



Daily tourism demand forecasting via card transactions: a multi-source, interpretable, framework for diverse destinations and markets

Jordi Grau-Escolano^{1,2} · Salvador Anton Clavé³ · Joan Borràs¹

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Abstract

This research introduces a novel comprehensive framework for accurate daily tourism demand forecasting by leveraging point-of-sale card transaction data and a variety of explanatory variables such as Google search trends, holiday data, and weather conditions. By employing a combination of statistical, machine learning, and deep learning models, the study generates daily forecasts across key urban and coastal localities in Catalonia, Spain, segmented according to tourists' nationalities. The results showcase the methodology's robust predictive power, maintaining high accuracy even amid the COVID-19 pandemic period, which was marked by severe uncertainties. Furthermore, the Temporal Fusion Transformer model's interpretability allows to provide valuable insights into the primary factors influencing predictions. The research further investigates the benefits of employing a unified forecasting model across various localities and nationalities, taking advantage of shared temporal patterns, finding that such an approach provides a more time-efficient training process without significantly compromising forecasting accuracy.

Keywords Tourism demand · Time series · Forecasting · Interpretability · Point-of-sale card transactions

✉ Jordi Grau-Escolano
jordi.grau@eurecat.org

Salvador Anton Clavé
salvador.anton@urv.cat

Joan Borràs
joanbn@gmail.com

¹ Eurecat: Centre Tecnològic de de Catalunya, Barcelona, Spain

² Universitat Politècnica de Catalunya, Barcelona, Spain

³ Rovira i Virgili University, Tarragona, Spain

1 Introduction

Tourism demand forecasting (TDF) is an essential tool in the industry's management for both private and public sectors. Accurate tourism demand predictions avoid unnecessary opportunity costs and potential losses (Ampountolas 2021), while also improving service quality and enhancing the overall tourist experience (Zhang et al. 2019). Hu et al. (2021) emphasized the critical role of such predictions in optimizing pricing, operational strategies, and managing crowds. Similarly, Song et al. (2019) highlighted their importance for destinations seeking to leverage market trends or maintain ecological and social balance. Moreover, forecasting aids in devising strategies to address the effects of fluctuating tourism activities (Starosta et al. 2019).

The digital revolution of the 2000s has considerably expanded the methodologies available for forecasting, leading to an increase in research and publications within the TDF domain (Song et al. 2019). This evolution has not only improved prediction accuracies but also refined their spatiotemporal granularity. However, despite these advancements, there is growing demand for even finer resolutions. Moreover, in the face of unpredictable disruptive events such as the COVID-19 pandemic, the resilience of these forecasts is put to the test due to the decreased tourism demand and uncertainty regarding recovery.

Forecasting future trends is critical from different perspectives. Current efforts are increasingly focused on fostering trust among stakeholders (Wu et al. 2023), highlighting the importance of communicating the factors driving predictions. Additionally, while traditional methods have preferred using separate models for each time series, the complex and multifaceted nature of tourism demand suggests the need to reconsider this approach by training models with multiple time series.

Given these challenges, this research makes a valuable contribution to existing literature by proposing a versatile, highly granular framework for TDF, applicable across various tourism contexts. Our methodology employs the number of point-of-sale card transactions as a source for measuring tourism demand, facilitating the generation of accurate forecasts even amidst the uncertainties following the COVID-19 pandemic. The study is organized around three primary objectives:

1. **Propose a comprehensive methodology for accurate daily TDF at the local destination level, segregating them by tourists' nationality.** This methodology consists of standardizing the selection of explanatory variables, enabling accurate predictions for local destinations and markets of diverse nature, even under the influence of the COVID-19 pandemic. To test this framework multiple forecasting models have been used.
2. **Interpret predictions by analyzing how the explanatory variables have influenced the outcomes.** It is well known that despite the remarkable predictive capabilities of machine learning models, they have limited interpretability and that this circumstance often leads to distrust in their forecasts. This study seeks to overcome this by presenting the interpretative outputs of the Temporal Fusion Transformer (TFT) models, giving detailed insights into the variables influencing the tourism demand predictions.

3. **Assess the efficacy of a single unified model for TDF.** Using the TFT ability of incorporating static covariates, this study examines the adequacy of training a single model for several destinations and tourists' nationalities instead of individual models for each scenario, considering both the training times and the prediction accuracies.

It is well known that big data opens new avenues in tourism research because when visiting cities, tourists generate massive amounts of digital data which can be very useful for exploring their behavior, expenditure, preferences, and other aspects. Even though it is difficult to obtain and has been used in only a few papers as a primary source in tourism research, bank card transaction data is particularly valuable, as it reflects real human behavior, generates large samples, and is non-intrusive. Compared to other data sources, point-of-sale card transaction data provides information about cardholders from both the bank that owns the point-of-sale device and other banks each time a card payment is made, allowing researchers to describe routines and identify locations (origin, destination, and intermediate geographical trajectories), timing, and the economic category of each cardholder's expenditure. A key question from the perspective of tourism research is how to distinguish between tourists' and residents' card transactions and how to identify and characterize their behavior. In this vein, as shown by Romero Palop et al. (2019), it is possible to identify tourists by clustering areas where cardholders carry out their daily spending, ultimately allowing transactions to be labelled as touristic when they occur outside the cardholders' usual environment. As the use of bank cards has become increasingly widespread in recent decades, this big data source provides very large samples of anonymized behavior information, with a high level of spatial and temporal granularity (Marques et al. 2023).

To test the ability to reach the proposed objectives, this paper generates daily 30-day forecasts on the post-pandemic period of August 2021, focusing on key urban (Barcelona and Girona) and coastal (Salou and Lloret de Mar) local destinations in Catalonia, Spain. These forecasts are segmented by the three main tourist nationalities: Spanish (ES), French (FR), and British (GB). Hence, by combining tourism demand metrics from card transactions data with a selection of standardized covariates, we provide a significant advancement in TDF studies through the application of TFT models, which offer built-in interpretability capabilities. This method enables generalization across various localities and markets and represents the first approach to simultaneously combine three key forecasting components: daily predictions, local destinations and segmentation by tourists' nationality. Indeed, the sample of the four major diverse tourist destinations includes places with varying shares of tourism markets by nationality, types of accommodation, and seasonality patterns, allowing us to test the robustness and generalizability of the forecasting methodology under varied tourism demand scenarios, including the critical COVID-19 event. The research also illustrates the benefits of employing a unified forecasting model across different destinations and markets, demonstrating that such an approach provides a more time-efficient training process without significantly compromising forecasting accuracy.

The rest of the paper is structured as follows: Sect. 2 reviews the relevant literature. Section 3 explains the data used and presents the methodology. Section 4 details

the results obtained. Finally, Sect. 5 provides discussion, conclusions, and managerial implications.

2 Literature review

Tourism demand at a specific destination is the aggregate interest consumers have for tourism-related products and services over a defined time frame (Song and Witt 2012). The most prevalent metrics for measuring this demand include tourist arrivals (Höpken et al. 2020; Rosselló-Nadal and HE 2020), number of nights stayed (Ampountolas 2021; Baggio and Sainaghi 2016; Zhang et al. 2019), or tourist expenditure (Ognjanov 2018; Sheldon 1993).

Traditionally, such data have been sourced from statistics and surveys performed by government agencies (Li et al. 2020) and international organizations like UNWTO or WTTC. However, these data sources typically exhibit low granularity and infrequent publication (Huang et al. 2017). In response, researchers have turned to big data and internet-based alternative sources, as they offer real-time insights into tourist preferences and behavioral changes, while also providing high granularity information (Huang et al. 2017; Li et al. 2017; Ramos et al. 2021; Zheng et al. 2021). However, relying exclusively on these types of data can lead to errors. For instance, an increased volume of website traffic or search engine data does not necessarily indicate greater consumer interest in visiting a destination and could even suggest the contrary (Li et al. 2020). Therefore, the consensus is to continue using traditional tourism demand measures with higher spatiotemporal granularities, and in addition, improve predictions by employing explanatory variables like search engine data (Höpken et al. 2020; Li et al. 2020; Zhang et al. 2019).

