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Progress in tourism demand research: Theory and empirics

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ABSTRACT

To explore recent progress in tourism demand research, we comprehensively survey current studies in the leading tourism and hospitality journals, asking six evaluative questions about the scientific merits of the studies and three explorative questions about emerging areas in the literature. The examination identifies potential flaws and their consequences in the field of tourism demand. A theoretical foundation is recommended for future tourism demand studies with a view to reduce bias in the empirical analysis of tourism demand. Several emerging areas of analysis in the field of tourism demand are recognized and discussed. Our study provides critical insights that will enable future tourism demand research to generate more reliable, impactful information than in the past.

1. Introduction

A rigorous methodology for quantifying and predicting tourism phenomena is critical in the development of tourism knowledge and practices. Following the Pythagorean epistemological principle that "all things are numbers," empirical tourism demand studies draw models and theories from various disciplines, convert tourism demand-related phenomena into mathematical equations, and use empirical data to explore and confirm claims related to tourism demand. In recent decades, the field has progressed significantly with the publication of many theoretical and empirical studies whose findings are referenced by decision-makers in destination governments and industries. However, the inverse of the Pythagorean epistemology, *all numbers are things*, does not hold true. In other words, a simple compilation and analysis of variables may not provide meaningful results that reflect reality. These results may prompt exploration, but they do not provide definitive conclusions. Conclusions drawn from them may mislead practitioners and have unintended consequences. Although most published tourism demand studies are empirical, not all of them have solid theoretical foundations, making the validity and reliability of their research findings questionable.

Several milestone reviews on tourism demand research have debated these issues and commented on progress in the field (for example, Buckley, 2018; Calero & Turner, 2020; Fernández-Hernández et al., 2016; Gunter et al., 2019; Song et al., 2012; Song et al., 2019). These studies have advanced the knowledge of tourism demand from various perspectives by mapping tourism economics knowledge (Song et al., 2012), commenting on the inertia of the tourism-led economic growth hypothesis (Song & Wu, 2021), assessing the methodological evolution and prospects of tourism demand forecasting (Song et al., 2019), and debating important issues in econometric tourism demand studies (Gunter et al., 2019). For example, Song et al. (2012) provided an overview of tourism economics research by classifying the relevant research topics and methodologies in terms of supply and demand analyses and estimating the economic and environmental impacts of tourism development at tourist destinations. They also indicated that the application of economic theories to the tourism domain generates knowledge that surpasses conventional economic principles and that both methodological advancements and cross-disciplinary perspectives help create a more comprehensive understanding of tourists and firm behaviors. However, continuous efforts to achieve methodological maturity and a strong theoretical foundation are required to assess the economic impact of tourism development (Song et al., 2012).

In response to the comment by Song et al. (2012) regarding the development of methodologies to assess tourism impacts, Gunter et al. (2019) assessed the scientific quality of the econometric tourism demand studies published between 2007 and 2017, concluding a lack of substantive interpretations of the size of the measured effects in many of these studies. This study is based on that of Gunter et al. (2019) and a few earlier reviews and critiques, such as Song et al. (2012) and Song and Li (2008). We extend and advance the debate by investigating the progress in tourism demand research between 2017 and 2022 and conducting a broader assessment of the latest developments in the field. Our findings show how researchers have developed the knowledge

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domain in a more rigorous and impactful direction in response to these critiques. We survey the tourism demand literature, examine whether the published studies were grounded in sound theoretical frameworks, and discuss those studies' measured effects in a broader context. We also identify studies that have misused economic models and misinterpreted their empirical results. Finally, we discuss emerging areas in tourism demand research involving the application of behavioral economics, the integration of macro- and microlevel analyses, and the appropriate methodological considerations and adjustments when modeling tourism demand and the effects of COVID-19.

Our purpose is to highlight the need for more rigorous, theoretically grounded econometric tourism studies that pay sufficient attention to the substantive importance of the economic impact of tourism development. To approach this task holistically, we adopt a broad definition of tourism demand that includes the demand for tourism products in both the tourism and hospitality industries at the macro- and microlevels. The remainder of this paper is organized as follows. The second section describes the procedure used to select articles and provides descriptive information. The third section discusses and evaluates recent progress and problems in econometric demand modeling. The fourth section presents emerging areas in tourism demand analysis. The fifth section concludes the paper.

2. Establishing the context

To fully assess the current status of the problems in tourism demand research, we surveyed tourism demand studies published in top journals in the recent five years. We developed nine survey questions based on a comprehensive benchmarking of milestone reviews (e.g., Gunter et al., 2019; Song et al., 2012), which served as the evaluation criteria for each article in our sample (n = 425, with 328 econometric articles among them).

2.1. Article selection

We conducted our article search in late March 2022, searching for topics such as "tourism demand," "tourist expenditure," "tourism receipt," "tourist arrival," "booking," "hotel revenue," and "occupancy." To select our keywords, we cross-referenced several review articles on tourism demand analysis, such as Song et al. (2012) and Song et al. (2019). Our search covered from 2017 to 2022 (five full years and the first quarter of 2022) and seven top tourism and hospitality journals, including *Annals of Tourism Research*, *Journal of Travel Research*, *Tourism Management*, *International Journal of Hospitality Management*, *International Journal of Contemporary Hospitality Management*, *Journal of Hospitality & Tourism Research*, and *Tourism Economics*, the last of which was included because of the goals of our paper. Overall, we collected 954 articles by searching Web of Science and then conducted a three-stage selection process to finalize our list. First, we marked 52 articles from the initial collection as reviews, editorial materials, or corrections and excluded them from the pool. Second, we briefly surveyed the abstracts of the remaining 902 articles to determine their relevance to tourism demand analysis. Approximately half (440) of the articles were irrelevant, as they were focused on areas such as revenue management, pricing and marketing strategy, and sustainability. Third, we conducted detailed surveys of the remaining 462 articles to answer our survey questions. During this process, another 37 articles were found to be irrelevant. Overall, we identified 425 articles relevant to tourism demand analysis (see Appendix).

