Impact of Distance on the Arrivals, Behaviours and Attitudes of International Tourists in Hong Kong: A Longitudinal Approach

ABSTRACT
This study revisits the impact of distance on international tourist behaviours in Hong Kong. This work is the first longitudinal research that divides and cross-validates the concept of distance into physical and cultural distance. This work also proposes an alternative cultural distance measure by introducing optimal weight amongst Hofstede's dimensions and then compares the proposed measure with the traditional Kogut and Singh's and Kandogan's measures. By using data from the Visitor Profile Report of the Hong Kong Tourism Board and the World Trade Organisation from 2002 to 2017, along with latent growth curve modelling, multivariate regression and panel data analysis, findings confirmed the impact of physical and cultural distance on tourist demands, behaviours and attitudes. In addition, quadratic relationships are detected using cross-validation methods. The effect of physical distance on tourist demands clearly dominates that of cultural distance in the overall market. The problem of spurious correlation and the results of three cultural distance measures are also discussed with potential for future studies.
Keywords: cultural distance, international tourist behaviour, tourism demands, latent growth curve modelling, multivariate multiple regression, panel data analysis

1. Introduction

Distance and culture are two crucial concepts applied by scholars to investigate the critical factors of the tourism phenomenon, such as tourist demands (e.g. Cheung & Saha, 2015; Crouch, 1994; Hanink & White, 1999), tourist arrivals (e.g. McKercher, 2008; McKercher, 2018; McKercher, Chan & Lam, 2008), tourists' attitudes towards a destination (e.g. Crotts & Pizam, 2003; Huang & Crotts, 2019; Leung, Woo & Ly, 2013; Qian, Law & Wei, 2018) and their subsequent behaviours at a destination (Ahn & McKercher, 2015; Crotts, 2004; Qian et al., 2018). In the case of tourism demand, which is popularly measured using tourist arrivals (Song & Li, 2008; Song, Li, Witt & Fei, 2010), McKercher et al. (2008) examined the association between distance and tourism by using a massive dataset that comprised 410 outbound markets and 146 target destinations. They detected various shapes of distance decay pattern. On the basis of these patterns, relationships between (1) distance and types of market segment and (2) distance and tourists' motivation with subsequent behaviours were found when the assumption of segment transformation was applied to divide the entire market into short- and long-haul. Given this heterogeneity of tourists in the short- and long-haul markets, specific characteristics, attitudes, motivations or behaviours, including age, occupation and time availability, can be predicted through distance (Ahn & McKercher, 2015). For example, young office workers who travelled primarily for pleasure, escape or relaxation were predicted to belong to the short-haul market (Yan, 2011). Meanwhile, highly educated high-income visitors or young backpackers who were motivated to travel for self-development (Bao & Mckercher, 2008) tended to be classified under the long-haul market. In this regard, distance performs a filtering effect (Ahn & McKercher, 2015; McKercher, 2008, 2018) and physical distance is subsequently used as a moderator to distinguish the overall market into short- and long- haul markets (e.g. Ho & McKercher, 2014; Qian et al., 2018) when scholars investigate distance from the perspective of destination.

Although distance is not a deterministic variable, culture is. The concept of culture is directly used to examine tourism demand and visitors' attitude and behaviour. Culture is deemed as a 'collective programming of mind' (Hoftede, Hofstede & Minkov, 2010) rooted in individuals, and occasionally, it can be perceived as a 'social glue' (Kastenholz, 2010) because culture can be used to distinguish a group of people from other societies. Moreover, culture encapsulates an individual's values, attitudes, behaviours and preferences (Warner & Joynt, 2002). For example, a series of three consecutive random-assignment experiments performed by Mahajan and Wynn (2012) found an inherited preference to like (or dislike) someone or something similar to 'us' (or to 'them'). This finding can be generalised to the tourism context. That is, the innate preference of tourists that results in the development of their judgment to like or dislike something is systematically and gradually shaped by their culture. Until a certain point when a set of mind-sets, attitudes or behaviours has matured, tourists' judgment is deemed autonomous, i.e. they can immediately evaluate and tell what is 'like' and 'dislike' without seeking for considerable information. Moreover, different travellers have varying mind sets or attitudes, and they tend to evaluate their experiences in different ways (Huang & Crotts, 2019). Consequently, visitors' attitude and behaviour are culture-bound instead of culture-free (Pantouvakis, 2013).

If travellers are culture-bound by nature, then not controlling the effect of culture when examining their behaviours is unrealistic because such situation implies that travellers think and behave in the same manner in every place they visit. To avoid this phenomenon, scholars have attempted to account for the impact of cultural value in their models. Researchers have applied individual-level culture measures, such as language proximity (Gil-Pareja, Llorca-Vivero & Martínez-Serrano, 2007) or ethnic union (Fourie & Santana-Gallego, 2013), to reflect the essence of culture. However, this step is oversimplified because culture is a multifaceted concept (Hoftede et al., 2010). Several scholars have proposed aggregate national-level culture measures with a multifaceted concept, such as the Hofstede index (Hoftede et al., 2010), the World Value Survey (WVS) (Inglehart, 2004; Inglehart & Baker, 2000) or the Schwartz framework (Schwartz & Zamboanga, 2008). With the availability of multifaceted culture measures, scholars have extensively relied on these aggregate national-level culture frameworks. For example, Qian et al. (2018) and Crotts (2004) applied the uncertainty avoidance index (UAI), one of the six dimensions of the Hofstede index, as a proxy of culture. Esiyok, Çakar and Kurtulmuşoğlu (2017) extracted four dimensions of the Hofstede framework, namely, power distance, individualism, uncertainty avoidance and masculine, to capture the effect of cultural distance on medical tourism demand. Amongst these available culture frameworks, Hofstede's is the most popular (Ahn & McKercher, 2015). Although several scholars have criticized the appropriateness of using the Hofstede framework to examine tourist behaviour due to its probable outdatedness (Y. Yang, Liu & Li, 2019) and lack of theoretical support (Steenkamp, 2001) or sample representativeness (Ahn & McKercher, 2015), Ng and Lim (2019) extended their analysis from the 2007 version and retested the predictive validity of the Hofstede and Schwartz frameworks and concluded that the former is better than the latter in examining consumer behaviour patterns. However, the Schwartz framework is better in capturing trade flows. The current study aims to determine the effect of cultural distance on tourists' attitudes and behaviours; thus, we selected the Hofstede framework as a proxy for aggregate national-level culture in this research.

Cultural distance, which is perceived as a derived construct of culture, refers to the extent to which the culture of the nation of origin deviates from that of the host nation (McKercher & Chow, 2001). Similar to physical distance, cultural distance is used to investigate tourism demand (e.g., Bi & Lehto, 2018; C. H. Lee, Chen, Liou, Tsai & Hsieh, 2018; Y. Yang et al., 2019; Y. Yang & Wong, 2012) but is rarely used to examine tourist attitudes and behaviours (Ahn & McKercher, 2015). Although empirical studies have attempted to establish the connection of cultural distance to tourist arrivals, attitudes and behaviours, the results of these studies are inconsistent. On the one hand, several studies have reported a positive association of cultural distance with tourist arrivals (Ahn & McKercher, 2015; Bi & Lehto, 2018), attitudes (Ahn & McKercher, 2015; Huang & Crotts, 2019; Leung et al., 2013) and behaviours (Qian et al., 2018). For example, Bi and Lehto (2018) showed that cultural distance exerts a positive impact on tourism demand but not in linear terms. Meanwhile, Qian et al. (2018) found a positive association between cultural distance and visitor's shopping behaviours.

Moreover, Watson and Wright (2000) determined the impact of cultural similarity on attitudes and subsequent behaviours. These findings were generally echoed by Ahn and McKercher (2015) who reported a positive relationship between (1) cultural distance and tourist arrival in the short-haul market and (2) cultural distance and overall satisfaction in the overall market. On the other hand, several studies have reported conflicting evidence. In medical tourism, Esiyok et al. (2017) applied econometric analysis and found a quadratic relationship with a negative simple slope between cultural distance and medical tourism demand drawn from 109 countries from 2012 to 2014. Similarly, using the panel data gravity model with the feasible generalised least squares (FGLS) approach on 18 central countries of origin, Y. Yang and Wong (2012) determined the negative impact of cultural distance on China's inbound tourism flow. By contrast, Liu, Li, Cárdenas and Yang (2018) found no significant impact of cultural distance on tourist destination choices. With regard to tourists' attitudes and behaviours, Qian et al. (2018) reported that the association between cultural distance and tourists' satisfaction is inconclusive and a positive association between cultural distance and shopping behaviours. Using a 12-year dataset from the Hong Kong Tourism Board (HKTB), Su, Min, Chen and Swanger (2018) conducted panel regression analysis to determine the relationship between cultural distance and tourist spending and found a U-shaped relationship. Their findings indicated that the negative association between cultural distance and spending is apparent in countries with a cultural distance lower than 3.93. However, when cultural distance is higher than 3.93, the negative relationship changes to a positive one. This finding is contrary to those of Ahn and McKercher (2015) and Qian et al. (2018). Hence, the impact of cultural distance on tourist arrivals, attitudes and subsequent behaviours remain inconclusive.

The extant literature provides insightful clues to the conflicting results of studies. For visitors' attitudes, two competing theories, namely, strangeness–familiarity (Cohen, 1972) and product–self congruity theory (Sirgy & Su, 2000) influence visitors' attitudes towards a destination, decision to visit and subsequent behaviours at a destination. That is, Sirgy's theory supports the negative association between cultural distance and visitors' attitudes and subsequent behaviours, whereas Cohen's strangeness theory supports a positive relationship between the two variables. The central thesis of Sirgy's theory is as follows: when people identify themselves with culturally similar objects, they tend to develop positive feelings towards the products or services offered by culturally similar countries and vice versa. The aforementioned studies (e.g., Esiyok et al., 2017; Su et al., 2018; Y. Yang & Wong, 2012) are supported and explained by the product–self congruity theory. However, the strangeness motive is another potential driving factor that affects the travel risk tolerance of tourists. This factor is widely used to support the positive association between tourists' attitudes and behaviours. For example, Yu and Littrell (2003) found a positive relationship between cultural distance and tourists' spending on souvenirs. Özdemir and Yolal (2017) confirmed this relationship when they found that tourists from the United States and Japan tend to spend more heavily on souvenirs in Turkey than those from Germany and Italy, which are located near Turkey. Hence, one of the factors that generates this conflict is the function of cultural distance as a demand generator and inhibitor. This function affects tourist attitudes and subsequent behaviours.

