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Future avenues for development in forecasting wine tourism

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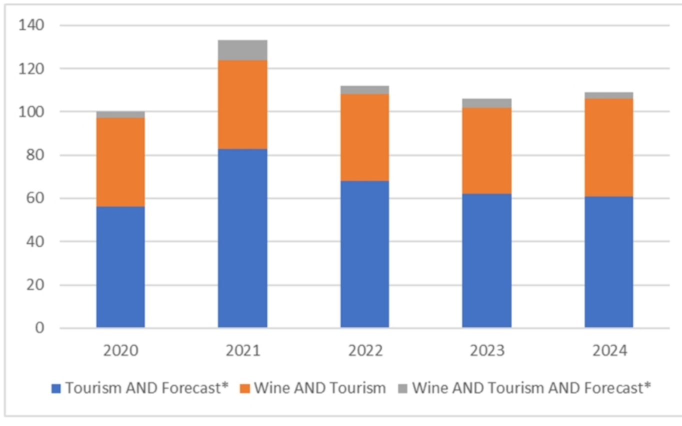

Figure 1. Evolution over time of publications obtained in stage 1

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Future avenues for development in forecasting wine tourism

Abstract

Purpose: The purpose of this paper is to analyse the developments in forecasting wine tourism.

Design/methodology/approach: The study applies a systematic review of the literature between 2020 and 2024.

Findings: The findings confirm unbalanced development where most publications are related to either forecasting tourism or wine tourism, separately. However, there are multiple possibilities for combining both areas to have active research in forecasting wine tourism.

Research limitations/implications: Limitations are related with the potential selection of articles in the systematic review. The field of wine tourism needs to link well-established descriptive analysis of wine tourists with predictive analysis through forecasting approaches, such as AI and simulation.

Practical implications: The paper provides a framework to support further research in forecasting wine tourism, which can be critical information for wineries' managers when they plan capacity and determine business investments related to wine tourism. Forecasting is a vibrant field with also many interesting insights in methodologies and data for academic researchers.

Originality/value: The paper contributes to the body of knowledge of wine tourism in an area where there is limited research.

Keywords: wine tourism, forecasting, simulation, Artificial intelligence

Introduction

Wine tourism has emerged as a cornerstone of the global tourism industry, particularly within established and nascent wine-producing regions worldwide (Hall & Mitchell, 2006). Beyond its recreational appeal, wine tourism serves as a powerful catalyst for comprehensive rural development, fostering economic prosperity through job creation and increased local revenue, enhancing social cohesion by promoting regional culture, and contributing to environmental sustainability through supportive agricultural practices (Alonso & Liu, 2012; Torres et al, 2021). For instance, in regions like Bordeaux, France, or the Napa Valley, USA, wine tourism has demonstrably transformed local economies, attracting millions of visitors annually and bolstering related sectors from hospitality to artisanal crafts.

Despite its profound socio-economic and environmental contributions, the sustainable growth and strategic management of wine tourism are heavily reliant on accurate forecasting. Effective forecasting enables wineries to optimize production and staffing, aids local authorities in infrastructure planning (e.g., managing visitor traffic and conserving natural sites), and allows tour operators to craft tailored experiences, thereby preventing resource strain and ensuring visitor satisfaction. However, while tourism forecasting is a well-established academic and practical domain, a critical research gap persists: there is scarcity of dedicated research and developed methodologies for forecasting specifically within the complex and multi-faceted context of wine tourism (Kunc, 2024a). This paucity of evidence presents significant challenges for stakeholders seeking to make informed decisions and capitalize on the full potential of this niche tourism sector.

Given this pressing need for robust predictive insights, the aim of this study is to explore and propose future avenues for the development of wine tourism forecasting. To achieve its aim, the study has several research objectives. Firstly, the study involves a systematic review of the literature of recent developments, last five years, to understand the state of the field in terms of forecasting and its use in tourism. Then, a systematic review of the recent literature in wine tourism, last five years, is performed to identify research that can support the development of wine tourism forecasting. Finally, a framework to perform forecasting in wine tourism is proposed, which is the main contribution of the paper. The framework is based on the identification of effective forecasting tools from Objective 1 and the critical variables and unique challenges specific to wine tourism uncovered in Objective 2. This framework will outline a multi-step process related to data collection and parameter estimation that can be adopted by researchers and practitioners. It will include recommended data sources (e.g., integrating traditional visitor statistics with non-traditional data like social media sentiment or winery visitors' data) and suitable quantitative forecasting techniques tailored to wine tourism's specific dynamics (e.g., weather, event-driven demand, influence of social media) considering the most recent developments in the literature, last five years. The decision to restrict the research to the last five years will leave previous work outside the scope of this paper, but the objective of the paper is to create a methodological framework based on the recent developments in technology, which have been significant in the last five years.

