Segmenting Tourism Markets Based on Demand Growth Patterns: A Longitudinal Profile Analysis Approach

Segmenting tourism markets based on demand growth patterns: A longitudinal profile analysis approach

Dr. Yulin Liu
Lecturer
Student Success Group
Learning and Teaching Unit
Queensland University of Technology, Australia
Email: y68.liu@qut.edu.au

Dr. Aaron Hsiao
Lecturer
Department of Tourism, Sport & Hotel Management
Griffith Business School
Griffith University, Australia
Email: a.hsiao@griffith.edu.au

Dr. Emily (Jintao) Ma (corresponding author)
Associate Professor
Department of Hospitality & Tourism Management
Isenberg School of Management
University of Massachusetts, United States
Email: ema@isenberg.umass.edu

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iD

Yulin Liu https://orcid.org/0000-0002-6893-6724

Emily Ma https://orcid.org/0000-0002-0161-7710

Author Biography

Yulin Liu teaches statistical methods and research design in business and engineering disciplines. His main research interests include travel behavior, tourist behavior, tourism marketing, project management, methodological innovation, and teaching statistics and scientific research in higher education.

Aaron Hsiao is a Lecturer in the Department of Tourism, Sport & Hotel Management, Griffith Business School, Griffith University, Australia. Aaron is an organizational behavior scholar who specializes in internal marketing, diversity management and cross cultural management. Drawing on his tourism and hospitality research expertise, Aaron possess extensive industry contacts and experience to regularly collaborate with organizations and community groups in conducting industry funded research projects, both locally and internationally.

Emily Ma is an Associate Professor in Department of Hospitality & Tourism Management, Isenberg School of Management, University of Massachusetts, United States. Her research interests include behavior and customer experience management in hospitality and tourism organizations.

ABSTRACT

Despite the abundance in methodologies for tourism demand modeling, most methods examine demand growth levels rather than growth patterns. The latter, however, can be of great value for destination management to minimize business risks and for authorities to prescribe effective policies. Meanwhile, describing demand growth as a simplex S-shaped life-cycle curve may oversimplify the heterogeneity in visitor flows. There is thus a need for methods that can identify market segments based on demand growth patterns to enable smart destination management strategies and provide theoretical insights. This article introduces a longitudinal profile analysis via multidimensional scaling (LPAMS) as an effective and easy to implement data-driven segmentation tool. This practitioner-friendly quantitative analytic tool is justified in the theoretical background of embracing complexity in business research, data disaggregation, and modeling interdependence in tourism forecasting. The conceptual and procedural details of LPAMS are explained at a level that is comfortably understood by researchers and practitioners, together with methodological comparisons with conventional methods. A demonstration of LPAMS is presented to identify five typical annual arrivals' growth patterns of Australia's 43 main inbound markets over 1991–2016. This study contributes to the methodologies for longitudinal tourism demand analysis and market segmentation techniques.

KEYWORDS

Demand growth pattern; Market segmentation; Profile analysis; Longitudinal tourism demand analysis; Multidimensional scaling; Australia's tourist arrivals

INTRODUCTION

Tourist flow analysis plays an important role in marketing and demand forecasting for a destination's sustainable growth. For example, understanding inbound international tourist flows is essential for every destination country in devising marketing strategies such as positioning national markets abroad (UNWTO, 2017). Although there is abundant literature on the methodologies for tourism demand modeling, most methods predict demand growth level rather than growth pattern (Song, Qiu, & Park, 2019). Understanding the demand growth pattern, however, can be especially valuable for destination management to minimize risks to business success and for authorities to prescribe effective regulation policies (Wan & Song, 2018). Tourism demand growth pattern contains high practical value for tourism-related businesses in private sector and macroeconomic policy prescription in public sector (Song & Li, 2008). For example, Faulkner (1988) examined the changing patterns of the structure of Australia's inbound markets in 1980s in terms of trip origins and purposes, and correctly identified considerable long-term potential of emerging Eastern Asian economies, which called for "a greater sensitivity to cultural variations in the needs of tourists and their implications for facility design and service provision" (p. 341).

Tourist destinations often experience an S-shaped exponential growth pattern in tourist arrivals (Rosselló, Aguiló, & Riera, 2005). This pattern in tourism demand growth has generally been theorized by Butler's (1980) hypothesis of a tourist area's life cycle of evolution, which is more likely to emerge in long time spans (Guizzardi & Mazzocchi, 2010). For instance, Nejad and Tularam (2010) fit a logistic curve to Australia's annual short-term international tourist arrivals from 1956 to 2009 and interpret such a half-century long trend line using Butler's life-cycle theory. Meanwhile, a destination is usually visited by different people doing different things at different times. Aiming at revealing the complexity of managing tourists in dynamic systems, Beritelli, Reinhold, Laesser, and Bieger (2015) introduced a destination-management model focusing on the presence of heterogeneous visitor flows. Figure 1 illustrates that by summing multiple types of visitors' flows, the resulting aggregate flow may appear like the S-shaped life-cycle curve. For practitioners, the left half of Figure 1 is probably more informative and useful:

> "Analyzing all types of flows one by one and assessing their evolution (dynamics) allows for a more focused understanding of the situation and more specific actions …The single lifecycle concept of the destination is a mental construct that can lead to a myopic view of reality and at best (worst) produce general (spurious) insights and actions." (P. Beritelli, Answer to Bob McKercher's question on TRINET, 31 October 2018)

[Insert Figure 1 here]

Smith (1956) introduced the concept of market segmentation as "viewing a heterogeneous market (one characterized by divergent demand) as several smaller homogeneous markets" (p. 6). As consumers are heterogeneous in their preferences, motives, needs, and behaviors (Levin & Zahavi 2001), "visitors cannot be lumped into a single group and cannot be expected to have the same level of satisfaction with a one-size-fits-all experience" (Arimond, Achenreiner, & Elfessi, 2003, p.54). Segmentation analysis can identify diverse customer groups to treat differently and is generally observed to be a useful practice in tourism management (Dolničar, 2017). Segmentation helps destinations to formulate marketing diversification strategies and develop suitable products to different markets, which helps enhance destinations' competitiveness (Dolničar, 2004). Identification of distinctive tourism market segments also provides insights into how the tourism sector and the economy interact (Lin, You, Lau, & Demir, 2019).

Theoretically, Morley (1995) explained the micro-economic rationales for the importance of market segmentation for tourism demand modeling and tourism product differentiation. Approximately five per cent of the published research on tourism and hospitality conducted market segmentation (Zins, 2008). Most existing data-driven segmentation approaches (Dolničar, 2004) are at individual-tourist-level from cross-sectional samples and mostly focused on individual motivations, behaviors, and socio-demographic characteristics' roles in market segmentation (e.g., Alén, Losada, & de Carlos, 2017; Carvache-Franco et al., 2020; Vassiliadis, Bellou, Priporas, & Andronikidis, 2018; Walters & Ruhanen, 2015). Although cross-sectional data have its due significance, longitudinal data and demand growth patterns should be paid more attention in tourism market segmentation, especially when growing demand over time is one major concern in a study. According to Song et al. (2019)'s review of 211 key studies published between 1968 and 2018, longitudinal data has been playing a dominant role in tourism demand forecasting. Recently, Zhang, Li, Muskat, Law, and Yang (2020) introduced a group pooling-based deep-learning procedure to improve the accuracy and robustness of inbound demand forecasting as this method enables the exploration of heterogeneity among source markets. Zhang et al. (2020, p.4) concluded that identifying tourists source markets with similar arrival patterns is crucial because it "allows the fusion of similar data into one model without increasing the noises in the overall data".

Geographic aggregation (e.g., at country or region level) is also worth more attention for international tourism market segmentation. As the economic globalization pushes many businesses to adopt a global strategy, international market segmentation becomes an even more important marketing concept for developing and selling products across national borders. As Walters (1997) stated when heterogeneity characteristics are observed in international tourism markets, it is necessary to develop tools to help identify similarity patterns of different markets to assist with the development of global integration strategies. International segmentation can aid businesses in structuring the heterogeneity among international consumers and identifying segments to target in an effective and efficient way due to economy of scale (Steenkamp & Hofstede, 2002).

Inbound international tourists are naturally heterogeneous at the source market level. Visitors from the same source market are subject to the same outbound travel regulations (Ma, Qu, Hsiao, & Jin, 2015) and tend to display same pattern of seasonality of flows (Senbeto & Hon, 2019). Tourism and hospitality businesses are affected by macroeconomic conditions and business cycle (Koh, Rhou, Lee, & Singal, 2018), which reflects economy-wide fluctuations in economic activities and people's expectations about future employment and income in relation to the economy's long-term growth trend. The influence of the business cycle is particularly prominent to international tourism due to its income-elastic nature (Guizzardi & Mazzocchi, 2010). For instance, Smeral (2012) found that the effect of income on tourism demand is dependent of phases of business development of specific source market, building on a analysis of international demands of Australia, Canada, U.S. and the European Union. Rosselló et al. (2005) found that British and German tourists went through an information acquiring process before making destination choices, suggesting that "the transmission process takes place among groups that share the same culture and habits, and a system of segmentation based on the nationality of the tourists is ideal" (Rosselló et al., 2005, p. 114).

Hence, there is a need to develop and promote methods that can describe, segment, or predict tourism demand growth patterns utilizing source-market-level longitudinal data. This study aims to introduce longitudinal profile analysis via multidimensional scaling (LPAMS) as a practitioner-friendly data-driven approach to segmenting inbound tourism markets based on demand growth patterns. Embracing the heterogeneity in visitor flow growth patterns has methodological and theoretical implications on tourism demand modeling. The next section of this article offers a new perspective on data disaggregation in demand forecasting, modeling interdependent flows, and inbound markets convergence, and calls for easy-to-use alternative tools for longitudinal tourism demand analysis. To avoid the perception of "black box" regarding segmentation methods among practitioners (Dolničar and Lazarevski, 2009), the third section presents the statistical procedure of LPAMS in technical details, with a summary of guidelines for applying LPAMS. The fourth section demonstrates LPAMS in the identification of five typical demand growth patterns of Australia's 43 main inbound markets over 1991–2016. This article concludes with a discussion about this study's methodological, theoretical as well as practical implications on the research and practice in the domain of tourism and hospitality management. This study provides valuable reading for destination management shareholders to build their capacity in understanding demand growth complexity and implementing strategic diversification in precaution for long-term risks.

IMPLICATIONS OF HETEROGENEOUS GROWTH PATTERNS ON TOURISM DEMAND MODELING

Data Disaggregation and Indirect Method

Song and Li (2008) pointed out that destination-level aggregate data like total tourist arrivals and expenditures receive conventional popularity; nevertheless, analysis at disaggregated levels such as country of origin and purpose of travel can provide more nuanced and detailed information. When disaggregated data are available, aggregate demand can be forecasted through two alternative approaches: direct forecasting (i.e. forecasting the aggregate demand directly through aggregate data) and indirect forecasting (i.e. forecasting individual components of the whole market first, then integrating the components to obtain aggregate forecasts) (Song & Witt, 2003). Although multiple studies have also been performed to explore how data disaggregating can affect forecasting accuracy using advanced forecasting techniques, the evidence is still debatable (Song & Li, 2008).