Apart from the opposite functions of cultural distance described earlier, various pieces of evidence from previous studies demonstrate that the source of conflict can be ascribed to the culture measure itself and the research design. Researchers have extensively applied the calculation technique proposed by Kogut and Singh (1988) to arrive at cultural distance. Two major concerns from the previous literature are zero covariance (Kandogan, 2012) and an equal weight of each dimension's assumptions (Shenkar, 2012). Firstly, Kogut and Singh's (1988) technique is based on Euclidean distance. Thereafter, Kandogan (2012) proved that Kogut and Singh's (1988) technique is a particular case of Mahalanobis distance. Whilst Kogut and Singh's (1988) assumption disregards the existence of every pair of covariance in a diagonal matrix, Kandogan (2012) proposed that cultural distance calculated using the traditional technique can be improved if researchers consider the existence of a covariance, which is disregarded in Kogut and Singh's method. To date, researchers still use the traditional approach to calculate cultural distance even if the technique proposed by Kandogan (2012) is convincing and easy to implement. To reflect the existence of non-zero covariance in the Mahalanobis method, our study considered the traditional cultural distance measure and Kandogan's (2012) method. Secondly, Kogut and Singh (1988) indicated that the weight of each dimension is assumed equal. Such assumption, which implies that all dimensions have the same importance, is unrealistic (Shenkar, 2012) and can be a potential source of inaccurate findings. To the best of our knowledge, however, no attempt has yet been made to improve the cultural distance measure such that appropriate weights are determined for each dimension. Therefore, we proposed a novel method for calculating cultural distance based on different weights from each dimension by utilising the advantages of the alternating least squares (ALS) algorithm (Kroonenberg & de Leeuw, 1980; Takane, Young & de Leeuw, 1977) from the generalised structured component analysis (Hwang & Takane, 2004; S. Kim, Cardwell & Hwang, 2017). Our proposed method for calculating cultural distance was compared with the traditional Kogut and Singh's and Kandogan's methods to determine which approach is the best for capturing the effect of cultural distance.

Research design problem. Firstly, cross-sectional data analysis is extensively used when analysing the effect of cultural distance on tourist attitudes (Ahn & McKercher, 2015; Huang & Crotts, 2019; Leung et al., 2013) and behaviours (Ahn & McKercher, 2015; Ho & McKercher, 2014; Qian et al., 2018). Although the advantage of cross-sectional data analysis is to provide an approximate picture of the association of cultural distance with the arrivals, attitudes and behaviours of international tourists visiting Hong Kong, the method cannot establish a causal relationship. Moreover, the problem of spurious correlation can easily occur in the cross-sectional design. This problem limits the ability to draw a conclusion about long-term impact. We argue that cultural distance should shift from a cross-sectional design to a longitudinal design when it is used to examine tourist attitudes and behaviours to mitigate the aforementioned problems and perceive the real effect of cultural distance in long run. Secondly, many studies (e.g. Ng, Lee & Soutar, 2007; Zhang, Seo & Lee, 2013) have assigned the aggregate national-level of a cultural index to individual visitors from each country. This practice exhibits an underlying unrealistic assumption that people from a given country are homogeneous; this assumption is deemed an ecological fallacy (Mezias et al., 2002). By contrast, our study does not suffer from such a problem because our dataset does not include individual-level data. Thirdly, the problem of statistical and practical significance should be briefly discussed before continuing. If the sample size is too small, then unreliability of parameter estimate can occur. Moreover, standard errors are increased to compensate for the small sample size. Hence, the chance of 'failing to reject' the null hypothesis (e.g. high effect size is rejected) is increased. This example exhibits a case of practical significance with statistical *in*significance.

By contrast, other studies have included too many observations in their analysis. Although parameter estimate is reliable, the chance to 'reject' the null hypothesis will still increase even if the effect is minimal or near zero due to the narrow standard error. This example presents a case of statistical significance with practical *in*significance. To consider the problem of practical and statistical significance, we carefully focused on practical significance because our sample size is small. Fourthly, previous research designs tended to use panel regression analysis (e.g. Bi & Lehto, 2018; Y. Yang, Fik & Zhang, 2013; Y. Yang et al., 2019; Y. Yang & Wong, 2012), separate univariate *t*-test or correlation (e.g. Ahn & McKercher, 2015; Huang & Crotts, 2019) and graphical illustrations (e.g. Qian et al., 2018); these methods disregard the case of measurement error (Huang & Crotts, 2019). A measurement error can cause the traditional ordinary least squares (OLS) method (e.g. used in Ahn & McKercher, 2015) to overestimate the relationship of cultural distance observed in traditional cross-sectional or longitudinal analysis. To prevent this problem, we applied latent growth curve analysis, a unique form of structural equation modelling (SEM), to control for measurement errors of the latent intercept and slope, and consequently, yielded more accurate analysis results. Lastly, previous cultural distance literature tends to regard physical distance as a moderator by classifying the overall market into short- and long-haul markets when examining the effect of cultural distance (e.g. Ahn & McKercher, 2015, 2019; Ho & McKercher, 2014; McKercher, 2008; Qian et al., 2018). We overcome this limitation in research design by simultaneously quantifying the effects of physical and cultural distance whilst forcing physical distance to perform the role of a moderator.

To fill the aforementioned gaps, we empirically investigated the systematic links of cultural distance to tourists' arrivals, attitudes and behaviours in a longitudinal manner. In particular, by using latent growth curve modelling (LGCM), we aimed to identify an overall temporal trajectory of change in repeated measures of tourists' arrivals, attitudes and behaviours and simultaneously evaluate the effect of cultural distance on the overall temporal trajectory, with physical distance as the moderator. Specifically, our objectives are as follows: (1) to improve and propose a cultural distance measure using generalised structured component analysis; (2) to compare our proposed method for calculating cultural distance with the traditional Kogut and Singh's and Kandogan's methods in determining the effects of cultural distance on tourist arrivals, attitudes and behaviours and (3) to investigate a series of cultural distance's effects, conditional on physical distance, on the arrivals, attitudes and behaviours of international inbound tourists using a dataset from HKTB.

2. Literature review

2.1 Impact of cultural distance on tourist arrivals

Tourist motivation and destination choice are two concepts used extensively by researchers to clarify the relationship between cultural distance and tourist arrivals. For example, McKercher and du Cros (2003) argued that a critical motivation for tourists to visit a culturally distant destination is to gain experience or self-development. This motivation is in line with escape and novelty seeking, which are ordinary motives in the tourism literature (Crompton, 1979) that drive people to travel. Their work signified that cultural distance exerts a positive impact on tourism demand. However, the Pacific Asia Travel Association (1995) reported that similarity in cultural background between tourists in Mainland China and those in Hong Kong is an essential factor that makes Chinese travellers specifically choose Hong Kong as their destination choice. This evidence connotes that cultural gap plays a negative role in predicting Chinese visitors to Hong Kong. Ng et al. (2007) found a negative association between cultural distance and intention to travel abroad of travellers in Australia. This finding implied that familiarity is a salient factor for Australian travellers in selecting a destination. Hence, the concept of cultural distance exhibits interplay with tourist apprehension and motivation when selecting a place to travel.

In accordance with previous studies, the influence of cultural distance on destination choice can be positive (e.g. Ahn & McKercher, 2015; Bi & Lehto, 2018) or negative (e.g. Y. Yang et al., 2019). In positive influence, the more significant cultural difference is between the destination and the origin, the more attractive a place will be from the tourists' viewpoint. This positive relationship implies that cultural distance functions as a demand generator by attracting tourists who want to escape their mundane life by seeking novelty or exotic experience from another place (Crompton, 1979; T. H. Lee & Crompton, 1992). In negative influence, the more considerable cultural similarity is between a tourist's cultural background and that of a destination, the more persuasive the destination is from the visitors' perspective. This inverse relationship is consistent with the findings of Litvin and Smith (2016) that psychocentric destinations attract psychocentric tourists by approximately 91.8%. However, on the basis of psychographic–allocentric typology (Litvin & Smith, 2016; Plog, 1974), cultural distance can be considered an appealing factor for allocentric tourists, but an inhibiting factor for psychocentric tourists. That is, cultural distance affects tourist arrivals, but its effect is ambiguous because it can be discerned as both a facilitator and an inhibitor of tourism demand. Cohen (1972, 1984) asserted that the primary motive that drives tourists to travel is novelty-seeking. Although people stay in luxury accommodations, such experience may one day become mundane, and this motive exerts pressure to seek another place to escape a mundane life (T. H. Lee & Crompton, 1992). By definition, cultural distance represents the gap between the cultural background of visitors and destinations. In this manner, culturally distant destinations can be the solution to tourism demand driven by novelty-seeking motives because of the promise of unique and exotic experiences to visitors. That is, if a destination has a physically and socially different environment from their place of origin, then tourists' attention can be drawn to visit this place. In such case, cultural distance can be regarded as a demand facilitator.

Although the novelty-seeking motive is a salient factor that drives tourists to choose a culturally distant destination, risk-averse tourists may perceive cultural distance as an inhibitor given that an increase in cultural gap induces a decrease in familiarity, and consequently, an increase in the risk and uncertainty of a trip. This phenomenon is in line with cultural risk, which is classified as one of the various risks that constitutes travel risk (Lepp & Gibson, 2003; Reisinger & Mavondo, 2006) and affects tourists' attitudes and behaviour when deciding to visit a destination. An environmental bubble is another example of affirming that potential tourists still demand familiarity. Anxiety uncertainty management (AUM) theory (Gudykunst, 1998) posits that tourists who unintentionally travel to an exotic environment experience worrying situations and suffer from the negative consequence of such unfamiliarity. In destination choice selection, empirical research agrees that perceived risk negatively affects tourists' intention to visit a destination. Reisinger and Mavondo (2006) and Lepp and Gibson (2003) indicated that safety and risk factors are indispensable when potential tourists make decisions to travel. Consequently, potential visitors tend to eliminate a destination from their selection when they feel risky and insecure (Sönmez & Graefe, 1998). In this regard, cultural distance can pose a formidable challenge to mid- and psychocentric tourists because of the possible risk and cultural shock that can trigger emotional discomfort amongst potential visitors (J. Yang, Ryan, & Zhang, 2013).

Interestingly, recent empirical findings have shown that the association between cultural distance and tourist arrivals remains inconclusive. For example, Y. Yang et al. (2019) gathered data from the United Nations World Tourism Organisation (UNWTO) on 94 countries from 1995 to 2012. They determined the negative relationship between cultural distance and tourist arrivals using the technique of compounding cultural distance from Kogut and Singh (1988) and three cultural frameworks, namely, Hofstede, World Value and Schwartz. Moreover, the effects of cultural distance calculated using the three frameworks were consistent. Although research results have persistently confirmed the adverse effects of cultural distance, the magnitude is decreasing compared with that in the past. Y. Yang et al. (2019) reported a series of robust adverse effects of cultural distance on tourist arrivals. Bi and Lehto (2018) determined that the impact of cultural distance on tourist arrivals in Mainland China is positive and tilts downward when the score of cultural distance is high. Bi and Lehto (2018) used secondary data from the 1995–2014 Tourism Statistics yearbook of UNWTO regarding Chinese visitors at the national borders of 68 destination countries to investigate the relationship between cultural distance and tourist arrivals. The Hofstede index was coupled with the technique proposed by Kogut and Singh (1988) to derive a cultural distance index. They found that cultural distance plays a decisive role in explaining the increase in Chinese tourist arrivals. In their analysis, OLS and FGLS confirmed the positive impact of cultural distance on Chinese visitor arrivals; however, this impact was diminished on the basis of the U-curve relationship. The empirical study of Ahn and McKercher (2015) is also significant because it examined the effects of cultural distance from the perspective of a destination, i.e. the Hong Kong Special Administrative Region, by using secondary data from HKTB (2010). Through the simple regression analysis of 17 countries and by classifying tourist arrivals into short- or long-haul, they found that cultural distance exert a positive effect on short-haul tourist arrivals. They concluded that the effect of physical distance outperforms that of cultural distance in explaining tourist arrivals. This finding is in line with that of Håkanson and Ambos (2010).