2.2. Descriptive information

Among the 425 articles on tourism demand research identified, the number published each year generally increased, with 59 articles published in 2017, 44 in 2018, 68 in 2019, 93 in 2020, 84 in 2021, and 77 in the first quarter of 2022. This sustained growth and the remarkable output in early 2022 reflect the importance of tourism demand research during both normal and turbulent times. The percentages of the articles published in each of the seven journals revealed the leading role of the "Big Three" journals (*Journal of Travel Research* [75 articles or 17.65%], *Tourism Management* [66 or 15.53%], and *Annals of Tourism Research* [59 or 13.88%]) and of *Tourism Economics* (161 or 37.88%), a specialized journal for tourism demand studies. In comparison, hospitality journals generally publish fewer articles devoted to tourism demand (64 out of 425). However, 84%, 76%, and 50% of the tourism demand studies in the *International Journal of Hospitality Management*, *Journal of Hospitality & Tourism Research*, and *International Journal of Contemporary Hospitality Management*, respectively, were published since 2021, suggesting a significant surge in such studies during the COVID-19 public health crisis.

As shown in Fig. 1, in our final collection of tourism demand articles, most of the analyses are at the macro level (313 articles or 73.65%), whereas 109 of the microlevel analyses focus on individual-level tourism demand. Three of the articles include investigations at both levels using methods such as agent-based models and multilevel regressions. Approximately one fifth of the articles (81 or 19.06%) are forecasting studies that focus on improving the accuracy of tourism demand forecasting models. The remaining 344 articles examine tourism demand.

With respect to their methods, 328 of the articles (77.18%) used econometric methods, 21 used structural equation models, 17 adopted purely AI-based techniques, and 59 used descriptive analysis, qualitative analysis, or other methods. Different methods have different aims: Structural equation modeling methods explore and confirm conceptual correlations and processes; AI-based techniques capture nonlinear relationships and improve predictive performance; and econometric methods estimate the influencing variables' impacts on tourism demand and the effect of those impacts. Econometric studies of tourism demand rely on the economic theory that underpins the causal relationship between tourism demand and its determinants. The econometric models in more recent investigations have incorporated theories from other disciplines, such as sociology and psychology, to capture the complexity of tourist behavior. For instance, concepts such as social preferences, risk perception/tolerance, and mental accounting have been integrated into the econometric analysis of tourists' choice of variety in tourism products (Li et al., 2022). Given the dominant proportion of econometric studies in the tourism demand literature, our investigation of the recent progress and problems in the field focused on the 328 econometric tourism demand articles, and the non-econometric studies are discussed in the section on emerging trends.

3. Progress and problems in econometric tourism demand studies

3.1. Theoretical foundation and variable selection of empirical models

Empirical research should either be based on an important theory or test aspects of such a theory (Patten & Galvan, 2019). In our collection of 328 econometric articles, although a few (32) began their empirical investigations with a theoretical derivation of an economic model, the majority based their empirical models on the relationship between tourism demand and its determinants, as suggested by demand theory. As tourism and hospitality research is bound up with the development of the tourism and hospitality industry and therefore must be relatively practical, it would be unrealistic (and inconsistent with the preferences of the readers of tourism and hospitality journals) to expect every econometric article to derive a unique theoretical model. Adding a variable to a regression and indicating its statistical significance is a practical and technically feasible approach, especially with the amount of available data. However, a theoretical underpinning that establishes a causal relationship between the newly added variables and the dependent variable is essential. Researchers must address this issue cautiously and explicitly. Although regression results can seem to provide

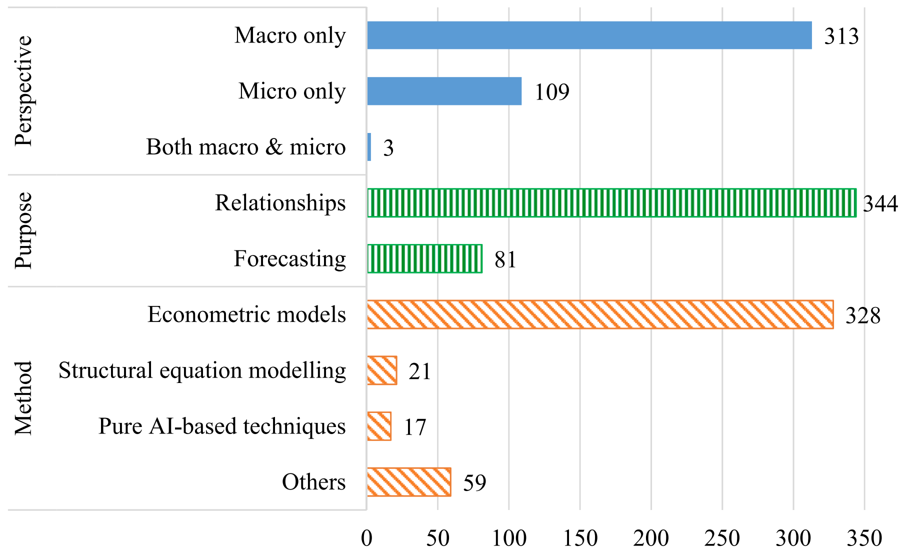

Fig. 1. Descriptions of selected articles.

interesting insights, Gunter et al. (2019) revealed that they can lack both theoretical justification and scientific value (i.e., substantive significance). In our survey of the tourism demand literature, we found several potential problems associated with the use of regression results that lack a solid theoretical justification.