This framework directly builds upon the gaps identified in the background, particularly the "paucity of evidence of wine tourism forecasting" and the lack of "effective methods." By bridging the divide between general tourism forecasting knowledge and the distinct needs of the wine sector, it aims to address the problem of underdeveloped forecasting practices in wine tourism. The intended uses of this framework are twofold: it will serve as a practical guide for wineries and regional tourism bodies to enhance their strategic planning, resource allocation, and investment decisions, thereby supporting more sustainable wine tourism development. Furthermore, it can provide future researchers with a methodological roadmap for conducting context-specific wine tourism forecasting studies, stimulating further academic inquiry in this under-researched area.

Literature review

Forecasting

More than 600 studies on tourism demand modelling and forecasting have been published until 2019, as the need for accurate forecasts increases over time (Song et al, 2019). Studies have focused on model development and evaluation, proposing simple and combined models, and contributing to the methodological development of the field (Song et al, 2019). In general, tourism demand forecasting aims to focus on international tourist flows since international tourism data is widely available compared with domestic tourism or specific tourism activities (Jiao and Chen, 2019; Song and Li, 2008). International tourism demand is measured in terms of tourist arrivals, tourism expenditure, or length of stay. These factors are generally analysed using aggregated rather than disaggregated data. These data are correlated with different types of volatility, such as the seasonality of both the origin and destination regions, the business cycles associated with exchange rates and income levels, or various externalities related to climate change or special events.

Traditionally, general, as well as tourism, forecasting techniques were grouped in four main categories: methods to explore (time series analysis, causal methods, and morphological analysis), subjective methods (Delphi, panel consensus, and individual expert opinion), normative methods (subjective probabilistic forecasting, Bayesian statistics, pattern identification or prospective scenarios) and integrative methods (multimethod models, dynamic systems models, and cross-impact analysis) (Van Doorn, 1984; Kunc, 2018). Following the review of the literature, Song et al (2019) limited the categorisation into two groups: qualitative, e.g., Delphi, and quantitative, which can be divided into three categories: non-causal time series models, causal econometric models, and AI-based models. A brief description of some relevant methods is presented in table I.

INSERT TABLE I HERE

Wine tourism

A synopsis of wine tourism literature was conducted by Mitchell & Hall (2006). They identified seven themes such as the wine tourism product and its development; wine tourism and regional development; the size of the winery visitation market; winery visitor segments; the behaviour of the winery visitor; the nature of the visitor experience; and biosecurity. However, there is no theme associated with forecasting wine tourism. Some issues are the lack of accurate historical data, multiple dimensions to use for forecasting and lack of effective methods. Getz and Brown (2006) also suggest a set of indicators related to wine tourism demand: winery visitation such as number of visitors and their patterns over time, wine tourists' profiles and segments, expenditures in wineries, destination attractiveness, visitor satisfaction, and awareness of destination in market.

Another important aspect to consider is the wine tourism strategy life cycle (Dodd & Beverland, 2001). In their paper, the life cycle consists of five stages (see table II). On the other hand, Carmichael and Senese (2012) propose a three-stage tourism model: stage 1, Winery Independence; stage 2, Wine Tourism Development, and Stage 3, Wine Tourism Integration. While they are different, similar principles are considered. The initial stage is called wine establishment. In this stage, cellar door sales are used for survival and wine tourism is developed to increase sales, e.g. like the case described in Bojnec et al (2007). The next stage, wine recognition, involves an increase in production with the focus on distribution. In this case, wine tourism events help to build brand awareness to cater for mass market tourists. In the first two stages, the focus of the winery is on economic and environmental sustainability, but sociocultural sustainability becomes increasingly important in the next stages of the life cycle (Poitras and Getz, 2006). During the regional prominence stage, wine tourism events aim to enhance the brand to achieve high brand recognition. The maturity stage implies an increase in sales obtained from cellar door activities, so it offers festivals and events to attract wine drinkers. Ferreira and Hunter (2017) provide a practical example, identifying the Stellenbosch Wine Routes in South Africa as being in a mature life cycle phase, characterized by well-established wine tourism destinations and hierarchical differentiation among wineries. Finally, the decline stage shows a higher percentage of wine drinkers hunting for bargains, so cellar door is in survival mode. Bojnec et al (2007) also provides a useful description of territorial stakeholder management that affects wine tourism life cycle and highlights the importance of additional actors supporting wine tourism. One of the impacts of the life cycle on forecasting wine tourism is the changes in type of tourists and volume of them (numbers may follow an S-shaped curve if they don't collapse completely).