2.1 Models for TDF

TDF has gained importance in literature—with over 600 studies identified (Song et al. 2019)—due to the tourism industry expansion (Zhang et al. 2020). The forecasting methods fall into three categories: time series models, econometric models, and AI-based models (Song et al. 2019; Song and Li 2008).

Time series models, which generate predictions based on the historical values of the time series being forecasted, have been widely used since the 1970s due to their ability to identify crucial patterns like trends and seasonalities, particularly important in the tourism sector. Early iterations, such as the naïve 1, naïve 2, single exponential smoothing, autoregressive and moving average models, often exhibit limited performance and are primarily used as benchmark models. Nonetheless, more sophisticated variants significantly enhanced TDF accuracies, leading to their broad adoption in the last decades of the 20th century. These models include the Holt Winter's exponential smoothing model (ETS) (Ampountolas 2021; Mamula 2015; Petrevska 2011), the autoregressive integrated moving average model (ARIMA) (Box and Jenkins 1970) (Álvarez-Díaz and Rosselló-Nadal 2010; Bonhaam et al. 2009), and its extension that includes seasonality (SARIMA) (Mamula 2015). Furthermore, time series models have evolved to include explanatory variables, leading to the creation of sophisti-

cated single-equation models such as the ARIMA model with exogenous variables (ARIMAX) (Li et al. 2020), the seasonal ARIMA with exogenous variables (SARIMAX) (Ampountolas 2021), and the structural time series model (Song et al. 2011).

Econometric models are statistical tools used in econometrics, a field that integrates economics, mathematics, and statistics. These models aim to understand and quantify economic relationships, tests economic theories, forecast economic trends, and analyze policy impacts. In TDF, the focus of econometric models extends beyond mere prediction. They are also employed to analyze causal relationships between tourism demand and its explanatory factors. The static regression model, known for its ability to analyze relationships between variables at a particular time point, is one of the most basic econometric models and was employed in early TDF studies (Laber 1969; Martin and Witt 1987).

Since the 2000s, however, the static regression model has primarily served as a benchmark model, and more advanced models like the distributed lag model, the autoregressive distributed lag model, and the error correction model have been utilized (Nadal et al. 2004; Ongan and Gozgor 2018). These models, account for the fact that economic effects often unfold over time, and the latter two, in particular, have played a significant role in the analysis of tourism demand due to their robust performance (Song et al. 2019). Moreover, building on the foundations of the static regression model, the vector autoregression and vector error correction model were developed. These models have been used since the 1990s, due to their ability of capturing the interdependencies of multiple time series through multi-equation formulations, however, they were outperformed by other econometric techniques (Song and Li 2008). On the other hand, explanatory variables have often been aggregated into the same frequency as the target variable even when they are available at higher resolution, usually leading to information loss. To address this issue, some studies have used methodologies designed to handle datasets where observations are recorded at different frequencies such as mixed data sampling (MIDAS) (Bangwayo-Skeete and Skeete 2015).

Unlike the former methods, AI-based models do not require any previous knowledge about the relationships between variables, even if they change over time, and can predict non-linear data with noise. AI-based models include support vector regression, fuzzy time series, genetic algorithms, and rough sets approach. However, the most used AI-based models in TDF are artificial neural networks (ANN), such as the multilayer perceptron, the radial basis function, and the long-short term memory model (LSTM) (Ampountolas 2021; Bi et al. 2020; Zhang et al. 2019). Despite being considered black boxes due to their limited explanatory capacity, these models have gained popularity due to their ability to generally outperform traditional methods (Bedi and Toshniwal 2019; Zhang et al. 2019). Nevertheless, they are time-consuming and require advanced computational resources.

A recent development in AI-based models are the Transformer architecture (Vaswani et al. 2017), which are being increasingly utilized in forecasting due to their ability to handle sequential data more effectively (Wen et al. 2022), and have presented promising accuracies in the field of tourism. Unlike traditional recurrent neural networks, transformer-based models such as the TFT use self-attention mechanisms to capture both short- and long-term dependencies in a single pass. This

allows the models to directly focus on the most relevant information across the entire input sequence, avoiding vanishing-gradient issues and improving their ability to learn complex temporal relationships. In contrast, recurrent neural networks process data sequentially at each timestep, which can lead to error accumulation over long sequences, and typically require more epochs and careful tuning to capture long-range effects.

In their review, Song et al. (2019), also discuss judgmental methods, which are applicable to both qualitative and quantitative forecasting (Lin and Song 2015). These methods rely on the expertise and accumulated experience of professionals. Lin and Song (2015) describe that this approach involves techniques of ‘asking’ insights from experts, stakeholders, and the public, as well as using judgment-aided methods to develop scenarios. Delphi techniques (Vanhove 1980) and scenario-building (Moutinho and Witt 1995) are the two most popular techniques (Song et al. 2019; Uysal and Crompton 1985).

Finally, in Jiao and Chen (2018)’s review, it is suggested that one promising direction is hybrid models. As all models have advantages and disadvantages, combining the benefits of models from different categories could improve forecasting accuracy. Since 2010, TDF studies have been proposing hybrid models, typically involving at least one AI-based model. Generally, these models combine a linear component, like the exponential smoothing, naïve, and ARIMA models, with a non-linear component like the support vector regression and ANN models (Chen 2011; Nor et al. 2018; Wen et al. 2019). However, combinations of two types of AI-based models are also suggested (Chen et al. 2015; Hong et al. 2011; Li et al. 2019; Lijuan and Guohua 2016; Pai et al. 2014).

2.2 Accuracy and interpretability in TDF

Research by Song et al. (2019) indicates that forecasting accuracy is influenced by factors such as destination, market, and prediction length. International flows of people, cross-border employment, cultural differences, movements, and globalization or deglobalization make tourism decision-making a complex process, both in terms of international and domestic travel. Additionally, forecasting becomes increasingly complex during unforeseen disruptions, such as those caused by the COVID-19 pandemic. For instance, when international travel resumed in most countries in the summer of 2021, Great Britain established a traffic light system that set restrictions on international travel to some countries (UK Government 2021). As Duro et al. (2021) noted, differing border control policies and mobility restrictions resulted in varied impacts across countries, regions, and local destinations. To reflect these complexities, disaggregated data is crucial for accurate TDF. This finer data allows for more refined predictions, with lower spatiotemporal granularities, and helps create forecasts specific to traveler types, including their origin markets.

In terms of time granularity, data and forecasts have traditionally been treated in large periods such as years or quarters, but thanks to big data, now predictions can be made daily (Bi et al. 2020), hourly (Zheng et al. 2021), and even at 5-minute intervals (Ramos et al. 2021). Likewise, geographical granularity of tourism destination usually considered big areas like countries, neglecting the tourists’ origin. However,

some studies now forecast for small locations (Bi et al. 2020; Ramos et al. 2021) and generate predictions segregated by tourists' nationality (Cortés-Jiménez and Blake 2010).

Prediction models have been improved by incorporating single explanatory variables such as weather (Muñoz et al. 2023), search engine (Li et al. 2017; Li and Law 2020; Önder 2017), or social network (Starosta et al. 2019) data. Internet big data have particularly been emphasized for their ability to measure and monitor tourist behaviors and satisfaction, overcoming the lag in traditional forecasting methods (Huang et al. 2017). Moreover, recent studies indicate that using big data from multiple sources can significantly improve the accuracy of TDF (Fronzetti Colladon et al. 2019; Li et al. 2020).