The first issue involves the misuse of theoretical models. One example is the debate over the tourism-led economic growth (TLEG) hypothesis, pointed out by Song et al. (2012) and Song and Wu (2021). Most TLEG studies (e.g., Benkraiem et al., 2021; Dibeh et al., 2020) have models based on the Solow-Swan model (Solow, 1956; Swan, 1956), adding tourism (measured either as tourist arrivals or tourism receipts) as an influencing factor in the production function. Although this specification has often generated satisfying empirical results, the theoretical justification for adding tourism as a factor input is questionable. Tourism is distinct from the typical factor inputs in the Solow-Swan model (i.e., labor-augmenting technology, capital accumulation, and labor [population] growth). The three factor inputs in the original model are stock variables in the economy, whereas the newly added variable, tourism, is a flow variable in a specific sector and cannot be considered a factor input. The nature and scope of the tourism variable are incompatible with the other factor inputs in the growth model. In addition, the textbook Solow-Swan model is constructed for a closed (i.e., no international trade) economy without government influence (i.e., no taxation). This construction starkly contrasts with the typical scholarly perception of tourism as a service export. Therefore, simply adding tourism as a factor input in a Solow-Swan model may not be an appropriate empirical strategy. The mechanism underlying the relationship between tourism and economic growth requires more rigorous model specifications.

The second issue is the inclusion of variables in the tourism demand model without theoretical support. Although the inclusion of relevant variables may provide valuable empirical evidence, a spurious regression may emerge if variables are added to the demand function on the basis of mere intuition. According to Song and Wu (2021), strong empirical evidence can be derived from variables that are utterly unrelated to tourism demand, and any conclusions based on that evidence could lead to undesirable practical outcomes. To further the discussion about theoretical support in tourism demand studies, the theoretical justifications for variable selection and model construction are a matter of cardinal importance. We therefore propose our first survey question as follows:

SQ1a. How is tourism demand measured?

As shown in Fig. 2, in terms of measuring tourism demand, most of the macro studies have used tourist arrivals to measure tourism demand, as indicated by Song et al. (2012). According to each study's needs, visitor arrivals can be domestic, inbound, or outbound; they can be based on the statistical caliber of the relevant destination; they can be classified according to transportation mode, i.e., air, cruise ship, road, or railway; or they can be limited to a country or specific tourist attraction. Other popular measures of tourism demand include tourism receipts (or expenditures for outbound tourism), bookings or revenue in the context of the demand for accommodation, length of stay at the destination or accommodation, or a generic tourism demand term (used in certain theoretical expositions). Our dataset provides further information about tourism demand measures from the micro perspective. Tourist bookings, choices, and expenditures are the primary targets of the microlevel econometric analysis, followed by individual decisions about travel frequency and length of stay. In some microanalyses of individual demands for hotel or Airbnb accommodations, the number of bookings or guests have been used to measure tourism demand.

SQ1b: What are the variables used as determining factors of tourism demand?

With respect to the factors that determine or influence tourism demand, the macro- and microlevel econometric analyses have unique perspectives. As shown in Fig. 3, word cloud diagrams of the determinants of tourism demand at the macro (left) and micro (right) levels reveals heterogeneity, consistent with our observation on the differences in the use of these factors to measure tourism demand. At the macro level, GDP, exchange rate, and relative prices are the main factors that determine tourism demand. Notably, the inclusion of certain variables yields different interpretations in different contexts. For example, the GDP included in tourism demand analysis can be the GDP of tourists' country of origin and is thus a proxy for tourists' income. Alternatively, it can be the GDP of the destination country, which geographical economists using the gravity model have often argued is a measure of local infrastructure development that attracts tourists. It is even possible to use the world's GDP, which can reflect global economic conditions when tourism demand is measured by tourist arrivals/expenditures for source market worldwide. Some of the studies we reviewed have included event dummies to reflect the influence of unique events, such

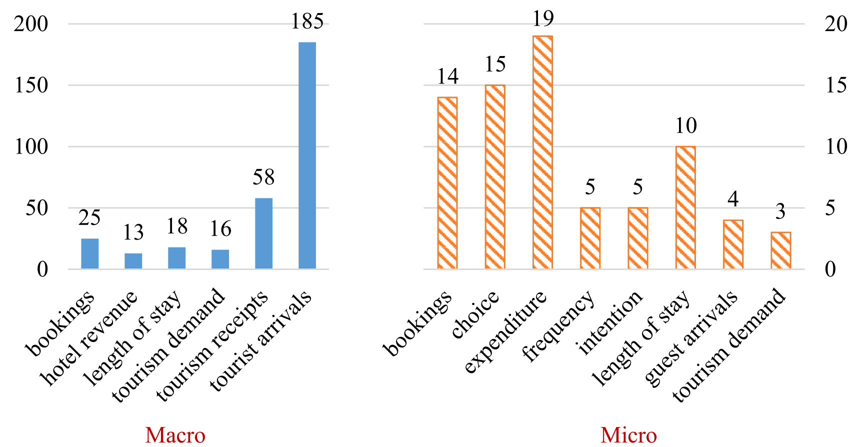

Fig. 2. Variables used to measure tourism demand.

Fig. 3. Word cloud of factors relevant to tourism demand.

as SARS, the avian flu, the financial crisis, the Olympic games, and terrorist attacks. The tourism demand studies conducted during the COVID-19 pandemic have used certain continuous/ordinal variables to describe the severity of the pandemic at the origin, destination, and/or global levels, such as the COVID-19 travelable index and the number of confirmed COVID-19 cases. At the micro level, the most important individual and travel-related characteristics are variables such as age (including generation and senior dummies), income, travel companion (travel party size and children), previous visits (first or repeat visit), price, and seasonality (including time trend, weekend, and holiday effects). Another emerging body of research has used online reviews, service/product ratings, photos, and review sentiments to explain tourism demand.

The observations from Figs. 2 and 3 extend the review of Song et al. (2012) by providing a bigger pool of variables from the empirical evidences as well as the popularity of various variables in the past five years. Popular variables (bigger font sized letters in Fig. 3) are frequently used not only due to their easy accessibility and relevancy to the research topics, but also because of the strong theoretical and empirical connections of these variables with tourism demand. Future studies should provide strong justifications and discussions in the absence of the key variables so that scientific rigorousness can be guaranteed (Gunter et al., 2019).