INSERT TABLE II HERE

To summarise, one of the limitations in forecasting tourism is the focus on numbers of tourists' arrivals to broad areas rather than specific activities. Forecasting specific activities has several issues such as lack of accurate historical data, multiple dimensions to use and lack of effective methods. Additionally, wine tourism is neither static over time, since it has a life cycle which affects type of tourists, activities, and volume, nor globally homogeneous, as it depends on spatial, historical and cultural factors (Fountain et al, 2021).

Research method

To inform the future avenues for development, it is necessary to review the current trends in the field through a systematic literature review. A systematic literature review is a synthesis of evidence within a particular domain by using a systematic method to search and categorise the literature (Connolly et al, 2012). The method for a systematic literature review has three stages: the selection of a database, the selection of keywords for search, and the selection of relevant articles followed by their analysis (Connolly et al, 2012).

In this research, articles were identified and gathered using Scopus (Connolly et al, 2012). Searching covered from 2020 until 2024 to focus only on recent developments. While this is a limitation, the study aims to develop a framework aligned with current data collection methods shaped by technological advances such as AI and digitalization. This paper complements Kunc(2024a) as it focuses on forecasting tourism and wine tourism rather than on the use of forecasting in wine in general terms, e.g., sales, production, etc.

The keywords employed were "Tourism AND Forecast*". Then, a second search was performed using "Wine AND Tourism" follow by a final search using "Wine AND Tourism AND Forecast*". The selection of keywords generates another limitation to the study, as it doesn't consider other quantitative approaches that can provide future values from current data, e.g. modelling, predicting, benchmarking. Duplicates were eliminated before reading all abstracts and further eliminating articles that were not suitable for this review, especially if they focus on non-recurrent situations like COVID-19. The objective of the review of the literature was to find sufficient evidence to generate a framework for forecasting wine tourism. Table III presents statistics about the process performed and the appendix has a list of the papers selected for reading.

INSERT TABLE III HERE

As can be seen in figure 1, the topics grew in similar fashion over the last 5 years with a peak in 2021 due to significant papers related to forecasting tourism during and after COVID. At the same time, the figure shows similar results as Kunc (2024a) for forecasting wine tourism. There are very few papers compared with forecasting tourism and wine tourism. Most of the work related to forecasting associated with wine is for production and sales, where Italian researchers have produced most of them, rather than tourism (Kunc, 2024a).

INSERT FIGURE 1 HERE

Results

This section contains three parts based on the three groups of papers from table II and the references to the papers are in the appendix. Firstly, there is a general description of recent developments and issues discussed in forecasting tourism. The second section presents a brief identification of concepts and activities described in the literature related to wine and tourism. Finally, there is a description of the research in forecasting wine tourism.

Forecasting Tourism

There are three themes in the literature: increasing use of internet content to complement time series of tourists, developments using Artificial Intelligence (AI) to generate multi-dimensional forecasts, and innovative datasets.

Increasing use of internet is observed in multiple forecasting models. For example, user-generated images (photos) can support tourism demand forecasting for online travel (Ma et al, 2024) and hotel demand (Xu et al, 2024), but Hu et al (2024) employ short videos instead of photos. All authors argue image aesthetics, as well as other descriptors such as popularity, together with search query data improve the accuracy of forecasts. Another example is the use of online reviews. Liao et al (2024) suggest the importance of identifying helpful reviews to enhance accuracy. Chen et al (2024) classifies news data into a sentiment index to combine with tourism demand for forecasting tourists. De Luca and Rosciano (2024), together with Havranek and Zeynalov (2021), use a prediction model based on Google trends data to forecast tourism arrivals, and Kantanantha and Awichanirost (2022) also employ Google metrics but to forecast online tour bookings. Zhang et al (2021) combines search data with data from multiple social media platforms to predict the frequency of tourists' arrivals to a site. An interesting article discusses the relative importance of search data depending on the sources, mobile or PC, where PC search is more useful as a predictor (Ramos et al, 2021).

Developments using AI refer to the creation of multi-dimensional forecasts that are supported with multiples sources of data. For example, Han et al (2024), Yin et al (2024), Madden et al (2023) and Bi et al (2020) present a deep learning model that combines historical tourist volume, search engine data, weather data, and school holidays/festive dates. Yoon et al (2024) present a complex approach to use image-based social medial, e.g., Instagram posts, together with deep learning visual image detection and text mining to identify tourism hotspots in an area. Puh et al (2023) and Wu et al (2022) use deep learning models to predict sentiment (positive, negative, neutral) and ratings (from 1 to 5 stars) from customer reviews from platforms like TripAdvisor. Kantanantha and Awichanirost (2022) employ several AI models that manage multiple dimensions from customer engagement with online tour websites to predict future bookings.