When using autoregressive distributed lag models to predict annual inbound tourist arrivals to South Korea from four major source countries, Song and Witt (2003) found that a single model specification across four markets was not appropriate. Kim and Moosa (2005) compared the accuracy between direct and indirect forecasting of monthly international tourist arrivals to Australia using seasonal autoregressive integrated moving average (ARIMA) models, regression-based time-series models and structural time-series models; the results were strongly in favor of the indirect approach with all three types of models. Cortés-Jiménez and Blake (2011) compared the indirect and direct forecasting of the expenditures of inbound tourism to the United Kingdom. Structural time-series models with the same set of explanatory variables were employed to predict aggregate and disaggregate tourism expenditures by the combinations of visit purpose and nationality. The indirect method improved forecast accuracy, while in some instances the direct method produced systematic estimation errors. In consequence, Cortés-Jiménez and Blake (2011) argue that modeling at less aggregate levels should be more routinely considered in tourism demand forecasting.

On the other hand, Vu and Turner (2005) drew the opposite conclusion in favor of direct forecasting when using Holt-Winters exponential smoothing and structural time-series models to forecast South Korea’s quarterly inbound tourist arrivals disaggregated by travel purpose, sex, and age. Kon and Turner (2005) compared the accuracy between direct and indirect forecasts of quarterly tourist arrivals with various trip purposes into Singapore from six major inbound markets using basic structural method, artificial neural network, and the naïve and Holt-Winters methods; they found no solid evidence to support either the direct or indirect method. Notwithstanding the mixed evidence regarding data disaggregation's effect on improving forecasting, Song and Li (2008, p. 216) stressed that "if the trends of individual market segments are of major concerns, disaggregated data should be used in tourism demand analysis".

Interdependence in International Tourism Demand

Contemporary economic globalization is characterized by interdependence, denoting integration and reciprocal relationships among economies, which justifies the significance of examining the interdependence of international tourism demand across markets (Cao, Li, & Song, 2017). Tourist flows from multiple sources to a particular destination (or from one source to multiple destinations) form a vector of multiple time series. Simply disaggregating data in indirect forecasting implicitly assumes no association among the multiple tourist flows. However, if the flows are interdependent, ignoring the dependence structure can affect forecasting performance (Zhu, Lim, Xie, & Wu, 2018). Given a rich cross-correlation structure, multivariate time series models can be expected to outperform univariate models (Du Preez & Witt, 2003).

The interdependence of international tourist flows can be explained by the synchronization of business cycles of source markets. Chan, Lim, and McAleer (2005) applied multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) models to examine the interdependence of monthly arrival volatility of four leading international markets (New Zealand, Japan, U.S. and the United Kingdom) for Australia from 1975 to 2000. They found interdependent effects in the conditional variances among the four markets. Gunter and Önder (2015) compared the predictive accuracy of various univariate and multivariate models in forecasting tourists to Paris from its five leading overseas source markets (Italy, Germany, U.S., Japan, and the United Kingdom). The results indicated that for the United States and United Kingdom, univariate models were more accurate; however, multivariate models performed better for the German and Italian markets. For the Japanese market, the results varied by the forecast horizon. Zhu et al. (2018) examined tourism demand for Singapore during1995–2013 from six origin countries in three geographic regions using copula-based model to accommodate the pairwise dependence of tourist flows in each region. They argued that international travel demand from origin countries located in the same region was likely to be influenced by common economic, social or climate factors; the forecast of their copula-based model out-performed the baseline model that assumed independence among the tourist flows.

The interdependence of international tourist flows can also be explained by either substitutive or complementary relations among destinations. Using the MGARCH model and vector error correction (VEC) model, Seo, Park, and Yu (2009) investigated Korean outbound tourist departures to four popular destinations: Jeju Island, Thailand, Singapore and the Philippines. Seo, Park, and Boo (2010) expanded the investigation to seven overseas destinations for Korean outbound tourists using vector autoregressive (VAR) model. Torraleja, Vázquez, and Franco (2009) used VEC model to detect the associations among the inbound tourist flows to five major coastal regions in Spain. Chang, Khamkaew, Tansuchat, and McAleer (2011) used MGARCH model to investigate the interdependence of international tourist arrivals in Indonesia, Malaysia, Singapore, and Thailand. Further, Divisekera (2016) predicted the tourism demand interdependence of New Zealand, Australia, and the United Kingdom and the United States, using an almost ideal demand system model and reflected three countries’ substitutive and complementary relationships.

Uisng international tourist's arrival data to New Zealand and Australia, Athanasopoulos and de Silva (2012) compared the traditional univariate model with the vector innovations structural time-series model and found that more accurate forecast results could be achieved by pool information of two similar neighborhood destinations. Furthermore, Cao et al. (2017) developed a global VAR model to quantify interdependent co-movements of tourism demand from 24 countries, which were both main source markets and destinations in current international tourism. Based on the observation of similar tourist arrival patterns across nine Asia-Pacific source markets for Hong Kong and Macau, Zhang et al. (2020) for the first time proposed a group pooling-based deep-learning model in conjunction with time series decomposition and dynamic-time-warping clustering in order to overcome model overfitting and improve forecasting accuracy. Their positive results encourage future research to examine grouping among a larger number of sources markets.

Knowledge of interdependent tourist flows can enable authorities and corporations to group similar markets for joint promotion and coordinated marketing strategies in order to optimize cost effectiveness (Athanasopoulos & de Silva, 2012; Zhu et al., 2018). Future research on demand modeling and destination marketing should capture the interdependence of multiple tourist flows. Analytical tools should be able to provide more easily interpretable results to the wider community of researchers and practitioners.

Patterns in Tourism Markets Convergence

by Narayan (2006) first proposed the convergence hypothesis for international tourism by investigating convergence of 13 inbound tourism markets for Australia during the period of 1991–2003. Narayan defined the tourism convergence as a reduction in tourist arrivals' differential: "if the tourism markets were converging, the ratio between total international visitor arrivals and visitor arrivals from a specific country would be stationary" (Tang, 2011,

p. 264). Understanding the convergence of tourism markets is significant for a destination country in two aspects (Narayan, 2007): the convergence indicates the effectiveness of marketing policies; and converging small markets mean sound market diversification and risk allocation. From market segmentation's perspective, convergence analysis could provide a better understanding of the structure of market for developing customized promotion strategies (Lin et al., 2019).

Over a dozen studies inspired by Narayan (2006) have tested the hypothesis of various numbers of converging tourism markets over different time periods for different destination countries, where economic growth is driven largely by international tourism. The number of markets in a study ranged from eight in Narayan (2007) to 81 in Lin et al. (2019), with the majority falling between 10 and 20. The length of period in a study spanned from eight years in Solarin (2018) to 32 years in Narayan (2007) and Tiwari (2016), while most studies examined between 10 and 20 years. The most researched destinations include Australia (Kourtzidis, Tzeremes, Tzeremes, & Heryán, 2018; Valadkhani & O'Mahony, 2018), Singapore (Lee, 2009; Tan & Tan, 2013), Malaysia (Lean & Smyth, 2008; Tang, 2011), and Turkey (Abbott, Vita, & Altinay, 2012; Hepsag, 2016; Kaplan, Öztürk, & Günger, 2017; Lin et al., 2019). Other popular destinations examined include Fiji (Narayan, 2007), the Seychelles (Solarin & Lean, 2014), the Caribbean (Lorde & Moore, 2008), South Africa (Solarin, 2014), India (Tiwari, 2016), Spain (Mérida, Carmona, Congregado, & Golpe, 2016), Greece (Katrakilidis, Konteos, Sariannidis, & Manolidou, 2017) and Taiwan (Solarin, 2018).

Various econometric testing approaches have been adopted based on different assumptions about the converging process's characteristics – for example, non-linearity (e.g. Solarin & Lean, 2014), structural breaks (e.g. Tang, 2011; Tan & Tan, 2013; Ozcan & Erdogan, 2017; Yilanci & Eris, 2012), monthly seasonality (e.g. Hepsag, 2016), club or clusters (e.g. Solarin, 2014; Kaplan, Öztürk, & Günger, 2017; Mérida et al., 2016) and dynamics (e.g. Lin et al., 2019; Valadkhani & O'Mahony, 2018). These quantitative analytical methods are mathematically sophisticated and interpretable only to econometrics experts. Additionally, different models tend to provide inconsistent conclusions. For example, Turkey is the most researched destination regarding tourism market convergence; however, the structure of its source markets is still not clearly understood, as previous studies report different and even contradictory findings (Lin et al., 2019).

Therefore, from the perspective of a practitioner or an applied researcher, there is still a strong need for powerful yet relatively simpler tools for identifying and describing meaningful patterns in the longitudinal change of tourism demand among related markets. There is no silver bullet when it comes to the technique for modeling complex tourism demand (Song et al., 2019). The remainder of this article explains and demonstrates LPAMS as an alternative rather than substitute statistical tool and practitioner-friendly method for longitudinal tourism demand pattern analysis.

LONGITUDINAL PROFILE ANALSYSIS VIA MULTIDIMENSIONAL SCALING

Profile Analysis, Cluster Analysis and Factor Analysis

A demand growth profile is characterized by its level and pattern. Figure 2 compares four symbolic profiles over three time points; profiles of the same shade of darkness have close levels, while profiles depicted with the same format of line present similar patterns. Methodologically, profile analysis, cluster analysis and factor analysis are all quantitative exploratory approaches that can be employed to reveal groups among individual profiles, although profile analysis focuses specifically on profile pattern rather than profile level.

[Insert Figure 2 here]

Pattern-based profile analysis, distance-based cluster analysis and correlation-based exploratory factor analysis appear to be similar statistical data reduction techniques, yet they are quite different in aim, assumption, procedure and the type of research question they are able to investigate. Cluster analysis (CA) identifies homogenous groups of objects – that is, clusters. Individuals in a specific cluster display common characteristics and are dissimilar to individuals outside that cluster. Clusters are assumed to be mutually exclusive. Proximities (e.g. Euclidean distance) in terms of a set of criteria variables between individuals are usually the input for clustering. If the criteria variables are not on the same metric scale, they are usually standardized. The mean values of the criteria variables within a cluster are used to describe the cluster's typical characteristics. When being applied to profile data, clusters "largely describe individual differences in overall profile level, rather than individual differences in profile pattern" (Kim, Frisby, & Davison 2004, p. 597).

Exploratory factor analysis (EFA) uncovers unobserved factors or dimensions that govern the patterns of correlations among a set of observed variables. EFA is often used to identify a small number of factors that explain most of the covariance within a larger number of observables. When EFA is applied to correlations among individuals rather than among variables in a data set, it is called Q-mode factor analysis (Cattell, 1952). Q-factor scores are used to describe each factor's typical characteristics and together with cluster analysis, they are considered as bottom-up approaches (Kim, Davison, & Frisby, 2007), starting from measurement of the inter-individual proximity such as Euclidean distance and linear correlation (the bottom) to identification of typical profiles (the top). However, those inter-individual proximity measures may fail to reflect (if not bias) the similarity in profile pattern, as illustrated by the examples in Figure 2 and Table 1.