2.2 Impact of cultural distance on tourist attitudes and behaviours

The concept of cultural distance and similarity has been used not only to predict tourism demand or tourist arrivals but also tourist attitudes and behavioural intention. For example, cultural distance has been applied to the marketing context to explain willingness to purchase foreign products or services. Ma, Wang and Hao (2012) asserted that cultural similarity exerts a significant positive effect on customer willingness to purchase exotic products and services from a distant destination. With the support of social identity theory, they explained that cultural affinity tends to make a customer feel that he/she is identified with products or services, and thus, a positive attitude is developed and the willingness level to buy exotic products is increased. This phenomenon can be generalised to the tourism context. For example, Leung et al. (2013) examined the relationship between cultural distance and visitor satisfaction with service received from local-based airlines, government services and public transportation. Using only the uncertainty avoidance dimension as a proxy for culture, they found that cultural distance exhibits a negative relationship with tourist satisfaction. Huang and Crotts (2019) conducted a rigorous research to investigate the effect of cultural distance on tourists' satisfaction by dividing their study into two sub-studies, i.e. Australia and Hong Kong, to cross-validate their findings. The first unique feature of this work is that the researchers used the traditional Kogut and Singh (1988) method to create a series of composite indices for cultural distance. These indices, which included CD2 [power distance index (PDI) and UAI], CD4 [CD2, individualism (IDV) and masculinity (MAS)] and CD6 [CD4, long-term orientation (LTO) and indulgence (IND)], aimed to explain tourist satisfaction in both studies. The second meaningful feature is that the researchers perceived cultural distance as a derived construct from the direct relationship between culture and satisfaction. Hence, they rigorously tested all the dimensions of the Hofstede culture index individually. The findings of the sub-studies signified that PDI, INV, LTO and IND are significantly correlated with trip satisfaction. Moreover, the associations between overall satisfaction and CD2, CD4 and CD6 are negative in the case of Australia. This result confirmed the negative effect of cultural distance on overall satisfaction in Australia. By contrast, CD4 and CD6 demonstrated a statistically significant positive relationship with overall satisfaction in Hong Kong. Kozak (2001, 2002) examined the differences in satisfaction level between British and German tourists visiting Turkey and Mallorca. They found that satisfaction level and motives differ between British and German tourists. National culture distinguishes tourists into meaningful subgroups based on travel motivations, behavioural patterns, perceptions and activities (Lew & McKercher, 2006). The preceding studies imply that cultural similarity partially shapes the attitudes of visitors (Y. Yang et al., 2019) because their action can be partly explained as being culture-bound. Given that individuals have developed their innate preference across time, they tend to like people who share common values. This homogeneous value in a group gradually shapes the judgment of its members to like or dislike a certain object; it is developed as an automatic judgment without requiring considerable time to react (Huang & Crotts, 2019). This uniqueness can be used to explain visitors' attitudes in the tourism context.

The aforementioned studies confirm the relationship between cultural distance and tourist attitudes; such relationship can be positive or negative. Moreover, cultural distance is extended to explain tourist behaviours arising from their attitudes. Theory of planned behaviour (TPB) posits that attitudes can be used to predict behaviours; thus, Quintal, Lee and Soutar (2010) applied TPB to investigate the effects of attitude and culture on tourist behaviours. They found that the relationship between attitude and intention (D. Y. Lee, 2000) and that between attitude and behaviour (Lam & Hsu, 2006) are higher in more individualist cultures. This finding indicates that cultural distance, which is a derived construct of culture, can be used to determine the heterogeneity of visitors' behaviours, such as tipping practice, preferred activities or behavioural patterns (S. Kim & McKercher, 2011). Moreover, specific behaviours have been observed amongst risk-averse tourists. Various risk-mitigation strategies, such as purchasing package tours and travelling in large groups in fewer destinations, are selected by risk-averse visitors when they travel to culturally distant places (Crotts, 2004; Lepp & Gibson, 2003; Litvin, Crotts & Hefner, 2004; Money & Crotts, 2003). In the case of Seoul visitors, Suh and McAvoy (2005) reported that preferred behaviours emerged from cultural distance. In particular, tangible attributes (e.g. sightseeing and shopping) are apparent amongst culturally similar tourists, whereas intangible attributes (e.g. visiting cultural heritage sites) is observed amongst tourists from culturally distant places.

2.3 Measuring cultural distance

Measuring physical distance is a straightforward process. Academicians widely use miles or flight times (e.g. Bao & Mckercher, 2008; McKercher, 2008) to measure distance. By contrast, cultural distance is controversial. Culture itself is difficult to measure accurately (Reisinger & Crotts, 2010) because it is multifaceted in nature. In accordance with Hofstede's definition, culture can be described as 'the collective programming of the mind which distinguishes the member of one human group from another' (Hoftede et al., 2010). In the tourism literature, researchers have adopted various variables to capture culture, such as uncertainty avoidance (Crotts, 2004; Crotts & Pizam, 2003; Leung et al., 2013; Litvin et al., 2004; Qian et al., 2018), common language (Cheung & Saha, 2015; Gil-Pareja et al., 2007), religion similarity (Ghani, 2016) or ethnic reunion (Fourie & Santana-Gallego, 2013). For example, UAI, one of the six dimensions of Hofstede's cultural framework, has been applied as a proxy for culture given that considerable literature in the fields of tourism and international business endorses UAI as the most appropriate dimension for forecasting cross-cultural behaviour (Ahn & McKercher, 2015; Barkema & Vermeulen, 1998; Money & Crotts, 2003). However, these measurements are unsuitable for capturing culture because they can reflect several aspects of culture's multifaceted nature. The CVSCALE multidimensional measurement was proposed by Yoo, Donthu and Lenartowicz in 2011. This scale was tested by Ahn and McKercher (2019) on the individual-level case of visitors in Korea. Although this measurement satisfies the multifaceted property of culture, the individual-level case cannot be applied to aggregate data at the national level, such as HKTB data in the case of the present study. Hence, we did not select the multifaceted individual-level cultural index to avoid the problem of ecological fallacy in our study.

For the measurement of culture at the aggregate national level, three frameworks, namely, WVS (Inglehart, 2004; Inglehart & Baker, 2000), Hofstede (Hoftede et al., 2010) and Schwartz (Schwartz & Zamboanga, 2008), are the most popularly used. Firstly, the WVS framework, which focuses on sociocultural and political changes, proposes a global cultural map (Inglehart, 2004; Snir & Harpaz, 2009) that can be grouped into the bipolar framework of (1) traditional and secular-rational and (2) survival and self-expression values. Many scholars have suggested the validity of this framework, as reflected by the rigorous and high-quality research design (Inglehart, 2004). However, the WVS framework can be perceived as a subset of the Hofstede framework because the two aforementioned dimensions are partially incorporated into the new Hofstede's dimensions, namely, LTO and IND (Ng & Lim, 2019). Researchers recommend WVS as an alternative data source to analyse aggregate national-level culture in accordance with the Hofstede framework. Secondly, the Hofstede framework originally collected data from IBM employees in 40 countries and proposed that culture can be grouped into four dimensions: (1) power distance, (2) IDV, (3) MAS and (4) uncertainty avoidance (Hoftede et al., 2010). Thereafter, two more dimensions, namely, LTO and IND, were added to the original four-dimension framework. The number of available countries has also been updated. Compared with only 40 countries when the framework was proposed, data from 65 out of 111 countries are provided in the revised version. Although the Hofstede framework is considered the most productive and influential in the research community (Ahn & McKercher, 2015, 2019; Soares, Farhangmehr & Shoham, 2007) due to its consistency with Kluckhohn and Strodtbeck's (1961) five fundamental problems (Huang & Crotts, 2019), compactness (Kirkman, Lowe & Gibson, 2006), multidimensionality and century-old roots (Ng & Lim, 2019), scholars have criticised this framework for the nonrepresentativeness of its sample (Steenkamp, 2001), outdatedness (Huang & Crotts, 2019) or lack of theory-based support (Baskerville, 2003). However, a recent empirical study of Ng and Lim (2019) confirmed the validity of using the Hofstede framework to predict customer consumption behaviour. Thirdly, the Schwartz framework, which focuses on the content and structure of human values, offers a comprehensive theory-based framework with seven cultural values (Y. Yang et al., 2019): conservatism, autonomy, hierarchy, egalitarianism, mastery, harmony and intellect. Ng and Lim (2019) reported that scholars have grouped these cultural values into three polar dimensions: (1) embeddedness and autonomy, (2) hierarchy and egalitarianism and (3) mastery and harmony. Several scholars recommend using the Schwartz framework rather than the Hofstede framework due to its theory-based conceptualisation (Yeganeh, Su,

& Sauers, 2009) and advanced analytical technique (Steenkamp, 2001). The Schwartz framework is considered one of the dynamic frameworks that frequently updates its datasets. In particular, this framework has gradually updated and increased its dataset from the initial publication scores of 38 countries in 1994 to 49 countries in 1999, 73 countries in 2008 (Schwartz & Zamboanga, 2008) and 80 counties in 2011 (Ng & Lim, 2019). Moreover, corrections have been implemented to reflect the present context. For example, the conservatism value was changed to the embeddedness value. Several scores have also been updated. For instance, the score for the egalitarian value of Finland published in 1994, i.e. 5.26, was changed to 5.03 in 2005 and to 4.90 in 2011 (Ng & Lim, 2019).

Given that two dimensions of the WVS framework are included in the Hofstede framework, selecting an aggregate national cultural framework is a choice between Hofstede and Schwartz. To clarify this issue, Y. Yang et al. (2019) used the WVS, Hofstede and Schwartz frameworks to calculate cultural distance values for explaining international tourism demand. All cultural distance values based on the three frameworks can capture the adverse effects of cultural distance on tourist arrival. This finding implies that the three frameworks are valid and can be interchangeably applied as proxy for cultural distance. Ng and Lim (2019) updated their last analysis from 2007 (Ng et al., 2007) by comparing predictability between the Hofstede and Schwartz frameworks on trade flows and the consumption behaviour of customers; they found that Hofstede is better than Schwartz in predicting consumption behaviour. Moreover, introducing LTO and IND improves the richness of the Hofstede framework in capturing the essence of culture (Ng & Lim, 2019). Our study focuses on determining the effect of cultural distance on tourists' attitudes and behaviours, which can be classified as consumption behaviour; accordingly, we selected all the dimensions of the Hofstede framework as representative of the cultural value of each tourist country. To calculate cultural distance, the most popular method based on aggregate national-level cultural indices used by researchers is the method proposed by Kogut and Singh (1988). This method is expressed as follows:

$$CD_j = \sum_{i=1}^{n} \frac{(I_{ij} - I_{ihk}^2)V_i^{-1}}{n},$$

where CD_j is the cultural difference of J_{th} country from Hong Kong, I_{ij} is Hofstede's score for the I_{th} cultural dimension of J_{th} country and V_i is the variance of the Hofstede's index for the I_{th} dimension. However, a major drawback of this index is its assumption of similar weights for all the dimensions. Such assumption does not reflect reality (Shenkar, 2012). Although this index does not reflect the real world, several cases (approximately 75%) that applied this method were reported in 2007 (Ng et al., 2007).