In terms of innovative datasets, the previous two themes have interesting innovative datasets, e.g., online reviews, photos, videos, news, weather data. One additional dataset is the use of population mobility, e.g., traffic flows, to forecast tourism volumes to scenic places (Li et al, 2022). In the case of Madden et al (2023), tourism (daily foot traffic) data is collected through counting sensors. Bausch et al (2021) show the use of weather data to describe multiple tourist behaviours: arrivals, duration of stay, repetitions, etc. Another innovative dataset is the use of geographic information systems together with remote sensing software to generate spatial data and topographic maps that can predict tourism (Bazazo and Alananzeh, 2020). An interesting dataset is created to overcome the lack of historical tourist volume data for a rural area (Yin, 2020). The authors modify a 'gravity model', which is used in transportation and urban planning, that employs qualitative variables such as an attraction index and relative origin from tourists. A summary of the key variables and their potential application to forecast wine tourism is in table IV. This table doesn't provide a hierarchy for variables because it is important to combine multiple variables, which aren't correlated, to obtain forecasts. The variables identified are employed in forecasting following the steps presented in the section Recommendations.

INSERT TABLE IV HERE

Wine Tourism

This area contains aspects related to the delivery of wine tourism experience, i.e., the supply side, and tourists' behaviour, i.e., the demand side.

In terms of aspects related to the delivery of wine tourism experiences, they can be arranged from intra- to inter-organizational factors. One intra-organizational factor is the right price for the experience, Gergaud and Livat (2024) investigate a set of variables: price of cellar tours, price of reference product (wine), type and style of experience, amenities, winemaking characteristics, visit length, number of wines tasted, and level of wine tourism activity around the winery (location). The authors indicate the price of cellar tours follows the price of the most expensive wine sold by the winery, which serves as a proxy for reputation, and longer experiences can have higher price together with the number of wines tasted during the visit. Another dimension of wine tourism delivery is the use of technology, such as industry 4.0 applications, to capture data and facilitate business, e.g., e-commerce wine sales (Strickland and Williams, 2024). Within the use of technology, Sousa et al (2024) and Gastaldello et al (2024) evaluate the impact of virtual reality to promote experiences. Lewis et al (2021) employ mobile technology to track wine tourists within an Australian wine region and obtain spatial-temporal data, and Gu et al (2021) perform a similar study in China using an app and surveys. Finally, general aspects of the winery are important to predict tourism. For example, Shin and Nicolau (2022) identify the attributes of a winery that affect visitors' satisfaction such as wine-related attributes, staff service and overall experience with the price of the experience negatively affecting satisfaction. Malerba et al (2023) focus on the key aspects of family-friendly wineries: fun and activities, facilities and attractions, service staff, setting, wine quality, food quality, atmospherics, and child-care functionality.

An inter-organization factor is the existence of a cluster, or agglomeration, Ostapenko et al (2024), or a network between the different actors arranged spatially (Gu et al, 2024). Harsányi and Hlédik (2022) offer an interesting categorisation of wine regions: wine dominant, wine tourist attraction dominant, multi-attractions and complex, and non-dominant wine regions, and how it relates with the type of wine tourists. Terziyska and Damyanova (2020) perform an online study for a wine tour company identifying six major elements of winescape from the perspective of organised travel: tour guiding, core wine product, tour planning and logistics, complementary activities, food and dining, and scenery. Brochado et al (2020) conduct an analysis on wine hotels located in 27 wine regions across 11 nations and conclude that type of wine, lodging, food service, scenery (view, vineyards), personnel, transportation and recommendations are valued by tourists.

From the analysis of the demand side, Gao et al (2024) analyses online review data using AI to identify the key variables for wine tourists: product-related aspects, sensory and affective aspects, cognitive and education aspects, and social-relation experiential aspects. Vecchio et al (2024) offers an evaluation of dimensions that attract sustainable wine tourists: wine involvement, environmental attitude, winery commitment to preserving biodiversity, and sustainability certification. Gastaldello et al (2024) identifies a set of variables associated with virtual wine experience: virtual experience features, wine involvement, intentions to visit wine regions, aversion to travel-related risk, and convenience. Amaral et al (2024) employ visitor reviews on TripAdvisor to define key variables describing experiences by wine tourists: intensity, entertainment, aesthetics, educational, interactions, escapism, and attributes (winery, wine, products and services, landscape), that can be associated with market segmentation profiles. Barbierato et al (2021), using a similar approach, add tour guide, logistical aspects, quality of food and wine, complementary tourist and recreational activities, and landscape and historic villages, and Brochado et al (2021) did similar study for wine hotels.