[Insert Table 1 here]

Profile Analysis via Multidimensional Scaling (PAMS)

Multidimensional scaling (MDS) is a class of exploratory statistical analysis of data that indicates the degree of dissimilarity (or similarity) between each pair of members among a defined set of objects (e.g. individuals, brands, destinations, companies). MDS can reveal the structure underlying the dissimilarity among objects by graphically displaying their relative positions with configuration mapping, typically in two or three dimensions. MDS results are therefore often further processed with clustering analysis and/or correlational analysis with other variables of the objects to obtain deeper insights. Davison and Sireci (2000) and Giguère (2006) provide approachable introductions to the statistical technique of MDS.

Despite its origin in psychometrics in the 1930s and MDS has now become a family of general data-analysis technique applied in a wide range of fields including tourism research. MDS started to appear in tourism research literature in the 1970s (Marcussen, 2014). Fenton and Pearce (1988) described the technical features of MDS along with some early adoptions of MDS in tourism research. Marcussen (2014) presented a systematic review of 64 tourism studies that applied MDS during 1975–2014, and he concluded that MDS was a useful tool for comparing relative positions or images among destinations (e.g., Li, Cheng, Kim, & Li, 2015).

MDS is not a novel method; however, interpreting dimensions as profiles is relatively recent (Davison, Gasser, & Ding, 1996). PAMS is considered an exploratory approach that identifies prominent patterns of profile and are represented by dimensions that are extracted from the MDS procedure. The PAMS approach to identifying latent profiles among individuals uses proximities among criteria variables rather than those among individuals, and it can estimate relationships between individuals' observed and latent profiles in terms of patterns. The process of PAMS orients from identification of major profiles in individual patterns (the top) to quantification of inter-individual similarity (the bottom) (Kim et al., 2007).

A PAMS model specifies an individual observed value as a linear combination of dimensions (Kim et al., 2007). A PAMS model that extracts *K* latent dimensions (i.e. prototypical profiles) from a set of individuals each observed on *V* criterion variables has the following general form:

$$\boldsymbol{y}_{\boldsymbol{i}(\boldsymbol{v})} = \boldsymbol{c}_{\boldsymbol{i}} + \sum_{\boldsymbol{k}=\mathbf{1}}^{\boldsymbol{K}} \boldsymbol{w}_{\boldsymbol{ik}} \boldsymbol{x}_{\boldsymbol{k}(\boldsymbol{v})} + \boldsymbol{e}_{\boldsymbol{i}(\boldsymbol{v})} \quad (1)$$

where $y_{i(v)}$ is an observed score of individual *i* on criterion variable *v*; c_i is a level parameter estimate, which indexes the overall level of individual *i*'s observed profile, and is usually the unweighted average of *V* variables' values for individual *i*,

$$c_i = (\frac{1}{V}) \sum_{v=1}^{V} y_{i(v)} \quad (2)$$

$x_{k(v)}$ is the location coordinate or scale value for criterion variable *v* along latent dimension *k*, and is obtained from MDS; w_{ik} is the profile match index for individual *i* on latent dimension *k*, indexing the degree of correspondence between individual *i's* observed profile over *V* variables and the prototypical profile represented by the *V* variables' scale values on latent dimension *k*; the *K* profile match indices of individual *i*' are estimated by regressing the individual *i*'s observed *V* values onto *K* dimensions' scale-values with the unweighted least squares method; and $e_{i(v)}$ is an error term for individual *i* on variable *v*, representing measurement error and systematic deviations from the model.

The data assumptions of PAMS are minimal, as PAMS allows for simultaneous estimation of non-linear intra- and inter-individual profiles without requiring multivariate normality (Ding, 2006). Despite this, to uniquely identify a PAMS model, the following constraints are imposed:

$$\sum_{v=1}^{V} x_{k(v)} = 0 \ for\ all\ k \tag{3}$$

$$\left(\frac{1}{I}\right)\sum_{i=1}^{I} w_{ik}^{2} = 1\, for\ all\ k \tag{4}$$

$$\sum_{i=1}^{I} w_{ik} \cdot w_{ik'} = 0\, for\ all\ (k,k'), k \neq k' \tag{5}$$

$$\left(\frac{1}{I}\right)\sum_{i=1}^{I} e_{i(v)} = 0\, for\ all\ v \tag{6}$$

$$\left(\frac{1}{I}\right)\sum_{i=1}^{I} e_{i(v)}^{2} = \sigma^2\ for\ all\ v \tag{7}$$

$$\left(\frac{1}{I}\right)\sum_{i=1}^{I} w_{ik} \cdot e_{i(v)} = \left(\frac{1}{I}\right)\sum_{i=1}^{I} e_{i(v)} \cdot e_{i(v\prime)} = 0\, for\ all\ (k,v)\ and\ (v,v'), v \neq v' \tag{8}$$

Equation 3 implies that each of *K* latent dimensions is ipsative, so that the mean of *V* scale values in each dimension equals zero. Therefore, *K* prototypical profiles will reproduce observed individual profiles' patterns, but not their levels, which are accounted for by the level parameter c_i. Equation 5 implies that *K* latent dimensions are orthogonal to one another in a geometric space. Equation 7 implies that the error variances are equal for all *V* variables, i.e., all *V* criterion variables in the profiles need to be of a common metric.

The Three Steps of PAMS

A PAMS often consists of three steps. First, a nonmetric (ordinal) MDS algorithm (Equation 9) based on Equation 1 is employed to identify *K* latent prototypical profiles and estimate the scale values of *V* criterion variables along each of the *K* dimensions. The non-metric MDS algorithm is expressed as

$$\delta_{vv'} = f(d_{vv'}) \tag{9}$$

and

$$d_{vv'} = \left[\sum_{k=1}^{K} (x_{k(v)} - x_{k(v')})^2\right]^{1/2} \tag{10}$$

where $f(\cdot)$ is a monotone function of pairwise distances ($d_{vv'}$) among *V* variables in their *K*-dimensional configuration; $x_{k(v)}$ and $x_{k(v')}$ are the scale values that locate criterion variables *v* and *v'* along latent dimension *k*. The input data of the nonmetric MDS procedure is a *V* by *V* matrix of proximities (i.e. Euclidean distance) among *V* criterion variables, with a pairwise proximity computed as

$$\delta_{vv'} = \left[\sum_{i=1}^{I} (y_{i(v)} - y_{i(v')})^2\right]^{1/2} \tag{11}$$

Since only the rank order of data is considered meaningful in most social scientific situations (Ding, 2007a), non-metric MDS procedure is used here, where only the rank order of observed proximity matrix ($\delta_{vv'}$) is assumed to be monotonically related to the rank order of distances ($d_{vv'}$) that are estimated from the model, except for measurement and sampling errors (Ding, 2006; Ding, Davison, & Peterson, 2005).

A prototypical profile is composed of the scale values $x_{k(v)}$, with large scales being salient criterion variables of the profile. The scale values do not have any particular metric and can be any real numbers. Similar to the practice of EFA and CA, the number of latent dimensions for a nonmetric MDS analysis is determined based on the interpretability of resulting prototypical profiles (usually via visualization) and MDS model (mis)fit statistics. The most commonly used badness-of-fit measure STRESS (S_1) (Kruskal, 1964) is defined as

$$S_1 = \sqrt{\frac{\sum_{(v,v')}\left(\hat{\delta}_{vv'} - d_{vv'}\right)^2}{\sum_{(v,v')} d_{vv'}{}^2}} \qquad (12)$$

where $\hat{\delta}_{vv'}$ is pairwise disparities among V variables, being monotonically related to the observed proximities $\delta_{vv'}$ and optimally re-scaled to approximate the MDS configured distances $d_{vv'}$ as much as possible. S_1 ranges from zero (a good fit) to 1.00 (a misfit, i.e., the rank order in the data could not be reproduced by the MDS procedure. The common arbitrary cut-off values of S_1 are 0.2 (fair), 0.1 (good), 0.05 (excellent), and 0.025 (nearly perfect) (Giguère, 2006). Based on S_1, dispersion accounted for (DAF) as a goodness-of-fit measure is defined as $1 - S_1^2$. DAF measures the proportion of the sum of squared disparities accounted for by the distances. Additionally, Tucker's congruence coefficient (TCC), the square root of DAF, is interpreted similar to correlation coefficient.

The second step of PAMS uses i observed individual profiles ($y_{i(v)}$) as dependent variables and the K sets of estimated scale values ($x_{k(v)}$) as independent variables to estimate each individual's K profile match indices (w_{ik}), level parameter (c_i) and fit statistic with the least squares method (Equation 1). These profile match indices reflect both intra-individual variability across profiles and inter-individual variability of a profile; the sign of profile match indices indicates that the individual profile exhibits either the prototypical profile or its opposite, the "mirror image" (Ding, 2006).

Based on the profile match indices (w_{ik}), the approximate posteriori probability of an individual's profile resemblance in the K prototypical profiles can be calculated (Ding, 2007b, 2015). In particular, for each individual i, the probability of profile membership in prototypical profile k is calculated as

$$p_i(k|w_{ik}) = \frac{p_i(w_{ik}|k)\pi_{ik}}{\sum_{k=1}^{K} p_i(w_{ik}|k)\pi_{ik}} \tag{13}$$

where $p_i(w_{ik}|k)$ is the estimated approximate posteriori probability of observed individual i belonging to prototypical profile k, given the individual's profile match index w_{ik}; π_{ik} is the estimated proportion of prototypical profile K's contribution to the total variance in the observed profile of individual i; The quantity $p_i(w_{ik}|k)$ is the probability of observing w_{ik} in individual i for a given prototypical profile k.

The individual fit statistic is the squared multiple correlation (R^2) in the individual regression, which indicates the variance in individual's profile that are accounted for by the model-derived prototypical profiles. This individual fit statistic can be used to identify atypical individuals with low R^2 values (e.g. Hon & Liu, 2016).

In the third step of PAMS, an analyst often likes to assess the association between types of individual profiles and other external variables by relating level parameter, profile match indices, model fit and so on to external variables in subsequent analysis.

Longitudinal PAMS

The PAMS model in Equation 1 can easily be extended to longitudinal data. The idea is to replace a set of V criterion variables with a series of T repeated measures so that the growth or change patterns can be examined. Thus Equation 1 can be rewritten as

$$\boldsymbol{y_{i(t)}} = \boldsymbol{c_i} + \sum_{\boldsymbol{k=1}}^{\boldsymbol{K}} \boldsymbol{w_{ik}} \boldsymbol{x_{k(t)}} + \boldsymbol{e_{i(t)}} \tag{14}$$

where the subscript t represents the repeated measures at time point t. Accordingly, the subscript v in Equations 2 to 12 will be replaced by t. It should be noted that although the time spacing must be the same for all individual time series, the time intervals do not need to be all equal (Ding, 2015). LPAMS's assumption homogeneity of error variance over time (Equation 7) can be challenging to meet in practice. Nevertheless, LPAMS can overcome several commonly seen challenges of most longitudinal modeling approaches because (1) it does not requires multivariate normality; (2) it can obtain stable solutions even with smaller samples, and (3) it can detect both idiographic (individual-centered) and nomothetic (variable-centered) components of longitudinal change patterns (Gold, Kivlighan, & Patton, 2014).