Another relevant factor in the prediction accuracy is the combination of the data time granularity and the forecast horizon. With low-granularity data, such as monthly or quarterly observations, the forecasting task primarily involves modeling persistent trends and seasonality. In these cases, classical time series and econometric models often excel. However, when high-granularity data such as daily observations are used for short-term forecasts, models must be more adaptive to capture abrupt changes and fluctuations. Deep learning models have demonstrated robust performance in this context through their flexible architectures and ability to integrate multiple covariates. The most challenging scenario arises when highly granular data are employed for long-term predictions; in this case, models like LSTM—which perform well in short-term variations—can struggle to capture and maintain long-term dependencies, whereas transformer-based models have shown superior. Additionally, unpredictable external factors—commonly known as black swan events (Nicholas 2008)—can affect forecast accuracy independently of data granularity and prediction horizon. Although these events are inherently unpredictable, achieving optimal accuracy hinges on both the model's capacity to rapidly adjust its forecasts once the shock occurs and the selection of high-quality, relevant input data.

Furthermore, understanding how tourism demand predictions are generated is crucial for informed decision-making. On the one hand, traditional forecasting models such as ETS and ARIMA are inherently interpretable because their explicit modeling of trend, seasonality, and error components provides clear insights into how different factors contribute to the forecasts; however, these methods are often limited in capturing nonlinear dynamics. On the other hand, while deep learning models that incorporate explanatory variables often achieve strong predictive performance, their 'blackbox nature' limits transparency. Traditional explainability techniques such as shapley additive explanations (SHAP) are grounded in a gametheoretical framework that allocates each feature's contribution to a model's prediction. However, SHAP is poorly suited to time series forecasting because it ignores temporal dependencies and requires computationally expensive perturbations of entire input sequences. In contrast, the TFT model offers builtin interpretability through its multihead attention and variable selection layers, which jointly quantify each covariate's contribution at every time step (Lim et al. 2021). This mechanism produces both global importance scores and timevarying insights without additional post hoc analysis. Wu et al. (2023) illustrate TFT's explanatory capabilities in their monthly 8-month predictions using

data from international airport arrivals, identifying as key factors the year, Google trends data, TripAdvisor posts historical data, and the monthly COVID-19 cases.

Lastly, a gap in TDF literature involves comparing the training of individual models for each time series versus a unified model for all of them. This comparison is very relevant in tourism demand, as time series that share some characteristics, such as the touristic destination that they represent, can share some of their temporal patterns. Leveraging these shared dynamics in a unified model could enhance accuracy and reduce training times, circumventing the need for multiple individual models.

2.3 Card transactions as tourism demand data for forecasting

Concerning the use of tourist expenditure as a proxy of tourism demand measures, it is worth highlighting that point-of-sale card transaction data represents a promising approach. With the increasing prevalence of point-of-sale systems, card transaction data has become a reliable source for gathering detailed information about tourism-related purchases, offering a greater spatiotemporal precision than previous sources (Burson and Ellis 2014; Demunter 2017; Marques et al. 2023). Furthermore, the relevance of point-of-sale data was enhanced during the COVID-19 pandemic as cash transactions declined in favor of social distancing practices (Kraenzlin et al. 2020; Marques et al. 2023; Wisniewski et al. 2021).

Even though they are privately owned, card transactions have been employed for multiple purposes in tourism research—primarily to explore tourists' expenditure patterns—and their availability under particular confidentiality restrictions is increasing. Donaire et al. (2021) identified key factors influencing tourist expenditure across Spain during COVID-19 times, while Buda (2019) examined how tourist expenditure near Istanbul relates to the demographics of tourists and the characteristics of destinations. Additionally, tourist itineraries were extracted, trip purposes were obtained with hierarchical clustering, and tourist expenditure was forecasted. Aparicio et al. (2022) demonstrated the potential of card transaction data by identifying expenditure clustering patterns in Madrid, distinguishing between locals, and national and foreign visitors, and explained the spatial distribution of visitor expenditure using ordinary least square and spatial regressions. Lastly, Romero Palop et al. (2019) addressed the challenge of measuring domestic tourism, typically harder to quantify than international tourism due to its smaller data footprint, by defining cardholder's 'usual environment' and classifying transactions as either 'touristic' or 'non-touristic'.

Card transactions have also been used to improve tourists' experiences through recommender systems that predict user preferences. Kothari et al. (2020) proposed travel itineraries and merchant recommendations based on card transaction data. Chen et al. (2022) developed a sequential recommender system by combining an auto-encoder with a recurrent model, significantly improving real-time recommendation accuracy. Furthermore, Hong et al. (2023a) leveraged Doc2Vec techniques to demonstrate the effectiveness of using spatial information and vector space representations in personalized tourism recommendations. Finally, Hong et al. (2023b) introduced TPEDTR, a model that addresses the absence of explicit feedback while integrating temporal, spatial, and demographic data to deliver personalized recommendations.

Enhancing tourists' experiences can also be achieved by improving service quality, which relies on the accurate management of tourism-related resources. This process can be significantly optimized through precise TDF (Zhang et al. 2019). Nevertheless, despite the vast collection of studies in this field, and the promising potential of card transaction data to improve prediction accuracy, to our knowledge, no studies have yet utilized this data at the local destination level with daily granularity and market segmentation for this purpose. Responding to this challenge, this research introduces a novel comprehensive forecasting framework by employing a combination of statistical, machine learning, and deep learning models to generate daily forecasts for a variety of local tourism destinations, segmented by tourists' nationalities. The approach leverages point-of-sale card transaction data alongside a variety of explanatory variables, including Google search trends, holiday data, and weather conditions. This constitutes an innovative approach to forecasting daily tourism demand by utilizing an unconventional big data source. Furthermore, this study contributes methodologically through the application of the TFT model, which provides valuable insights into the main factors driving tourism demand forecasts based on the explanatory variables, and confirms that, while unified TFT models perform slightly worse than individually trained models in terms of forecasting accuracy, they require significantly less training time.

3 Materials and methods

3.1 Empirical validation context

This research uses four tourism destinations in Catalonia, Spain, to validate the proposed forecasting methodology. The goal is to create models that generate daily predictions for different local destinations and markets. The selected localities—Barcelona, Girona, Lloret de Mar, and Salou—were chosen because they represent diverse tourism contexts in terms of destination type, market composition, and seasonality patterns. Specifically, they include both urban and coastal destinations: Barcelona, a top global urban tourism hub; Girona, a mid-sized emergent urban destination; and Lloret de Mar and Salou, well-known mass tourism coastal destinations (Table 1). This diversity allows for a robust evaluation of the forecasting framework across a range of tourism demand scenarios. The intensity, complexity, and heterogeneity of tourism activity in these destinations provide a suitable testing ground to validate the methodology and demonstrate its scalability and generalizability beyond the selected cases.

Barcelona and Girona are both urban destinations but differ significantly in their tourism profiles. Barcelona is a worldwide tourism destination, ranked among the world's top 10 city destinations (Popova et al. 2022). In contrast, Girona is a medium-sized city with an emergent tourism activity since the late 1990s. Located 100 km away from Barcelona, it has recently been acknowledged as an urban satellite destination of Barcelona (Blasco et al. 2023).

Salou and Lloret de Mar are both popular seasonal coastal destinations. Lloret de Mar, located in the Costa Brava, has continuously adapted to evolving societal

Table 1 Nights spent in tourist accommodation by domestic and international tourists in the selected destinations

Destination	Year	Tourists Overnights		% Overnights of main markets in regular accommodations ^a			
		Total ^b	% Regular Accommodation	% ES	% FR	% GB	% Top 3 markets
Barcelona (global urban destination)	2019	32,133,838	68.9	21.8	9.1	9.7	40.6
	2020	9,095,957	58.5	37.7	12.9	7	57.6
	2021	13,758,993	72.1	38.5	14.8	4.2	57.5
	2022	25,933,381	75.2	27.1	10.9	8.3	46.3
	2023	29,732,976	74.6	22.4	10.3	9.6	42.3
Girona (mid urban destination)	2019	716,204	65.9	48.1	12.1	7.7	67.9
	2020	278,699	57.7	64.8	11.1	2.6	78.5
	2021	428,241	66.9	64.4	11.6	2.4	78.4
	2022	684,102	67.8	45.6	12.5	6.6	64.7
	2023	802,454	65.1	49.9	14.3	5.9	70.1
Lloret de Mar (international seasonal coastal destination)	2019	6,836,955	81.3	26.1	22.5	12.2	60.8
	2020	2,119,263	65.3	64.8	20.2	1.5	86.5
	2021	3,353,222	74.4	62.7	19.9	1.1	83.7
	2022	5,448,370	81.6	34.7	22.6	9.8	67.1
	2023	5,888,977	85.4	32.5	21.7	12.2	66.4
Salou (international seasonal coastal destination)	2019	9,079,588	89.1	38.5	11.3	18.4	68.2
	2020	1,771,707	70.8	78.1	12.3	1.4	91.8
	2021	4,361,906	84.8	70.4	15.6	1.6	87.6
	2022	8,186,183	89.4	48.1	16.4	16.3	80.8
	2023	8,575,242	91.0	44.8	14.9	16.7	76.4