García Rodea et al (2024) surveyed wine tourists in Mexico to identify motivating factors for wine tourism (vineyard experience, knowledge and exploration, and marketing influence or suggestions) and consumer types (knowledgeable consumers, interested consumers, and novice consumers). Kladou et al (2024) performed a similar study to García Rodea et al (2024) but located in Greece and focused on small family wineries, which provides similar variables and new variables: loyalty towards small family wineries, staff behaviour and quality of wine. In terms of segmentation, Cunha et al (2022) offer a set of useful variables: level of wine involvement, gender, age, attractions visited, travel behaviour, to create types of wine tourists. Santos et al (2023) investigate similar variables for wine tourists looking for a cultural experience: involvement, winescape attributes, excitement, and sensorial attraction.

On the other hand, Napolitano et al (2022) examine the role of social interaction as part of winescape experience through few variables such as social interaction with service personnel, travel companions and other tourists to define wine tourist segments. In a similar area, Sassenberg et al (2022) look at the effect of atmosphere, e.g., live music and environment, in the winery on purchasing behaviour. Leri and Theodoridis (2021) consider the effect of personality traits (Big Five personality traits: openness, extraversion, agreeableness, conscientiousness, neuroticism) on visitor's experience in terms of emotions and revisit intention. Vorobiova et al (2020) and Nella et al (2021) also create a market segmentation for wine tourists using variables such as origin of the tourists, level of experience in wine, first-time or repeat, individual or group, and gender. Crespi-Vallbona and Mascarilla-Miró (2020) identify key concepts such as participation, hedonism, significance, knowledge, nostalgia, tasting, novelty, and local culture for experienced wine tourists during their wine experiences. A summary of the key variables and their potential application to forecast wine tourism is in Table V, organized in two areas, service delivery and tourist experience, from closely related to the tourist to more distant from the tourist). Closely related variables may be more accurate to predict tourism, but distant variables can account for place-specific contingencies.

INSERT TABLE V HERE

Wine Tourism Forecasting

The only article that partially fits with the topic is Duarte Alonso et al (2024). In this article, the authors identify the key drivers of wine tourism growth in Chile using a simulation model. Through in-depth semi-structured interviews with 69 wine managers, they map five key drivers: word-of-mouth recommendations, product attractiveness, tourism services, information available on the internet (e.g., websites, social media, reviews), and tour operators' recommendations. Then, they simulate the model to identify long-term vs short-term impacts on growth trajectories supported with feedback loop analysis.

Recommendations

The previous section provides an overview of forecasting practices and wine tourism, but only one paper partially combines both areas. This section discusses a framework to develop forecasting practices, which can support winery tourism life-cycle stages (Dodd and Beverland, 2001). Three steps comprise this framework: a survey to obtain the data for the forecasting model, a forecasting model based on simulation and/or AI, and scenario development to test different futures.

Step 1 – Survey the wine tourists and wine tourism services

From the systematic review of wine tourism and forecasting tourism, variables from tables IV and V can be used to make the segmentation of the wine tourists detailed and identify relationships between different components. However, we must consider the availability of the data for the whole market and over a period time, not only from an ad-hoc survey. While a clear segment may be selected, the main question is to find the closest market (in terms of distance) where this segment is present, or make it clear the differences between local tourists vs. outside (foreigners or out of the region) tourists. The forecasting model needs to account for the potential market size of the tourist segment that is the target of either a winery or wine region/wine route. The segments may change over time considering the life cycle explained in table I. Another information to collect is how many times they expect to have the wine tourism experience, e.g., repeat experience. Since wine tourism is a service and it is not observable by potential adopters, there is a reduction of the experience effects over time as wine tourists forget about their wine experience and they may not generate additional word-of-mouth, which is denoted as coefficient of forgetting in the model, unless it is captured by, for example, online reviews. The information can be collected using demographic information complemented with market research using surveys or from online platforms. Additional data needs to be captured to measure the effect of word-of-mouth and advertising campaigns on the intention of making a future visit to a winery (Kunc, 2009; Torres et al, 2021).

Step 2 – Forecasting models

There can be two approaches: diffusion models, which are suitable for forecasts of emerging wine tourism services either at winery or wine region level and require low amount of data, or AI-based models, which can be used for forecasts with multiple large datasets containing multiple dimensions.