LPAMS is less known in tourism research literature than "conventional growth models" (Ding, 2007a) in the framework of either structural equation modeling or multi-level analysis models (e.g. Xu & Martinez, 2018). The conventional growth models (e.g. latent growth curves models, mixed/random effects models of growth) are special cases of growth mixture modeling (GMM) (Ram & Grimm, 2009). GMM assumes that the population contains distinct unobserved sub-groups, each are defined by a prototypical mean growth curve. GMM has two purposes including modeling growth trajectories for each group and identifying qualitatively distinct groups in the population (Ding, 2007a, 2007b). Ding (2015) specifies LPAMS in the context of GMM, which integrated latent growth curve modeling and latent class analysis into one coherent modeling system to identify and describe latent or unknown a priori sub-populations in terms of longitudinal change pattern.

The fundamental difference between LPAMS and other latent growth modeling approaches lies in LPAMS being an exploratory method of data-visualization that focuses on the pattern, not the level, of change (Ding, 2015). LPAMS is also more flexible because it does not restrict the functional form of latent growth trajectories, random distribution in variables, or sample size (Ding, 2007a; Shin, 2007). The model-building process of LPAMS is in reverse order of that of GMM – first identifying typical growth patterns and then gauging individual resemblance to the typical patterns, which makes LPAMS easier to implement and less computationally intensive (Ding, 2015). It should be noted that LPAMS is proposed here not to replace commonly used growth mixture models but to offer an alternative growth modeling technique that complements conventional methods.

Guidelines for Applying LPAMS

To facilitate the application of LPAMS among readers of this article, we summarize herewith practical guidelines regarding MDS algorithms in commonly used computer packages, determination of the number of latent dimensions to extract from data, and recommendations for statistical inference and cross-validation.

MDS algorithms are available in commonly used statistical software such as SAS, SPSS, R and Stata. Ding (2006) provides SPSS and SAS codes for PAMS. The ‘pams’ function in R package ‘profileR’ (Bulut & Desjardins, 2018) implements PAMS. A commonly used early MDS algorithm is ALSCAL (Alternating Least squares SCALing). A more current algorithm is PROXSCAL (PROXimity SCALing) as implemented in SPSS, while that in SAS is called proc MDS (Marcussen, 2014). ALSCAL weights the fit of large dissimilarities much more heavily than the fit of small dissimilarities, which can yield sub-optimal solutions. PROXSCAL treats small and large distances equally in finding an optimal solution and is generally preferred nowadays (Borg, Groenen, & Mair, 2013). On MDS maps, PROXSCAL spreads object points more even in the low-dimensional space, while ALSCAL may generate cluttered, uneasy to interpret configurations, especially in cases with more than 20 object points (Marcussen, 2014).

As a rule of thumb (Davison, 1983, cited in Ding et al., 2005, p. 178), five or more variables are needed to define a dimension in MDS. We can ask whether increasing the dimensionality of a MDS solution can significantly reduce STRESS. We can compute MDS solutions in a number of increasing dimensional spaces and then assess how STRESS decreases as dimensionality increases. Similar to the scree plot in exploratory factor analysis, we look for an “elbow”, which indicates that additional dimensions represent only randomness in the data. “The ‘nullest of all null’ answers to the question on number of latent dimensions is that the observed STRESS must be clearly smaller than the STRESS expected for random data” (Borg et al., 2013, p. 23). Through simulation, Spence and Ogilvie (1973) provide the average STRESS values of nonmetric MDS solutions with one to five dimensions applied to sets of pseudo random proximities among 12 to 48 objects.

Like most data-driven exploratory segmentation techniques (Dolničar, 2004; Ernst & Dolničar, 2018), MDS procedure does not provide standard errors for the estimates of dimension coordinates. To facilitate the test of whether estimated scale values are significantly different from zero, Kim et al. (2004) pioneered the application of non-parametric bootstrapping with 200 bootstrapped samples in estimating the scale values’ standard errors. Kim (2010) further used 2,000 bootstrapped samples to construct the sampling distributions of scale values and their empirical confidence intervals. Bratkovič (2013) found that 200 bootstrapped samples were sufficient to produce stable results of confidence intervals for scale values in PAMS.

As advised by Ernst and Dolničar (2018), to avoid random market segmentation solutions, cross-sample validation is recommended since one single analysis with a random sample is not enough in data-driven market segmentation. While PAMS was developed for exploratory purposes, its results can be verified in a different sample with confirmatory factor analysis (CFA) in the SEM framework. Kim et al. (2007) described the CFA parameterization of PAMS model and demonstrated how to validate profile patterns derived from a MDS solution, where CFA model fit indexes were used to indicate whether the CFA re-parameterization works for validating PAMS exploratory results.

DEMAND GROWTH PATTERNS OF AUSTRALIA'S INBOUND TOURISM MARKETS

Case Study Data

In order to verify the efficacy of LPAMS in the domain of tourism demand analysis and to demonstrate implementation of LPAMS with a renowned real-world case, we chose the case study of Australia's annual inbound short-term visitor arrivals over 1991-2016. As one of the most attractive tourism destinations (Ma, Hsiao, & Gao, 2018), Australia has been ranked the seventh most competitive globally since 2015 in terms of natural environment, infrastructure, travel and tourism policy, and resources (Crotti & Misrahi, 2017). International tourism is a major sector of Australia's tourism industry and has sustained strong growth over the last decade (Tourism Research Australia, 2017), largely driven by emerging markets like China (Ma, Liu, Li, & Chen, 2016). The tourism industry currently employs 5.2 per cent of the country's workforce and contributes 3.1 per cent of GDP and 9.3 per cent of total export earnings (TRA, 2018). For Australia to pursue new growth opportunities in inbound international tourism, understanding the growth patterns of its source markets would help not only with the proactive planning of goods and services for international tourists, but also the precise identification of strategic focus for international tourism marketing.

The Australian Bureau of Statistics (2017a) website publishes monthly short-term international visitor arrivals from January 1991 onwards. The monthly arrivals from January 1991 to December 2016 are aggregated to annual arrivals in this study. Arrivals from unspecified origins are excluded, resulting in the data from 43 source markets, which account for nearly 97 per cent of the total arrivals over the 26 years. This provides a set of high quality data with long enough and diverse demand growth trajectories for applying LPAMS.

Figure 3 presents the geographical distribution of total arrivals among the 43 inbound markets. The distribution almost perfectly follows the power law (e.g. Koo, Lau, & Dwyer, 2017) and reflects Pareto's rule (McKercher, Chan, & Lam, 2008), where approximately 80 per cent of the total arrivals came from the top 20 per cent of inbound markets. Figure 3 also displays the timelines of annual arrivals from those 43 inbound markets and labels the top five markets (58%) in total arrivals: New Zealand, Japan, the United Kingdom, the United States and Mainland China. The general trends are increasing among the 43 markets with great variation in patterns and levels. There are numerous tourism studies in the Australian setting, but not many have investigated the similarity in demand growth patterns. LPAMS is conducted to examine the annul arrivals from 43 inbound tourism markets to Australia between 1991 and 2016 in order to (1) identify underlying prototypical growth pattern(s) and (2) segment the markets according to their demand growth patterns.

[Insert Figure 3 here]

Prototypical Profiles

As the first step of LPMAS, non-metric multidimensional scaling, was performed on the proximity data measured as pairwise Euclidean distances among 26 years' annual arrivals. The PROXSCAL algorithm in SPSS23 was employed with SIMPLEX as the initial solution. The number of latent dimensions to model was determined according to model (mis)fit indices, cross-validation against expected results from random data, and the results' interpretability. The scree plot of S_1, DAF, and TCC in Supplement Figure 1 indicates an optimal MDS solution with three dimensions. The S_1 of the three-dimension MDS model in this case is markedly smaller than the expected STRESS value (0.235) of three-dimension non-metric MDS model of random proximities among 26 variables (Spence & Ogilvie, 1973).

Supplement Figure 2 illustrates the three prototypical profiles of demand growth patterns identified with the three-dimension MDS model: a linear pattern, a quadratic pattern and a cubic pattern. Each inbound market's observed growth pattern is assumed to be a linear combination of the three prototypical patterns, allowing for 'mirror image'.

Individual Models

As the second part of LPAMS, each market's growth pattern is regressed on the three prototypical patterns to obtain profile matching indices (the linear regression coefficient estimates), individual model fit (R^2) and average annual arrivals (the intercept estimate). We then calculated each market's posterior probabilities of representing the three prototypical patterns. A ternary plot (Supplement Figure 3) was constructed to summarize the posterior probabilities, model fits and average levels of all 43 markets. The linear prototypical pattern 1 (Pr_1) is reflected by more markets than the quadratic (Pr_2) or the cubic (Pr_3) prototypical pattern. The average individual model fit (R^2) is 0.87 with a standard deviation of 0.15.

The assumption of stable variance over time was assessed with the Durbin-Watson statistic from the individual regressions. The Durbin-Watson statistic ranges from 0.30 to 1.87 with a mean of 0.94 and standard deviation of 0.31. At 1 per cent significance level with 26 time points, the acceptable lower and upper bounds of the Durbin-Watson statistic are 0.93 and 1.41. Thus, some individual models may have positively auto-correlated error terms. This can affect the standard error of individual regression but does not bias regression coefficient estimate (i.e. profile matching index).

Clustering Inbound Markets

Each individual profile being a linear combination of the three prototypical patterns including mirror images, there are thus eight (2^3) possible combinations of the signs of three latent profiles. To control for the variation in market scale, the semi-partial correlation coefficients (*sr*) from individual models in Step 2 of LPAMS are then used to represent the direction of strength of each prototypical profile's contribution of each individual observed profile. Further, hieratical clustering (using Euclidean distance measure and Ward's linkage method in SPSS23) of the markets was performed on the semi-partial correlations, reaching a five-cluster solution. Supplement Figure 4 shows the dendrogram of the agglomerative hierarchical clustering. Supplement Table 1 compares the average semi-partial correlations among five clusters. Supplement Figures 5 to 9 display the timelines of standardized annual arrivals of markets within each of the five clusters, respectively.

These five clusters can be considered as five segments of Australia's inbound tourism markets based on their demand growth patterns during 1991–2016. Figure 4 visualizes the 43 markets' shares, their geographical regions, and their segment (cluster) membership. Australia's inbound tourism markets seem to present a healthy diversification (Lin et al., 2019). The first segment (New Zealand, United States, Germany, etc.) shows a line increase, reflecting the "development" stage in Butler's (1980) model (Figure 1). The second segment (Mainland China, India, Malaysia, etc.) shows an exponential increase, reflecting the "involvement" and "exploration" stages. The third segment (United Kingdom, South Korea, etc.) shows a levelling-off, reflecting the "consolidation" and "stagnation" stages. The fourth segment (Singapore, Hong Kong, Taiwan, etc.) shows an inverse-S increase, a reflection of "rejuvenation". Japan itself is a segment, showing a sharp decrease, the "decline".