^(a) Tourist night data from hotels and similar accommodations (NACE Group 55.1), camping grounds (NACE Group 55.3), and regulated holiday and other short-stay accommodations (NACE Group 55.2) by the Tourist Data System of Catalonia

^(b) Tourist night data from the same sources as in footnote a (NACE Groups 55.1, 55.2, and 55.3), combined with data on nights spent at short-stay accommodations offered via AirBnB, sourced from AirDNA

Source: authors elaboration

dynamics and tourist preferences (Marin et al. 2021). Salou has undergone restructuring since late 1990s, including the development of a top European theme park and experiencing a profound process of renovation and diversification (Anton Clavé 2010).

As previously stated, the four destinations are in Catalonia, which, according to the Tourist Movement at Borders statistics (Frontur) from the Spanish National Statistical Office, recorded 18 million international tourists in 2023. This represents 21.2% of all international arrivals to Spain and about 2.6% of Europe's total international tourism movements. Additionally, the Residents Tourism Survey (ETR) indicated that Catalonia hosted 18.7 million domestic trips in 2023.

Table 1 provides data on tourist nights across the four destinations, covering aggregated tourist nights not only from hotels and similar accommodations (NACE Group 55.1, the European classification for economic activities) but also from camping grounds (NACE Group 55.3) and other regulated short-stay accommodation (NACE Group 55.2). Moreover, it includes estimates of guest nights spent at

short-stay accommodations offered via online collaborative platforms like Airbnb, reflecting the growing importance of these alternatives in the tourism market. This is crucial for understanding the results of this paper, as they don't just reflect tourists staying in traditional accommodations but capture the overall destination demand. In Barcelona, for instance, Airbnb stays account for 25% to 40% of total tourist nights, depending on the year, while the proportion is lower for the coastal destinations and Girona. Therefore, this data illustrates substantial differences in the scale, market composition, and accommodation preferences across these destinations. Such diversity underscores the rationale behind selecting these localities, as it allows us to validate the forecasting methodology across genuinely distinct tourism realities. Additionally, the table highlights the growing significance of platform-based accommodations during the COVID years (2020–2021), which are included into the forecasting framework validation thanks to card transaction data.

3.2 Data availability

This research uses an anonymized card transactions dataset from CaixaBank's point-of-sale systems in Catalonia, Spain, spanning from 2018 to 2021 (Galli and Borràs 2021a). Each entry in the dataset corresponds to a single card transaction performed through the point-of-sale system, and this data is used to generate the time series that serve as indicators of tourism demand of the municipalities under study, forming the basis for the target time series. Each transaction of the dataset, which contains no missing values, includes:

- Card ID: a unique, anonymized identifier for each card.
- Cardholder's reference location: the most likely place of residence of the card owner.
- Terminal postal code: the postal code where the point-of-sale terminal is located.
- Terminal commercial category: the business category of the point-of-sale terminal.
- Transaction timestamp: the date and time when the transaction occurred.
- Transaction amount: the monetary value of the transaction.

The "cardholder's reference location" is defined as the most likely place where the card owner resides. For foreign-issued cards, this corresponds to the country of issuance, while for Spanish-issued cards, it indicates the province where the highest spending occurred.

However, when the reference location falls within the Spanish province of Catalonia, a specific municipality is assigned instead of a province or a country. Additionally, for cardholders of Catalonia with less than 70% of transactions in their primary municipality, a secondary municipality is noted, accounting for individuals who live and work in different locations. Therefore, the granularity of the geographic data enables accurate identification of tourists' origins, accounting for various scales of tourism (international, national, and local).

The use of card transactions as the main source of information for TDF may be affected by several factors that influence how individuals use card payment methods.

These include visitors' familiarity and trust in digital payments, the availability of point-of-sales devices, individuals' life style characteristics and life cycle stage, and other behavioral practices related to health, social norms, gender, age or culture. For instance, Marques et al. (2023) show that card transactions data in Portugal exhibited greater volatility and a less adverse year-on-year variation during the COVID-19 pandemic. Compared with survey data on guest stays at tourist accommodations, the authors found that card transaction data tended to estimate variations with a positive bias. As the time series from the two data sources analyzed show similar patterns, the authors conclude that this bias may be due to guests avoiding cash and favouring cashless payments during the COVID-19 pandemic. Nevertheless, even though this bias is acknowledged, the authors argue that the finer geographical granularity and broader spatial coverage of the card transactions data allow for a more accurate representation of disparities in COVID-19 recovery. Hence, despite such limitations, the few existing studies that have utilized this sort of data have tested the robustness of the results derived from its use (see also Aparicio et al. 2022).

3.3 Target time series

The card transaction dataset was utilized to derive time series representing tourism demand in the four municipalities, categorized by the visitor's nationality. Although each transaction includes the cardholder's reference location, this alone doesn't confirm tourist activity. Therefore, following (Galli and Borràs 2021b), we applied a series of filters to isolate genuine short-stay visits characteristic of tourism.

For cardholders whose reference location lies outside Catalonia—including both international visitors and Spanish nationals from other regions—transactions were classified as tourist-related only if they occur in a single municipality for no more than 8 weeks or 60 days within a year. By excluding transactions beyond this duration, we remove spending by local residents, second-home owners, and long-term visitors, ensuring our time series reflect actual tourism.

For Catalanian-issued cards, the same time-bound criterion applies, but additionally transactions need to take place at least 50 km from the cardholder's primary municipality and more than 10 km from their secondary municipality. Then, this spatial filter not only excludes local residents, second-home owners, and long-term visitors, but also daily commuters and other habitual local activity.

After excluding non-tourist transactions and retaining only those relevant to tourism based on the point-of-sale commercial category, the target time series were created, representing the count of card transactions made by tourists in the four municipalities. In addition, the three tourist nationalities with the greatest number of transactions have been filtered for each locality, obtaining time series for ES, FR and GB nationalities. This process resulted in 12 daily time series from January 1st, 2018, to August 31st, 2021 (Fig. 1). After normalization, the August 1st – 30th, 2021 period was used to evaluate prediction accuracy in the COVID-19 uncertain time, the previous 30 days for model validation, and the rest for training.

It is important to note that, while these filters substantially reduce the presence of non-tourist activity, some degree of misclassification may remain. In particular, seasonal workers or business travelers whose activity in a municipality lasted less than

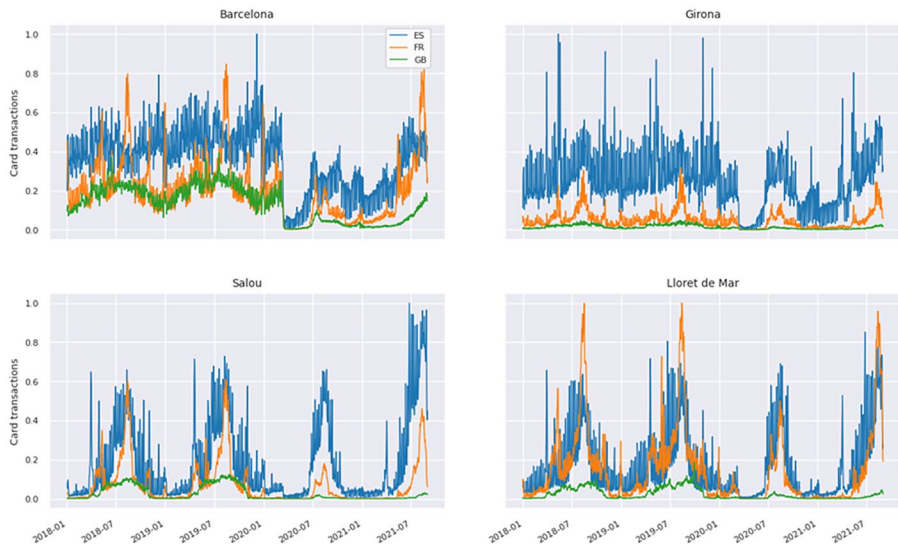


Fig. 1 Number of card transactions in the four main touristic destinations of Catalonia, Spain, categorized by tourists' country of origin and normalized by destination

8 weeks or 60 days could still be classified as tourists, as they fall within the same temporal threshold applied to genuine short-term visitors.