The contextual meaning of including a variable in the model should be carefully articulated in research. In our review, some articles combined the demand and supply variables in their model specification. Although changes in supply-side factors influence market equilibrium, the majority of their effects are channeled through market prices. This means that changes in the cost structures of tourism suppliers influence tourism demand only if those suppliers adjust their prices. Accordingly, if tourism prices and/or travel costs are considered in the model, other proxies for tourism prices, such as oil or aviation fuel prices, lose their explanatory power. The inclusion of both fuel costs and tourism prices in the demand model is likely to cause multicollinearity and identification issues. For example, in an investigation of the impact of low-cost carriers on domestic tourism demand in New Zealand, Tsui (2017) incorporated the number of available seat kilometers on budget flights, thus approximating the changes in travel costs faced by tourists. As a result, aviation fuel prices, a supply-side variable, had an insignificant influence on tourism demand.

Some model specifications combine different types of tourism demand in a single model without theoretical justification. From a macro perspective, the demand for different types of tourism (such as business and leisure tourism) should have different determinants. Trade volume is a strong predictor of the demand for business travel between two markets (Tsui et al., 2018), but it is a poor covariate for leisure tourism demand. Instead, household income, household size, and children at different levels of schooling have a strong impact on leisure tourism demand (Stråle, 2021; Zhang & Feng, 2018). Accordingly, different types of tourism demand are generated by different sets of explanatory variables, and each tourism type has its own demand dynamics. This issue is reflected in the study by Gholipour and Foroughi (2020), who assumed without theoretical justification that outbound leisure tourism has a positive influence on outbound business tourism; the results of their model estimation showed that leisure tourism had a negligible and insignificant effect on business tourism demand.

Some tourism demand studies have confused the influencers (determinants) and the indicators (reflectors) of tourism in their analysis. Tourism demand is a realized quantity at market equilibrium in a given period. In microeconomic analysis, a change in a product's price leads to movement along the product's demand curve, whereas a shift in the demand curve is caused by changes in other factors, such as consumers' incomes or tastes, the market structure of substitutes and complements, or expectations of future price changes (Mankiw, 2015, p. 67). Although the factors causing these movements and shifts can be considered influencers, market equilibrium may be indicated by other signals either before or after the realization of actual tourism volume. Search queries using Google Trends or the Baidu Index can provide examples of the indicators (reflectors) that have recently become popular in tourism demand models and that rank as one of the most frequently selected variables (see Fig. 3). Search queries as indicators may be useful when forecasting tourism demand (Tang et al., 2021; Wen et al., 2019), but their role in explaining tourism demand is unclear.

In addition, as the indicators reflect the volume of tourism demand caused by the influencers, there might be an indirect causal relationship between the indicators and influencers. Therefore, a model with both indicators and influencers might have a multicollinearity problem. Additionally, indicators are often noisy: tourists who search for the same hotel may visit at different times; a student of tourism may visit a hotel's website with no intention to visit the hotel; and not all tourists write online reviews after their hotel stays. These noises in the data might make multicollinearity undetectable in some regressions. In recent tourism demand analyses, many Internet-related variables have been indicators (e.g., search queries and Web traffic as leading indicators and the number of reviews as a lagging indicator). Although these indicators provide useful information for predicting tourism demand, extreme caution should be used when interpreting their roles in tourism demand models.

3.2. Functional form and specification tests

Linear regression, in which the relationships between variables are specified as an additive linear function, is one of the most powerful tools used in econometric analysis. In some situations, the linear functional form can also be used to approximate multiplicative power functions by taking the natural logarithm on each side of the power function. For some studies, additional terms can be considered in a linear regression to model nonlinearity. The cross-terms between two variables capture the interaction between two independent variables and identify the potential moderating effect of one independent variable on the relationship between the other independent variable and the dependent variable. Polynomial terms are used when the underlying relationship between the independent variable and the dependent variable is presumed to be nonmonotonic. The inclusion of these nonlinear terms can help researchers to further explore the relationships between the dependent variable and the independent variables, and it can generate interesting insights into these relationships. However, the usefulness of these nonlinear terms should not be determined solely by the statistical significance of their coefficients. We therefore propose our second survey question as follows:

SQ2. How is nonlinearity in tourism demand modeled?

Among the 328 econometric articles examined in this paper, 45 articles (13.72%) use the cross-terms of the variables and 20 (6.10%) utilize the polynomial (squared) terms. For example, Luo et al. (2021) used the cross-terms between credit information and Airbnb room and host information to capture the moderating effect of information credibility on the relationship between the information in Airbnb listings and their booking performance. Their research findings emphasized the important role of information credibility in customers' choice of Airbnb listings. In addition to its direct impact on listings' booking performance, information credibility determines the marginal impacts of positive reviews, listing price, hosts' rate of accepting bookings, and hosts' replies to reviews (Luo et al., 2021). In an investigation of the spending and travel frequency of Korean tourists, Pak (2020) noticed an inverted U-shaped relationship between respondents' age and travel frequency and expenditures. Korean tourists' travel frequency (expenditure) increases with their age until they are in their late 50s (60s), and exhibits a decreasing trend thereafter (Pak, 2020).

These examples illustrate the effectiveness of using cross and polynomial terms to reveal the nonlinear relationship between tourism demand and its influencing factors. However, in other cases, the nonlinear functional form is "fake" even when it contains statistically significant estimates. For example, in their investigation of how a World Heritage Site (WHS) designation influences a city's tourist arrivals, Lin et al. (2020) found statistically significant coefficients on the linear and squared terms of the number of WHSs in a region. An inverted U-shaped relationship between tourist arrivals and the number of WHSs seemed logical until the sample statistics were examined, particularly the variable range of the number of WHSs in a region. Their estimate indicated a positive relationship between a region's tourist arrivals and its WHS designations when there are fewer than 5.29 WHS and a negative relationship thereafter. However, in their sample of 31 provinces/municipalities in Chinese mainland, only one city had more than 5.29 WHS (Beijing = 7). Thus, the inverted U-shaped relationship was inconclusive. Boto-Garicía and Baños-Pino (2021) encountered a similar problem in their study of habit and travel resilience after the COVID-19 pandemic. The coefficients of the linear and squared terms suggested a critical value of 9.54 trips on the inverted U-shaped relationship between prior travel intensity and future travel intention. This critical value was well above two standard deviations of the mean of travel intensity. Instead of an inverted U-shaped relationship, the study found that "travel resilience increases (at a decreasing rate) with intensity of past travel patterns" (Boto-Garicía & Baños-Pino, 2021, p. 5). In these two examples, despite their statistical significance, the inverted U-shaped relationships generated by the regressions were inaccurate representations of reality. Without careful interpretation of the model estimates, variable statistics, and their meaningfulness, any research findings could be misleading.

