to the field of duty-free shopping forecasting by introducing an innovative computational model: the Attention-Aided, Interaction-Driven Long Short-Term Memory-Convolutional Neural Network Model (AI-LCM). Methodologically, this study stands out by incorporating an interaction-based CNN layer explicitly designed to identify both intra- and inter-modal correlations within the multivariate time-series data. Consequently, AI-LCM not only enhances the accuracy of duty-free shopping demand forecasts but also serves as a valuable Information Technology (IT) artifact. This sophisticated modeling approach empowers various stakeholders ranging from government agencies to industry professionals with data-driven strategic decision-making capabilities characterized by enhanced confidence and precision.

The paper is organized as follows: Sect. 2 provides a literature review on duty-free shopping and tourism demand forecasting techniques. Our proposed method is detailed in Sect. 3. In Sect. 4, we present the datasets and empirical setting. The experimental results and practical implications are discussed in Sect. 5. Finally, the conclusion and potential future research directions are presented in Sect. 6.

2 Literature review

We review two literature streams: (1) recent studies on duty-free shopping to position our research within the context of existing duty-free shopping research, and (2) tourism demand forecasting techniques to identify the prevailing forecasting models.

2.1 Duty-free shopping research

Previous studies on duty-free shopping have primarily focused on two key areas: operations management (Christiansen & Smith, 2008; Hsu & Tang, 2019; Lee, 2016; Song & Lee, 2020; Weaver, 2017) and tourist behaviors (Choi & Park, 2017, 2020; Doong et al., 2012; Han & Hyun, 2018; Han et al., 2021, 2018a, 2018b, 2018a, 2018b; Hwang et al., 2021; Kwon et al., 2015; Martín et al., 2019; Sohn & Lee, 2017). We summarize the research focuses of these studies in Table 1. Operations management encompasses aspects such as optimal commodity taxation, strategic alliance partnerships, license assessment and duty-free leasing. For instance, Song and Lee (2020) propose a novel real-options pricing model to examine the impact of three determinants on airport duty-free leasing prices. Tourist behaviors encompass factors like satisfaction levels, shopping experiences, perceptions and purchasing patterns. As an example study in this area, Han et al., (2018a, 2018b) present a theoretical framework that investigates the influence of perceived value, satisfaction levels alternative attractiveness on tourist loyalty during duty-free shopping.

While duty-free shopping has been extensively researched, there is a scarcity of studies focusing on forecasting the demand for such shopping. Cha et al. (2020) exemplifies one

Table 1 Summary of selected duty-free shopping research

Category	Study	Research focuses
Tourist behavior	Han et al. (2021)	Traveler satisfaction and willingness
	Hwang et al. (2021)	Rapport between customers and salespersons
	Choi and Park (2020)	Factors affecting the behavioral intention
	Martin et al. (2019)	Duty-free shoppers' satisfaction
	Han et al., (2018a, 2018b)	Quality factors, value dimensions, trust and satisfaction
	Han et al., (2018a, 2018b)	Triggers of traveler loyalty
Operations management	Song and Lee (2020)	Pricing airport duty-free leasing
	Hsu and Tang (2019)	Strategic alliance partnerships
	Weaver (2017)	Relationships between mobility and sales strategies
	Lee (2016)	Business license assessment

study that employs linear regression to forecast future demand for frequently purchased items in airport duty-free shops. However, linear regression may not adequately capture nonlinear relationships between the dependent variable and independent variables, potentially impacting forecasting accuracy. Deep learning models have the ability to capture nonlinear correlations among independent variables and thus offer potential for improved forecasts of duty-free shopping demand. This constitutes the central focus and contribution of our study to the field of duty-free shopping research.

2.2 Tourism demand forecasting techniques

As duty-free shopping falls under the category of shopping tourism (Choi et al., 2017), we conduct a review of forecasting techniques used in tourism demand to identify prevailing methods and guide the development of our approach for duty-free shopping demand forecasting. In the of tourism demand studies, forecasting models can be categorized into three types: time series, econometric, and machine learning models. Table 2 provides an overview of relevant literature in each category.

Previous studies have primarily focused on time series and econometric models. Time series models can be classified as basic or advanced, both utilizing sequential values at regular intervals to predict future values (Peng et al., 2014). Basic time series models include naive, autoregressive, and moving average models (Song et al., 2019), while autoregressive integrated moving averages (ARIMAs) and their variants, such as seasonal ARIMAs (SARIMAs) (Jiao et al., 2020). The distinction between basic and advanced time series models lies in their consideration of trends and seasonality. However, it is important to note that time series models assume a linear relationship between independent variables and the dependent variable which may adversely affect forecast accuracy when dealing with nonlinear relationships (Yang et al., 2013).

Econometric models, which focus on the causality between economic factors and tourism demand, have garnered continuous interest in recent years. There are two types of econometric models: single equation models and multiple equation models. Single equation models forecast demand using a single demand equation, while multiple equation models employ

Table 2 Summary of selected studies on tourism demand forecasting

Category	Study	Method(s)	Research focuses
Time Series	Hu et al. (2021)	ARIMA	Search queries in tourism demand forecasting
	Chen et al. (2019)	M-STSM	Seasonal tourism demand forecasting
	Millan et al. (2018)	SARIMA	Rural tourism demand Forecasting
	Li et al. (2018)	ARX	Seasonal tourism demand forecasting
	Balli et al. (2018)	MWC	Policies uncertainties on tourism demand
Econometric	Nguyen (2022)	ADLM	Forecasting outbound tourism demand
	Jiang et al. (2021)	Copula-ECM	Forecasting inbound tourist arrivals
	Park et al. (2021)	SARIMAX	Forecasting tourism demand with online news
	Assaf et al. (2019)	BGVAR	Forecasting regional tourism demand
Machine learning	Li et al. (2022)	GCN	Forecasting tourism demand with spatiotemporal features
	Bi et al. (2022)	LSTM	Forecasting daily tourism demand
	Yi et al. (2021)	Encoder-decoder	Forecasting tourism demand
	Höpken (2021)	ANN	Forecasting tourist arrivals
	Zhang et al., (2020a, 2020b)	LSTM	Forecasting tourist flow with search query

ARIMA: autoregressive integrated moving average; M-STSM: multi-series structural time series model; ADLM: autoregressive distributed lag model; SARIMA: seasonal ARIMA; BGVAR: Bayesian global vector autoregressive; GCN: Graph convolutional network; LSTM: Long short-term memory; ANN, Artificial neural network

multiple demand equations (Song et al., 2019). Various types of single equation models exist, including single static regression, autoregressive distributed lag models (ADLM), error correction models (ECM), and autoregressive integrated moving averages with explanatory variable (ARIMAX). ADLM utilizes lagged influencing and demand variables for forecasting purposes, whereas single static regression only considers current influencing factors. ECM builds upon ADLM by additionally considering short-run error correction and long-run relationships between independent variables and the dependent variable. ARIMAX places greater emphasis on comprehending the dynamics of tourism demand rather than solely focusing on causality between independent variables and tourism demand. Multiple equation models, such as almost ideal demand system (AIDS), vector autoregressive (VAR) model and its variants like Bayesian VAR (BVAR), as well as vector error correction model (VECM), enable the capture of interdependencies among multiple time series data points, leading to promising forecasting performance. However, it is important to note that econometric models assume a causal relationship between independent variables and tourism demand; assumption can pose challenges when dealing with correlated factors (Assaf et al., 2018).

Recently, there has been a growing interest in the application of machine learning-based models for tourism demand forecasting. These models can be categorized into traditional machine learning models and deep learning models. Among traditional machine learning models, support vector regression (SVR) is widely utilized in the field of tourism forecasting (Chen & Wang, 2007; Ping-Feng et al., 2006). Unlike traditional machine learning models that require prior feature engineering, deep learning enables automatic feature extraction, thereby achieving state-of-the-art accuracy in tourism demand forecasting. Among deep learning models, ANN has been frequently employed for forecasting tourism demand (Chen et al., 2012; Höpken et al., 2021). Moreover, there has been an increased interest in leveraging LSTM and its variants to capture long-term dependencies within time series data for accurate forecasting (Bi et al., 2022; Bi et al., 2020; Huang & Zheng, 2021; Law et al., 2019; Y. Zhang et al., 2020a, 2020b). For instance, Law et al. (2019) successfully utilize LSTM to forecast monthly Macau arrival volumes with superior performance compared to other methods. Additionally, graph convolutional network (GCN) has also found applications in tourism demand forecasting by characterizing correlations among destinations and incorporating temporal dependency using LSTM (Li et al., 2022). While previous studies have made significant contributions to the field of tourism demand forecasting, it is crucial to acknowledge that real-world multivariate time series often exhibit complex nonlinear cross-correlations between time steps and variables within the series itself. Existing hotel demand forecasting models primarily focus on modeling cross-correlations in time dimension, failing to consider the nonlinear local correlations between variables within a given time series contextually leading to potential inaccuracies. Consequently, there is a necessity to develop more precise forecasting models that capture the complex and nonlinear cross-correlations within multivariate time series.