3.4 Explanatory time series

Building on the evidence that multi-source explanatory data enhances forecasting accuracy (Fronzetti Colladon et al. 2019; Li et al. 2020), this paper introduces a forecasting framework that captures tourism demand variability by integrating a diverse set of covariates organized into three categories. These covariates are classified as past (or historical), future (or known-future), and static (or time-invariant) covariates. **Past covariates** consist of variables whose values are available to the model only up to the forecast start date, capturing historical patterns that precede the prediction. **Future covariates** include variables whose values are available to the model both before the forecast and throughout the entire forecast horizon, allowing the model to learn from their past influence and account for their expected impact on predictions. Common examples include calendar-based features, such as day of week or month of year, which are predetermined and therefore available both before the forecast begins and throughout the entire prediction period. **Static covariates** remain constant throughout the entire forecasting period, providing contextual metadata that helps a model learn shared patterns across multiple time series. The following sections detail the variables selected for each covariate category.

3.4.1 Past covariates

Past covariates supply the model with historical information up to the forecast start date. In this study, two types of past covariates have been used.

- **Google trends:** data was gathered to gauge travelers' interest in vacations. Due to some time series having excessive noise two time series were collected: one using the locality as a keyword in the 'travel' category and another combining the locality with 'hotel' without filters (e.g., 'Barcelona' and 'Barcelona hotel'). The nationality of the tourists was also included as the country of origin for the searches.
- **Weather:** likewise, the weather prior to the forecast also influences the desire to go on vacation. The introduction of weather data can help in predicting target time series with strong annual seasonalities and in the modeling of events with a much lower granularity. For example, on rainy days tourists spend less. Consequently, for each locality, daily temperature (maximum, minimum and average) and precipitation (maximum, average and total) data has been used.

3.4.2 Future covariates

Unlike past covariates, future covariates are known both before the forecast begins and throughout the entire prediction horizon, allowing the model to incorporate information about upcoming events while still leveraging their historical patterns. The following future covariates were used:

- **Temporal variables:** to account for complex seasonal patterns, the following set of calendar variables has been chosen: day, week, and month of the year, day of the week and day of the month.
- **Holidays:** holidays significantly influence vacation length and spending. For this reason, a binary variable indicating the national holidays of the tourists' origin country has been included in each case.
- **COVID restrictions:** the worldwide COVID-19 restrictions have greatly altered the global tourism dynamics. Thus, with the start of the pandemic the behavior of the target series and the relationships they have with their covariates have changed. Moreover, as the removal of Spanish restrictions has been progressive, these changes vary over time. For this reason, binary covariates were created to reflect the changes on the restrictions approved by the authorities:
 - *State of Alarm 1* (2020-03-14–2020-06-20): movement in all Spain was restricted to essential needs and almost all retail establishments were closed. Cultural, sports, hotel and restaurant activities were suspended.
 - *New Normality* (2020-06-21–2020-10-24): period of gradual return to various social and economic activities at national level.
 - *State of alarm 2* (2020-10-25–2020-11-08): national state of alarm that didn't establish a new general confinement of the population. A curfew was imposed throughout the national territory from 11 p.m. to 6 a.m., autonomous communities had the possibility to close their borders and carry out partial or total confinements, and meetings of more than six people were prohibited.
 - *Catalonia restrictions* (2020-10-25–2021-01-28): with the second state of alarm, the Spanish government transferred powers to the Autonomous Communities. Making use of these powers, Catalonia established restrictions related to the closure of restaurants, cultural events, and nightlife.

- *Interior mask* (2020-03-14–2022-02-10): mandatory mask-wearing indoors was implemented with the first state of alarm.
- *Exterior mask* (2020-03-14–2022-04-20): mandatory mask-wearing outdoors was also implemented.

Finally, it is relevant to clarify that although restrictions are not definitely known in advance, governments and media often signal drastic measures beforehand. This information could be incorporated into models before the implementation of restrictions, allowing for the evaluation of potential future impacts.

3.4.3 Static covariates

Static covariates, which are explanatory variables that remain constant over time, cannot improve models trained on a single time series but can enhance those trained on multiple series by providing additional context. Therefore, for training a unified model with multiple time series, the study included the following static covariates:

- **Destination municipality.**
- **Tourist's nationality.**

3.5 Models

Following the “No Free Lunch” theorem (Wolpert and Macready 1997), which states that no single method consistently outperforms others in all scenarios and that all methods have their own limitations, this study carefully selected prediction models based on their distinct methodological paradigms and ability to process different types of covariates.

The **benchmark models** were chosen as baseline comparisons due to their simplicity and widespread use, serving as a standard for evaluating more complex models. These models, which only require the target time series, include **naïve 1**, **naïve 2**, and **naïve mean** models, which set their forecasts to be the value of the target's last observation, the target's last value from the previous season, and the target's mean value, respectively.

ETS and Trigonometric seasonality, Box-Cox transformation, ARIMA errors, Trend and Seasonal components (**TBATS**) models, which rely solely on the target time series, were selected due to their status as well-established classical models capable of effectively handle time series with trends and seasonality—common characteristics of tourism demand data. For these seasonal models, the 365 days prior to the forecast were used as input, as annual seasonality was identified as the primary seasonality across all target time series.

- **ETS:** utilizes a weighted average approach with decay, allowing it to adapt to time series with evolving patterns.
- **TBATS:** derived from the ETS model, it excels at managing complex seasonalities, making it particularly suitable for the dataset at hand.

For models incorporating covariates, Long-Short Term Memory (LSTM), Prophet, and Temporal Fusion Transformer (TFT) were chosen for their ability to handle various types of covariates:

- **LSTM**: an autoregressive model based on recurrent neural networks that allows to capture long-term dependencies by controlling information flow through remember, forget, and output gates (Hochreiter and Schmidhuber 1997). In this paper, the Darts implementation (Herzen et al. 2021) was used, with the model receiving the target time series and their past covariates as inputs.
- **Prophet**: is an additive model that captures trends, multi-period seasonality, and the effects of holidays and other types of future events (Taylor and Letham 2018)—features especially relevant in tourism forecasting. Accordingly, it natively incorporates both the target time series and its future covariates as input. Although other methods, such as CNN-based and hybrid approaches, can generate predictions using future covariates, many of them do not support these covariates natively and require additional architectural modifications. Moreover, since deep learning models are already represented by our use of LSTM and TFT, we intentionally diversify our forecasting architectures—following the “No Free Lunch” theorem (Wolpert and Macready 1997).
- **TFT**: integrates data filtering components with recurrent and self-attention layers (Lim et al. 2021) (Fig. 2), enabling it to learn complex temporal relationships while incorporating both past and future covariates. TFT also supports static covariates, enhancing its ability to generalize across multiple time series. Importantly, the model provides interpretability through attention mechanisms and feature selection, which help assess the variable importance. With its encoder-de-