Temporal structure is another important element in the model specification of econometric tourism demand analysis. Researchers can examine the time trend, business cycle, and seasonality of tourism demand by looking at data in the time dimension. The analysis of dynamic structure allows researchers to understand the intertemporal relationships of variables in forms such as autocorrelation. For example, tourists' destination choice process may exhibit a status quo bias and habit persistence, giving the lagged volume of tourism demand considerable explanatory power for future trends (Song et al., 2009). The past volume of tourism demand may also be considered a market signal for first-time visitors to proxy the popularity and quality of a destination (Lin et al., 2022).

Among the 328 econometric articles, 254 (77.44%) have a temporal element in their model specification. Most of the macro tourism demand studies in our survey (243/260 or 93.46%), but far fewer of the micro studies (12/65 or 18.46%), include a time element in their models. Recognizing the time stamps in the data, those articles use techniques such as time-series or panel-data analysis. For good reasons, some articles drop the temporal element from their investigations. For example, it might not be rational to include the temporal element in the model if the study's focal variable is only published once or irregularly. In that situation, a cross-sectional study might keep the investigation more focused. In their investigation of the role of cultural distance in determining bilateral tourism demand, Liu, Fan, and Qiu (2021) adopted a cross-sectional analysis instead of the panel data model because their focal variables—the Hofstede National Cultural Dimensions (Hofstede et al., 2010) and the physical distance between the origin and the destination—are time invariant.

Panel data models can capture trends in tourism demand across years or seasons with fixed or random effects in the time dimension. These models can also be used to investigate the treatment effects of policies or events. However, static panel data model lacks a sequential feature, and thus either an autoregressive component or lagged variable values are required. To investigate the use of temporal dynamics in econometric tourism demand studies, we surveyed the articles according to our third survey question as follows:

> **SQ3**. How are intertemporal dynamics in tourism demand accounted for?

Tourism demand responds to changes in its influencing factors both simultaneously and with time lags caused by habit persistence. Thus, tourism demand models must quantify such responses. Among the 254 econometric studies that we surveyed, approximately two-thirds (172 or 67.72%) incorporate intertemporal dynamics into their tourism demand models. For example, lagged tourist arrivals can be used to capture both structural dependency and habit persistence (e.g., Fu et al., 2020); lagged GDP can account for the influence of the long-term economic conditions in the source markets (e.g., Husein & Kara, 2020); and the lagged value of a search query can be utilized to model search behavior in predicting tourism demand (e.g., Liu et al., 2019).

The inclusion of autoregressive dependent variables and distributed lags of the influencing factors has been proven to be useful in describing the intertemporal dynamic structure in the context of tourism demand. Researchers should consider both the theoretical rationale and data empirics when choosing how many lags to include in a model. Approximately 60% of the articles that used dynamic models (104 of 172) explicitly described their lag selection process. The optimal lag length can be determined by information criteria, such as the Akaike information criterion (AIC), the Bayesian information criterion (BIC), the Schwarz information criterion (SIC), and the Hannan-Quinn criterion (HQC), or the final predictive error (Liew, 2004), which provides researchers with a degree of confidence that a time series (dependent or independent variable) is either a long memory series or a short memory series. It also gives them confidence about whether a cointegration relationship between the variables in the demand model is robust. In most of the remaining 40% of the studies, the researchers adopt a one-period-lag or one-seasonal-lag without an explicit description and discussion of the determination of the lag structure of the model. In their specification, although the intertemporal dynamics are (partially) captured, the audience cannot be sure that the proposed model has the optimal lag structure.

Another specification issue associated with the intertemporal feature of the demand model is the stationarity of the data used in the estimation of the models. The time series is said to be stationary if its statistical properties (e.g., mean, variance, and autocorrelation) are time invariant. As shown repeatedly, a time-series analysis with nonstationary data can yield spurious regressions and have undesirable conclusions (e.g., Hyndman & Athanasopoulos, 2021). With this in mind, we surveyed the literature while considering our fourth survey question, which is as follows:

> **SQ4**. Are the properties of the time series used in estimating the demand models properly assessed?

Among the 254 studies with (inter)temporal model structures, 127 articles (50%) explicitly mention the stationarity feature of their data. Although this does not necessarily mean that the remaining 50% of the articles have spurious regressions, the "withholding" of stationarity check results casts doubt upon the validity of their results.

There are several reasons for this "withhold" problem in the stationarity check. Some of the articles took the natural logarithm or first difference of their variables as a "default" procedure, but whether this transformation successfully achieves stationarity in the time-series data is unclear. In the studies utilizing panel data with many members in the cross-section dimension and a relatively short time span, the power of the panel unit root tests can be relatively low (Baltagi, 2005). Other advanced tests and treatments can be considered under these circumstances (Hurlin & Mignon, 2007). The software or statistical packages used for some articles have built-in functions to treat nonstationarity series. For example, the "forecast" package in R has a built-in stationarity check in its "auto.arima" function (Hyndman et al., 2021; Hyndman & Khandakar, 2008). Researchers using this function do not need to be concerned about the nonstationarity of time-series because the function automatically differences the time-series data to achieve stationarity. Although these facts provide researchers with excuses to withhold a discussion of stationarity in their empirical modeling exercises, it is still worthwhile to explicitly discuss the stationarity treatments for the time-series. Such a debrief can relieve doubts and enhance the audience's confidence in the results.