[Insert Figure 4 here]

Relation to Economic and Immigration Growths

Source market people's income and immigration to Australia have been found to be the most dominant push-and-pull factors for short-term visits to Australia (e.g. Seetaram, 2012; Van De Vijver, Derudder, O'Connor, & Witlox, 2016). Therefore, it is worth exploring the association between inbound tourism demand growth patterns and those two factors. Following the previous research, the estimated resident population born overseas (ABS, 2017b) is used as the proxy for the immigration stock in Australia; and GDP per capita (World Bank, 2018, supplemented with data from IMF, 2018 for Taiwan) in US dollars at purchasing power parity (PPP) is used as a proxy for disposable income.

For each of the 43 inbound markets, we calculated the average level of GDP per capita over the period 1990–2016 (GDP_pc_Avg) and its average annual growth rate (GDP_pc_AAGR) as well as average immigration population over the period 1992–2016 (IM_Avg) and its average annual growth rate (IM_AAGR). Supplement Table 2 presents some summary statistics of those four indicators for the five market segments respectively. Supplement Figure 10 scatter plots average annual GDP p.c. and average annual immigration population of the 43 inbound markets' in five segments. The markets in exponential increase segment (yellow points) have clearly lower average annual GDP p.c. than those in other segments. Supplement Figure 11 scatter plots average annual growth rate of GDP p.c. and average annual growth rate of immigration. The markets in linear increase segment (blue points) tend to experience low growth rates of income and immigration, whereas the markets in exponential increase segments (yellow points) appear to have high growth rates.

DISCUSSION

Methodological Implications

Although it is of both theoretical and practical significance to examine similarity in demand growth patterns across inbound markets (Zhang et al., 2020; Steenkamp & Hofstede, 2002), there are limited choices of quantitative tools available for theoretical researchers, industry analysts and practical managers. This study has illustrated LPAMS as one possible solution for this methodological gap. Positioned as a methodological endeavor, this study primarily aims to introduce a quantitative tool (i.e., LPAMS) into the communities of theoretical researchers, industry analysts, and practical managers in regard to tourism demand analysis, market segmentation, and potentially other topics. There are methodological studies with a similar research purpose in the domain of tourism market segmentation and demand modeling. For example, Arimond and Elfessi (2001) and Arimond et al. (2003) introduced multiple correspondence analysis embedded in two-stage clustering for market segmentation of hotel guests and holiday vacationers; Hsu and Kang (2007) introduced a decision-tree based approach to segmenting inbound visitors; and Zhang et al. (2020) adapted group-pooling-based deep learning algorithm for tourism demand forecasting. They all introduced or adapted a relatively established method from other fields into tourism and hospitality research.

We have described LPAMS in technical details for interested readers. With a case study of Australia's inbound tourism growth over 1991 to 2016, LPAMS demonstrates to be an effective and flexible data-driven approach to segmenting inbound tourism markets based on demand growth patterns. The identification of five typical annual arrivals' growth patterns of Australia's 43 main inbound markets contributes to the theoretical discussion on tourist area's life cycle (Butler, 1980) by recognizing heterogeneous visitor flows (Beritelli et al., 2015) that display different growth patterns at different development stages. A paradigm shift from theorizing one single aggregate visitor flow to multiple heterogeneous flows resonates with Woodside's (2014) advocacy for adopting complexity theory and modeling multiple realities in business research to formulate parsimonious theories of patterns in phenomena. After all, the central task of scientific inquiry is "not [to] seek the absolutely simplest law but the law that is simplest in relation to the range of phenomena it explains, i.e., [the] most parsimonious" (Simon, 2002, p. 36).

Compared with conventional theory-driven methods, LPAMS requires less assumption in data and, particularly, does not restrict any underlying functional form of growth or stationary data generation process as required by most inferential procedures and predictive algorithms. Thus, from the epistemological perspective, LPAMS is more useful for descriptive and inductive investigations than for inferential and deductive studies. There is no silver-bullet technique for modeling complex tourism demand (Song et al., 2019). The exploratory nature of LPAMS complements confirmatory and predictive demand modeling techniques by overcoming the methodological paradox of analyzing data in an exploratory trial-and-error manner using confirmatory statistical procedures.

Theoretical Implications

This study has verified the efficacy of LPAMS in identifying five demand growth patterns of 43 inbound markets of Australia's international tourism. The idea of segmenting or grouping markets at a geographic level based on similarity in growth patterns has theoretical implications on at least two areas of tourism management research, namely international tourism market segmentation and international tourism demand forecasting.

Segmentation is a critical long-term marketing decision at the strategic level that a destination must make (Dolničar, 2017). Traditional market segmentation strategies consider each country as a separate segment, and specific products and services are designed to meet the needs of customers from each country, and no coordination of marketing strategies is required across country segments (Steenkamp & Hofstede, 2002, p.185). However, such a widely used "commonsense segmentation" may leave little room for competitive advantage to be gained in today's globalized international tourism business, which pronounces the importance to thoroughly explore market structure and necessitates data-driven segmentation (Dolničar, 2004).

Geographic segmentation (e.g., at country or region level) can construct cost-effectively accessible segments through centralization of marketing activities; meanwhile, geographic aggregation may miss the fine differences between countries or regions with the same segment, affecting market responsiveness (Steenkamp & Hofstede, 2002, p.195). Therefore, a "two-stage international segmentation" is recommended, where countries are grouped on general bases in the first (aggregate) stage, and in the second (disaggregate) stage, based on domain-specific bases, market segments are identified within a target geographic segment (Steenkamp & Hofstede, 2002). Such a two-stage approach offers a solution to the debate on adaptation versus standardization by combining the benefits of adaptation (e.g. better at meeting consumers' needs) and standardization (e.g. better quality at lower cost) (Steenkamp & Hofstede, 2002). As shown in the Australian case, LPAMS provides a tool for constructing geographic segments in the first stage based on demand growth patterns, which can assist destinations or organizations pursuing a geographic differentiation marketing strategy.

After reviewing 50 years of key studies on tourism demand forecasting, (Song et al., 2019, p.355) concluded that "the ambiguity of performance in previous models has called forth an emerging trend of using combined and hybrid models for tourism demand forecasting”. For instance, Zhang et al. (2020) combined traditional time series decomposition with recently developed dynamic-time-warping clustering and long-short-term-memory deep learning algorithm to forecast inbound tourism demand, and they found that pooling data through grouping source markets with similar demand growth patterns improved forecasting accuracy and robustness.

As pointed out by Zhang et al. (2020), the existing studies that investigated similarities in tourist arrival growth patterns across multiple inbound markets of a destination focus on explanations of cultural homogeneity or convergence but lack insights for tourism demand modeling. LPAMS offers an alternative quantitative tool for identifying and describing demand growth patterns among a set of markets of a destination. Subsequent research can dig into the source markets of homogeneous arrival patterns to find out their common factors because this could offer new avenues of research to better understand inter-organizational collaboration for destinations and help leverage knowledge as a strategic capability for tourism marketing (Zhang et al., 2020).

Song et al. (2019) also advocated the combination of data-driven techniques and judgmental methods (e.g., Delphi method) for tourism demand forecasting, where judgmental forecasting can “provide a complete and definitive description of future developments by using the accumulated experience and insight of individual experts or groups of stakeholders” (p.353), for “the integration of experts’ opinions with statistical techniques can provide outstanding forecast accuracy” (p.356). As a data exploration tool with interpretable visual illustration, LPAMS can support both qualitative and quantitative forecasting.

Practical Implications

This study expects audience in tourism and hospitality industry practitioners, such as business analysts, marketing managers of private companies and public agencies, and policy prescribers for developing tourism economy at various levels. Management of organizations or tourism destination can gain deeper insights into the structure of market by considering various available possibilities (Dolničar, 2004). As a quantitative gadget in the toolkits for longitudinal data analysis, LPAMS can be used stand-alone or in combination with other tools to support decision-making in tourism and hospitality management.

However, considerable divide between theory and practice exists in market segmentation (Dolnicar & Lazarevski, 2009). For example, nearly 70 per cent of marketing managers raised the concern on the difficulty of interpreting data-driven market segmentation analysis, which is like a “black box”. This also poses additional risk and pressure on market segmentation research. Moreover, industry practitioners are constrained by limited access to funding and thus are in favor of more cost effective and practical approach of market segmentation analysis approaches (Arimond et al., 2003).

As demonstrated in the Australia case, LPAMS is practitioner-friendly in terms of two merits: first, procedure is convenient to implement using general-purposes statistical packages like SPSS on simply structured data; second, results are straightforward to interpret with visual illustration. These are in line with the two key criteria for “user-friendly” (Arimond et al., 2003, p.49) innovation of market segmentation methods within the tourism industry, i.e., simple data collection and graphic display of segment characteristics (Arimond & Elfessi, 2001, p.392). We also upheld transparency when describing LPAMS’ technical details and demonstrating its application step-by step in the Australia case in hope that this study could help mitigate the theory-practice divide and facilitate transforming research findings into managerial decisions.

Besides due efforts of building data capacity among managers and their staff, data analysts and researchers who prepare data-driven market segmentation solutions should also clearly explain how segmentation solution is achieved, what the results mean, and provide practical recommendations (Dolnicar & Lazarevski, 2009). Data-driven segmentation is exploratory in nature and the segments achieved are generally "constructed" rather than "naturally occurring" (Dolnicar, 2004, 2017; Ernst & Dolnicar, 2018). Any arbitrary market segmentation can lead to a solution; therefore, it is crucial to "capitalize on practitioners' wisdom" (Meyer, Tsui, & Hinings, 1993) to interpret data and results. It is only in the collaboration of practitioners and data analysis experts that the most meaningful segmentation solution can be identified.

CONCLUSION

This study introduced LPAMS as a data-driven segmentation technique into tourism research. We only tested the efficacy of LPAMS in the context of segmenting the inbound markets of Australia's international tourism by relating our findings to the theory of tourist area's life cycle of evolution. LPAMS demonstrated its effectiveness and flexibility as a statistical tool for segmentation based on market-level heterogeneity in growth patterns. We expect LPAMS to be applied in future research in broader domains and various settings of tourism and hospitality management, e.g., outbound travel demand profiling (Li, et al., 2015) and within-day booking fluctuation in revenue management (Noone, Enz, & Canina, 2019), to further understand its strength and weakness.

REFERENCES

Abbott, A., Vita, G., & Altinay, L. (2012). Revisiting the convergence hypothesis for tourism markets: Evidence from Turkey using the pairwise approach. *Tourism Management, 33*(3), 537–544. doi: 10.1016/j.tourman.2011.06.003.

Alén, E., Losada, N., & de Carlos, P. (2017). Profiling the segments of senior tourists throughout motivation and travel characteristics. *Current Issues in Tourism, 20*(14), 1454-1469. doi: 10.1080/13683500.2015.1007927.

Arimond, G., & Elfessi, A. (2001). A clustering method for categorical data in tourism market segmentation research. *Journal of Travel Research, 39*(4), 391–397. doi: 10.1177/004728750103900405.

Arimond, G., Achenreiner, G., & Elfessi, A. (2003). An innovative approach to tourism market segmentation research: An applied study. *Journal of Hospitality & Leisure Marketing, 10*(3/4), 25-56. doi: 10.1300/J150v10n03_03.

Athanasopoulos, G., & de Silva, A. (2012). Multivariate exponential smoothing for forecasting tourist arrivals. *Journal of Travel Research, 51*, 640–652. doi: 10.1177/0047287511434115.