3 Research gaps and questions

Our literature review reveals several critical research gaps that require attention. First, existing literature on duty-free shopping has on areas such as operations management and tourist behavior. However, there is a notable absence of studies explicitly addressing the forecasting of duty-free shopping demand. The ability to accurately this demand is not just an academic exercise; it plays a crucial role in informed tactical and operational decision-making processes within the duty-free retail sector. Second, while machine learning-based models have been extensively used in tourism demand forecasting, they mainly capture cross-correlations in the temporal dimension alone. These models exhibit a noticeable limitation: they overlook cross-correlations arising from diverse data sources like economic indicators, search queries, and pandemic-related data. Based on these research gaps, we propose the following research questions:

(1) How can complex and nonlinear cross-correlations be extracted from multisource data and incorporated into duty-free shopping demand forecasting?
(2) Can we leverage the extracted cross-correlations to improve the performance of duty-free demand forecasting?

4 Methodology

In this reserach, we propose a novel computational framework called the AI-LCM, designed to accurately forecast impending demand in the duty-free shopping sector. The AI-LCM architecture comprises four interconnected layers: the Encoding Layer, Interaction-Based CNN Layer, Attention Layer, and Output Layer. Initially, the Encoding Layer plays a crucial role in encoding multivariate time-series data into a suitable format for further processing. Subsequently, the meticulously engineered Interaction-Based CNN Layer captures both intra- and inter-modal correlations to gain a nuanced understanding of variable interdependencies. Following that is the Attention Layer which acts as a computational mechanism to isolate and emphasize salient features and temporal dependencies within the processed data. Finally, accurate forecasts for duty-free shopping demand are generated using the Output Layer. A comprehensive visualization of AI-LCM architecture is presented in Fig. 1.

The model's design primarily focuses on the impacts of intra- and cross-modal interactions. Intra-modal interactions, which scrutinize the dynamics within a single data source, play a critical role in detecting subtle but essential market trends. This analysis is vital for forecasting as it dissects complex layers within individual variables to uncover patterns that may be obscured in a more general analysis. For instance, an examination of economic indicators such as the Purchasing Managers' Index (PMI), Consumer Confidence Index (CCI), and Real Effective Exchange Rate Index (REERI) reveals how shifts in one indicator often herald changes in others, thereby providing insights into emerging market trends. A case in point is how an increase in PMI, indicative of robust manufacturing activity, can foreshadow a rise in CCI, suggesting enhanced consumer confidence and potentially leading to an increase in duty-free shopping.

In contrast, inter-modal interactions are crucial for comprehensively understanding the convergence of different data sources in shaping market dynamics. In the context of duty-free shopping, where consumer decisions are influenced by various external factors, analyzing these interactions becomes imperative. Such analyses enable the model to present a holistic perspective, illustrating how diverse data sources such as economic conditions, public health data, and consumer search trends intersect to impact purchasing behaviors. For example, studying how improved REERI figures indicating favorable exchange rates combined with a decline in COVID-19 cases lead to an increase in travel-related searches provides valuable insights. Generally, this synergy between positive economic indicators and improving health conditions correlates with a rise in duty-free shopping as it enhances consumer confidence and willingness to spend.

4.1 Encoding layer

The LSTM architecture in the encoding layer is illustrated in Fig. 2, serving as the encoder for time series forecasting tasks by encapsulating multifaceted time series information. Specifically, LSTM excels at capturing long-term dependencies, effectively addressing the of vanishing and exploding gradient issues.

Supposing the input at time step t is $\mathrm{x}_t = \left(x_t^1, x_t^2, \ldots, x_t^n\right)$ and the hidden state at time step t-1 is h_{t-1}, where n represents the number of variables. The LSTM architecture includes three gates: the input gate, forget gate, and output gate. The input gate i determines how input data is integrated into candidate memory cell $\widetilde{c}$, while the forget gate f controls the retention of information (c_{t-1}) in memory cell. Previous memory can be stored and utilized in current time steps, if the forget gate remains approximately 1 and the input gate remains

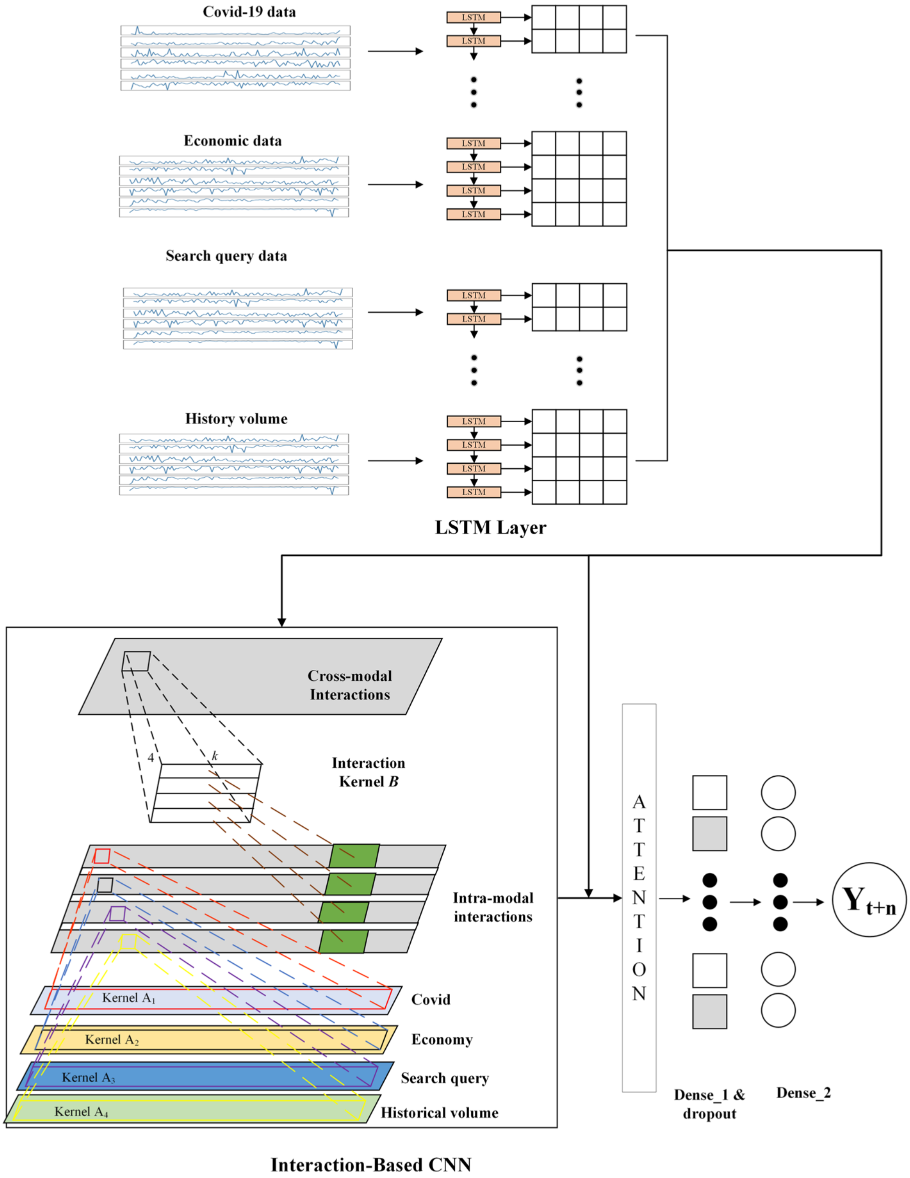


Fig. 1 AI-LCM Model

approximately 0 over time. This property enables LSTM to effectively capture long-term dependencies in issues such as vanishing and exploding gradient problems. The computation of these gates at time step t can be performed as follows:

$$i_t = \sigma(W_i[\mathrm{x}_t, h_{t-1}] + b_i) \tag{1}$$

$$f_t = \sigma\left(W_f[\mathrm{x}_t, h_{t-1}] + b_f\right) \tag{2}$$

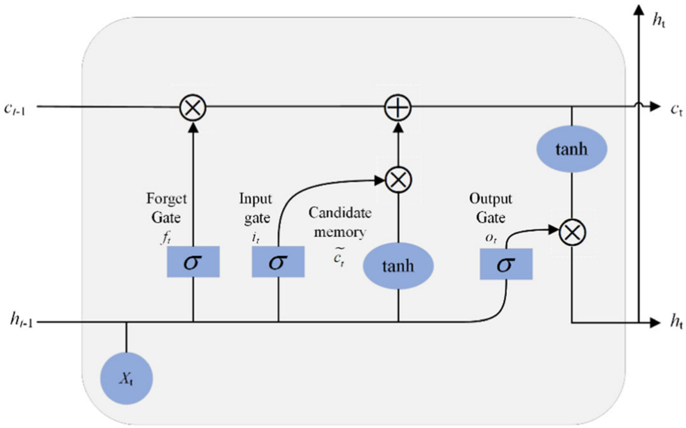


Fig. 2 LSTM Architecture

$$\widetilde{c}_t = \tanh(W_c[\mathrm{x}_t, h_{t-1}] + b_c) \tag{3}$$

$$c_t = f_t \otimes c_{t-1} + i_t \otimes \widetilde{c}_t \tag{4}$$

$$o_t = \sigma(W_o[\mathrm{x}_t, h_{t-1}] + b_o) \tag{5}$$

$$h_t = o_t \otimes \tanh(c_t) \tag{6}$$

where W_i, W_f, W_c, W_o represent the weight parameters, while b_i, b_f, b_c, b_o denote the bias parameters; additionally, σ and tanh are employed as activation functions. Finally, the temporal information of x_t is encoded and subsequently fed into the CNN layer.

We standardized the output dimensions of the LSTM across covid-19, economic, search query, and history volume data by setting them to be equivalent. Specifically, we ensured that the number of LSTM memory cells was set to l. Consequently, when applying LSTM to covid-19 data, the resulting output is denoted as $H^C = \left(h^c_{t-n+1}, h^c_{t-n+2}, \ldots, h^c_t\right) \in \mathbb{R}^{n \times l}$. Similarly, for economic data, search queries, and historical volume data, the output are $H^{\mathrm{E}} = \left(h^e_{t-n+1}, h^e_{t-n+2}, \ldots, h^e_{t-n+1}\right) \in \mathbb{R}^{n \times l}$, $H^S = \left(h^s_{t-n+1}, h^s_{t-n+2}, \ldots, h^s_{t-n+1}\right) \in \mathbb{R}^{n \times l}$, and $H^{\mathrm{D}} = \left(h^d_{t-n+1}, h^d_{t-n+2}, \ldots, h^d_{t-n+1}\right) \in \mathbb{R}^{n \times l}$, respectively.

4.2 Interaction-based CNN layer

Transitioning from the strengths to limitations of LSTM, it becomes evident that while LSTM excels at capturing temporal dependencies, it encounters challenges in identifying intricate relationships between heterogeneous data sources. Our primary focus lies in extracting intra- and cross-modal interactions, where intra-modal interactions denote correlations within the same data source's features and cross-modal interactions refer to correlations among features from different data sources. Conventional CNNs are typically applied directly on a adjacent rows with a length of b for capturing correlations within the focal region (as depicted on the left side of Fig. 3). However, these conventional CNNs fail to extract cross-modal correlations. To bridge this gap, we propose a specialized Interaction-Based CNN (I-CNN) layer designed explicitly for capturing both intra- and inter-modal interactions as illustrated in Fig. 3.

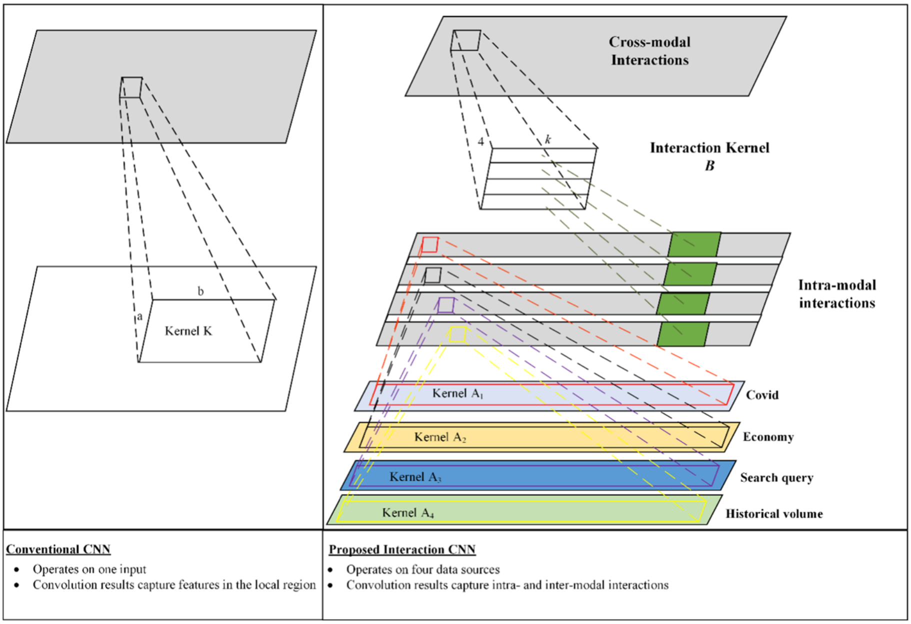


Fig. 3 Architecture of the interaction-based CNN Layer

The components of the I-CNN are described in detail as follows.

(1) The intra-modal interaction extraction layer is introduced. By employing 1D convolution, features within each data source are extracted. To align the dimensions between LSTM output 1D CNN input, Pytorch's permute function is utilized. This layer applies various kernelsA_1 to A_4, on $H^C = \left(h^c_{t-n+1}, h^c_{t-n+2}, \ldots, h^c_t\right) \in \mathbb{R}^{n\times l}$,$H^{\mathrm{E}} = \left(h^e_{t-n+1}, h^e_{t-n+2}, \ldots, h^e_{t-n+1}\right) \in \mathbb{R}^{n\times l}$, $H^S = \left(h^s_{t-n+1}, h^s_{t-n+2}, \ldots, h^s_{t-n+1}\right) \in \mathbb{R}^{n\times l}$, and $H^{\mathrm{D}} = \left(h^d_{t-n+1}, h^d_{t-n+2}, \ldots, h^d_{t-n+1}\right) \in \mathbb{R}^{n\times l}$, to extract intra-modal interactions. The convolution results are computed as follows:

$$c^{A_1}_{i^c, j^c} = \sum_{m^c=1}^{M^C} \sum_{f^c=1}^{F^C} w_{m^c, f^c} \cdot x_{i^c+m^c, j^c+f^c} + b^c \tag{7}$$

$$c^{A_2}_{r^e, j^e} = \sum_{m^e=1}^{M^E} \sum_{f^e=1}^{F^E} w_{m^e, f^e} \cdot x_{i^e+m^e, j^e+f^e} + b^e \tag{8}$$

$$c^{A_3}_{i^s, j^s} = \sum_{m^s=1}^{M^S} \sum_{f^s=1}^{F^S} w_{m^s, f^s} \cdot x_{i^s+m^s, j^s+f^s} + b^s \tag{9}$$

$$c^{A_4}_{r^d, j^d} = \sum_{m^d=1}^{M^D} \sum_{f^d=1}^{F^D} w_{m^d, f^d} \cdot x_{i^d+m^d, j^d+f^d} + b^d \tag{10}$$

where $c^{A_1}_{i^c, j^c}$, $c^{A_2}_{r^e, j^e}$, $c^{A_3}_{i^s, j^s}$, and $c^{A_4}_{r^d, j^d}$ denote the output values on convolution kernels A_1, A_2,A_3, and A_4, respectively. The respective $m^c \times f^c$, $m^e \times f^e$, $m^s \times f^s$, and $m^d \times f^d$ weight matrix of convolution kernels A_1, A_2, A_3, and A_4 are denoted by w_{m^e, f^e}, w_{m^s, f^s} and w_{m^d, f^d}. The bias values are represented by b^c, b^e, b^s, and b^d.