Kandogan (2012) illustrated that cultural distance coupled with Kogut and Singh's (1988) method can be expressed as a special case of the Mahalanobis distance with zero covariance in $cv_{i,j}$. For simplicity, the variance–covariance matrix of Kogut and Singh (1988) can be expressed as follows:

$$R_{KGI} = \begin{bmatrix} V_i^{PDI} & 0 & \dots & 0 \\ 0 & V_i^{INV} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & V_i^{IND} \end{bmatrix},$$

$$R = \begin{bmatrix} V_i^{PDI} & cv_{12} & \dots & cv_{16} \\ cv_{21} & V_i^{INV} & \dots & cv_{16} \\ \vdots & \vdots & \ddots & \vdots \\ cv_{61} & cv_{62} & \dots & V_i^{IND} \end{bmatrix}.$$

where the matrix R_{KGI} stands for the covariance matrix of Kogut and Singh (1988) and the matrix R represents the variance–covariance matrix of Kandogan's (2012) method. The diagonal elements of the two matrices are nearly identical, except for the off-diagonal elements of R_{KGI} that are forced to be zero. Therefore, R_{KGI} is the zero-covariance matrix, which Kandogan (2012) implied is unreliable because it does not consider the real covarying relationships amongst dimensions. Kandogan also claimed that using R_{KGI} can overestimate or underestimate the true value by approximately 60%. Notably, Kandogan (2012) compounded cultural distance using only four dimensions. The complete calculation of Kandogan's cultural distance based on the Mahalanobis formula is shown as follows:

$$MM_{ij} = \frac{1}{4}\begin{bmatrix} I_i^{PDI} - I_j^{PDI} \\ I_i^{IDV} - I_j^{IDV} \\ I_i^{MAS} - I_j^{MAS} \\ I_i^{UAI} - I_j^{UAI} \end{bmatrix}^T \begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} \\ c_{21} & c_{22} & c_{23} & c_{24} \\ c_{31} & c_{32} & c_{33} & c_{34} \\ c_{41} & c_{42} & c_{43} & c_{44} \end{bmatrix} \begin{bmatrix} I_i^{PDI} - I_j^{PDI} \\ I_i^{IDV} - I_j^{IDV} \\ I_i^{MAS} - I_j^{MAS} \\ I_i^{UAI} - I_j^{UAI} \end{bmatrix}.$$

Kandogan (2012) advanced cultural distance knowledge by improving cultural distance measure when he considered the non-zero covariance amongst dimensions. However, the issue of weight similarity persists. In the present study, we addressed the issue of weight similarity amongst dimensions by applying the generalised structured component analysis (GSCA) technique (Hwang & Takane, 2004) with the ALS algorithm (Takane et al., 1977). The starting value is calculated on the basis of the constraint principal component analysis. In addition, our proposed method can be calculated using a covariance matrix, as discussed in the subsequent section.

2.4 Proposed method for cultural distance calculation

Our method for calculating cultural distance applies the concept of a composite variable. To illustrate, we assume that C_{PD} denotes the Hofstede cultural value of the first dimension, i.e. power distance. C_{IDV} denotes the second dimension, i.e. IDV. C_{MAS} denotes the third dimension, i.e. MAS. C_{UAI} denotes the uncertainty avoidance dimension. C_{LTO} refers to the LTO dimension. C_{IND} is the IND dimension. d_1 and d_2 indicate tourist demand measured via d_1 and d_2, respectively. L_1 to L_8 are the factor loadings. γ_C and γ_d are the composite variables of culture and demand, respectively. ϵ_1 to ϵ_8 represent the error terms of each indicator. We can graphically present the prototype model as follows.

(Insert Figure 1.)

The measurement and structural models are similar to the traditional SEM, which can be expressed as follows:

$$\begin{bmatrix} C_{PD} \\ C_{IDV} \\ C_{MAS} \\ C_{UAI} \\ C_{LTO} \\ C_{IDG} \\ d_1 \\ d_2 \end{bmatrix} = \begin{bmatrix} L_1 & 0 \\ L_2 & 0 \\ L_3 & 0 \\ L_4 & 0 \\ L_5 & 0 \\ L_6 & 0 \\ 0 & L_7 \\ 0 & L_8 \end{bmatrix} \begin{bmatrix} \gamma_C \\ \gamma_d \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ \epsilon_6 \\ \epsilon_7 \\ \epsilon_8 \end{bmatrix},$$

which can be reduced into matrix form as

$$z = C'\gamma + \epsilon, \quad \text{…………………………….. (1)}$$

where z is the indicator vector with J (indicators) × 1. C is the loading matrix with P (composites) × J (indicators). γ_d is the composite vector with J (indicators) × 1. ϵ is the error term vector with J (indicators) × 1. The structural model can be expressed as follows:

$$\begin{bmatrix} \gamma_C \\ \gamma_d \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ b_1 & 0 \end{bmatrix} \begin{bmatrix} \gamma_C \\ \gamma_d \end{bmatrix} + \begin{bmatrix} 0 \\ \zeta_d \end{bmatrix},$$

which can be reduced into matrix form as

$$\gamma = B'\gamma + \zeta, \quad \text{…………………………….. (2)}$$

where B is the path coefficient matrix with P (composites) × P (composites) and ζ is the residual vector with P (composites) × 1.

The difference from the traditional SEM used in commercial software (e.g. PLS-graph, PLS-visual, AMOS or LISREL) is as follows. This GSCA framework explicitly expressed the weight relation equation, and the primary objective of this analysis is to solve for w_{PD}, w_{IND}, w_{MAS}, w_{UAI} and w_{IDG}. The equation for weight relation can be summarised in matrix form as follows:

$$\begin{bmatrix} \gamma_C \\ \gamma_d \end{bmatrix} = \begin{bmatrix} w_{PD} & w_{IDV} & w_{MAS} & w_{UAI} & w_{LTO} & w_{IDG} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{d1} & w_{d2} \end{bmatrix} \begin{bmatrix} C_{PD} \\ C_{IDV} \\ C_{MAS} \\ C_{UAI} \\ C_{LTO} \\ C_{IDG} \\ d_1 \\ d_2 \end{bmatrix}.$$

The reduced form can be written as

$$\gamma = W'z, \quad \text{…………………………….. (3)}$$

where W is the weight matrix with J (indicators) × P (composites). Given the advantage of this weight relation equation, we can use the unstandardised cultural indices drawn from Hofstede's website and multiply them with the weight matrix to obtain cultural scores. The resulting cultural scores are not cultural distance. Readers cannot regard these cultural values as a cultural distance index. Subsequent modification is required to derive a cultural distance index.

To calculate optimal weight, the three preceding equations can be merged into one matrix equation as follows:

$$\begin{bmatrix} z \\ \gamma \end{bmatrix} = \begin{bmatrix} C' \\ B' \end{bmatrix} W'z + \begin{bmatrix} \epsilon \\ \zeta \end{bmatrix}.$$

Given that $\gamma = W'z$, γ can be replaced with $W'z$.

$$\begin{bmatrix} z \\ W'z \end{bmatrix} = \begin{bmatrix} C' \\ B' \end{bmatrix} W'z + \begin{bmatrix} \epsilon \\ \zeta \end{bmatrix}$$

z is a common factor in the first matrix. When z is removed from the $\begin{bmatrix} z \\ W'z \end{bmatrix}$ matrix, the result is the identity unit matrix (I) as follows:

$$\begin{bmatrix} I \\ W' \end{bmatrix} z = \begin{bmatrix} C' \\ B' \end{bmatrix} W'z + \begin{bmatrix} \epsilon \\ \zeta \end{bmatrix}.$$

To simplify the entire equation, let $V = \begin{bmatrix} I \\ W' \end{bmatrix}$, $A = \begin{bmatrix} C' \\ B' \end{bmatrix}$ and $e = \begin{bmatrix} \epsilon \\ \zeta \end{bmatrix}$. We can write the GSCA model in reduced equation form as follows:

$$V'z = A'W'z + e. \qquad \text{……………………………..} (4)$$

From Equation (4), A' and W' include the weights (w_i) and path coefficients (b_i) if we formatively specify the measurement model. However, if we reflectively specify the measurement model, then a set of factor loadings is also incorporated into A' and W'. Notably, the error term makes no assumption of multivariate normality because the traditional SEM already has. Hence, the means, variances or covariances of error terms should no longer be estimated. All the unknown parameters incorporated into A' and W' are estimated using the prespecified criterion value with the objective of minimising the error terms based on the sum-square procedure, which can be expressed as follows:

$$\phi = \sum_{i=1}^{N} e_i' e_i = \sum_{i=1}^{N} (V'z_i - A'W'z_i)'(V'z_i - A'W'z_i).$$

In the reduced form equation, let Ψ denote ZV and Γ refer to ZW. Hence, the reduced form is written as follows:

$$\phi = ss(ZV - ZWA).$$

The reduced form equation can be simplified to

$$\phi = ss\big(Z(V - WA)\big) = ss(\Psi\Gamma A).$$

Given that $ss(ab)$ is $trace(b'a'ab)$, therefore

$$\phi = trace((V - WA)'Z'Z(V - WA)).$$

Let $Z'Z = M = nR = nDSD$. Then,

$$\phi = trace((V - WA)'M(V - WA)).$$

M can be directly calculated from the raw Hofstede cultural value indices and is similar to the concept of the variance–covariance matrix used in Kogut and Singh's or Kandogan's cultural distance.

The parameter within A' and W' is extremely difficult to estimate efficiently because it contains several fixed values, e.g. zero in Equation (3). To minimise the criterion value, ALS (Takane et al., 1977) is applied. Conceptually, this method randomly distinguishes parameters into numerous subsets. The process begins by randomly selecting the starting value for a targeted subset. The method assumes that the other subsets will remain the same when optimising the starting value. Each subset will be updated one by one until completion. The process reiterates until the criterion value is less than the threshold value. In our preceding analysis, only two subsets are described. These subsets can be divided into A' and W'. An issue of global minimal convergence is noted. Our objective function is to minimise the criterion value and the ALS algorithm will gradually decrease the criterion value to the lower boundary; thus, we can say that this algorithm is convergent. The two primary methods require selecting a starting value (Hwang & Takane, 2004). The first method uses constraint principal component analysis (Takane, Kiers & de Leeuw, 1995) and the second method uses a trial-and-error method (Hwang & Takane, 2014). The process of minimising ϕ after obtaining the starting value does not require normality assumption. However, the standard error is generated on the basis of bootstrapping and not on traditional asymptotic estimations, such as OLS or maximum likelihood (ML).

Lastly, the weight is obtained and the composite cultural index can be directly calculated using the following equation:

$$\gamma = W'z = W'D(z - \overline{z}).$$

We then modify this cultural distance index to our cultural distance using the standardised composite cultural indices (SCI_i).

$$SCI_i = (\gamma_i - \overline{\gamma}) * S(\gamma)^{-1}$$

Lastly, we deducted the vector of the composite cultural indices with the composite cultural index of Hong Kong to obtain our cultural distance as follows:

$$CD_i = SCI_i - SCI_{HK}.$$

3. Methods

In this study, we used a series of HKTB datasets from 2002 to 2017. The HKTB dataset comprises aggregate national-level data that are published annually; previous studies have used this dataset to examine tourist arrivals, behaviours and attitudes (Ahn & McKercher, 2015; Bao & Mckercher, 2008; Ho & McKercher, 2014; McKercher, 2008; Qian et al., 2018), and thus, the validity of this dataset is ensured. The reports identified four types of visitors. Amongst the four types, only the overnight vacation visitor group was selected to fully reflect the discretionary pleasure tourism sector. The inclusion of other groups, such as business or same-day in-town groups, can hinder the acquisition of the true picture.