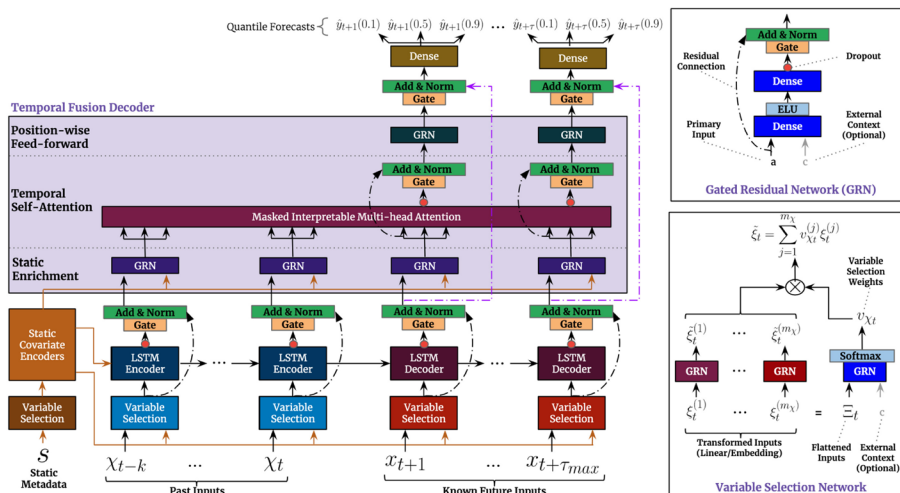


Fig. 2 The TFT model inputs static metadata, along with past and known future data. It uses Variable Selection to highlight key features and Gated Residual Networks to ensure efficient information flow. LSTMs handle local time processing, while multi-head attention integrates data across different time steps. Source: (Lim et al. 2021)

coder architecture, the TFT's encoder processes historical data, while the decoder handles both past and future information. This study utilized Pytorch forecasting's TFT implementation (Beitner 2020).

3.6 Hyper-parameter optimization

The optimization framework Optuna(Akiba et al. 2019) was used to automate the ANN hyper-parameter search. A 500-trial study was created for each case using the TPEsampler for hyper-parameter sampling and the MedianPruner to stop unpromising trials. Each trial involved training for 100 epochs using the Adam optimizer, a learning rate of 0.001, batch size of 64, and Mean Absolute Error (MAE) as the loss function. The LSTM optimized hyper-parameters included encoder length (30–365), hidden size (32–264), and dropout (0, 0.1, 0.2, 0.3). TFT optimization added the attention head size (1–4). The best architectures were validated with data from July 2nd–31st, 2021, and used to predict the following August.

3.7 Accuracy measures

To compare the accuracy of the predictive models, two metrics have been used: the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE). Both metrics are presented in Eqs. 1 and 2, where p_t and $\hat{p}_t$ are the actual and forecasted number of transactions, and T is the total number of time-steps in the evaluated period.

RMSE, a non-proportional metric with the same units as the target variable, highlights larger forecasting errors. MAPE, expressed in percentage units, represents the average absolute deviation between forecasted and actual values. Both metrics are straightforward to interpret: lower values indicate better model performance.

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T (p_t - \hat{p}_t)^2} \quad (1)$$

$$MAPE = \frac{1}{T} \sum_{t=1}^T \left| \frac{p_t - \hat{p}_t}{p_t} \right| * 100 \quad (2)$$

4 Results

In this section the outcomes derived from the application of our proposed TDF methodology are presented. Results are examined considering three key objectives: developing a robust methodology for accurate forecasting, interpreting the predictive power of variables, and evaluating the effectiveness of a generalized model across different destinations and tourist nationalities.

4.1 Prediction accuracies

The application of the proposed methodology for card transaction data, which incorporates multiple explanatory variables across a variety of forecasting models, has achieved significant levels of accuracy. In most target time series, at least one model reached a MAPE of 13% or lower (Table 2), though, no model consistently outperformed others.

Classical and covariate-based models generally surpass naïve models. This holds true across both urban and coastal touristic destinations, with no significant differences observed between the two settings. Notably, even without covariates, classical models yield commendable forecasts. This is particularly evident in the case of ETS models, with MAPE typically below 25% and sometimes close to 10%. However, covariate-based models performed best overall: Prophet models (using future covariates) outperformed LSTM (using past covariates), while TFT models, which integrate both past and future covariates, generally delivered stronger results across many series. Thus, the integration of diverse covariates, coupled with the application of transformer-based models, yields the most consistent, accurate overall predictions. These aggregate patterns are reinforced by the statistical comparisons reported in Appendix A. TFT and Prophet achieved the strongest accuracies overall, with TFT slightly ahead in terms of mean absolute error and direct head-to-head wins (7 vs. 2, with 3 ties) (Table A2 and Figure A1). Robustness checks (Figures A2–A4) further demonstrate that rankings were broadly stable between validation (July) and test (August), particularly for ES and FR tourists, although—as expected—absolute errors increased in the test set.

Despite these general trends, it's crucial to recognize that tourists' origin significantly affects accuracy. Notably, covariate-based models—TFT, Prophet, and LSTM—underperformed for GB tourists, indicating unique tourism demand patterns compared to ES and FR tourists. This may be due to GB-specific flight restrictions, such as the UK's traffic light system of summer 2021, which were not captured by the study's covariates.

4.2 Predictions interpretability

The interpretability of TFT models has enabled an analysis of how input variables influence predictions (Fig. 3). While the importance of these variables varies across the different time series used to train the models, it is important to interpret these findings with caution, considering prediction accuracy as well.

Temporal variables are highly influential, likely due to the pronounced seasonality of tourism in Catalonia. In the encoder, longer time periods, such as the day, week, and month of the year, have the greatest impact. This trend continues in the decoder, but shorter periods like the day of the week gain importance too. FR time series exhibit strong annual seasonality, explaining the significant impact of variables representing longer time spans. Conversely, ES time series show marked weekly seasonality, affecting variable importance in the decoder, where the day of the week becomes more important. GB models show importance for both annual and weekly seasonality, though their lower accuracy limits interpretation reliability. Moreover,

Table 2 Test set forecasting accuracies

	Barcelona			Girona			Salou			Lloret de Mar		
	ES	FR	GB	ES	FR	GB	ES	FR	GB	ES	FR	GB
MAPE												
Naïve 1	10.99	34.15	13.74	17.15	31.84	15.4	12.47	49.17	20.33	26.36	39.46	19.2
Naïve 2	44.66	74.19	67.76	27.14	42.41	49.01	37.38	65.45	69.28	19.97	56.88	35.51
Naïve mean	18.46	66.11	12.6	46.67	64.1	32.63	78.2	76.25	18.52	71.11	78.66	19.53
TBATS	10.04	29.82	8.89	26.83	31.22	28.43	22.42	60.04	14.17	34.26	21.26	19.27
ETS	9.23	22.19	13.73	11.19	26.49	36.51	11.94	39.85	12.24	22.33	25.79	12.76
Prophet	15.27	16.54	43.35	15.56	13.12	28.38	7.64	13.71	46.12	12.32	15.64	17.51
LSTM	8.03	24.06	21.59	25.0	21.47	30.49	57.51	45.1	59.65	20.2	33.5	32.92
TFT	6.85	9.57	46.39	11.47	13.88	24.36	18.56	15.69	35.35	13.15	6.22	33.54
RMSE												
Naïve 1	1485.9	6060.2	655.3	493.1	319.1	20.9	763.2	1094.4	39.3	622.8	1313.2	30.7
Naïve 2	4948.5	11480.3	2424.3	750.5	394.4	60.5	1845.0	1408.0	108.2	508.8	1688.7	58.8
Naïve mean	2348.2	11018.9	585.2	1377.2	620.7	43.8	3922.6	1815.8	28.5	1779.3	2577.6	38.2
TBATS	1260.6	5545.2	445.7	817.1	343.9	40.8	1257.1	1265.3	28.0	918.3	781.4	24.1
ETS	1194.6	3853.1	654.7	372.1	223.6	47.3	685.0	732.8	22.2	559.3	821.9	20.7
Prophet	1776.3	2963.25	1568.3	488.44	168.04	39.26	469.0	239.43	78.03	339.91	481.47	27.59
LSTM	1024.66	4457.8	964.22	752.48	264.46	41.76	3030.18	992.08	89.51	533.21	1197.09	54.26
TFT	1140.3	1944.1	1756.1	392.6	167.8	33.7	1027.4	357.9	64.1	352.3	203.2	58.3

no relevant differences in variable importance were observed across the different destinations.