After the convolution stage, we employ the rectified linear unit (ReLU) to introduce non-linearity in mapping the output of the convolution stage. The resulting outputs represent interactions within covid-19, economic, search query, and history volume data as ReLU($c^{A_1}_{i^c, j^c}$), ReLU($c^{A_2}_{i^e, j^e}$), ReLU($c^{A_3}_{i^s, j^s}$), and ReLU($c^{A_4}_{r^d, j^d}$), respectively. Subsequently, these outputs are flattened to obtain V^C = Flattern[ReLU($c^{A_1}_{i^c, j^c}$)] $\in \mathbb{R}^{1\times g}$, V^E = Flattern[ReLU($c^{A_2}_{i^e, j^e}$)] $\in \mathbb{R}^{1\times g}$, V^S = Flattern[ReLU($c^{A_3}_{i^s, j^s}$)] $\in \mathbb{R}^{1\times g}$, and V^D = Flattern[ReLU($c^{A_2}_{r^d, j^d}$)] $\in \mathbb{R}^{1\times g}$, where g denotes the hidden dimension. By concatenating V^C, V^E, V^S, and V^D together, we derive $V \in \mathbb{R}^{4\times g}$. Notably, the first row focuses on COVID-19 variables' interactions while the second row explores correlations among economic demand indicators. Additionally, the third row delves into intricacies of search query data interactions. Finally, capturing correlations within historical sales volume data is emphasized in the fourth row.

(2) Inter-modal interaction extraction layer. In this layer, we employ a CNN to capture the inter-modal interactions. We expand the dimension of V and input it into the CNN. The calculation of Inter-modal interactions can be expressed as follows:

$$c^B_{i^b, j^b} = \sum_{m^b=1}^{4} \sum_{f^b=1}^{k} w_{m^b, f^b} \cdot x_{i^b+m^b, j^b+f^b} + b^b \tag{11}$$

where $c^B_{i^b, j^b}$ represents the output value obtained from convolution kernels B, w_{m^b, f^b} denotes respective $4 \times k$ weight matrix of convolution kernels B, and $x_{i^b+m^b, j^b+f^b}$ denotes the element in i^b row and j^b column of V. Additionally, b^b is the bias value. By utilizing kernel B, we can able to jointly capture sources.

The rectified linear unit (ReLU) is employed post the convolution stage to introduce non-linearity into the model, thereby enhancing its performance. A max-pooling layer is utilized for dimension reduction and local scale invariance augmentation. Subsequently, the output of the interaction-based CNN is flattened into a vector, as represented by:

Z = Flattern[MaxPool(ReLU($c^B_{q,t}$))](12).

4.3 Attention layer

Operating at the intersection of the model's architecture, this layer synergistically combines the outputs from the LSTM and Interaction-Based CNN layers. By doing so, the attention layer functions as a computational spotlight, focusing on pivotal features and temporal dependencies within the combined outputs. The inclusion of an attention layer is motivated by two considerations. Firstly, it enhances predictive accuracy by capturing critical temporal and feature-dependent subtleties in the combined outputs. Secondly, it plays a crucial role in understanding complex interactions among features such as COVID-19 effects, economic indicators, and search query data to provide actionable insights for stakeholders involved in duty-free shopping.

The attention mechanism employs a soft attention mechanism that computes a weighted sum of these outputs as follows.

$$O^A = Attn\left(\left[H^C, H^E, H^S, H^D, Z\right]\right) \tag{13}$$

where O^A represents the output of attention mechanism.

4.4 Output layer

During the forecasting stage, we input O^A into two fully connected layers and employ a layer to predict the hotel demand at time $t + n$. The computation of hotel demand Y_{t+n} at time $t + n$ is follows:

$$d_i = \mathrm{ReLU}(W_{d,1} O^A + b_{d,1}) \tag{14}$$

$$Y_{t+n} = \mathrm{Linear}\big(W_{d,2}\mathrm{Drop}(d_i) + b_{d,2}\big) \tag{15}$$

where $W_{d,1}$, $W_{d,2}$, $b_{d,1}$, $b_{d,2}$ represent parameters that undergo training. It should be noted that dropout layer has been incorporated between the two fully connected layers to mitigate overfitting.

5 Empirical setup

5.1 Data collection

In recent years, China's duty-free industry has experienced rapid development, with its total sales now ranking among the top in the world. According to the Moodie Davitt Report,[4] China Duty Group (CDFG) achieved the highest turnover globally and was recognized as the largest travel retailer in 2020. The Haikou market serves as a prime example of a booming duty-free shopping sector characterized by high transaction volumes. The generous tax exemptions in Haikou create a vibrant and dynamic marketplace that provides an ideal testing ground for our model's validation and applicability. The accurate demand forecasting demonstrated by our model within such a dynamic market environment attests to its robustness and potential adaptability across various settings, even those with different market characteristics.

Additionally, the distinctive attributes of the Haikou market facilitate the capture of intricate patterns and relationships that may not be discernible in markets with more constrained duty-free shopping environments. Consequently, this yields a comprehensive dataset that potentially enables more nuanced insights a holistic understanding of various factors influencing demand for duty-free shopping. Therefore, we retrieve the monthly duty-free shopping volumes from Haikou Customs of China encompassing the period from January 2012 to March 2022. Figure 4 illustrates the shopping volumes in Haikou market.

In this study, we incorporate a variety of data sources, including search queries, economic indicators, and the COVID-19 pandemic, to forecast duty-free shopping demand. It is important to note that airport passenger traffic volume can have a direct and significant influence on duty-free shopping demand. However, due to limitations in accessing comprehensive and reliable datasets on passenger traffic during our research period. We discuss the multisource data as follows.

Search query. Previous research has demonstrated the potential of search query data to enhance tourism demand forecasting accuracy, making it a promising indicator of tourism demand. Building on prior research (Liu et al., 2015; Xie et al., 2021a, 2021b), we identified relevant duty-free shopping-related keywords using Baidu Search's query section developed

[4] https://www.moodiedavittreport.com/china-duty-free-group-leads-global-travel-retailer-rankings-for-2020/.

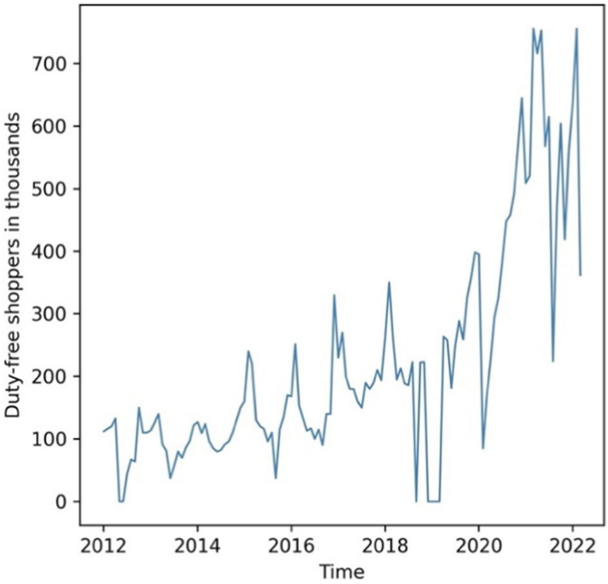


Fig. 4 Monthly shopping volumes of Haikou Customs of China

a Python program to extract corresponding search index data from Baidu. Due to low volume limitations imposed by Baidu, only ten keywords were included in this study and are presented in Table 3.