In our HKTB dataset, the analysed variables were classified into six groups: tourist inflows, tourist characteristics, travel details, shopping activities, spending and attitude towards satisfaction. The first group, i.e. tourist inflows, had two key variables: the numbers of (1) vacation overnight tourist arrivals and (2) departures of tourists in each country reported by the World Trade Organisation (WTO). These variables were used as inputs to calculate the portion between tourist arrivals per total departure, which is unavailable in the original HKTB dataset. The second group, i.e. tourist characteristics, had four key variables: (1) average age, (2) percentage of males, (3) percentage of married tourists and (4) percentage of working tourists. The third group, i.e. travel details, had five key variables: (1) average length of stay, (2) percentage of tourists who travelled alone, (3) percentage of tourists who participated in non-guided tours, (4) percentage of first-time visitors and (5) percentage of tourists who visited only Hong Kong. Only shopping activity was selected as a proxy for this group because longitudinal analysis requires data that are arranged in a similar format. Considering the format variation of the annually reported HKTB data, several activities presented in the 2017 HKTB report were not provided in the 2014 HKTB report. This situation made our analysis impossible. The fifth group, namely, spending pattern, had six major variables: (1) spending per capita and spending pattern on (2) shopping, (3) hotel, (4) meals, (5) entertainment and (6) sightseeing. Lastly, attitude towards satisfaction had 10 core variables: attitude towards (1) value for money, (2) hospitality of staff in retail shops, (3) shopping, (4) hotels, (5) dining, (6) entertainment, (7) sightseeing, (8) overall satisfaction, (9) word-of-mouth and (10) revisit intention.

The analysis unit comprised nine long-haul markets, which are the United States, Canada, the United Kingdom, the Netherlands, Germany, France, Italy, Australia and New Zealand, and eight short-haul markets, namely, Japan, South Korea, Indonesia, Malaysia, the Philippines, Singapore, Thailand and India. This analysis excluded Mainland China because determining heterogeneity amongst nations is intractable. For example, assume that the mode of arrival to Hong Kong from many countries, such as Thailand, Germany or Japan, is by air. By contrast, travellers from Mainland China have various options to visit Hong Kong. The different origins of travellers from Mainland China significantly affect distance measure and such data are not provided in the HKTB reports. Given the small sample size (17 countries), our interpretation considered practical significance to counterbalance statistical significance.

To calculate cultural distance, six dimensions were extracted from the Hofstede's website. Kogut and Singh's (1988) method for calculating cultural distance is considered the most popular; thus, two assumptions are missing, namely, zero covariance amongst the six dimensions and weight equality in the six dimensions. These assumptions were considered in our study. To account for the non-zero covariance assumption, the Mahalanobis concept proposed by Kandogan (2012) (i.e. Kandogan's cultural distance) was computed along with the traditional cultural distance (i.e. Kogut and Singh's cultural distance). Our analysis was extended to determine the optimal weight for each dimension using the concept discussed in the section on measuring cultural distance. By utilising the advantage of GSCA, we can determine the optimal weight through constraint component analysis to identify the starting value and then optimise the result using the ALS algorithm to obtain the optimal weight for each dimension. To increase the robustness of the weight estimates, we applied a series of component analyses and used the trial-and-error method to determine weights and then compared them with the results of the ALS algorithm. If all the methods achieved similar results, then we selected the lowest boundary. If all the methods exhibited divergent results, then we averaged them to obtain the weight. Subsequently, we used the weight relation equation to derive the composite cultural index, which was prepared for use in the subsequent analysis. To compute cultural distance with varying weights, we standardised the matrix of the computed composite cultural index and excluded the vector of Hong Kong's cultural index. Finally, our vector of the composite cultural distance index was ready for testing and comparison with two existing cultural distance indices. Hence, we had three cultural distance indices, namely, Kogut and Singh's, Kandogan's and ours.

Given the small sample size, practical significance was highlighted to mitigate the chance of misinterpretation by relying only on statistical significance. For example, the minimal negative correlation coefficient between overall satisfaction and cultural distance (−0.063 and −0.091) reported by Huang and Crotts (2019) was deemed statistically significant with a large number of observations (n = 2,456 and 7,372, respectively) because the underlying mechanism to calculate these standard errors is dependent on sample size. The higher number of observations, the narrower the standard error. Thus, the chance to reject the null hypothesis that the correlation coefficient is equal to zero is enhanced because of the higher value of the t-ratio. In case of a small sample size, even a correlation coefficient of 0.4 can be statistically deemed to be not different from zero. We focused on the 17 countries and covered nearly all the countries based on the dataset provided by HKTB. Hence, the results of our analysis not only relied on statistical significance but also on practical significance.

3.1 Analysis design

This work is the first longitudinal study to compare three cultural distance measures to three key variables (tourists' arrival, attitude and behaviour). Given the small sample size, we carefully interpreted the results by considering statistical and practical significance. Moreover, we divided our analysis into three studies with the objective of cross-validating our findings from the perspective of different methodologies, namely, LGCM, multivariate multiple regression analysis (MMRA) estimated explicitly via ML using robust ML (MLR) and traditional panel data with pooled OLS (P-OLS) and random effects (RE). The first study used the LGCM technique to fit the trajectory of the longitudinal data on the basis of the SEM framework. The second study applied MMRA to capture the direct effects of cultural and physical distance on key variables. The third study used the traditional panel data to reestimate the effects of cultural distance with controlled variables. The details of each study are provided in the subsequent sections.

3.1.1. Study 1

LGCM assumes that unobserved latent factors cause the trajectory of tourist' arrivals, attitudes and behaviours over time, as depicted in Figure 2 (i, s and q). This stage is called unconditional or unrestricted LGCM. When the effects of these latent factors are confirmed, cultural and physical distance will be introduced into the model called conditional or restricted LGCM.

(Insert Figure 2.)

Scholars have applied this technique to fit longitudinal data because LGCM is a flexible and powerful framework for discerning the trajectory patterns of a dataset. In particular, LGCM allows us to model random factors, namely, intercept, random slope and random quadratic. Through this attribute, we can perceive the trajectory of each country over time. These random coefficients are similar to the random intercept and slope in the random effects model used in Study 3. Whilst the random effects in traditional panel data analysis regard random coefficients as observed variables, random coefficients from LGCM are deemed as latent variables, which are similar to the latent variables used by scholars in the traditional SEM framework. Hence, this step allows controlling for measurement errors and directly applying the ML algorithm to estimate all the parameters. In this case, missing data can be imputed and a nonlinear relationship can be simultaneously estimated. Other latent variables can be introduced, mediation analysis can be performed and model fit indices are provided. However, the major limitations of this technique are the requirement that a large sample size should have a reliable result and the algorithm is occasionally nonconvergent. Hence, cross-validation analysis is required.

In the first study, we used the dataset from 2002 to 2017, i.e. a 16-year timespan. Unconditional LGCM was initially conducted to extract and confirm the existence of latent factors that cause the trajectory in tourists' arrivals, attitudes and behaviours. Thereafter, we introduced physical distance into the model. Physical distance acted as a moderator by dividing the overall market into short- and long-haul markets. We selected tourist arrivals, overall satisfaction and spending per capita as representatives of tourism demands, attitudes and tourist behaviours, respectively. To cover the entire 16-year timespan in this analysis, LGCM requires more observations. For the 17 counties, the timespan was reduced to 7, 6 and 4 years to determine the effects on tourist arrivals, attitudes and behaviours, respectively. Subsequently, the direct effect of physical distance was simultaneously added to the short- and long-haul markets.

Once the effects of physical distance were controlled, we started testing cultural distance by adding Kogut and Singh's cultural distance measure into the model. We then removed Kogut and Singh's cultural distance measure and added Kandogan's cultural distance measure. Next, we removed Kandogan's cultural distance measure and introduced our cultural distance measure. In summary, we ran 21 models to confirm the existence of latent factors in unconditional LGCM. We ran 6 models to confirm the filtering effects of physical distance as a moderator. Another 6 models were run to quantify the effects of physical distance in the short- and long-haul markets. Lastly, 18 models were run to quantify the effects of each cultural distance measure on the latent factors.

3.1.2. Study 2

Instead of assuming the existence of a latent factor (latent intercept, slope and quadratic), we directly linked cultural distance with repeatedly observed measures. As shown in Figure 2, physical distance acted as a moderator by dividing the market into short- and long-haul markets, whilst being forced to perform simultaneously as a direct effect along with cultural distance in both markets. This multivariate multiple regression was estimated using MLR instead of OLS because MLR is more robust to a non-normal distribution and can simultaneously estimate short- and long-haul markets. Using the timespan from 2012 to 2017 due to the limited degree of freedom (df), we started our testing without introducing cultural distance into the model to ensure the filtering effect of physical distance in the short- and long-haul markets. After we perceived the effect of physical distance, the first cultural distance measure was added to the model to discern the effects. We performed this process until all cultural distance measures were used. We ran 120 models to thoroughly examine the relationship between each cultural distance and the key variables, i.e. tourist arrivals, attitudes and behaviours. Apart from the comparison of cultural distance measures, all possible cases of spurious correlations were also reported.

3.1.3. Study 3

Panel data analysis is another technique that is used widely by scholars to examine the effect of cultural distance on tourism demands. The three perspectives that pertain to the panel data analysis framework should be clarified. In the first perspective, if the random sample is drawn from a different period, then the set of random samplings is regarded as 'independently pooled cross-sectional data'. In such case, we can apply P-OLS to estimate all the parameters. Given that the HKTB dataset was created on the basis of random samplings from different observations over time, the dataset can be considered an independently pooled cross section. With P-OLS, we can expect our results to be estimated more precisely and the test statistics are expected to have higher power analysis. As argued by Wooldridge (2010), P-OLS can be applied if scholars believed that the relationship between dependent and independent variables is constant. In our analysis, we added more dummy variables to each time span to reflect that the distribution of each observation may vary over time.

In the second perspective, scholars may assume that although various controlled variables are introduced into the model to mitigate omitted variable bias, this problem persists and negatively affects the conclusion. Hence, another treatment to this problem is to assume the possibility of an unobserved error that affects the entire system over time as denoted by α_i. Given that α_i is constant over time, it is called a 'fixed effect', as expressed in the following equation:

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \cdots + \beta_k x_{itj} + \alpha_i + u_{it}. \quad (5)$$

Whilst α_i captures the unobserved effects that are constant over time, u_{it} is referred to as the unobserved effects of time-varying errors or idiosyncratic errors. To estimate this model, we can obtain the average ($\overline{x}$) as follows:

$$\overline{y}_i = \beta_1 \overline{x} + \cdots + \beta_k \overline{x}_j + \alpha_i + \overline{u}_i. \quad (6)$$

Then, we subtract (x) from (x) and derive

$$y_{it} - \overline{y}_i = \beta_1(x_{it1} - \overline{x}_{i1}) + \cdots + \beta_k(x_{itk} - \overline{x}_{ik}) + u_{it} - \overline{u}_i. \quad (7)$$

When α_i is eliminated, we can estimate the parameters using P-OLS. This process is called the fixed effects estimator or the within estimator.

The third perspective perceives Equation (5) from a different angle. The objective of the second perspective is to remove α_i from the equation because α_i is assumed to exhibit a certain correlation with x_{itj}. If $Cov(\alpha_i, x_{itj}) \neq 0$, then using the fixed effects estimator is inefficient (Wooldridge, 2010). In this regard, we estimate this equation using random effects analysis. To do so, we combine α_i and u_{it} into the composite error ($v_{it} = \alpha_i + u_{it}$). Although P-OLS can be used to estimate this random effects equation, we do not recommend this step because P-OLS disregards the serial correlation problem within the system. Instead, the generalised least squares (GLS) approach is used for estimation.