In addition to stationarity, other time-series properties may be salient in certain contexts. Dynamic econometric modeling often relies on economic theories that have underlying assumptions about the property of the data. Failure to meet these assumptions can have invalid and misleading results. For instance, the autoregressive conditional heteroscedasticity (ARCH) and generalized ARCH (GARCH) models are proposed both to model stochastic processes and to describe the dynamics of the variance of the error term in time-series data. These models have been used extensively in analyzing financial data due to the seemingly random change feature in financial markets (Steele, 2001). Based on the assumption of an efficient market, the GARCH model has frequently been used to predict the variance of returns—i.e., volatility—in the financial market (for a detailed explanation of the GARCH model, please see Francq & Zakoian, 2019). Analogously, the ARCH component has been used in tourism studies to capture the "volatility" of tourism demand (for example, in 8 of the 172 articles that incorporated intertemporal dynamics). However, the tourism market is quite different from the financial market. Although the financial market's return is unpredictable based on the assumption of the efficient market theory, numerous empirical studies have proven that tourism demand is explainable and predictable (Song et al., 2019). Therefore, fluctuations in tourism demand are deterministic; they do not follow a random walk process. Hence, applying a GARCH model to tourism demand analysis violates the initial market efficiency theory used to develop the GARCH model.

3.3. *Interpretation of model estimates*

In addition to model specification requiring caution from researchers, the explanations of all of the model's estimates require multi-aspect information. Consider what occurs when statistical significance is discussed but the effect size is not mentioned. This type of oversight primarily applies to the statistical significance of regression coefficients. From a theoretical perspective, a statistically significant coefficient only provides evidence of the independent variable's non-zero effect on the dependent variable. The statistical significance does not convey the magnitude of this influence.

The problem with effect size can be partially addressed by transforming the regression estimates into elasticities so that the discussion of the results is framed in percentage terms and the units of the variables are irrelevant. In their survey of econometric tourism demand studies between 2007 and 2017, Gunter et al. (2019) found that 114 of 115 (99%) articles discussed their model estimates in either elasticity or other interpretable forms. However, transforming model estimates into elasticities is only one step of the process. Small percentage values can still indicate a trivial economic impact. Researchers should discuss the results in terms of effect size to convey the value of their findings to the audience. We therefore propose our fifth survey question as follows:

SQ5. Is effect size properly discussed in tourism demand studies?

Unlike the 99% articles using elasticities found in Gunter et al. (2019), our investigation only identified 165 articles that explicitly discuss their model estimates in terms of effect size. Considering that 54 of the 328 tourism demand studies surveyed are forecasting oriented, with a goal of generating the most accurate forecasts instead of exploring casual relationships, a base of 274 articles (328 minus 54) should be considered when interpreting this result. That is, approximately 60.22% of the studies we surveyed make explicit statements about the effect sizes of their found relationships. In addition to statistical significance, their discussions evaluate the size of the influence of a specific factor on tourism demand. This directly establishes the economic meaning of these variables and relationships. Although 60.22% is not a low number and far above the <10% proportion found in Gunter et al. (2019, p. 15), it is alarming nevertheless given that we reviewed the best articles in the field. Shouldn't we expect the proportion to be somewhere above 90%, if not closing in on 100%?

For articles that lack an explicit discussion of effect size, the audience can discern the marginal effect of the relationships using model estimates and the descriptive statistics of the variables. We then investigated our sixth survey question, which is as follows:

SQ6. Are descriptive statistics of the variables useful in tourism demand modeling?

Either because of space limitations or for other reasons, only 122 of the 274 articles (44.53%) surveyed list the descriptive statistics of their variables, which slightly advances the <30% proportion found by Gunter et al. (2019, p. 9). Among these articles, some report the range (minimum and maximum) of the variables, whereas others list the moment statistics, such as mean, standard deviation, and skewness. Either way, the descriptive statistics of the variables can help the audience understand the data specifics of the investigation and judge the marginal impact of its estimates.

Combining the survey results for *SQ5* and *SQ6*, 206 articles either explain their results explicitly in terms of effect sizes or provide enough information for the audience to deduce those results. That is, 68 studies (or 24.82%) neither mention effect size nor provide the descriptive statistics of their variables. As a result, their audiences have less information about the economic significance of the research findings. The arguments in those studies are established based on statistical significance and may be considered "asterisk econometrics" (Ziliak & McCloskey, 2004). Statistical significance is not economic significance (Gunter et al., 2019; Ziliak & McCloskey, 2004). Statistical tests merely provide evidence about the confidence level of a certain statement, where the statement itself—discussing the effect size of the estimates—is the gold standard of scientific research. This confusion between the two significances is already worrisome; indeed, statistical significance itself is to be used with caution. The common practice of a statistical test dichotomizes the estimation results into "significant" or "insignificant" according to a cut-off value. However, the results with significance levels around the cut-off points deserve extra attention. It is illogical to treat a result with a p-value of 5.01% as fundamentally different from a result with a p-value of 4.99%, regardless of whether the cut-off point is set at 5%. The statistics community has argued in favor of retiring the dichotomization of p-values (Amrhein et al., 2019), instead continuously evaluating the statistical significance so that "related prior evidence, plausibility of mechanism, study design and data quality, real world costs and benefits, novelty of finding, and other factors that vary by research domain" can be prioritized (Wasserstein et al., 2019, p. 14).

4. Emerging research directions in tourism demand research

4.1. Features of behavioral economics

Many economic theories rely on the assumption of rationality, although violations of this assumption are frequently observed in real life. The field of behavioral economics combines elements of economics with psychology and sociology to better understand people's real-world behavior. Notably, five Nobel Prizes in Economic Science related to behavioral economics have been awarded, beginning with the 1978 prize given to Herbert A. Simon for his concept of bounded rationality. Subsequently, Gary S. Becker won in 1992 for his work on motives and consumer mistakes; Daniel Kahneman shared the 2002 prize for his work on prospect theory and anchoring bias (the work in collaboration with Amos N. Tversky); Robert J. Shiller won in 2013 for his analysis of asset pricing from the perspective of behavioral finance; and Richard H. Thaler won in 2017 for nudge theory—a theory that models predictable irrationality and defies classic economic theory. The tourism demand literature has also embraced the concepts of behavioral economics and investigated tourist behavior from both rational and irrational perspectives. We explored the selected articles with our seventh survey question, which is as follows:

SQ7. Which behavioral economic concepts have been applied in tourism demand analyses?