Economic indicators. Regarding economic indicators, we utilize widely recognized metrics in previous studies, namely the Purchasing Managers' Index (PMI), Consumer Confidence Index (CCI), and Real Effective Exchange Rate Index (REERI) (Xie et al., 2021a, 2021b). PMI, obtained through a monthly survey of supply chain managers across 19 industries encompassing both upstream and downstream sectors, provides insights into the prevailing direction of economic trends. The CCI is based on the premise that optimistic

Table 3 The Selected Keywords from Baidu

No	Keyword
1	Hainan duty-free policy
2	Sanya duty-free shopping guide
3	Hainan duty-free
4	offore duty-free
5	Hainan duty-free shop
6	Haikou duty-free shop
7	Sanya duty-free shop
8	Hainan duty-free official website
9	Haikou duty-free official website
10	Sanya duty-free official website

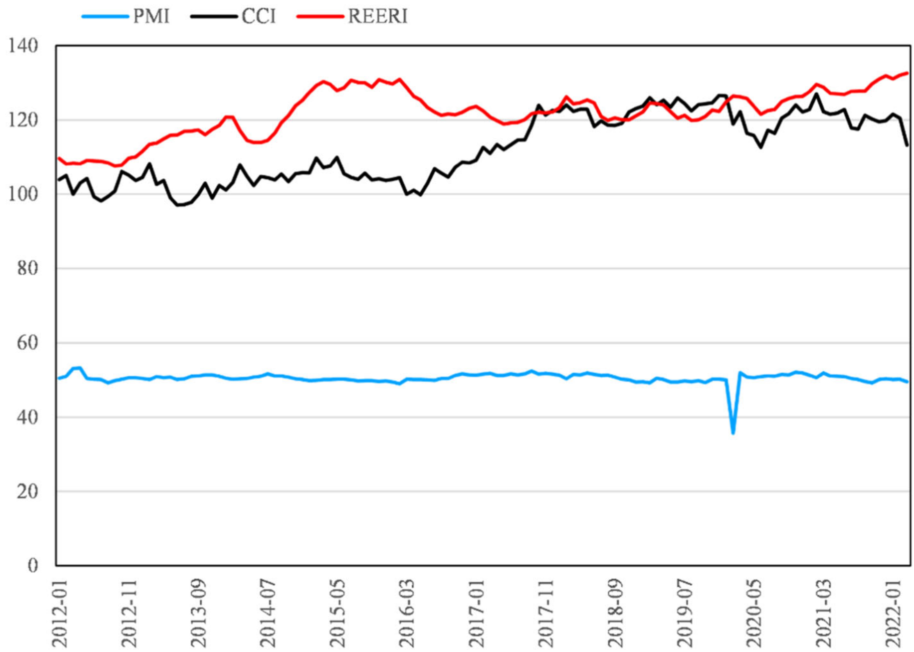


Fig. 5 Monthly PMI, CCI, and REERI

consumers tend to increase spending and stimulate economic growth, while pessimistic consumers may slow down or even trigger a recession. Calculated by averaging the currencies of a nation's major trading partners, REERI assesses the value of that nation's currency. Notably, REERI changes in currencies among key trading partners while excluding inflation to provide a more accurate reflection of a nation's international competitiveness. Figure 5 illustrates monthly trends for PMI, CCI, and REERI.

COVID-19 pandemic data. Considering the COVID-19 pandemic, the number of new cases reported each month is used to forecast duty-free shopping demand. Specifically, we collected the monthly new COVID-19 cases in China Mainland, including Hainan province and others. Figure 6 shows the monthly new COVID-19 cases in China Mainland.

5.2 Experiment design

We have designed two categories of experiments in this research. The first experiment thoroughly examines the forecasting accuracy of multisource data compared to historical data, utilizing a set of baseline models. The second experiment provides a comprehensive comparative analysis by contrasting our approach with various benchmarks that also leverage multisource data.

Dataset details and size. In this study, we utilized a meticulously designed compact dataset to extract precise insights. To ensure authenticity and reliability of the findings, we implemented a fourfold walking forward validation technique (as depicted in Fig. 7) that preserved the chronological order of data. The specifics of the data splits are detailed as follows:

- Split 1 comprises 52 training samples and 16 test samples.

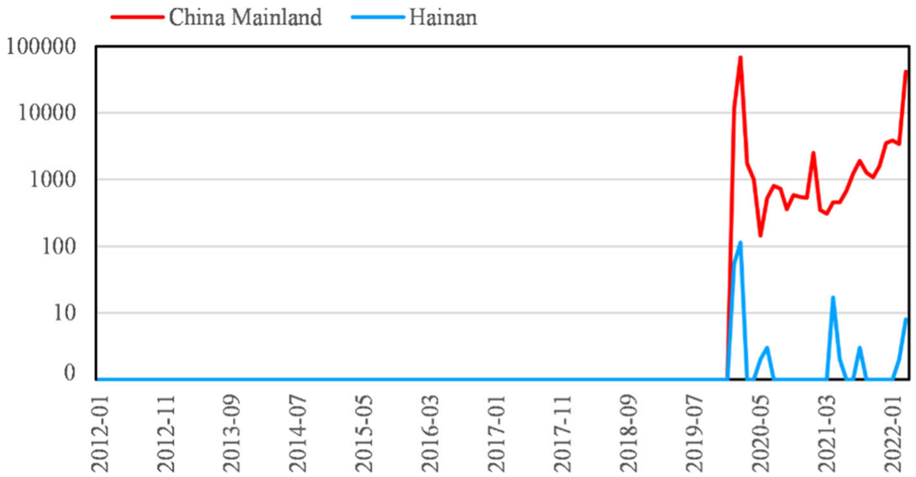


Fig. 6 Monthly new COVID-19 cases in China Mainland

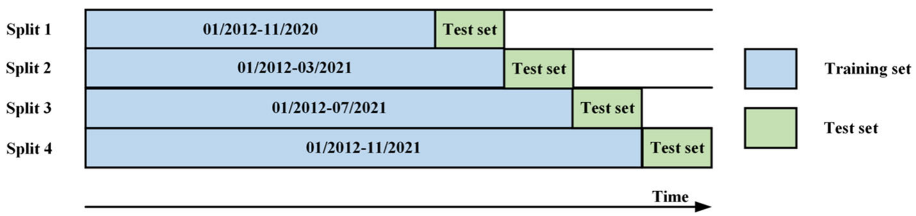


Fig. 7 Walk-forward cross-validation

- Split 2 comprises 68 training samples and 16 test samples.
- Split 3 comprises 84 training samples and 16 test samples.
- Split 4 comprises 100 training samples and 16 test samples.

This structured approach was conceived to harmoniously balance the size of the dataset with robust model training and testing requirements, thereby fostering an analysis grounded in rigor and precision.

Benchmark model selection. We have refined our benchmark selection to encompass models thatize sophistication in the contemporary field of duty-free shopping forecasting. This expanded range includes SVR and ANN. This progression leads to a suite of advanced neural network architectures, including LSTM, Attention Long Short-Term Memory (A-LSTM), Bidirectional Long Short-Term Memory (Bi-LSTM), Convolutional Neural Network integrated with Long Short-Term Memory (CNN-LSTM), and culminates in the Gated Recurrent Unit (GRU). Thus, we offer a comprehensive and nuanced comparative framework.

5.3 Performance metrics

The forecasting performance of our proposed model is evaluated using three well-established metrics: mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). These measures have been widely employed in previous studies to assess the disparity between actual and predicted demand (Chen et al., 2022; Hu, 2021; Jabeur et al., 2021; Özmen, 2021; Vovan et al., 2022). They are computed as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \overline{y_i}| \tag{16}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \overline{y_i})^2} \tag{17}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \frac{|y_i - \overline{y_i}|}{y_i} \tag{18}$$

where y_i represents the observed hotel demand in week i, while $\overline{y_i}$ denotes the predicted duty-free shopping demand in week i.

6 Results and discussions

6.1 Experiment 1: forecasting performance between models utilizing all features versus historical volumes

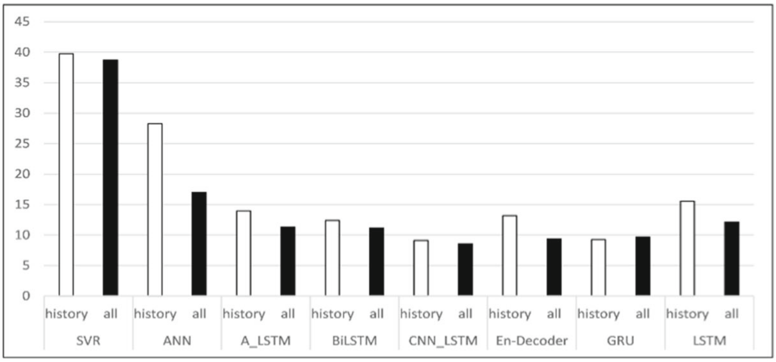
The primary objective of Experiment 1 is to address this essential requirement by examining the comparative performances of various well-established models using both historical and multisource data. The analyses are structured around three pivotal metrics: RMSE, MAE, and MAPE. Our findings are presented in Fig. 8, which illustrates the performance comparison between models utilizing all features versus historical volumes.