The previous literature generally used the Hausman test to choose between fixed and random effects. If the null hypothesis is rejected, then the key assumption of random effects ($Cov(\alpha_i, x_{itj}) \neq 0$) is wrong. Hence, fixed effects will be selected. However, our study aims to examine the effects of cultural distance. Such effects are regarded as constant over time. Therefore, using fixed effects is impossible because the effects of cultural distance are removed in the subtraction process to derive Equation (7), as described in Equation (5) minus Equation (6). Technically, Equation (7) can be transformed into

$$y_{it} - \theta\bar{y}_i = \beta_0(1-\theta) + \beta_1(x_{it1} - \theta\bar{x}_{i1}) + \beta_k(x_{itk} - \theta\bar{x}_{ik}) + (v_{it} - \theta\bar{v}_i),$$

where $\theta = 1 - \sqrt{\frac{\sigma_u^2}{\sigma_u^2 + T\sigma_\alpha^2}}$ and $\hat{\theta} = 1 - \sqrt{\frac{1}{1+T(\frac{\hat{\sigma}_\alpha^2}{\hat{\sigma}_u^2})}}$. (8)

Thereafter, we can use P-OLS to estimate Equation (8), called GLS. If we use $\hat{\theta}$ rather than θ, then this random effects estimator will be called feasible GLS (FGLS). If θ = 0, then we obtain P-OLS. If θ = 1, then we derive the fixed effects. The random effects estimator ranges from 0 to 1. In our study, we estimate P-OLS and random effects FGLS and then provide θ to compare the results. Moreover, we add age, male, length of stay, first-time visitor, physical distance and gross domestic product (GDP) as covariates and control for random events occurring in a given year by using dummy variables from 2003 to 2017. R programming language with lavaan (Rosseel, 2012), blavaan (Merkle & Rosseel, 2016), gesca (S. Kim et al., 2017) and plm (Croissant & Millo, 2008) packages is used to complete the analysis in this study.

4. Results

4.1. Study 1

The first study aims to observe the existence of latent factors that presumably cause the trajectory of critical variables in each country. This study is specifically designed to answer a set of pre-analysed questions as follows. (1) What is the trajectory for the entire group? (2) Do we need distinct trajectories for each country? (3) Can we identify the relevant predictors of the trajectories for each country? The answer to the first question relates to the mean of the trajectory parameter estimates (fixed effects components) and that to the second answer relates to country differences in trajectory over time (random effects components). That is, if evidence indicates that latent factors (latent intercept, slope and quadratic) cause changes in the focal variables over time, then we gradually added physical and cultural distance to the model to predict individual country trajectories to answer the third question. To complete this task, we started from the most restrictive model (Model 1) and ran a series of increasingly less-restrictive LGCM for 21 models for each variable, as shown in Tables 1, 2 and 3.

(Insert Table 1.)

(Insert Table 2.)

(Insert Table 3)

Dividing into seven models enables us to identify which model is the fittest for our subsequent analysis. The first model calculated a mean latent intercept and fixed the residual variances of tourist arrivals from 2002 to 2017. The fit indices exhibited very poor fit [standardised root mean square residual (SRMR) = 0.8598 and comparative fit index (CFI) = 0]. Our second model allowed the mean latent intercept to vary, but the residual variance was still set as constant. The fit indices significantly improved but remained unacceptable (SRMR = 0.1318 and CFI = 0.3225). Subsequently, we added the slope, but the slope was not allowed to vary to reflect the fixed effects condition. The results from the third model indicated that many countries exhibited statistical difference at the starting point [Var (i) = 0.17], but their slopes were not statistically different from the grouped slopes [Var (s) = 0.001]. Hence, using only fixed effects components can worsen the overall fit indices because SRMR increased to 0.4319. Then, we relaxed the latent slope to move freely in the fourth model. The fit indices improved again (SRMR = 0.0855 and CFI = 0.4898). In this model, we found that each country started at different points [Var (i) = 0.166] and the common trend was increasing (latent slope = 0.017). Although the starting point of tourist arrivals was different, the average values tended to converge [Cor (i,s) = −0.201]). We further explored the curvilinear relationship between the latent factors and the trajectory of tourist arrivals by introducing the latent quadratic in Model 6; however, this model still assumed that all residual variances were constant. The fit indices were improved (SRMR = 0.0615 and CFI = 0.5516). Lastly, we relaxed the residual variances to vary in Model 7. The fit indices were significantly improved (SRMR = 0.073 and CFI = 0.7052). With the complete set of analysis, we can detect the existence of latent factors that explain the trajectory of tourist arrivals over time. That is, the common slope tends to increase in decreasing trends (Question 1). This quadratic trend can be adequately explained by all the latent factors (Question 2); hence, the pertinent predictor should be identified to explain their movements (Question 3).

Similar to the case of tourist arrivals, we ran seven models to investigate the trajectories of overall satisfaction and spending per capita with samples drawn from 2011 to 2017 for overall satisfaction and from 2012 to 2017 for spending per capita. However, both model fit indices were unacceptable (overall satisfaction: SRMR = 0.0897 and CFI = 0.3213; spending per capita: SRMR = 0.1608 and CFI = 0.1373). The result may be attributed to the small sample size that made the detection of the heterogeneous trajectory of each country difficult for an extremely long period. Hence, the subsequent analysis introduced physical distance as a moderator to examine its filtering effect.

(Insert Table 4.)

As shown in Table 4, the fit indices of tourist arrivals (SRMR = 0.0738 and CFI = 0.9376) and overall satisfaction (SRMR = 0.0642 and CFI = 0.9721) were acceptable, whereas those of spending per capita (SRMR = 0.5615 and CFI = 0.3952) were unfit. This result strongly confirmed the role of physical distance as a moderator in filtering tourist arrivals and overall satisfaction. Interestingly, we found from the overall satisfaction analysis that although the latent slopes of short- and long-haul markets differed, a downward trend of the short-haul market appeared too diverse, whilst the upward trend of the long-haul market converged.

(Insert Table 5)

(Insert Table 6.)

(Insert Table 7)

Subsequently, we introduced physical distance into the model to observe its effects on tourist arrivals, overall satisfaction and spending per capita, as shown in Tables 5, 6 and 7, respectively. Notably, Bayesian estimation replaced MLR if MLR produced the Heywood case (e.g. negative variance) or a nonconvergence case. Three cultural distance measures were tested in this analysis. For tourist arrivals, Kogut and Singh's and our cultural distance measures predicted similar signs of the latent intercept, slope and quadratic in the short-haul (+,+,+) and overall (+,−,+) markets. By contrast, the effect of physical distance dominated cultural distance in all market types. For overall satisfaction, our and the traditional Kogut and Singh's cultural distance measures again predicted the same signs in the overall market (+,+,−), and Kandogan's cultural distance measure predicted the same signs of the latent slope and quadratic factors (−,+,−). For spending per capita, all cultural distance measures predicted similar signs of the latent intercept, slope and quadratic (+,+,−). Using the LGCM framework, we can conclude that the Kogut and Singh's cultural distance measure was consistent with our cultural distance measure in predicting the signs of latent factors. These factors are assumed to cause the trajectory of tourist arrivals, overall satisfaction and spending per capita.

(Insert Table 8.)

We ran the final LGCM analysis by selecting only tourist arrivals as our interest variable because it was proven to exhibit the most consistency in the previous analysis. In the final analysis, we limited our analysis on the linear relationship because our sample size is too small to draw a reliable conclusion on the curvilinear relationship. A nonlinear relationship will be reexamined in the third study with P-OLS and the random effects model. We used the time frame from 2013 to 2017 to avoid the problem of a nonpositive definite matrix, the nonconvergence issue and the Heywood case. Moreover, reducing the time span increases df, and thus, we have room to model several error variances and add more covariates to control the result. Similar to the process we conducted earlier, this analysis began by estimating the unconditional model and introducing more variables to account for the confounding effects. The unconditional model fits the empirical data well, as indicated by the following fit indices: $\chi2$ = 16.758, p-value = 0.08, df = 10, goodness of fit (GFI) = 0.995, CFI = 0.978, incremental fit index (IFI) = 0.978, confidence interval of root mean square error of approximation (CIRMSEA) = [0.000, 0.361] and standardised root mean square residual (SRMR) = 0.013. Therefore, the introduction of additional variables was appropriate to control for the confounding effect. To improve the accuracy of the explanatory power of tourist arrivals in the conditional model, two covariates, namely, revisit intention (McKercher & Tse, 2012) and GDP (Cho, 2001; Fourie & Santana-Gallego, 2011; Long, Liu & Song, 2018; Pérez-Rodríguez, Ledesma-Rodríguez & Santana-Gallego, 2015), were introduced into the model to partial out the implicit effect of physical distance. The findings confirmed that the economic factor played a salient role in explaining tourist arrivals every year. By contrast, revisit intention did not statistically influence tourist arrivals every year ($\chi2$= 648.560, p-value = 0.00, df = 56, GFI = 0.992, CFI = 0.650, IFI = 0.652, CIRMSEA = [0.735, 0.844] and SRMR = 0.042), as shown in Figure 3. However, when a series of revisit intentions was omitted from the model, the fit indices improved considerably as follows: $\chi2$ = 648.560, p-value = 0.051, df = 56, GFI = 0.996, CFI = 0.995, IFI = 0.998, root mean square error of approximation (RMSEA) = 0.086 and SRMR = 0.027.

(Insert Figure 3.)

To explain the underlying logic of this design, we introduced a set of revisit intentions into the model as an additional time-varying covariate to investigate the trajectory of tourist arrivals over time. Then, the aggregate effects were extracted, called the latent intercept and slope, and illustrated as (i) and (s) in Figure 3, respectively. As shown in the figure, these latent factors were time-invariant. They were regressed on miles to denote physical distance and the relative cultural distance value to ascertain the impact of these time-invariant distances.

The findings presented in Tables 9 and 10 confirmed the impact of physical and cultural distance, respectively. In this analysis, GDP exerted the most significant impact on tourist arrivals annually, but no evidence was found that a 1-year lagged revisit intention can be used to predict tourist arrivals for the following year. This result is consistent with that of McKercher and Tse (2012). The result confirmed that the impact of physical distance considerably dominated that of cultural distance. This finding is in line with previous studies (Ahn & McKercher, 2015; Qian et al., 2018).

(Insert Table 9)

(Insert Table 10)

4.2. Study2

By considering physical distance (as shown in Table 11), the significance level of cultural distance exerted a powerful impact on the average age of tourists in the overall market. Interestingly, cultural distance outperformed physical distance only in the long-haul market and physical distance impact was not observed in the short- and long-haul markets. Notably, the impact of physical distance was captured only in the 2017 short-haul market. Without the advantage of this analysis design, researchers who conducted the traditional cross-sectional study using regression with OLS estimates might have misinterpreted the results because of spurious regression. In summary, no evidence of the impact of physical distance on the average age of visitors was detected in the short- and long-haul markets.

(Insert Table 11)

The impact of physical distance was higher than that of cultural distance in the overall market. This result implied that male tourists, with the other factors remaining the same, tended to travel more to farther places than female tourists. With regard to the effect on each market, physical and cultural distance exerted significant and robust impact on the percentage of males across time in the short-haul market. In such a case, the impact of physical distance was apparent.

For the long-haul market, evidence of cultural distance decay was prevalent. In this stage, observing the overall picture can lead to a wrong interpretation because the impact of cultural distance played an essential role in the percentage of males in the short- and long-haul markets. We did not perceive such effect in the overall market because the effect magnitudes from the extreme cases between cultural distance in the short- and long-haul markets cancelled each other out, and consequently, the overall market became insignificant.