Australia Bureau of Statistics (ABS) (2017a). Table 5: Short-term movement, visitor arrivals – selected countries of residence: Original. In *Overseas arrivals and departures, Australia*, cat. no. 3401.0. Canberra: ABS. Retrieved from http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3401.0Dec%202016?OpenDocument.

Australia Bureau of Statistics (ABS) (2017b). Table 9.1: Estimated resident population by country of birth – 30 June 1992 to 2016. In *Migration, Australia, 2015–16*, cat. no. 3412.0. Canberra: ABS. Retrieved from https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3412.02015-16?OpenDocument.

Beritelli, P., Reinhold, S., Laesser, C., & Bieger, T. (2015). *The St Gallen model for destination management*. St Gallen, Switzerland: IMP-HSG.

Bratkovič, P. P. (2013). A first look on smaller sized samples for bootstrap derived patterns of profile analysis via multidimensional scaling. *Metodološki zvezki*, *10*(1), 49–64. Retrieved from http://www.stat-d.si/mz/mz10.1/Bratkovic2013.pdf.

Bulut, O., & Desjardins, C. D. (2018). profileR: Profile analysis of multivariate data in R. Retrieved from https://cran.r-project.org/web/packages/profileR/index.html.

Butler, R. (1980). The concept of a tourist area life cycle of evolution: Implications for management of resources. *Canadian Geographer, 19*(1), 5–12. doi: 10.1111/j.1541-0064.1980.tb00970.x.

Borg, I., Groenen, P. J. F., & Mair, P. (2013). *Applied multidimensional scaling.* Dordrecht: Springer.

Cao, Z., Li, G., & Song, H. (2017). Modelling the interdependence of tourism demand: The global vector autoregressive approach. *Annals of Tourism Research, 67*, 1–13. doi: 10.1016/j.annals.2017.07.019.

Carvache-Franco, W., Carvache-Franco, M., Carvache-Franco, O., & Hernández-Lara, A. B. (2020). Motivation and segmentation of the demand for coastal and marine destinations. *Tourism Management Perspectives, 34*, 100661. doi: 10.1016/j.tmp.2020.100661.

Cattell, R. B. (1952). The three basic factor-analytic research designs—their interrelations and derivatives. *Psychological Bulletin*, 49(5), 499–520.doi: 10.1037/h0054245.

Chan, F., Lim, C., & McAleer, M. (2005). Modelling multivariate international tourism demand and volatility. *Tourism Management, 26*(3), 459–471. doi: 10.1016/j.tourman.2004.02.013.

Chang, C. L., Khamkaew, T., Tansuchat, R., & McAleer, M. (2011). Interdependence of international tourism demand and volatility in leading ASEAN destinations. *Tourism Economics, 17*(3), 481–507. doi: 10.5367/te.2011.0046.

Cortés-Jiménez, I., & Blake, A. (2011). Tourism demand modeling by purpose of visit and nationality. *Journal of Travel Research, 50*, 408–416. doi: 10.1177/0047287510363615.

Crotti, R., & Misrahi, T. (2017). *The travel & tourism competitiveness report 2017*. Geneva: World Economic Forum. Retrieved from http://www3.weforum.org/docs/WEF_TTCR_2017_web_0401.pdf.

Davison, M. L., Gasser, M., & Ding, S. (1996). Identifying major profile patterns in a population: An exploratory study of WAIS and GATB patterns. *Psychological Assessment*, 8, 26–31. doi: 10.1037/1040-3590.8.1.26.

Davison, M. L., & Sireci, S. G. (2000). Multidimensional scaling. In H. E. A. Tinsley, & S. D. Brown (Eds.), *Handbook of applied multivariate statistics and mathematical modelling* (pp. 323–352). San Diego, CA: Academic Press.

Ding, C. S. (2006). Multidimensional scaling modelling approach to latent profile analysis in psychological research. *International Journal of Psychology, 41*(3), 226–238. doi: 10.1080/00207590500412219.

Ding, C. S. (2007a). Modeling growth data using multidimensional scaling profile analysis. *Quality & Quantity*, 41(6), 891–903. doi: 10.1007/s11135-006-9031-9.

Ding, C. S. (2007b). Studying growth heterogeneity with multidimensional scaling profile analysis. *International Journal of Behavioral Development*, *31*(4), 347–356. doi: 10.1177/0165025407077756.

Ding, C. S. (2015) Studying behavioral change: Growth analysis via multidimensional scaling model. In: M. Stemmler, A. von Eye, & W. Wiedermann (Eds), *Dependent data in social sciences research* (pp. 327–343). Dordrecht: Springer. doi: 10.1007/978-3-319-20585-4_14

Ding, C. S., Davison, M. L., & Peterson, A. C. (2005). Multidimensional scaling analysis of growth and change. *Journal of Educational Measurement*, *42*(2), 171–191. doi: 10.1111/j.1745-3984.2005.00009.

Divisekera, S. (2016). Interdependencies of demand for international air transportation and international tourism. *Tourism Economics, 22*(6), 1191–1206. doi: 10.1177/1354816616669007.

Dolničar, S. (2004). Beyond “commonsense segmentation”: A systematics of segmentation approaches in tourism. *Journal of Travel Research*, *42*, 244-250. doi: 10.1177/0047287503258830

Dolničar, S. (2017). Market segmentation. In L. L. Lowry (Ed.). *The SAGE international encyclopedia of travel and tourism* (pp. 801-805). Thousand Oaks, CA: SAGE Publications, Inc. doi: 10.4135/9781483368924.n297.

Dolničar, S., & Lazarevski, K. (2009). Methodological reasons for the theory/practice divide in market segmentation. *Journal of Marketing Management*, 25, 357-374. doi: 10.1362/026725709X429791.

Du Preez, J., & Witt, S. F. (2003). Univariate versus multivariate time series forecasting: An application to international tourism demand. *International Journal of Forecasting, 19*(3), 435-451. doi: 10.1016/S0169-2070(02)00057-2.

Ernst, D., & Dolničar, S. (2018). How to avoid random market segmentation solutions. *Journal of Travel Research*, *57*(1), 69–82. doi: 10.1177/0047287516684.

Faulkner, B. (1988) Tourism demand patterns. *International Journal of Hospitality Management, 7*(4), 333–341. doi: 10.1016/0278-4319(88)90044-8.

Fenton, M. & Pearce, P. (1988). Multidimensional scaling and tourism research. *Annals of Tourism Research, 15*(2), 236–254. doi: 10.1016/0160-7383(88)90085-0.

Giguère, G. (2006). Collecting and analyzing data in multidimensional scaling experiments: A guide for psychologists using SPSS. *Tutorials in Quantitative Methods for Psychology, 2*(1), 26–38. doi: 10.20982/tqmp.02.1.p026.

Gold, P. B., Kivlighan, D. M., & Patton, M. J. (2014). Non-metric multidimensional scaling profile analysis of non-growth change in groups: A demonstration. *Small Group Research*, 45(3), 235–265. doi: 10.1177/1046496414528050.

Guizzardi, A., & Mazzocchi, M. (2010). Tourism demand for Italy and the business cycle. *Tourism Management*, *31*, 367–377. doi: 10.1016/j.tourman.2009.03.017.

Gunter, U., & Önder, I. (2015). Forecasting international city tourism demand for Paris: Accuracy of uni- and multivariate models employing monthly data. *Tourism Management*, *46*, 123–135. doi: 10.1016/j.tourman.2014.06.017.

Hepsag, A. (2016). Testing convergence of tourism markets: Evidence from seasonal unit root test. *Anatolia: An International Journal of Tourism and Hospitality Research*, *27*(2), 177–188. doi: 10.1080/13032917.2015.1075892.

Hon, C. K. H., & Liu, Y. (2016). Exploring typical and atypical safety climate perceptions of practitioners in the repair, maintenance, minor alteration and addition (RMAA) sector in Hong Kong. *International Journal of Environmental Research and Public Health*, *13*, 935. doi: 10.3390/ijerph13100935.

Hsu, C. H. C., & Kang, S. K. (2007). CHAID-based segmentation: International visitors' trip characteristics and perceptions. *Journal of Travel Research*, *46*. 207-216. doi: 10.1177/0047287507299571.

International Monetary Fund (IMF) (2018). GDP per capita, current prices. Retrieved from https://www.imf.org/external/datamapper/PPPPC@WEO/TWN.

Kaplan, F., Öztürk, E., & Günger, S. (2017). Is the club convergence hypothesis valid for Turkey's tourism market? *Research in Applied Economics*, *9*(3), 24–30. doi: 10.5296/rae.v9i3.11334.

Katrakilidis, C., Konteos, G., Sariannidis, N., & Manolidou, C. (2017). Investigation of convergence in the tourist markets of Greece. *European Research Studies Journal*, 20(4), 707-729. https://www.ersj.eu/dmdocuments/2017-xx-4-a-51.pdf.

Kim, J. H., & Moosa, I. A. (2005). Forecasting international tourist flows to Australia: A comparison between the direct and indirect methods. *Tourism Management*, *26*, 69–78. doi: 10.1016/j.tourman.2003.08.014.

Kim, S. K. (2010). Evaluating the invariance of cognitive profile patterns derived from profile analysis via multidimensional scaling (PAMS): A bootstrapping approach. *International Journal of Testing*, *10*, 33–46. doi: 10.1080/15305050903454549.

Kim, S. K., Davison, M. L., & Frisby, C. L. (2007). Confirmatory factor analysis and profile analysis via multidimensional scaling. *Multivariate Behavioral Research*, 42(1), 1–32. doi: 10.1080/00273170701328973.

Kim, S. K., Frisby, C. L., & Davison, M. L. (2004). Estimating cognitive profiles using profile analysis via multidimensional scaling (PAMS). *Multivariate Behavioral Research*, 39(4), 595–624. doi: 10.1207/s15327906mbr3904_2.

Koh, Y., Rhou, Y., Lee, S., & Singal, M. (2018). Does franchising alleviate restaurants' vulnerability to economic conditions? *Journal of Hospitality & Tourism Research, 42*(4), 627–648. doi: 10.1177/1096348015619411.

Kon, S. C., & Turner, W. L. (2005). Neural network forecasting of tourism demand. *Tourism Economics, 11*, 301–328. doi: 10.5367/000000005774353006.

Koo, T. T. R.; Lau, P., & Dwyer, L. (2017). The geographic dispersal of visitors: Insights from the power law. *Journal of Travel Research*, *56*(1), 108–121. doi: 10.1177/0047287515625131.

Kourtzidis, S. A., Tzeremes, P., Tzeremes, N. G., & Heryán, T. (2018). Integration of tourism markets in Australia: An international visitor arrivals' convergence assessment. *Tourism Economics, 24*(7), 901–907. doi: 10.1177/1354816618776184.

Kruskal, J. B. (1964). Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis. *Psychometrika*, *29*, 1–27. doi: 10.1007/BF02289565.

Lean, H. H., & Smyth, R. (2008). Are Malaysia's tourism markets converging? Evidence from uni-variate and panel unit root tests with structural breaks. *Tourism Economics*, *14*(1), 97–112. doi: 10.5367/000000008783554820.