Diffusion models, usually logistic regression models or simulations (Kunc, 2018), are used for forecasting the diffusion of new products among a population of potential consumers when the product is at the beginning of its lifecycle (Kunc, 2009). The data requirements data are lower than using AI-based models, and simulation allows using multiple factors with uncertain values (Kunc, 2018). One of the strengths of this simulation model is it only requires four parameters, which can be associated with the variables identified in tables IV and V.

(1) innovativeness behaviour originated from advertising campaigns and social media (a). This parameter represents the impact on behaviour from user-generated photos and videos, online revies and new coverage, search engine data. This data measures the response from tourist to these effects, and it is usually considered in forecasting tourism methods (see table IV).

(2) persuasion from previous wine tourists generated by word-of-mouth (b). This parameter measures the impact of positive sentiment on the behaviour of tourists originated from online reviews, as summarised in table IV. The characteristics of the experience can be important factor determining the value for this parameter (see table V)

(3) the maximum potential market size by number of wine tourists (m). Traffic sensor data and geographical data (see table IV) are the sources to estimate the maximum potential market size for a wine tourism activity. Additional sources can be expert judgment related to the location of markets (see table IV). On the other hand, the

price elasticity to wine tourism activities can help to estimate potential market size (see table V)

(4) the cumulative number of wine tourists in period t (N(t)) and

(5) the forgetting rate (at which wine tourists forget their experience) (c).
This parameter measures the time that wine tourists forget about their experience. The data sources for this parameter can come from the characteristics of wine tourists, e.g. involvement, or the dimensions of the experience, e.g. education aspects, sensory and affective aspects (see table V).

The model is:

$$\frac{dN(t)}{dt} = \frac{a\big(m - N(t)\big) + b}{mN(t)\,\big(m - N(t)\big) - cN(t)}$$

AI-based models can include multiple methods such as Artificial Neural Network (ANN), Support Vector Regression (SVR) (Song et al, 2019). AI-based forecasting models, particularly those leveraging machine learning and deep learning algorithms, excel at capturing nonlinear relationships and high-dimensional interactions within large, heterogeneous datasets (Salazar and Kunc, 2024). These models can adapt to dynamic environments and improve predictive accuracy through continuous learning (Salazar and Kunc, 2024). However, their performance is contingent on the availability of high-quality, granular data—often lacking in niche domains like wine tourism (Salazar and Kunc, 2024). Additionally, AI models can suffer from interpretability issues, limiting transparency and stakeholder trust, as well as requiring strong expertise (Salazar and Kunc, 2024). Overfitting, data sparsity, and model generalizability remain critical challenges (Song et al, 2019). Thus, while AI offers substantial forecasting potential, its deployment must be accompanied by rigorous validation (Song et al, 2019).

Step 3 – Scenarios

Decision makers may be interested in testing strategies, e.g., promotions or marketing campaigns, considering differences in tourism behaviour, e.g., level of loyalty or repeat visits. This activity is usually performed through scenarios (Kunc, 2024b). For example, one scenario to consider is to include different levels of repeated tourists, those tourists who become enthusiast visitors. The new version of the model with a returning coefficient (r) is:

$$\frac{dN(t)}{dt} = \frac{a\big(m - N(t)\big) + b}{mN(t)\,\big(m - N(t)\big) - cN(t) + rN(t)}$$

Other scenarios to consider are related to the uncertainties in terms of social changes and economic performance of the country. Using these uncertainties, a set of scenarios can be developed following Kunc and O'Brien (2017)'s methodology to understand future changes on the external effects mentioned in steps 2. Then, the model can predict different future paths by changing the parameters.

Conclusions

While forecasting in general tourism and descriptive analyses of wine tourism are well-established, there's a scarcity of studies that specifically combine both areas to create predictive models for wine tourism. This paper addresses this gap by proposing a practical framework for future research and application.

The unbalanced development of research, where most publications focus on either forecasting tourism or wine tourism separately, is a critical limitation in literature, as the unique and multi-faceted nature of wine tourism—influenced by factors like the winery's life cycle, and specific cultural and spatial elements—presents different challenges than general tourism forecasting. Traditional tourism forecasting often relies on aggregate data like international tourist flows, which is not suitable for a niche activity like wine tourism. The paper highlights the lack of accurate historical data, multiple dimensions for analysis, and effective methods as key issues in this area. Only one report, called ACEVIN - RUTAS DEL VINO DE ESPAÑA (Wine Routes Spain), showing wine tourism information at national level was found but there are not reports at local wineries.

This study's contribution lies in its effort to address this unbalance by leveraging recent technological developments and methodologies, particularly those from the last five years, which have been significant in areas like AI and digitalization. The proposed framework integrates findings from two separate literature reviews: one on forecasting tourism and another on wine tourism.