Notably, Fig. 8 demonstrates a significant improvement in model accuracy and precision when transitioning from a historical data framework to a multisource data schema. This positive trend is supported by consistent reductions in RMSE, MAE, and MA across nearly all evaluated models. For instance, the integration of multisource data leads to a substantial decrease in MAE for the ANN model from 24.0887 to 14.5545, highlighting its robustness.

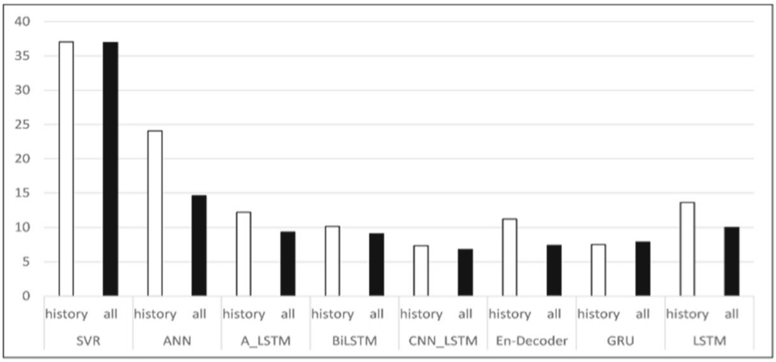
Additionally, Table 4 presents a comprehensive evaluation of the predictive performance demonstrated by various machine learning models. The analysis reveals a prominent trend indicating significant enhancements in both accuracy and precision of the models. Importantly, metrics such as RMSE, MAE, and MAPE exhibit statistically significant reductions for the majority of models. For instance, the incorporation of multisource data leads to a substantial decrease in MAE by 39.58% for the ANN model, thereby confirming its efficacy.

However, amidst this overarching pattern of enhanced performance, a fascinating anomaly emerges in the form of the GRU model. Contrary to initial expectations, the GRU model exhibits a marginal increase across all performance metrics when incorporating all features. This intriguing deviation raises inquiries regarding the model's sensitivity towards feature selection and suggests intricate interactions between features that may not follow a linear or straightforward additive relationship. Such divergent behavior serves as an intellectual catalyst for further research, stimulating exploration into the nuanced dynamics of feature interaction within neural network architectures.

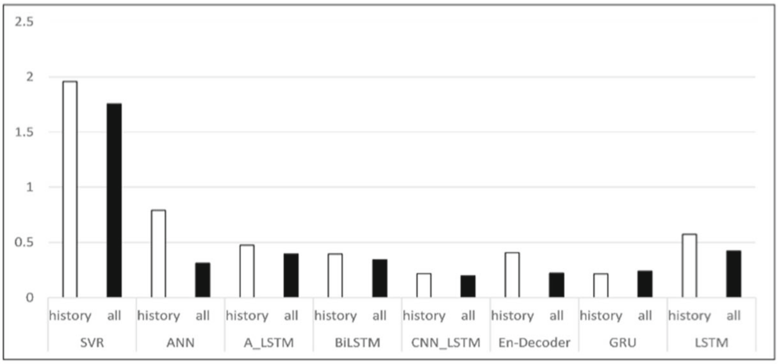
In conclusion, the empirical findings overwhelmingly endorse the efficacy of integrating multisource data in duty-free forecasting models. The statistically significant improvements observed in RMSE, MAE, and MAPE for most models present a compelling rationale for embracing such a comprehensive approach.



(a) Comparative Analysis of RMSE Between Models Utilizing All Features versus Historical Volumes



(b) Comparative Analysis of MAE Between Models Utilizing All Features versus Historical Volumes



(c) Comparative Analysis of MAPE Between Models Utilizing All Features versus Historical Volumes

Fig. 8 Performance comparison between models utilizing all features versus historical volumes

Table 4 Error reduction of model with all features vs. historical volumes

Model	RMSE	MAE	MAPE
SVR	2.60% (↓)***	0.23% (↓)***	10.27% (↓)**
ANN	39.83% (↓)	39.58% (↓)	60.48% (↓)**
A-LSTM	18.91% (↓)**	23.45% (↓)**	16.82% (↓)**
Bi-LSTM	9.86% (↓)*	10.06% (↓)*	13.31% (↓)
CNN-LSTM	6.14% (↓)*	7.13% (↓)*	9.86% (↓)***
Encoder-Decoder	28.87% (↓)***	33.55% (↓)***	45.33% (↓)***
GRU	− 4.25% (↑)	- 4.67% (↑)	− 12.30% (↑)
LSTM	22.30% (↓)*	26.23% (↓)*	26.73% (↓)

*, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$

6.2 Experiment 2: forecasting performance between our model and baseline models

This section presents a hierarchical evaluation of our proposed model compared to benchmark models, providing an in-depth analysis based on RMSE, MAE, and MAPE. The empirical results of this evaluation are summarized in Fig. 9 and Table 5. Figure 9 illustrates the performance comparison between our model and baseline models, while Table 5 offers a comprehensive assessment of the predictive performance of our proposed AI-LCM model against baseline models.

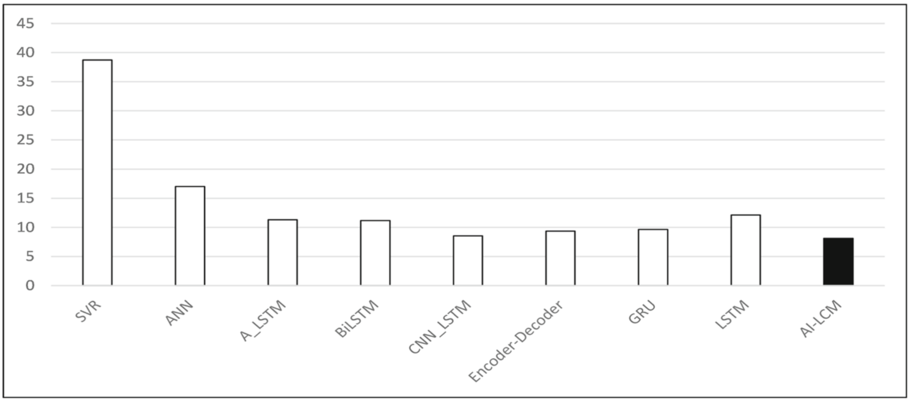
Several critical findings from the results are observed. Firstly, the most remarkable finding is the undeniable superiority of our model across all performance metrics. With an RMSE of 8.1306, MAE of 6.4147, and MAPE of 0.1892, our model surpasses all benchmarks, including advanced neural network architectures. When compared to CNN-LSTM, which emerged as the second-best performer, our model still exhibits statistically significant improvements, thereby emphasizing its robustness and predictive power.

Secondly, it is imperative to emphasize the remarkable performance of CNN-LSTM, which exhibits the second-lowest error metrics among benchmark models. With an RMSE of 8.5404, MAE of 6.8137, and MAPE of 0.1956, CNN-LSTM exemplifies that hybrid architectures can yield highly accurate forecasts despite not being as optimized as our model does; thus reinforcing the case for continuous exploration into hybrid neural network architectures.

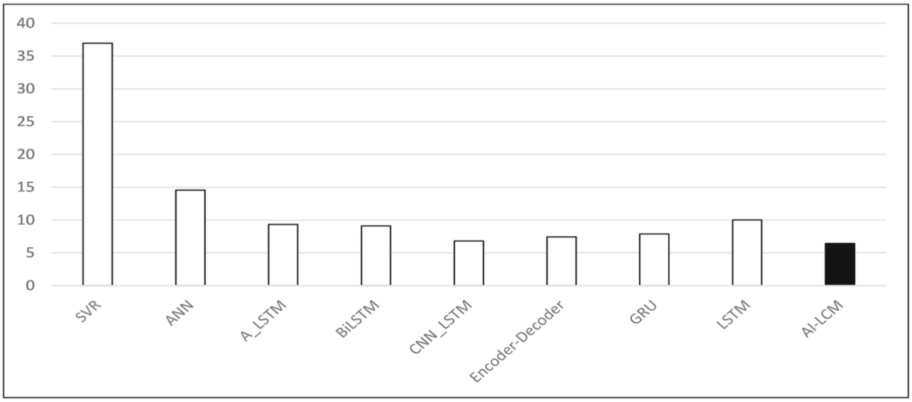
Thirdly, as demonstrated in Table 5, contemporary neural network architectures clearly outperform traditional methodologies such as SVR, which lags considerably behind. The significantly elevated RMSE of SVR, nearly 4.8 times greater than that of our model's, accentuates the limitations inherent in older methodologies and amplifies the merits associated with incorporating contemporary and sophisticated algorithms.