Meanwhile, the overall market presented different results compared with those of the short- and long-haul markets. No significant impact was observed in the overall market, but physical distance was detected in the short-haul market and cultural distance was observed in the long-haul market to influence the percentage of married visitors. Again, the effects were cancelled out. This result implied no effect from both types of distance.

Lastly, for the percentage of working tourists, the impact of cultural distance was captured only in the short-haul market. By contrast, the effect was detected in the long-haul market only in 2014. Thus, the result is prone to spurious regression. Given the complexity and scarcity of data, ML estimates could not find a converged solution for several cases (designated as NC or 'not converged' in Table 11).

For average length of stay, physical distance exerted a positive impact on the short-haul market, whilst cultural distance did not have any effect (Table 12). Interestingly, this result implied that an increase in physical distance positively resulted in an increase in the average number of nights to stay. However, the impact diminished across time, i.e. from 0.38 in 2013 to 0.11 in 2017. Changes in the economic factor should be included in future analysis to provide more information.

(Insert Table 12)

However, including more explanatory factors require larger sample sizes to render the ML technique efficient. Therefore, the analysis hereafter is limited without introducing additional covariates. For the long-haul market, insufficient evidence concluded the existence of physical and cultural distance impact on average length of stay, although cultural distance was significant in 2017 and physical distance decay was observed in 2016. The situation was the opposite when the overall market was considered. The impact of cultural distance dominated that of physical distance. However, this outcome could be distorted by other factors, such as the economic condition or financial status of visitors each year. Future studies should test a specific research design that can sort out these factors to perceive a clearer picture.

For travel composition, the percentage of tourists who travelled alone was associated with physical and cultural distance, particularly for the long-haul market. In summary, sufficient evidence confirms the existence of cultural distance decay in the overall and long-haul markets.

Physical distance decay was detected on the percentage of non-guided tours since 2013 for the long-haul market, but was not observed in the short-haul and overall markets. Visitors can probably mitigate risk (Crotts, 2016; Ng et al., 2007) by using technology or smartphone applications rather than joining a guided tour, which is considerably more expensive. Moreover, unlike Asians, long-haul visitors tend towards individualism and not collectivism. Therefore, these visitors tend to travel alone. Separating this effect by including economic and technological factors to strengthen the usability of the findings will be extremely meaningful in future research. However, the results are still in line with the increasing trend of the percentage of tourists who travel alone, as mentioned earlier.

Physical distance decay was apparent in the overall market (Table 13). For the short-and long-haul markets, impact was detected only in the long-haul market. Nevertheless, physical distance decay still outperformed cultural distance decay in the long-haul market across time. This outcome is consistent with those of prior studies that demonstrated that physical distance decay plays an essential role in the long-haul market (McKercher, 2008, 2018). Such result implies that long-haul visitors tend to have less interest in shopping compared with visitors in the short-haul market.

(Insert Table 13)

Table 14 indicates that physical and cultural distance exerted robust consecutive impact on the overall market since 2013. Moreover, a series of physical decay effects was detected in the long-haul market, except in 2015 and 2016. However, the constant negative sign confirmed the robust negative association across time and cultural distance also had an impact on the overall and long-haul markets.

(Insert Table 14)

The significance level of physical distance impact across time confirmed that the effect of physical distance was higher than that of cultural distance when considering the percentage of spending on shopping, hotels and meals on the overall picture. For the short-haul market, physical distance decay was detected in the percentage of spending on shopping and hotels. By contrast, cultural distance was detected only in the percentage of spending on entertainment, except in 2017. For the long-haul market, the impact of physical distance decay on the percentage of spending on entertainment and sightseeing was apparent. In summary, physical distance decay clearly outperformed cultural distance decay in spending per capita and spending patterns on shopping in the short-haul and overall markets.

The impact of distance decay was unclear in this section, as shown in Table 15. For the overall market, an association between physical distance decay and revisit intention was detected. Cultural distance exhibited several positive associations with dining satisfaction. For the long-haul market, physical distance exerted considerably more impact than cultural distance on tourist attitudes. Distance decay was confirmed in the cases of entertainment and sightseeing satisfaction and a positive association was found on overall satisfaction. For the short-haul market, physical distance remained dominant. The result exhibited decay effects on satisfaction with value for money, shopping and dining. Cultural distance presented decay effects on value for money and positive association with dining.

(Insert Table 15)

4.3. Study 3

By conducting panel data analysis, this cross-validation study aimed to recapture and reconfirm the exploratory results of Studies 1 and 2. Given that the testing of pool ability rejected the null hypothesis, using pool data analysis may be inappropriate. Moreover, although data, such as tourist arrivals or satisfaction, were regarded as repeated measures, these year-by-year data were not collected from the same observation each year. Pool data analysis fits in this situation. Moreover, cultural distance, which remains constant across time, is the focus of our study. Using the 'fixed effects' analysis with 'time-demeaned' as previously demonstrated in equation (7) will automatically eliminate the effect of cultural distance. Hence, our analysis in Study 3 applied P-OLS and RE.

We divided this analysis to examine the linear effect of cultural distance with the control of what we tested in the first and second studies, namely, physical distance, GDP, male, age, length of stay and the dummy of time to control for random events each year. The quadratic effect of cultural distance was also investigated because the first study detected the quadratic role of distance decay in explaining the trajectory of tourist arrivals, although the cultural distance effects on tourist attitudes and behaviours exhibited a nonconvergence issue. To perceive the complete picture, this analysis implemented the pure effect of cultural distance on three key variables: tourist arrivals, overall satisfaction and spending per capita.

(Insert Table 16)

(Insert Table 17)

As expected, our proposed cultural distance measure can capture the effect of cultural distance on tourist arrival. Without controlling for any effect from other variables, as shown in Table 17, cultural distance alone can explain the variability of tourist arrivals at approximately 28.8%, as shown by the $\bar{R}^2$ (higher than 2.1% from Kandogan's and 4.3% from Kogut and Singh's cultural distance measures). For overall satisfaction, all cultural distance measures presented similar results. Again, our proposed cultural distance measure outperformed the others, as indicated by the highest $\bar{R}^2$. Our cultural distance measure can explain approximately 40.6% of overall satisfaction variability compared with 8.5% from Kandogan's and 14.8% from the traditional Kogut and Singh's cultural distance measures. For tourist spending, however, although our cultural distance still achieved the highest explainability and the direction of the coefficient was similar to that of Kogut and Signh's cultural distance measure, Kandogan's cultural distance measure captured the quadratic relationship between cultural distance and tourist spending. Table 17 validates the existence of a complex association between cultural distance and the three key variables.

Interestingly, Table 18 indicates that when we controlled for the effects of physical distance, GDP, male, ages, length of stay and time-varying effects, the effect of cultural distance was mitigated. Table 18 is informative because it confirms that physical distance decay plays an active filtering role in visitor arrivals and spending. Kogut and Singh's cultural distance measure cannot capture any effect on the three variables, and Kandogan's cultural distance measure can be used to explain the negative association with tourist satisfaction, although Kogut and Singh's and our cultural distance measures reported a positive relationship. For tourist spending, only our proposed cultural distance measure can be used to predict tourist spending. This analysis confirmed the effect of cultural distance on overall satisfaction and spending. Moreover, our proposed cultural distance measure can be used to effectively explain two of the three critical variables. By contrast, Kandogan's cultural distance measure can be used to explain only overall satisfaction, and the traditional Kogut and Singh's cultural distance measure cannot detect any variable.

(Insert Table 18)

However, modelling cultural distance in quadratic form resulted in a statistically significant predictor of tourist arrivals. Our and Kandogan's cultural distance measures can capture such effects, but Kogut and Singh's measure cannot. In the case of overall satisfaction, all cultural distance measures can capture the effect in a quadratic relationship. In tourist spending, only Kandogan's cultural distance measure was a valid predictor and the relationship was consistent with our cultural distance measure. We can conclude from the three analyses that the effect of cultural distance is extremely complex and the real effect of cultural distance with the assumption of a linear relationship is difficult to capture. A quadratic relationship was detected in Study 1 and retested in Study 3. The quadratic relationship was reconfirmed in the third study by using P-OLS and RE. However, spurious correlation was apparent in the second study. Therefore, using only cross-sectional analysis must be carefully implemented. To prevent the spurious correlation problem, longitudinal data analysis is highly recommended. Lastly, a quadratic relationship also showed the dual roles of cultural distance, i.e. demand generator and inhibitor.

5. Discussion

5.1 Theoretical implications

The literature has perceived the significance of cultural distance as an imperative factor that drives not only tourist decisions regarding which place to visit (Bi & Lehto, 2018; C. H. Lee et al., 2018) but also their attitudes (Huang & Crotts, 2019) and subsequent behaviours at their destination (Ahn & McKercher, 2015). In examining the role of cultural distance in explaining tourist arrivals, attitudes and behaviours, we acknowledged the calls for further research on the impact of cultural distance on tourist destination choices (Y. Yang et al., 2019), attitudes (Huang & Crotts, 2019) and behaviours (Ahn & McKercher, 2015). Previous analyses relied heavily on the cultural distance measure developed by Kogut and Singh (1988). This measure is based on four to six dimensions of Hofstede's cultural values. Given that Hofstede's cultural framework is valid, the extant literature has two major critics on the application of Kogut and Singh's cultural distance measure. The first criticism involves the ignorance of covariance amongst dimensions because the original Kogut and Singh's cultural distance measure assumes no correlation amongst Hofstede's dimensions. The improvement by Kandogan (2012) has relaxed this assumption. Kandogan (2012) improved the standard cultural distance measure by using the full covariance matrix within the Mahalanobis distance's framework to capture a nondiagonal covariance matrix, which is assumed zero in Kogut and Singh's framework. The second criticism, however, incorporates the unrealistic assumption that all of Hofstede's dimensions are equally important as demonstrated by the equal weight expressed in Kogut and Singh's formula. Our study fills this gap by proposing a dynamic weight determination process using the GSCA framework (Hwang & Takane, 2004; Hwang & Takane, 2014). Our study is the first to directly compare three cultural distance measures. Our findings provide insight into the capability to capture the beneficial effect of the three cultural distance measures on different variables in the HKTB reports. Moreover, our careful analysis still uses cross-validation methods, namely, LGCM, MMRA, P-OLS and RE, to conclude the results of using the three cultural distance measures to capture the cultural effect. Moreover, we resolve the contradiction perspective of the role of cultural distance as 'a demand generator versus a demand inhibitor' by proposing a quadratic relationship rather than a simple linear association. Thus, we contribute to the existing body of cultural distance knowledge in tourism.

(Insert Table 19)

To elaborate, Table 19 summarises the 120 tests of the three cultural distance measures using MMRA on each item. Notably, our proposed cultural distance measure achieves the highest capturing rate (63.34%). The conventional Kogut and Singh's measure effectively catches the impact of cultural distance (approximately 48.83%), and Kandogan's measure can capture 6.67%. However, after we introduced physical distance into the analysis, the effective capturing rate of cultural distance significantly declined because the effects of physical distance tend to diminish the effects of cultural distance. In particular, Kogut and Singh's cultural distance measure decreased from 48.83% to 17.5%, and our measure declined from 63.34% to 49.17%. Interestingly, the effective capturing rate of Kandogan's measure improved from 6.67% to 23.34%.