The adoption of behavioral economic concepts in the tourism and hospitality field can be traced back to Nicolau (2008), who examined reference dependence, loss aversion, and diminishing sensitivity to tourism prices in the context of Spanish tourism. The number of tourism and hospitality studies employing behavioral economics has notably increased since 2016 (Li et al., 2022). Reference-dependent behavior has been tested in the contexts of long-haul destination choices, winery trip expenditures, and Spanish vacation budgets (Masiero & Qiu, 2018; Park & Nicolau, 2018; Sellers & Nicolau, 2021). It has been found that tourists make decisions according to a reference point based on their prior travel experiences. Wen et al. (2021) observed the phenomenon of mental accounting in the context of tourists' choice of tour packages. In that context, which focused on the Chinese custom-tour market, tourists tended to resist reductions in benefits and services more than they appreciated gains of the same magnitude. In the Western context, the degree of variety seeking has been observed to increase when tour packages were framed as all-inclusive rather than à la carte (Kim et al., 2018). In an exploration of the US tourism market, Kim et al. (2019) confirmed both the decoy and the compromise effects on tourists' destination choice process, and they discovered the different magnitudes of these effects in choice and rejection tasks.

It is noteworthy that the majority of the studied articles employing behavioral economic concepts are conducted at the micro level. This is not a surprise because behavioral economic theories are more relevant to individual behavior than to group behavior. Nevertheless, some recent studies incorporate a microlevel analysis into a macro-level aggregation, which provides a possible avenue to elevate the utilization of behavioral economic concepts from micro to macro tourism demand analyses.

4.2. When micro meets macro

Another emerging area in tourism demand analysis involves the aggregation of micro analysis in macro models. Macro and micro studies are typically separated because of their different data, models, and goals. Consequently, they are both limited by their scopes in the sense that studies often omit certain areas of inquiry. For instance, macro-level studies include no descriptions of individual behavior, particularly individual heterogeneity; and micro level studies provide no inferences related to market trends and fluctuations. A study that incorporates models at both levels can fill the gap and provide a more comprehensive perspective on the problems investigated. We surveyed a few hybrid articles to answer our eighth survey question, which is as follows:

SQ8. How are macro and micro frameworks integrated in tourism demand studies?

Three of our surveyed articles attempt this type of aggregation. Yang et al. (2017) modeled an individual multidestination route using a conventional probit model and incorporated individual choices into a geographic information system. Their results suggested that the itineraries of long-haul multidestination tourists revealed a preference for destinations that are close to previously visited destinations but far from their residences, and the heterogeneities in terms of the individuals and destinations were aggregated into a tourism spillover index at the macro level (Yang et al., 2017). Wong et al. (2017) used hierarchical linear regression with tourist behaviors at a micro level and economic conditions at a macro level and captured not only the association between tourists' demographics and their destination preference but also the broader link between travel distance and tourism market demand. By hypothetically categorizing three types of visitors, Li et al. (2021) adopted an agent-based model to capture the travel route choices of multidestination tourists. The model captured the tourists' individual destination choices and the duration of their visits, and it simulated the interaction between tourists and between tourists and their destinations. Their simulation provided insights into the cross-border movements among Chinese cities and revealed different levels of tourism spillover in different regions (Li et al., 2021).

Despite the limited number of studies incorporating both micro and macro analyses, this research direction is promising. The insights from the micro level not only help the audience to understand individual behavior but also provide explanations of macro-level phenomena. When micro meets macro, the analysis of tourism demand rises to a new level.

4.3. Tourism demand analysis under crisis

Unfortunately, another emerging area relates to the ongoing COVID-19 pandemic. Incorporating the impacts of crises into tourism demand is critical because the market is affected by changes in both determinants and external events (Song et al., 2019). Thus, numerous studies have estimated the effect of event dummies in tourism demand models, such as dummy variables for SARS, the global and Asian financial crises, 9/11, the 2004 tsunami disaster (Adedoyin et al., 2021), and economic policy uncertainties (Tiwari et al., 2019). Sociopolitical instability at destinations has received wide attention as it is closely interwoven with the tourism market and tourists' risk perceptions, on the other hand, Liu and Pratt (2017) found that terrorism has only a short-term impact on tourism demand in a particular destination and that its global and long-term effects are very limited.

Unlike the studies proving that tourism is resilient to crises, tourism economists are cautious about the impacts of the ongoing COVID-19 pandemic on the future development of the tourism industry and the economy. Recent tourism demand studies in the context of the COVID-19 pandemic not only help us understand the current status of the market and prepare for its recovery but also establish a body of tourism demand analyses in a prolonged pandemic, which could be significant for future research. We explore this stream of the literature with our last survey question, which is as follows:

SQ9. How has COVID-19 affected tourism demand analyses?

Efforts have been made to examine various aspects of the pandemic and their links to the tourism industry. Pham et al. (2021) adopted the Tourism Satellite Account framework and a computable general equilibrium model to estimate the effects of the COVID-19 pandemic on the tourism industry and economy in Australia. Qiu et al. (2020) surveyed three Chinese cities to measure the social costs of tourism during the pandemic. Tourists were hesitant to travel because of the health risks, and local communities at destinations opposed inbound tourism for fear that the virus would spread (Qiu et al., 2020). Various pandemic-related factors have been recently incorporated into tourism demand analyses to measure the impact of the pandemic. As the pandemic has spread worldwide, these factors involve both origin and destination regions, such as the number of confirmed cases in the origin and destination; tourism subsidies and promotions (Matsuura & Saito, 2022); the COVID-19 travelable index's four indicators, which are the pandemic situation, vaccination coverage, health resilience, and policy responses in source countries (Zhang & Lu, 2022); and lockdown measures at destinations (Provenzano & Volo, 2022).