Fourthly, upon delving into the performance of alternative neural network architectures such as A-LSTM, BiLSTM, and GRU, it becomes evident that despite their competence, they fall short in matching the forecasting accuracy achieved by our model, particularly in terms of MAE and MAPE. Notably, although not leading the pack, GRU exhibits consistent performance which suggests potential for further improvements through architectural tuning.

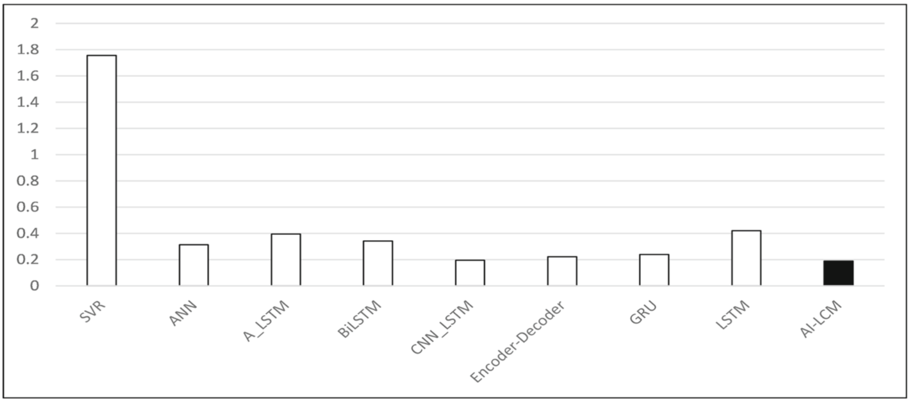
In summary, this hierarchical evaluation strongly supports the effectiveness of our proposed model across all key metrics. These findings play a crucial role in underlying this research and establish a new benchmark in duty-free shopping forecasting. Consequently,



(a) Comparative Analysis of RMSE Between Our Model and Baseline Models



(b) Comparative Analysis of MAE Between Our Model and Baseline Models



(c) Comparative Analysis of MAPE Between Our Model and Baseline Models

Fig. 9 Performance comparison between our model and baseline models

Table 5 Error reduction of our model vs. benchmarks with multisource data

Model	RMSE	MAE	MAPE
Our model vs. SVR	79.00% (↓)***	82.64% (↓)***	89.23% (↓)***
Our model vs. ANN	52.18% (↓)***	55.93% (↓)***	39.49% (↓)***
Our model vs. A-LSTM	28.19% (↓)***	31.27% (↓)***	52.05% (↓)***
Our model vs. Bi-LSTM	27.07% (↓)***	29.43% (↓)***	44.58% (↓)**
Our model vs. CNN-LSTM	4.80% (↓)*	5.86% (↓)	3.27% (↓)
Our model vs. Encoder-Decoder	13.26% (↓)***	13.63% (↓)***	14.77% (↓)***
Our model vs. GRU	15.77% (↓)***	18.51% (↓)**	21.23% (↓)***
Our model vs. LSTM	32.85% (↓)***	35.96% (↓)***	55.04% (↓)**

*, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$

this study contributes significantly to both academic discourse and practical applications while setting the stage for future research endeavors.

6.3 Feature importance analysis

The aim of this section is to determine the relative importance of various features that contribute to the prediction model for duty-free shopping forecasting. The analysis is systematically conducted over a three-month temporal horizon with lags, and the attention weights are presented in Fig. 10.

Several significant findings can be observed from Fig. 10. First, the feature group identified as ‘Interactions’—encompassing the dynamic relationships among COVID-19 data, economic indicators, search queries, and historical volumes—emerged as particularly influential, commanding an attention weight of approximately 44.7%. This finding underscores the criticality of the synergy between diverse features in augmenting the precision of duty-free shopping demand forecasting. To elucidate the significance of these interactions, consider the following instances:

- Combined Impact during the Pandemic: An illustrative example of complex inter-source interactions is the scenario where a rise in COVID-19 cases precipitates increased travel restrictions. This situation typically leads to a downturn in economic activities, manifesting in reduced consumer spending and shifts in consumer behavior. Concurrently, there is a noticeable shift in search queries towards health and safety products, moving away from luxury goods. This shift aligns with a decrease in historical sales volumes in duty-free shops due to diminished foot traffic. The AI-LCM model proficiently captures these concurrent fluctuations across various data sources, providing a comprehensive perspective of their combined impact on duty-free shopping demand.

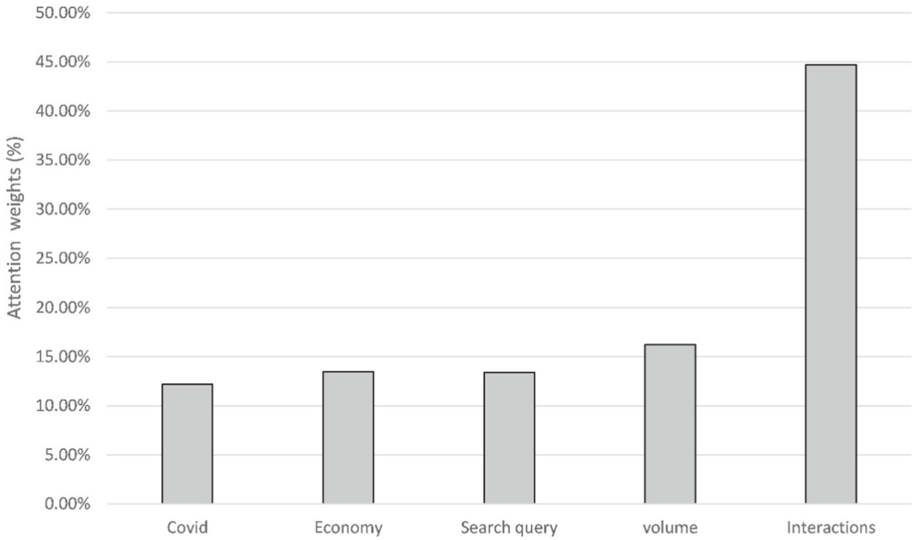


Fig. 10 Distribution of attention weights across different feature groups

- Economic Recovery Phase: In the economic recovery phase following the pandemic, there is often a noticeable increase in economic indicators, such as employment rates and consumer confidence. This improvement typically aligns with a rise in search queries for travel and luxury goods, indicating a latent demand for duty-free shopping. Concurrently, historical sales data often exhibit an upward trend, reflecting the market's recovery. The AI-LCM model's capacity to intricately analyze these concurrent interactions offers crucial predictive insights into the resurgence of duty-free shopping demand, demonstrating its utility in navigating post-pandemic market dynamics.

Second, the feature group 'Volume', which pertains to historical sales data, commands a notably high attention weight of approximately 16.24%. This emphasizes the intuitive yet critical role played by past demand trends in shaping future shopping behavior.

Third, the economic indicators and search query metrics are given almost equal weightage in the attention scores, with approximately 13.48% and 13.41% respectively. This emphasizes the balanced contribution of both micro and macroeconomic factors, as well as consumer interest reflected through search queries, to the forecasting model.

Fourth, among all considered groups, the 'Covid' feature group receives the lowest attention weight at around 12.18%. While it may seem less significant compared to other features, this non-negligible weight implies that pandemic-related variables still exert influence on duty-free shopping trends.

In our final discussion, we delve into a notable finding: the 'Interactions' feature group eclipsing the 'Volume' feature group in its contribution to prediction accuracy within the duty-free shopping market. The predominance of 'Interactions' over 'Volume' can be attributed to several factors:

- Dynamic Market Conditions: A pivotal factor in this trend is the substantial transformation the duty-free market has undergone, especially due to the COVID-19 pandemic. This shift has rendered historical sales data less predictive of future trends. The pandemic's extensive impact on consumer behavior, travel patterns, and economic conditions is not fully represented in past sales figures. Consequently, the ’Interactions’ feature, encompassing a wider array of current influencing factors, becomes a more accurate predictor of future market trends.