The review of forecasting tourism highlights three key trends that can be applied to wine tourism: the increasing use of internet content (like user-generated photos and online reviews), the development of AI for multi-dimensional forecasts, and the use of innovative datasets (such as population mobility and weather data).

On the other hand, the review of wine tourism literature reveals a rich set of variables from both the supply (delivery of services) and demand (tourist behaviour) sides. These include intra-organizational factors like pricing and technology use (e.g., e-commerce, mobile tracking) together with winery' experience characteristics, and demand-side variables like tourist segments, motivations, and the role of social interaction.

The paper links these trends and variables described in Table IV and V into a forecasting framework. The proposed framework offers a multi-step process for researchers and practitioners comprising three steps:

1. Surveying tourists and services to collect essential data.

2. Selecting an appropriate forecasting model, either a diffusion model for emerging services or an AI-based model for established ones with large datasets.

3. Developing scenarios to test different strategies and account for uncertainties.

This approach acknowledges that different forecasting methods are appropriate for different stages of the wine tourism life cycle, a concept highlighted in the literature. For instance, a winery in the early "wine establishment" stage might use a simpler diffusion model with less data, while a mature region could benefit from a more complex AI-based model that leverages large datasets.

The framework has practical implications for winery managers, enabling them to make more informed decisions about capacity planning and investments. For academic researchers, it provides a methodological roadmap to stimulate further inquiry in this under-researched area. This study's originality lies in this synthesis to provide a forward-looking and practical guide for the future of wine tourism forecasting. However, future research can improve the framework through additional research questions such as:

1. How managers in wineries, wine routes or wine regions use forecasting in decision making?
2. What is the role of technologies for automatic data collection, e.g., apps, to support forecasting?
3. What are the key variables to predict wine tourists?
4. What methods are used for forecasting? What are the strengths and weaknesses for each method?

In conclusion, the proposed framework offers a step toward advancing methodological approaches for wine tourism forecasting, highlighting the potential of simulation and AI-based approaches to address current data limitations and guide future empirical research.

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Appendix

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Forecasting Wine Tourism

Id	Reference
1	Torres, J. P., Barrera, J. I., Kunc, M., and Charters, S. (2021). The dynamics of wine tourism adoption in Chile. *Journal of Business Research*, 127, 474-485.

Tables

Method	Description
Time series analysis	It is a statistical technique used to analyse data points arranged over time. This method helps identify patterns and trends. There are simple methods such as Naive, Simple Moving Average (SMA), and Single Exponential Smoothing (SES) models, as well as more sophisticated like exponential smoothing adjusted by trend (ESAT), autoregressive moving average (ARMA) (Song et al, 2019).
Causal methods	These techniques evaluate the strength and nature of the relationships between variables to generate forecasts. Simple methods are based on regression analysis, while more complex models are econometric models and structural equation modelling (Kunc, 2018).
Delphi	The Delphi method employs a panel of experts who participate in multiple rounds of questionnaires until consensus emerges among the panel of experts. This is a subjective and qualitative method (Van Doorn, 1984; Kunc, 2018).
AI-based models	AI-based models capture nonlinear components among large datasets with multiple dimensions more effectively than other quantitative methods. Some examples include Artificial Neural Network (ANN), Support Vector Regression (SVR), and deep learning. While AI-based methods have better forecasting accuracy, they may not be theoretically grounded when they identify the relationships between tourism demand and other variables compared with econometric models (Song et al, 2019).

Table I. Forecasting methods: brief description

Concept	**Life cycle stage**				
	Winery establishment	**Winery recognition**	**Regional prominence**	**Maturity**	**Tourism decline**
Type of tourism	Rural tourism	Industrial tourism	Special interest tourism	Entertainment, festivals, and events	Bargain hunting
Visitors	Unintended visits	Connoisseurs	Aspiration and Connoisseurs	Wine drinkers	Traditional and new drinkers
Cellar door	Survival	Brand awareness	Brand enhancement	Increased percentage of sales	Survival
Brand awareness	Unknown	Becoming known	Known locally and internationally	Needs enhancement	Negative
Media	Unknown	Wine press General media	Wine press, general media, strong interest, international recognition	Media saturation	Difficult to obtain coverage
Sustainability critical aspects	Economic and environmental	Economic and environmental	Economic, environmental and sociocultural	Environmental and sociocultural	Sociocultural
Territorial stakeholders management	Limited to co-located wineries	Increasing linkages with restaurants, promotion programmes, tour operators	Fostering additional linkages with other wineries to create a regional brand.	Linkages with local partners related to culture	Linkages with destination management operators