Google trends variables, both general and hotel-specific, also emerged as highly relevant in the encoder, highlighting the predictive power of online search trends for tourism demand. Since the encoder processes historical input data, this suggests that past search behaviors are indicative of future activity. Interestingly, in over half of the time series, the importance of these variables peaks at around 15% for at least one of them, though they rarely hold equal relevance in the same model. Notably, hotel-specific trends are particularly relevant for the ES models.

The strong relevance of the aforementioned variables reduces the influence of the historical card transactions and weather data. In fact, TFT models find that these covariates explain the variability in card transactions more effectively than the card transactions data itself, resulting in a lower percentage of importance for CT in the encoder. Google trends data largely explains the variability in card transactions, while the annual seasonality of weather is already captured by temporal variables. Furthermore, tourism demand in these destinations may have limited sensitivity to weather changes. Likewise, COVID-19 mobility restrictions show low importance, as Google trends data accounts for their impact. Finally, holiday data holds minimal relevance, as it only accounts for information of specific days.

4.3 Assess potential general models

When forecasting time series for all destinations and nationalities, training individual TFT models for each case proved to be the most accurate approach (Table 3). These models consistently performed well, with MAPE typically below 13 for ES and FR cases but exceeding 30 for some GB time series. Conversely, the Unified TFT model 1 (U1), trained on all time series, showed reduced accuracy and no clear accuracy pattern across destinations or nationalities. Its mean MAPE was double that of the individual models, with some series reaching over 50 units. Although U1 had slight improvements in certain cases, its large errors in others highlight its insufficient generalization, likely due to the challenge of extracting general features from time series with distinct temporal patterns, such as GB versus ES and FR series. Although individual models were more accurate, they took significantly longer to train than U1, with 0.27 times more training time required. However, this extra time is justified by the much higher accuracy of the individual models.

Addressing the unique temporal patterns in the GB series, a second unified model (U2) was trained using only the ES and FR series. This approach proved successful, as it exhibited similar forecasting accuracy to the individual models, with a mean MAPE of 14.68 compared to 11.88. U2 also required less training time, taking 16% less time than the individual models. The close accuracy and shorter training time of U2 demonstrate the viability of training with multiple time series, especially when temporal patterns are similar and the explanatory variables are sufficiently robust to account for the variability in the target time series.

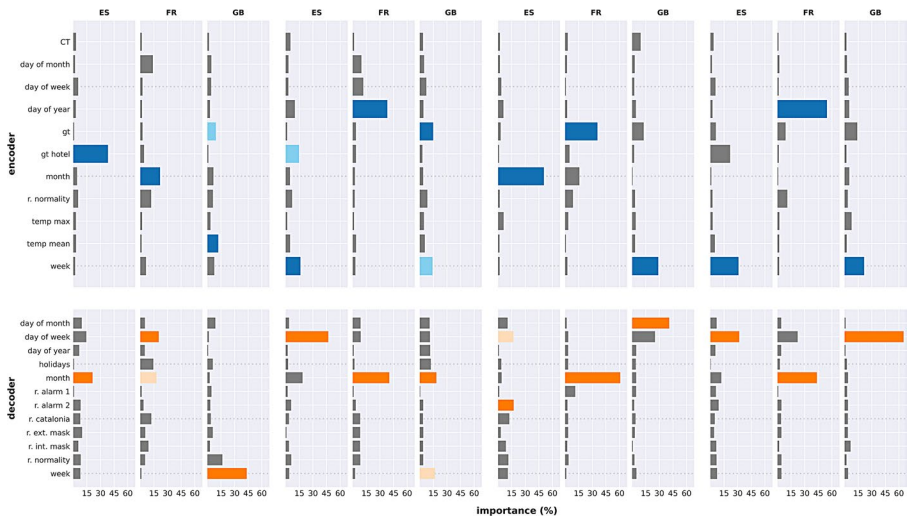


Fig. 3 Variable Importance in TFT Models. The TFT encoder processes all historical data, while the decoder focuses on future covariates. Only variables with over 7.5% of importance in at least one target time series are presented. The most critical variable for each time series in both the encoder and decoder is highlighted. Lighter colors indicate variables exceeding 75% of the maximum value. Variables that their name contains “r.” refer to COVID-19 restrictions, and “gt” refers to Google trends

Table 3 Comparison between training individual and unified TFT models for time series. Unified model 1 (U1) includes all destinations and nationalities, while unified model 2 (U2) only uses ES and FR tourist data across all destinations. The time shown represents the hours spent on hyperparameter optimization per model, excluding parallelization for easier comparison. The last row presents total training times and mean accuracies. Values in parentheses indicate hours of training and mean MAPE without GB series

		Time (h)			MAPE		
		Individual	U1	U2	Individual	U1	U2
Barcelona	ES	166			7.01	5.558	7.151
	FR	215			9.58	8.844	13.339
	GB	122			46.93	11.262	-
Girona	ES	217			11.51	10.399	15.340
	FR	287			13.90	11.843	8.291
	GB	215			24.58	24.131	-
Salou	ES	162			18.57	40.618	29.455
	FR	289			15.07	22.109	10.912
	GB	283			35.59	143.026	-
Lloret de Mar	ES	324			13.17	46.85	17.890
	FR	295			6.22	18.115	15.052
	GB	310			33.80	52.242	-
Total/Mean		2,885 (1,995)	2,261	1,691	19.66 (11.88)	32.92	14.68

5 Conclusions and discussion

According to Song et al. (2019), though considerable progress has been made in generalizing TDF models, more detailed, disaggregated data is crucial to avoid model mis-specifications. Similarly, Wu et al. (2024), in a bibliometric review of 1,213 tourism forecasting articles, highlighted the need for rational use of big data and improving credibility and interpretability. More particularly, they noted that incorporating exogenous variables and refining models can significantly enhance forecasting accuracy.

The main goals of this research straightforwardly address the needs highlighted of these two reviews. We have introduced an innovative comprehensive approach to forecasting daily tourism demand using an unconventional big data source such as card transactions, demonstrating its ability to generalize predictions across diverse local destinations and markets. Moreover, in response to calls for incorporating multisource data for better short-term forecasting and improved interpretability, our approach incorporates both past and future covariates of diverse natures, not limited to internet available data, and clarifies the influence of these explanatory variables through the TFT interpretative capabilities. Finally, this research assesses the efficiency in terms of time and accuracy of training separate models for each time series versus using a singular model for multiple time series.

As noted by Song et al. (2019) the use of big data in TDF is still in its infancy stage. In this sense, this study leverages card transaction data, already shown to be valuable in analyzing tourism expenditure (Aparicio et al. 2022; Buda 2019; Donaire et al. 2021; Romero Palop et al. 2019), to provide precise daily tourism demand indicators segmented by tourist nationality and destination. Consistent with prior research (Burson and Ellis 2014; Demunter 2017; Marques et al. 2023), this study demonstrates that card transactions offer an unprecedented level of detail, overcoming past challenges in acquiring high-resolution data.

However, despite these strengths, several limitations must be acknowledged. First, access to point-of-sale data remains limited. Nonetheless, as the global trend towards digital transactions continues to grow, it is anticipated that access to such data will become more widespread, thereby enhancing the future applicability and scalability of this approach. Second, even when such data is available, card transaction data are subject to inherent biases. These relate to the persistent use of cash, which varies depending on personal characteristics, behavioral shifts during holidays, and the uneven availability of card payment infrastructure across destinations. In addition, tourists' payment habits can differ across nationalities and destinations. Consequently, card transaction data provides partial coverage of visitor activity, serving as a proxy rather than a comprehensive record, and may underrepresent certain tourist segments or markets. Finally, while the tourist spending filtering approach used in this study is effective in excluding clear non-tourist transactions, it may still misclassify certain frequent short-term visitors—such as seasonal workers or second-home owners who visit intermittently—as tourists.