Lee, C. G. (2009). The convergence hypothesis for tourism markets: Evidence from Singapore. *Tourism Economics, 15*(4), 875-881. doi: 10.5367/000000009789955080.

Levin, N., & Zahavi, J. (2001). Predictive modeling using segmentation. *Journal of Interactive Marketing*, *15*(2), 2–22. doi: 10.1002/dir.1007.

Li, X., Cheng, C.-K., Kim, H., & Li, X. (2015). Positioning USA in the Chinese outbound travel market. *Journal of Hospitality & Tourism Research, 39*(1), 75–104. doi: 10.1177/1096348012461548.

Lin, Z., You, K., Lau, C. K., & Demir, E. (2019). Segmenting global tourism markets: A panel club convergence approach. *Annals of Tourism Research, 75*, 165–185. doi: 10.1016/j.annals.2019.01.007.

Lorde, T., & Moore, W. (2008). Co-movement in tourist arrivals in the Caribbean. *Tourism Economics, 14*(3), 631-643. doi: 10.5367/000000008785633523.

Ma, E**.**, Hsiao, A., & Gao. J. (2018). Destination attractiveness and travel intention: The case of Chinese and Indian students in Australia. *Asia Pacific Journal of Tourism Research, 23(*2), 200-215. doi: 10.1080/10941665.2017.1411964*.*

Ma, E., Liu, Y., Li, J., & Chen, S. (2016). Anticipating Chinese tourists arrivals in Australia: A time series analysis. *Tourism Management Perspectives, 17*, 50-58. doi: 10.1016/j.tmp.2015.12.004.

Ma, E., Qu, C., Hsiao, A., & Jin, X. (2015). Impacts of China Tourism Law on Chinese outbound travelers and stakeholders: An exploratory discussion. *Journal of China Tourism Research, 11*(3), 229-237. doi: 10.1080/19388160.2015.1077182.

Marcussen, C. (2014). Multidimensional scaling in tourism literature. *Tourism Management Perspectives, 12*, 31–40. doi: 10.1016/j.tmp.2014.07.003.

McKercher, B., Chan, A., & Lam, C. (2008). The impact of distance on international tourist movements. *Journal of Travel Research, 47*(2): 208–224. doi: 10.1177/0047287508321191

Mérida, A. L., Carmona, M., Congregado, E., & Golpe, A. A. (2016). Exploring the regional distribution of tourism and the extent to which there is convergence. *Tourism Management, 57*, 225–233. doi: 10.1016/j.tourman.2016.06.012.

Meyer, A. D., Tsui, A. S., & Hinings, C. R. (1993). Configurational approaches to organizational analysis. *The Academy of Management Journal*, 36(6), 1175-1195. doi: 10.2307/256809.

Morley, C. L. (1995). Tourism demand: Characteristics, segmentation and aggregation. *Tourism Economics, 1*, 250–267. doi: 10.1177/135481669500100401.

Narayan, P. K. (2006). Are Australia's tourism markets converging? *Applied Economics, 38(*10), 1153–1162. doi: 10.1080/00036840500391377.

Narayan, P. K. (2007). Testing convergence of Fiji's tourism markets. *Pacific Economic Review, 12*(5), 651–663. doi: 10.1111/j.1468-0106.2007.00377.x.

Nejad, S. A. H. S., & Tularam, G. A. (2010). Modeling tourist arrivals in destination countries: An application to Australian tourism. *Journal of Mathematics and Statistics, 6*(4), 431-441. doi: 10.3844/jmssp.2010.431.441.

Noone, B. M., Enz, C. A., & Canina, L. (2019). The uniqueness of revenue management approaches in nontraditional settings: The case of the golf industry. *Journal of Hospitality & Tourism Research, 43*(5), 633–655. doi: 10.1177/1096348019828094.

Ozcan, B., & Erdogan, S. (2017). Are Turkey's tourism markets converging? Evidence from the two-step LM and three-step RALS-LM unit root tests. *Current Issues in Tourism, 20*(4), 425–442, doi: 10.1080/13683500.2015.1040741.

Ram, N., & Grimm, K. (2009). Growth mixture modeling: A method for identifying differences in longitudinal change among unobserved groups. *International Journal of Behavioral Development*, *33*(6), 565–576. doi: 10.1177/0165025409343765.

Rosselló, J., Aguiló, E., & Riera, A. (2005). Modeling tourism demand dynamics. *Journal of Travel Research, 44*, 111–116. doi: 10.1177/0047287505276602.

Seetaram, N. (2012). Immigration and international inbound tourism: Empirical evidence from Australia. *Tourism Management*, 33, 1535–1543. doi: 10.1016/j.tourman.2012.02.010.

Senbeto, D. L., & Hon, A. H. Y. (2019). A dualistic model of tourism seasonality: Approach–avoidance and regulatory focus theories. *Journal of Hospitality & Tourism Research, 43*(5), 734-753. doi: 10.1177/1096348019828446.

Seo, J. H., Park, S. Y., & Boo, S. (2010). Interrelationships among Korean outbound tourism demand: Granger causality analysis. *Tourism Economics, 16*(3), 597–610. doi: 10.5367/000000010792278400.

Seo, J. H., Park, S. Y., & Yu, L. (2009). The analysis of the relationships of Korean outbound tourism demand: Jeju Island and three international destinations. *Tourism Management, 30*(4), 530–543. doi: 10.1016/j.tourman.2008.10.013.

Shin, T. (2007). Comparison of three growth modeling techniques in the multilevel analysis of longitudinal academic achievement scores: Latent growth modeling, hierarchical linear modeling, and longitudinal profile analysis via multidimensional scaling. *Asia Pacific Education Review*, *8*(2), 262–275. doi: 10.1007/BF03029261.

Simon, H. A. (2002). Science seeks parsimony, not simplicity: Searching for pattern in phenomena. In A. Zellner, H. A. Keuzenkamp, & M. McAleer (Eds.), *Simplicity, inference and modelling: Keeping it sophisticatedly simple* (pp. 32–72). Cambridge, UK: Cambridge University Press. doi: 10.1017/CBO9780511493164.003.

Smeral, E. (2012). International tourism demand and the business cycle. *Annals of Tourism Research*, *39*, 379–400. doi: 10.1016/j.annals.2011.07.015.

Smith, W.R. (1956). Product differentiation and market segmentation as alternative marketing strategies. *Journal of Marketing, 21*(1), 3–8. doi: 10.2307/1247695.

Solarin, S. A. (2014). Revisiting the convergence hypothesis of tourism markets: Evidence from South Africa. *Margin: The Journal of Applied Economic Research, 8*(1), 77-92. doi: 10.1177/0973801013506403.

Solarin, S. A. (2018). Convergence hypothesis in tourism markets and activities in Taiwan. *Tourism Economics, 24*(8), 1037–1044. doi: 10.1177/1354816618795526.

Solarin, S. A., & Lean, H. H. (2014). Nonlinearity convergence of tourism market in Seychelles. *Current issues in Tourism*, *17*(6), 475-479. doi: 10.1080/13683500.2013.810612.

Song, H., & Li, G. (2008). Tourism demand modelling and forecasting: A review of recent research. *Tourism Management, 29*, 203–220. doi: 10.1016/j.tourman.2007.07.016.

Song, H., Qiu, R. T. R., & Park, J. (2019). A review of research on tourism demand forecasting: Launching the *Annals of Tourism Research* curated collection on tourism demand forecasting. *Annals of Tourism Research*, 75, 338–362. doi: 10.1016/j.annals.2018.12.001.

Song, H., & Witt, S. F. (2003). Tourism forecasting: The general-to-specific approach. *Journal of Travel Research, 42*, 65–74. doi: 10.1177/0047287503253939.

Spence, I., & Ogilvie, J. C. (1973). A table of expected stress values for random rankings in nonmetric multidimensional scaling. *Multivariate Behavioral Research, 8*, 511–517. doi: 10.1207/s15327906mbr0804_8.

Steenkamp, J.-B. E. M., & Hofstede, F. T. (2002). International market segmentation: Issues and perspectives. *International Journal of Research in Marketing, 19*(3), 185-213. doi: 10.1016/S0167-8116(02)00076-9.

Tan, S. H., & Tan, S. K. (2013). Research note: Are Singapore's tourism markets converging with structural breaks? *Tourism Economics*, *19*(1), 209–216. doi: 10.5367/te.2013.0193.

Tang, C. F. (2011). Old wine in new bottles: Are Malaysia's tourism markets converging? *Asia Pacific Journal of Tourism Research, 16*(3), 263–272. doi: 10.1080/10941665.2011.572661.

Tiwari, A. K. (2016). Research note: Whether tourist arrivals in India convergent? *Annals of Tourism Research*, *61*, 252–255. doi: 10.1016/j.annals.2016.09.009.

Torraleja, F. A. G., Vázquez, A. M., & Franco, M. J. B. (2009). Flows into tourist areas: An econometric approach. *International Journal of Tourism Research, 11*(1), 1–15. doi: 10.1002/jtr.657.

Tourism Research Australia (TRA) (2017). International Visitors in Australia. December 2017 year ending results of the International Visitor Survey. Retrieved from https://www.tra.gov.au/tra/ivs/ivs_dec_2017.html.

Tourism Research Australia (TRA) (2018). Tourism Satellite Account 2017-18. Retrieved from https://www.tra.gov.au/data-and-research

UNWTO (2017). *Yearbook of tourism statistics, data 2011–2015.* Retrieved from https://www.e-unwto.org/doi/book/10.18111/9789284418428.

Valadkhani, A. & O'Mahony, B. (2018). Identifying structural changes and regime switching in growing and declining inbound tourism markets in Australia. *Current Issues in Tourism*, *21*(3), 277–300. doi: 10.1080/13683500.2015.1072504.

Van De Vijver, E., Derudder, B., O'Connor, K., & Witlox, F. (2016). Shifting patterns and determinants of Asia-Pacific tourism to Australia, 1990–2010. *Asia Pacific Journal of Tourism Research*, *21*(12), 1357–1372. doi: 10.1080/10941665.2016.1175490.

Vassiliadis, C. A., Bellou, V., Priporas, C.-V., & Andronikidis, A. (2018). Exploring the negotiation thesis application among ski resort tourists: A segmentation approach. *Journal of Hospitality & Tourism Research*, *42*(5), 716–739. doi: 10.1177/1096348015597030.

Vu, C. J., & Turner, L. W. (2005). Data disaggregation in demand forecasting. *Tourism and Hospitality Research, 6*, 38–52. doi: 10.1057/palgrave.thr.6040043.

Walters, P. G. P. (1997). Global market segmentation: Methodologies and challenges. *Journal of Marketing Management*, *13*,165–177. doi: 10.1080/0267257X.1997.9964465.

Walters, G., & Ruhanen, L. (2015). From white to green: Identifying viable visitor segments for climate-affected Alpine destinations. *Journal of Hospitality & Tourism Research, 39*(4), 517–539. doi: 10.1177/1096348013491603.

Wan, S. K., & Song, H. (2018). Forecasting turning points in tourism growth. *Annals of Tourism Research*, *72*, 156–167. doi: 10.1016/j.annals.2018.07.010.