Table II. Winery tourism life-cycle stages (adapted from Table 3 in Dodd & Beverland, 2001, Poitras & Getz, 2006; Bojnec et al, 2007; Carmichael & Senese, 2012)

Stage	Number of papers	Commentary
1. Search		Keyword:
	330	Tourism AND Forecast*
	207	Wine AND Tourism
	23	Wine AND Tourism AND Forecast*
2. Elimination		Duplicates and non-useful papers
	309	Tourism AND Forecast*
	179	Wine AND Tourism
	22	Wine AND Tourism AND Forecast*
3. Read		Final selection
	21	Tourism AND Forecast*
	28	Wine AND Tourism
	1	Wine AND Tourism AND Forecast*

Table III. Paper selection process

Variable	Potential use in forecasting wine tourism
Variables linking consumer sentiment with behaviour	
User-generated photos and videos	The increasing use of social media to show the places visited by wine enthusiasts can be a useful source to calculate seasonality, attractiveness, and segment tourists (Ma et al, 2024; Xu et al, 2024).
Online reviews and news coverage	These variables can provide a sentiment towards a wine tourism experience and combined with historical data to generate useful forecasts (Liao et al, 2024; Chen et al, 2024; Zhang et al, 2021)
Variables linking consumer interest with behaviour	
Search engine data / Google trends	It can indicate popularity of a certain wine tourism experience and predict tourists flows (De Luca and Rosciano 2024; Kantanantha and Awichanirost, 2022)
Weather data	While pleasant weather is immediately associated with wine tourism, there may be instances that weather data can predict types of tourists visiting a winery or wine preferences (Han et al, 2024; Yin et al, 2024; Madden et al; 2023; Bi et al, 2020; Bausch et al, 2021).
Variables linking consumer behaviour with consumer preference	
Traffic sensor data (cars, people, etc.)	It can help to forecast tourist flows in wine routes or wine trails (Li et al, 2022, Madden et al, 2023).
Geographical data	It may suggest preferences for wine tourists and predict optimal wine routes (Bazazo and Alananzeh, 2020).
Variables linking experts' knowledge with behaviour	
Expert judgment on qualitative aspects: attractiveness, location of markets	With the adequate model, it can support forecasting potential tourists flows (Kunc, 2018).

Table IV. Forecasting Tourism: key variables

Variable	Potential use in forecasting wine tourism
Wine tourism service delivery perspective (ordered from intra- to inter-organizational dimensions)	
Pricing	An analysis of price elasticity by segments can identify potential number of tourists (Gergaud and Livat, 2024).
Enabling technologies	Apps, sensors, GIS, smart phones, and virtual environments can generate multi-dimensional data to understand tourist' behaviour (Sousa et al, 2024; Strickland and Williams, 2024; Lewis et al, 2021).
Characteristics of the experience: amenities, wine, visit length, tastings, and additional activities.	An analysis of the impact of characteristics of the experience by segments can identify potential number of tourists (Malerba et al, 2023; Harsányi and Hlédik, 2022; Shin and Nicolau, 2022).
Supporting actors	Hotels and tour operators can impact the number of tourists (Terziyska and Damyanova, 2020; Brochado et al, 2020).
Cluster/network/importance of wine in a geographical area	The existence of more than one company, e.g., a winery, located in a geographical area recognised is critical to the development of wine tourism (Ostapenko et al, 2024; Gu et al, 2024).
Wine tourists' experience perspective (ordered from internal to external dimensions)	
Characteristics of wine tourists: wine involvement, attitude towards issues, e.g., sustainability, level of wine involvement, gender, age,	The potential number of tourists can be different depending on each market segment defined by their characteristics (Vecchio et al, 2024; Cunha et al, 2022, Santos et al, 2023; Napolitano et al, 2022; Leri and Theodoridis, 2021; Vorobiova et al, 2020; Nella et al, 2021; Crespi-Vallbona and Mascarilla-Miró, 2020).
Dimensions of the experience: product-related aspects, sensory and affective aspects, cognitive and education aspects, and social-relation experiential aspects.	There is a relationship between the potential number of tourists and the dimensions of the experience, which can be different for each market segment (Barbierato et al, 2021; Brochado et al, 2021; Kladou et al, 2024; García Rodea et al 2024).
Enablers of the experience: personal or virtual access, logistics (tour guides, routes), amenities (family-friendly, accessible, etc.), atmosphere.	There is a relationship between the potential number of tourists and the existence of enablers of the experience, which can be different for each market segment (Gao et al, 2023; Gastaldello et al, 2024; Amaral et al, 2024); Sassenberg et al, 2022).

Table V. Wine Tourism: key variables