Utilizing tourism demand metrics derived from card transactions data, we have presented a comprehensive methodology for TDF. This approach standardizes the selection of covariates, providing forecasting models with a means to account for

most of the variability in the tourism demand metrics. This represents a significant advancement in TDF studies, enabling generalization with daily granularity across various localities and markets. While previous research has achieved daily predictions (Bi et al. 2020), focused on small locations (Bi et al. 2020; Ramos et al. 2021), and segmented predictions by tourists' nationality (Cortés-Jiménez and Blake 2010), this methodology is the first to combine all three. Applied to four major tourist destinations of Catalonia, Spain, and their three main tourist nationalities, it generates accurate predictions even under post-pandemic conditions. Utilizing these tourism demand metrics derived from card transactions data, we present a comprehensive methodology for TDF. This approach standardizes the selection of covariates, providing forecasting models with a means to account for most of the variability in the tourism demand metrics. This represents a significant advancement in TDF studies, enabling generalization with daily granularity across various localities and markets. While previous research has achieved daily predictions (Bi et al. 2020), focused on small locations (Bi et al. 2020; Ramos et al. 2021), and segmented predictions by tourists' nationality (Cortés-Jiménez and Blake 2010), this methodology is the first to combine all three. Applied to four major tourist destinations of Catalonia, Spain, and their three main tourist nationalities, it generates accurate predictions even under post-pandemic conditions.

In general, covariate-based models show higher accuracy, validating the covariates effectiveness in capturing tourism demand variability. Nonetheless, no model excelled across all time series. Models without covariates sometimes outperformed their more complex counterparts, reaffirming the “No Free Lunch” theorem (Wolpert and Macready 1997), which posits that no single model works best in every case. Therefore, employing a variety of models might be the best strategy when the sole objective is to enhance forecasting accuracy. Within this context, the TFT model, which integrates both past and future covariates, often delivered strong performance (particularly for ES and FR tourists) compared to models that either do not utilize covariates or rely solely on future or past covariates. This confirms findings in the broader TDF literature, which increasingly emphasizes the value of integrating diverse data sources (Huang et al. 2017; Li et al. 2020; Li and Law 2020; Muñoz et al. 2023). Moreover, the success of TFT also highlights the advantages of transformer models over recurrent neural networks and statistical models.

Despite these promising results, the forecasting accuracies should be interpreted in light of the previously discussed data representativeness issues. As the empirical analysis focuses on destinations within Catalonia, generalization to other regions should be approached with caution, since differences in tourism structures, digital maturity and card transaction payment generalization, visitor profiles, or payment preferences may influence model performance.

Although the careful selection of covariates has allowed high prediction accuracies in many cases, the varying performance across tourists' nationalities in covariate-based models highlights the need for tailored approaches in tourism forecasting. This is especially crucial during the post-pandemic period, where mobility restrictions vary by country. For example, the additional restrictions imposed by the UK on travel to countries like Spain (UK Government 2021), negatively impacted prediction accuracy due to the absence of a variable representing these measures. More-

over, other factors such as the economic conditions of both origin and destination countries, as well as currency fluctuations can also influence travel patterns. Future research should explore these aspects further, emphasizing the importance of integrating market-specific considerations into forecasting models to better capture the evolving dynamics of global tourism.

While forecasting accuracy is crucial for resource allocation, building stakeholder trust is equally vital to ensure confidence in using these predictions for commercial strategies. A major contribution of this study is the exploration of TFT model interpretability. The importance of temporal variables and Google trends highlights the weight of seasonality and online search behavior in TDF, validating past research (Wu et al. 2023) and offering deeper insights into their varying effect across nationalities and destinations. Conversely, the relatively low significance of COVID-19 restrictions suggests that such events may already be captured through shifts in search behavior and immediate indicators of tourist intent. However, in situations with uncertainties tied to a crisis, the dynamics of the crisis itself are as crucial as the responses to the crisis through policy. Therefore, incorporating policy responses could be essential for enhancing the accuracy of forecasts. Additionally, the low relevance of weather variables likely stems from their predictable seasonality, already encapsulated into more influential variables.

Additionally, this study is the first to explore the balance between accuracy and time efficiency in training TDF models. A comparative analysis of TFT models trained on individual or multiple time series revealed that individual models offer higher accuracy, especially for ES and FR time series. However, a unified model is more efficient and broadly applicable, particularly when excluding the less predictable GB time series. This highlights the potential for leveraging shared temporal patterns across different time series to reduce training time without incurring a major loss in forecast performance. For practitioners, these insights are crucial: in real-world applications, a forecasting model's practical value is measured not only on its accuracy but also on its efficiency and ease of deployment. Faster training and lower computational demands enable more frequent model updates, reduced operational costs, and easier scalability—essential factors for systems operating under resource constraints and requiring timely decisions.

Overall, the results of this study suggest several concrete avenues for future research directions for TDF. First, the framework could be enhanced by exploring new covariates—such as school holidays, weather forecasts, and relevant economic indicators (e.g., exchange rates, inflation)—to more accurately capture factors that directly influence tourist behavior and destination choices. Second, developing automated methods that can identify and quantify distinct temporal patterns among groups of time series—in aspects such as trend, seasonality, and exogenous influences—would be remarkable. Such approaches would not only streamline the data exploration process but also help preserve accuracy in unified models. Third, adopting probabilistic forecasting techniques would enable the generation of prediction intervals or full probability distributions, thereby offering stakeholders a range of possible outcomes rather than a single point estimate and facilitating more robust decision-making under uncertainty. In this regard, while classical models such as ARIMA and ETS inherently provide prediction intervals, some models that incorpo-

rate covariates—like the TFT—can also be used to generate probabilistic predictions. Finally, to assess the generalizability of the proposed method, future research should assess the effectiveness and robustness of the individual and global models by training them on larger, more diverse datasets encompassing time series from multiple destinations over extended prediction horizons.

Finally, from the perspective of industry professionals, accurate forecasts are crucial for enhancing decision-making for both private and public managers (Li et al. 2020). More precisely, this research unveils managerial implications, mainly for destination managers. First, the TFT model proposed in this study helps them to generate daily forecasts, enhance public resources planning, and manage expected circumstances that can diminish tourist satisfaction levels. Second, policymakers could leverage the highly accurate forecasting results for mid- and long-term planning purposes. Third, accurate TDF is also valuable for assisting private operators in strategic business planning. Fourth, even though the TFT approach proposed in this study can be applied across different types of destinations, the empirical results highlight the importance of accounting for the specific characteristics of each destination and the composition of visitors by market origin. In fact, results indicate that tourists' origin significantly affects forecasting accuracy. Lastly, since point-of-sale data can theoretically be collected in near real-time and processed at high speed, this type of big data can revolutionize tourism forecasting systems associated with destination management organizations in the long run. Reaching agreements with credit card companies to provide Destination Management Organizations with adjusted short-term daily demand predictions could enhance information systems that support public resources planning, short-term business dynamic strategies, and even the management of visitor flows within destinations.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s40558-025-00350-2>.

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Author contributions J.G.E. and J.B. conceptualized the study and developed its methodology. J.G.E. carried out the investigation, performed the formal analysis, created the figures, and drafted the original manuscript; J.B. curated the data, oversaw project administration, and contributed to investigation; S.A.C. contributed to writing through review and editing. All authors reviewed and approved the final manuscript.

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Data availability The transfer of these data is conducted within the framework of a formal collaboration agreement between CaixaBank S. A. and Eurecat for a High Impact Project (Galli & Borràs, 2021b), facilitated through the sponsorship of the Centre of Innovation for Data tech and Artificial Intelligence (CIDAI). Therefore, restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available.

Declarations

Competing interests The authors declare no competing interests.

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