- Complex Data Interplays: Our AI-LCM model’s ability to discern complex interplays among diverse data sources affords a more detailed perspective of the current market environment. The convergence of economic impacts from the pandemic, as reflected in indicators like PMI and CCI, with the fluctuating trends in search queries, yields a more holistic and immediate understanding of the market. This comprehensive view enhances the predictive strength of the model beyond what historical volume data can offer.
- Predictive Power of Real-Time Data: In the swiftly changing landscape of duty-free shopping, real-time data sources such as economic indicators and search queries provide a more contemporaneous snapshot of market conditions. These sources excel at detecting rapid shifts in economic situations, which are essential for accurate short-term forecasting. Therefore, the focus of the ’Interactions’ feature group on these real-time elements significantly enhances its importance in predictive modeling, highlighting its pivotal role in understanding and forecasting market trends.

6.4 Ablation analysis of AI-LCM model components

Our ablation study focused on assessing the individual contributions of the Interaction-Based CNN (I-CNN) and the Attention (ATTN) layers, alongside the model’s LSTM component, to the overall performance of the AI-LCM model. The analysis involved evaluating variations of the AI-LCM model, each excluding one of its key components, and comparing their performance against the complete AI-LCM model. The results are summarized in Table 6.

Analysis of Table 6 yields the following crucial observations. First, the elimination of the I-CNN component resulted in a marked increase in error rates, signifying its critical role in the model. The I-CNN layer, responsible for capturing both intra- and inter-modal interactions, is integral to the model’s accuracy. Its proficiency in discerning complex correlations among various data sources substantially bolsters the model’s predictive capabilities.

Second, the removal of the LSTM layer led to a significant increase in errors, highlighting its essential role in processing time-series data. The LSTM is particularly crucial for recognizing long-term dependencies and trends, which are fundamental for precise forecasting in the duty-free shopping context.

Third, the exclusion of the ATTN layer also impacted model performance negatively, although its effect was less severe compared to the removal of the LSTM or I-CNN layers. The ATTN layer, which concentrates on identifying salient features within the data, contributes

Table 6 Ablation Analysis of AI-LCM Model Components

	RMSE	MAE	MAPE
AI-LCM/LSTM	12.5129	10.0560	1.2759
AI-LCM/I-CNN	14.2229	12.1205	0.4856
AI-LCM/ATTN	8.9166	6.9456	0.2166
AI-LCM	8.1306	6.4147	0.1892

AI-LCM without LSTM (AI-LCM/LSTM); AI-LCM without I-CNN (AI-LCM/I-CNN); AI-LCM without ATTN (AI-LCM/ATTN) meaningfully to the model's forecasting accuracy, albeit to a lesser extent than the LSTM and I-CNN components.

In summary, the ablation study underscores the hierarchical significance of the model's components. While each element plays a role in the overall efficacy of the AI-LCM model, the I-CNN layer emerges as the most pivotal for performance, followed by the LSTM, and then the ATTN layer. This delineation of component importance highlights the architectural strengths of the model and its adeptness in navigating the complexities inherent in forecasting for the duty-free shopping sector.

6.5 Practical implications

In recent years, there has been a significant increase in duty-free shopping, driven by evolving consumer behaviors and complex macroeconomic dynamics. This study presents pivotal insights into this landscape through the utilization of our AI-LCM, highlighting its superior forecasting capabilities compared to benchmark methods. Our model provides benefits for three key stakeholders: professionals, governments, and duty-free shops. We will discuss each category in detail.

- *Professionals*
- Decision support: Empirical evidence suggests that our model demonstrates exceptional performance across multiple metrics, establishing itself as a reliable decision-support tool. It enables professionals to enhance real-time decision-making, particularly in navigating the challenges posed by COVID-19, which is identified as an influential feature according to our comprehensive feature importance analysis. For instance, professionals can utilize our AI-LCM model to accurately predict duty-free shopping demands during the holiday season and subsequently adjust staffing and supply-chain strategies accordingly.
- Feature importance for strategic consideration: The meticulous analysis of feature importance sheds light on the dynamic contributions of various features at different time intervals. This empowers professionals to into factors such as economic indicators and consider their lagged effects on demand forecasting.
- *Government*.
- Resource allocation and infrastructure planning: Our model's demonstrated predictive accuracy empowers governments to strategically invest in various facilities, such as cafes and shopping districts, as well as broader infrastructural developments that synergize with the tourism, aviation, and hospitality sectors. These initiatives have the potential to significantly uplift the local economy and enhance international competitiveness.
- Regulatory adaptability: By comprehensively understanding how COVID-19 influences demand for duty-free shopping, governments can proactively formulate and adjust regulations to bolster industry resilience. If our model indicates a strong correlation between COVID-19 regulations and shopping demand, the government may consider implementing more lenient tax measures to stimulate the duty-free market.
- *Duty-free shops*.
- Targeted promotional strategies: The precise forecasts generated by our model facilitate the implementation of data-driven marketing campaigns. This extends to social media initiatives that can significantly broaden consumer reach and elevate product sales. For instance, duty-free shops could leverage limited-time promotions to capitalize on an upsurge in interest for specific brands or products.
- Inventory optimization: Armed with accurate forecasts, these retail establishments can optimize their inventory strategies effectively. This in a sector characterized by a diverse

range of products, spanning from luxury goods to essential travel items. Precise forecasts for high-demand goods like luxury watches during the holiday season can guide stock levels, preventing situations of excess inventory or stock-outs.

7 Conclusions

Duty-free shopping has gained increasing prominence in the airport business due to its significant revenue generation potential. Accurate forecasting of duty-free shopping demand plays a crucial role in maximizing profits and ensuring customer satisfaction by providing stakeholders with valuable information for informed decision-making. However, existing literature on duty-free shopping primarily focuses on operations management and tourist behaviors, overlooking the need for improved forecasting techniques. Furthermore, current forecasting methods struggle capture the intricate and nonlinear cross-correlations within multivariate time series data, leading to inaccurate predictions. There is a substantial opportunity for tourism scholars to develop innovative computational IT artifacts that leverage diverse data sources to enhance the performance of duty-free shopping forecasting.

We propose the AI-LCM as an innovative approach to address the complexities and nonlinear interdependencies inherent in multisource data. This model strategically incorporates LSTM networks for effective encoding of hidden representations within duty-free demand time-series data. Subsequently, we introduce an interaction-based CNN layer to extract both intra- and inter-modal correlations from the data. Following this extraction process, an attention mechanism is employed to focus on salient features. Rigorous empirical validation using a comprehensive real-world dataset demonstrates that the AI-LCM outperforms existing state-of-the-art methodologies in terms of predictive performance. This achievement signifies a significant advancement in the field of duty-free shopping demand forecasting, contributing to efforts aimed at enhancing predictive.

Our research presents a comprehensive analysis and application of the AI-LCM model in the context of duty-free shopping demand forecasting. While the results are promising, it is crucial to acknowledge the model's inherent limitations. A primary constraint of the AI-LCM model is its reliance on the quality and diversity of the input data. The model's proficiency in handling complex data sources is noteworthy; however, its effectiveness is intrinsically linked to the representativeness and completeness of the datasets. Any limitations or biases within these data sources can significantly undermine the model's ability to identify nuanced correlations and produce accurate forecasts. Furthermore, the generalizability of the AI-LCM model, though seemingly promising in the initial trials with the Haikou dataset, necessitates further investigation in varied contexts. This study lays the groundwork for utilizing the AI-LCM model in specific forecasting scenarios. Yet, its adaptability and performance in alternative datasets or different application domains require extensive exploration and rigorous validation. Future research should focus on addressing these limitations to enhance the model's applicability and accuracy in diverse settings.

There are several promising avenues for future research. Firstly, the COVID-19 pandemic has exerted a significant impact on consumer behavior in recent years. Subsequent investigations could explore strategies to integrate consumer behavior into duty-free demand forecasting. Secondly, our model has been validated using data collected from a duty-free shopping center (Haikou) in China. It is plausible to extend our model's applicability to other duty-free such as those in Korea. Future endeavors may involve gathering datasets from additional duty-free shopping centers to validate and corroborate our model. Thirdly, the magnitude of airport passenger traffic exerts a direct and substantial influence on duty-free shopping demand. Unfortunately, this study encountered constraints in accessing comprehensive and reliable datasets pertaining to airport passenger traffic. We acknowledge the potential value of including the volume of airport passenger traffic and encourage future studies to integrate such data.

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Declarations

Conflict of interest The authors declare that there is no conflict of interest.

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