Two approaches stand out from other efforts to model and understand tourism demand during the COVID-19 crisis. During a crisis, statistical models are less effective than at other times (Qiu, 2022). Accordingly, researchers seek other model components. Some investigations have incorporated contextual expert opinions and adjusted their estimations from the statistical model accordingly (Lin & Qin, 2022). These judgmental adjustments can utilize information that would not be used in a statistical model and provide insights during times of crisis. These adjustments can be done purely qualitatively, like the Delphi surveys in Zhang et al. (2021), or systemically with macroeconomic data and expert opinions (e.g., Liu, Vici, et al., 2021; Qiu et al., 2021). Another significant approach to the study of tourism demand, especially in forecasting-related investigations, relates to the generation of multiple scenarios. Although uncertainty is a substantial issue during times of crisis, multiple scenarios can cover a wider variety of possibilities to help the investigator to understand the future and the practitioner to design a contingency and recovery plan (Qiu, 2022).

5. Conclusion

This paper assesses the recent progress in tourism demand research and critiques several major analytical flaws noted in the assessment process. The insights from our assessment not only provide the most recent and holistic view of tourism demand research but also identify critical flaws that must be addressed. Our discussions reflect our own observations and by no means include all of the potential problems that may be encountered while conducting tourism demand research. Section 3 focuses on the econometric tourism demand literature and identifies several crucial elements in the research process. It shows that a solid theoretical foundation is necessary for an empirical study to generate valid and robust results, and a clearly defined research context allows the researcher to interpret these results accurately. Section 4 explores emerging areas in tourism demand analysis, including the inclusion of behavioral economic concepts, the integration of micro- and macro-level investigations, and the assessment of the impacts of and prolonged crisis related to the COVID-19 pandemic. These areas have not been extensively investigated but are of significant importance in understanding tourists and the tourism market.

According to Gunter et al. (2019), the scientific quality of econometric studies in our discipline needs improvement. In general, the needed improvements can be identified by comparing our observations with the results of Gunter et al. (2019), while bearing in mind that different article selection criteria were used. Nevertheless, there is substantial room for improvement in the scientific quality of the studies in the tourism and hospitality field. To avoid the problems identified in this paper, researchers should design their studies based on existing theory. Tourism demand is a complex subject that includes elements of economics, geography, psychology, and sociology, all of which have solid and broad theoretical bases. When we borrow a functional form or a framework from a theory, it is also necessary to adopt the assumptions of that theory. Failing to do so is like building a house using only the blueprint of a wall: it will not provide the intended shelter. Empirical research without theory may have undesirable consequences if the results are used to guide practice. Therefore, it is our responsibility as researchers to ensure the scientific rigor of our investigations and publications.

Some researchers have attempted to improve the use of theory and interpretation of results. Some statistical software and packages include built-in functions to prevent misuse of statistical methods or misinterpretation of results. For example, in addition to generating regular regression coefficients, SPSS provides standardized coefficients that describe the marginal effects of variables in the scale of data variation. This may assist researchers in understanding the effect sizes of the independent variables in the estimated model. As noted above, the "forecast" package in R has also a built-in stationarity check of its "auto.arima" function so that researchers can use the package free of the stationarity problem. These components and procedures help researchers to accurately obtain and interpret their empirical findings. However, through no fault of the software, its functions may have a detrimental effect if used inappropriately. If a researcher learns about statistics from statistical software programs, he/she may overlook the importance of the field's components and procedures and become unable to perform a statistical analysis without the built-in functions, leading to less rigorous analysis in the future. Accordingly, our call for more rigorous and theoretically sound empirical studies also extends to education in tourism economics and empirical research practices.

Although we repeatedly emphasize the importance of a theoretical justification of model specification, variable selection, and result interpretation, we do not intend to discourage empirical innovations. Indeed, explorations are encouraged, as they can generate exciting results. However, these results must be further examined through a rigorous research process to either identify their connection with or extension from existing theories. Empirical evidence should be defined as an exploration instead of an innovation if the theoretical perspective related to the evidence is unresolved. From a logical empiricism perspective and according to Hempel's deductive nomological model (Hempel & Oppenheim, 1948), a series of laws and conditions is necessary to declare a logical explanation of an event. In a tourism demand study, theories from various disciplines can serve as the laws that logically shape the explanation. When existing theories fail to provide a complete explanation, an extension of those theories can be generated inductively. In addition to the data specifics of a study, researchers should consider a broader range of information related to the cultural background, geopolitical environment, or contemporary technology to provide a holistic context for the logical explanation. For example, although data-mining studies make few theoretical contributions and do not contribute to our understanding of the laws of social and economic behavior, their results may highlight interesting phenomena that could inspire further theoretical studies, enhancing our understanding of people, markets, and the world. However, it should be acknowledged that the findings of data-mining investigations are only applicable to the adopted data set and are not (yet) generalizable to broader contexts. Future theory-based studies could fill these gaps related to generalizability.

This study also has limitations. First, the articles surveyed were collected through a keyword search of titles, abstracts, keywords, and keywords plus. Some tourism demand articles that failed to meet this criterion may have been excluded. Second, all of our evaluations and discussions are based on our observations and expertise, which may be subjective and limited in scope. Future investigations could select a different pool of studies and adopt a more objective evaluation algorithm to extend the horizon of this type of research. However, it remains important to heed the call for more rigorous and theoretically sound empirical tourism demand studies.

Author statement

Haiyan Song: Investigation; Methodology; Formal analysis; Writing – original draft; Writing – review & editing **Richard T.R. Qiu:** Investigation; Methodology; Formal analysis; Writing – original draft; Writing – review & editing. **Jinah Park:** Investigation; Methodology; Formal analysis; Writing – review & editing.

Impact statement

This article assesses the progress in tourism demand research. Instead of summarizing and categorizing topics in the existing literature, this article surveys and examines the theoretical foundations of empirical tourism demand studies and identifies reasons that may lead to model misspecifications and result misinterpretations. This article echoes the debates and discussions in mainstream research such as econometrics and statistics, and suggests tourism demand researchers to design empirical studies from the stemmed theories. Only then can the empirical tourism demand studies generate solid and generalizable results, which can be used to guide practice without risking undesirable consequences.

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Appendix A. Supplementary data

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