Woodside, A. G. (2014). Embrace · perform · model: Complexity theory, contrarian case analysis, and multiple realities. *Journal of Business Research, 67*, 2495–2503. doi: 10.1016/j.jbusres.2014.07.006.

World Bank (2018). GDP per capita, PPP (current international $). World Bank, International Comparison Program database. Retrieved from https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD.

Xu, S., & Martinez, L. (2018). Applications of latent growth curve modeling: A research agenda for hospitality management. *International Journal of Contemporary Hospitality Management*, *30*(11), 3268–3328. doi: 10.1108/IJCHM-10-2017-0650.

Yilanci, V., & Eris, Z. A. (2012). Are tourism markets of Turkey converging or not? A Fourier stationary analysis. *Anatolia: An International Journal of Tourism and Hospitality Research, 23*(2), 207–216. doi: 10.1080/13032917.2012.665010.

Zhang, Y., Li, G., Muskat, B., Law, R., & Yang, Y. (2020). Group pooling for deep tourism demand forecasting. *Annals of Tourism Research, 82*, 102899. doi: 10.1016/j.annals.2020.102899.

Zhu, L., Lim, C., Xie, W., & Wu, Y. (2018) Modelling tourist flow association for tourism demand forecasting. *Current Issues in Tourism, 21*(8), 902–916. doi: 10.1080/13683500.2016.1218827.

Zins, A. (2008). Market segmentation in tourism: A critical review of 20 years' research effort. In C. Kronenberg, S. Müller, M. Peters, B. Pikkemaat, & K. Weiermair (Eds.), *Change management in tourism: From 'old' to 'new' tourism* (pp. 289-301). Berlin, Germany: Erich Schmidt Verlag.

Table 1

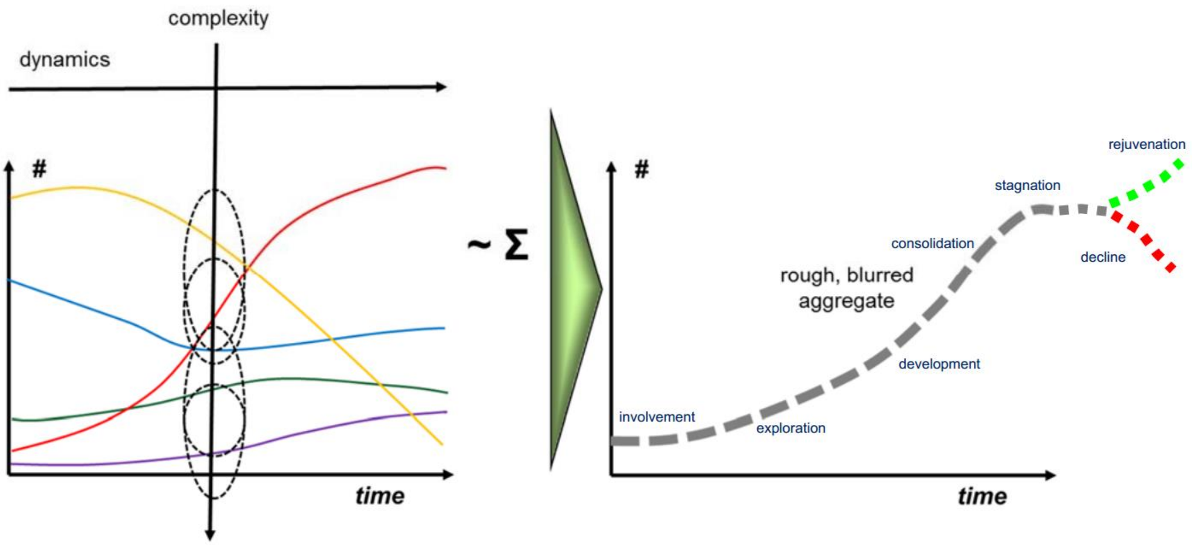
Data of Individual Profiles In Figure 2 and Their Pairwise Linear Correlations and Euclidean Distances

Individual profile (T1, T2, T3)	*P1*	*P2*	*P3*	*P4*
P1 (20, 50, 30)	33.33	20.52	48.07	51.46
P2 (32.7, 34.2, 33.2)	1.00	33.37	47.54	46.83
P3 (2, 15, 2.4)	0.95	0.95	6.47	10.35
P4 (6.27, 6.42, 6.32)	1.00	1.00	0.95	6.34

Note: linear correlations (Euclidean distances) are below (above) the leading diagonal. Values on the diagonal are average levels. All pair-wise Spearman's rank correlations equal 1.

Figure 1

Illustration of Complexity in Tourism Demand Growth



Adopted from P. Beritelli (Answer to Bob McKercher's question on TRINET, 31 October 2018) and incorporating Butler's (1980) hypothetical multi-stage evolution of a tourist area

Figure 2

Profile Level versus Profile Pattern

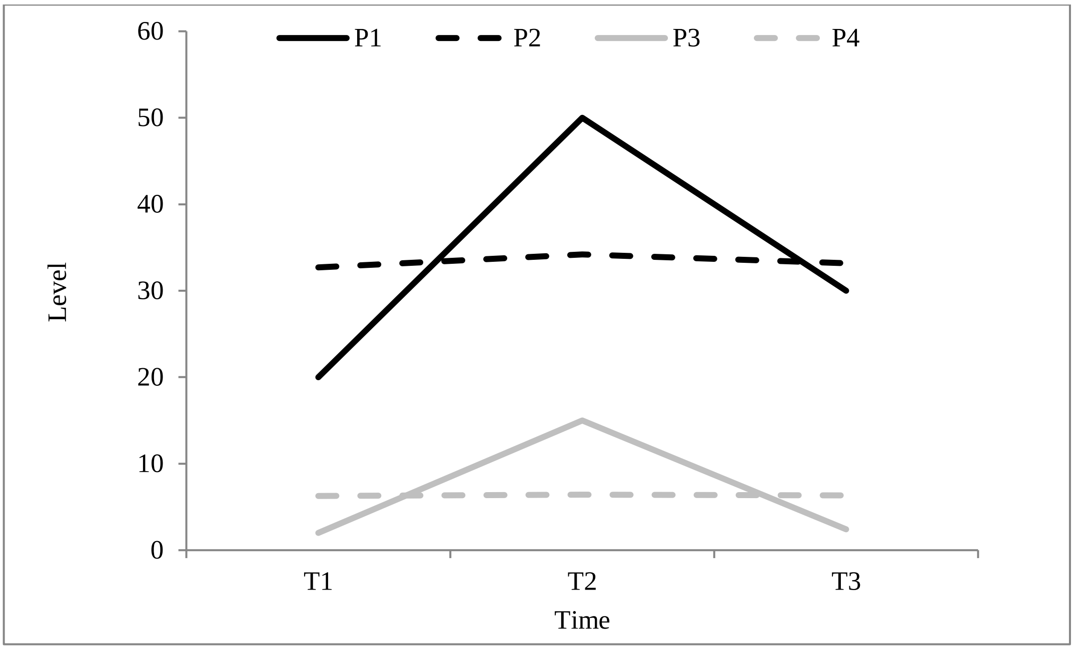


Figure 3

Geographical Distribution and Timelines of Tourists Arrivals to Australia in 1991–2016 among 43 Inbound Markets

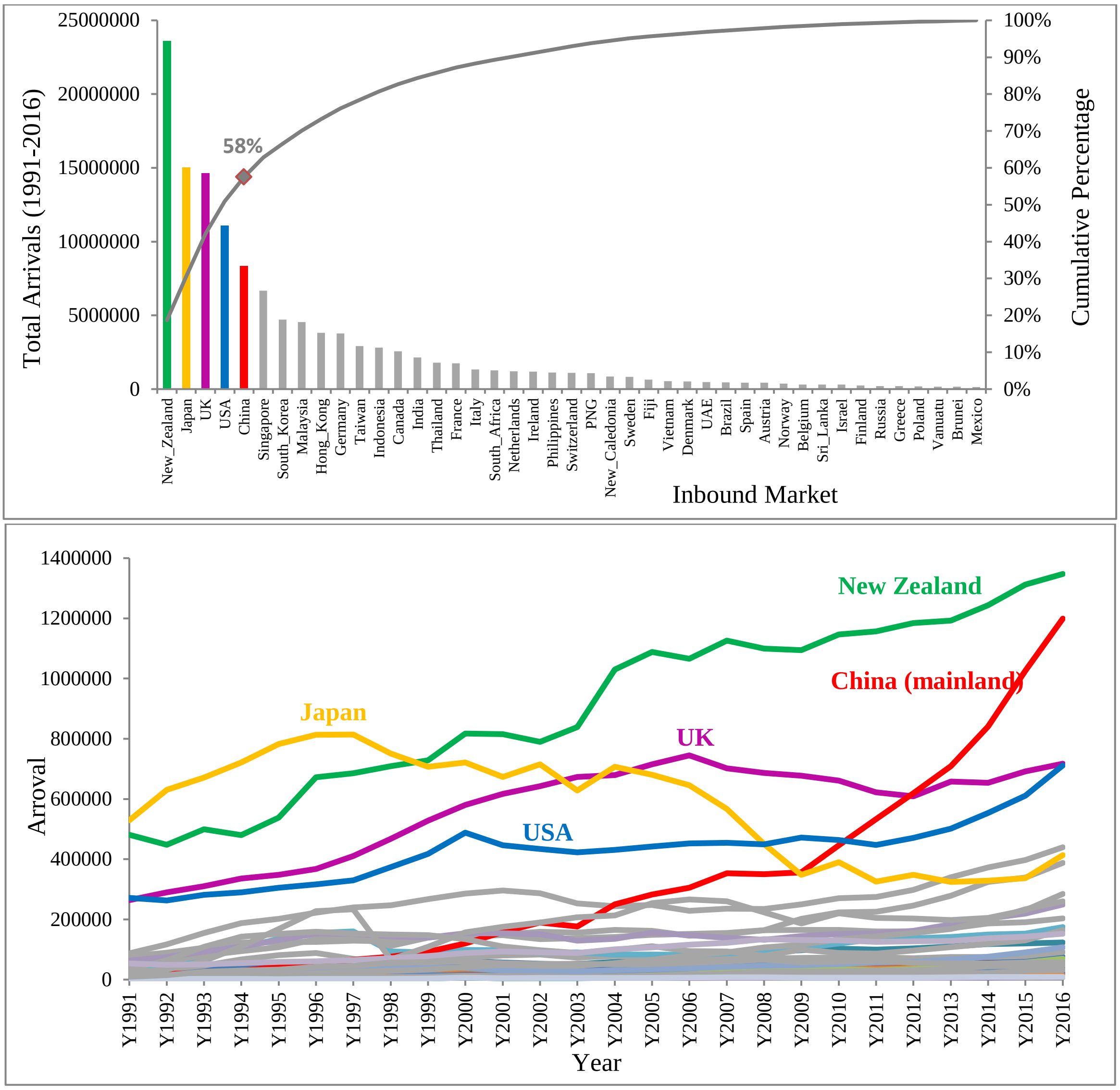


Figure 4

Relations between Markets, Segments, and Geographical Regions (Ribbon Width by Total Arrivals, Left Side Colored by Market, Right Side Colored by Segment)