(Insert Table 20)

(Insert Table 21)

Table 20 summarises the analysis results of our rigorous cross-validation methods in three studies. LGCM, which assumes the latent factors, cause the trajectory of tourist arrivals, overall satisfaction and spending per capita. It shows that the latent slope and quadratic of the three cultural distance measures are consistent across variables. In particular, the positive latent slope and negative latent quadratic (i,+,−) are discerned in overall satisfaction and spending per capita, whilst the negative latent slope and positive latent quadratic (i,−,+) are apparent in tourist arrival.

Interestingly, our cultural distance measure reports consistent latent slope and quadratic signs (i,−,+) on tourist arrivals across methods (MMRA, P-OLS and RE). In terms of overall satisfaction, the three cultural distance measures report similar results (i,+, −) across methods. For spending per capita, our and Kandogan's measures report similar signs (+) of the latent slope in P-OLS and RE. However, only Kandogan's measure presents a consistent sign of the latent slope (+) and quadratic (−) in P-OLS and RE. The findings contribute to the cultural distance literature given that our cultural distance measure outperforms traditional measures in several cases, and conventional cultural distance measures can generate similar slope and quadratic signs that are consistent with LGCM if scholars apply RE. We recommend using all cultural distance measures, if possible, when analysing the effect of cultural distance because the information produced by the three measures may either converged or diverged. To ensure accuracy of these measures, comparison the results is inevitable. If scholars cannot use our proposed measure, then the conventional measure can be selected because of the consistency signs across items between our and Kogut and Singh's measures. Moreover, the total effective rates of our (63.34%) and Kogut and Singh's (48.83%) measures and the correlation between the two measures are extremely high (Table 22). For Kandogan's measures, we advise using it with physical distance and other covariates, particularly in the case of RE.

(Insert Figure 4)

(Insert Figure 5)

Apart from the comparison of the capability to capture the effect of cultural distance from the three measures, we focus on quantifying the effects of cultural distance on tourist arrivals, attitudes and behaviours. We also verify the statistically significant curvilinear relationship between cultural distance and tourist (1) arrival and (2) overall satisfaction. Figure 4 illustrates the complicated relationship of arrivals. This finding contributes to the body of tourism knowledge by resolving the contradicting roles of cultural distance as a demand generator or inhibitor. In the case of Hong Kong, cultural distance initially acts as a demand inhibitor when the cultural distance score is lower than 1.63. Tourist arrivals reach the minimum point when cultural distance is at 1.63. When the score of cultural distance is higher than 1.63, tourist arrivals tend to increase. This result implies the interaction effect between tourist motivation and perceived risk. From our analysis, tourists from countries such as South Korea, Indonesia, Singapore, Malaysia, the Philippines, Thailand and India tend to visit culturally similar destinations. Once cultural distance increases, several arrivals significantly dropped, as evidenced in countries, such as France, Germany and the Netherlands. However, when cultural distance exceeds the threshold of 1.63, it works like a magnet by appealing to tourists from countries such as Canada, the United Kingdom, the United States or New Zealand to visit a culturally different place. That is, the risk factor can be a potential factor for visitors when cultural distance is between 1 and 1.63. However, when the score of cultural distance is higher than 1.63, tourist travel motive outshines travel risk, and cultural distance reoperates as a demand generator. In the case of attitudes (Figure 5), the association between cultural distance and overall satisfaction is positive. This result indicates that culturally far countries, such as the Netherlands, Canada, the United States, Australia and New Zealand, rate overall satisfaction higher than culturally similar countries, such as South Korea, Indonesia, Singapore, Malaysia, the Philippines and Thailand. Notably, when the cultural distance score approaches 2.67, the increase in satisfaction level increases but at a decreasing rate. This result confirms the nonlinear relationship and contradicts the previous discovery of a negative association between cultural distance and satisfaction by Leung et al. (2013). However, the positive relationship between cultural distance and satisfaction is in line with the result of Huang and Crotts (2019). A possible reason for such result is that tourism-related products and services from a culturally different place can better satisfy tourists whose motive is driven by novelty-seeking. However, this result may be a case of the ceiling effect (Austin & Brunner, 2003). To illustrate, the satisfaction level of tourists ranges from 7.7 to 8.55 out of 10. Historically, visitors tend to rate their satisfaction score stably in the past 16 years. Hence, our standard errors from this analysis are narrower than the absence of the non-ceiling effect and result in a false significance conclusion (Austin & Brunner, 2003). Lastly, in terms of behaviours, our cultural distance measure statistically significantly captures the effect on spending in the case of RE, as shown in Tables 19 and 20. The last figure is presented on the basis of Kandogan's measure using RE because only Kandogan's measure can statistically significantly detect the positive slope and negative quadratic relationship. Although the shape is different from that of our cultural distance measure, the information obtained from its findings is consistent with our measure. This positive impact of cultural distance can be explained by visitors tending to pay more if they have limited information regarding culturally different products and services (Alegre & Cladera, 2010; Alegre & Juaneda, 2006). Hence, they tend to spend more to compensate for risk reduction.

5.2 Practical implications

This study finds a nonlinear relationship between cultural distance and key variables. The findings have far-reaching implications for destination marketing organisations (DMOs) and practitioners. Hence, stakeholders should create a strategic or marketing plan to enhance the competitiveness of Hong Kong to attract visitors who love to travel to culturally similar places and culturally different destinations. Figure 6 is a reminder to adhere to the basic relationship of revenue generation. Tourist arrival and spending per head are two key components in generating revenue. From our findings, the relationships between cultural distance and tourist arrivals and spending per capita are determined. Practitioners can map these relationships based on our proposed cultural distance in one facet, as shown in Figure 7. Given that the ceiling effect problem does not arise, if DMOs can improve the overall satisfaction of tourists who come from culturally different places, then the result can be a significant increase in spending per capita, as indicated in Figure 7.

(Insert Figure 6)

(Insert Figure 7)

Given that culture is an innate preference (Mahajan & Wynn, 2012), this knowledge can be extended to tourism, such that tourist decisions and attitudes are culture-bound (Pantouvakis, 2013). With this knowledge, assuming that visitors will behave similarly when they travel to different places around the world is naive. Hence, DMOs and practitioners should consider the cultural factor when making strategic or marketing decisions. However, the HKTB dataset does not provide information about the culture of tourists. In such case, HKTB is encouraged to prepare approximately 5 to 10 questions related to the explicit and implicit properties of culture. For example, the CVSCALE is an individual-level cultural measure that has already passed the desired psychometrics property with the variance explained at approximately 66% (Ahn & McKercher, 2019). Five questions from five dimensions (IDV, UAI, LTO, PD and MAS) can include explicit and implicit element information, which can be reflected in the questionnaire through the systematic preparation of such information from the raw dataset (or in a report with only the mean and standard deviation). The responses will considerably assist researchers in analysing the impact of cultural distance more accurately than using a universal composite index for evaluation, and thus, avoid the case of ecological fallacy. Moreover, the accuracy of the comparison between the traditional Hofstede's dimensions and the one generated from HKTB can be tested. This type of investigation will substantially contribute to the cultural distance literature because the new set of questions in the survey will allow researchers to account for the slow change in culture.

5.3 Limitations and future study

Although this study is deemed to have made crucial contributions to the body of cultural distance knowledge in tourism, limitations still exist. Similar to any research, the limitations of our study offer an avenue for future research. Firstly, although all 17 countries in our study are nearly wholly representative as reported in HKTB, this sample size is considered extremely small. Parameters estimated in such a small sample size, particularly for the case of using the ML algorithm, are difficult to converge and we encounter the Heywood case and the non-positive definite problem numerous times. Moreover, the standard error tends to be wider to compensate for the small sample size, and thus, insignificant results are produced. Our study addresses such effects by considering the practical significance and statistical significance. Given that analysis based on secondary data is increasingly being conducted in examining tourist arrivals, attitudes and behaviours (e.g., Ahn & McKercher, 2015; Bao & Mckercher, 2008; Bi & Lehto, 2018; Ho & McKercher, 2014; Huang & Crotts, 2019; Qian et al., 2018), we highly recommend focusing more on practical significance in future research.

Secondly, we use Hofstede's cultural index as inputs to create our cultural distance measure. The Hofstede's framework has been criticised for oversimplifying the conceptualisation of culture (Ahn & McKercher, 2019; Ng et al., 2007) and its sample size is drawn from IBM employees (McSweeney, 2002) with the aim of studying diverse national cultural issues in a working environment. However, we contend that the Hofstede's framework is still a valid tool that scholars can use to analyse countries at the aggregate level. Hofstede's result is in accordance with those of Schwartz and WVS framework. For example, Y. Yang et al. (2019) compared the three aggregate cultural frameworks analysed with tourist arrival data from 94 countries from 1995 to 2012. The three cultural frameworks produced desirably consistent results, which are in line with the findings of Ng and Lim (2019), who analysed results on the basis of the Hofstede's and Schwartz's frameworks. Moreover, using our proposed cultural distance measure developed from the Hofstede's framework, we can capture the significance of cultural distance effects under various situations. We suggest using the Hofstede's framework to perform an aggregate analysis in a future study and then verifying its robustness with the Schwartz's or WVS frameworks.

Thirdly, our study proposes a cultural distance measure with dynamic weights based on the GSCA framework. The weight is considered dynamic because if the countries used in the analysis change, then the weight also changes because the new set of countries within the new analysis changes the environment used in the situation to minimise the sum-squares residual (SSR). For future research, analysts can change dynamic weights into static weights by including all the nations provided in the Hofstede's website. By using all the countries, the environment for minimising SSR is equal to the population of Hofstede's cultural framework. Thereafter, when analysts select several countries to perform cultural distance analysis, the weights calculated from the total population will be deemed static across subtests. Apart from the dynamic issue of optimal weights, our study uses raw Hofstede's cultural values as inputs to calculate optimal weights. This procedure implies two avenues for future studies. Firstly, our process to obtain cultural distance can be performed to derive direct cultural values, and this process can resume obtaining cultural distance, which is the derived construct of cultural values to reflect the concept proposed by Huang and Crotts (2019). Secondly, analysts can use the sum-squared value based on Kogut and Singh's or Kandogan's cultural distance measures as inputs rather than as raw scores. Given that Hong Kong is the base country, as denoted by CV_{hk} in Equation (8), future research can calculate the sum-squared values on the basis of Kogut and Singh's framework and then plug in the sum-squared values into Equation (8), as expressed below to solve for optimal weights.

$$\begin{bmatrix} (CV_i^{PDI} - CV_{hk}^{PDI})^2 V_i^{-1}) \\ (CV_i^{IDV} - CV_{hk}^{IDV})^2 V_i^{-1}) \\ (CV_i^{MAS} - CV_{hk}^{MAS})^2 V_i^{-1}) \\ (CV_i^{UAI} - CV_{hk}^{UAI})^2 V_i^{-1}) \\ (CV_i^{LTO} - CV_{hk}^{LTO})^2 V_i^{-1}) \\ (CV_i^{IND} - CV_{hk}^{IND})^2 V_i^{-1}) \\ d_1 \\ d_2 \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ \lambda_2 & 0 \\ \lambda_3 & 0 \\ \lambda_4 & 0 \\ \lambda_5 & 0 \\ \lambda_6 & 0 \\ 0 & \lambda_7 \\ 0 & \lambda_8 \end{bmatrix} \begin{bmatrix} \gamma_{CV} \\ \gamma_d \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ \epsilon_6 \\ \epsilon_7 \\ \epsilon_8 \end{bmatrix} \quad (8)$$

Fourthly, the literature uses the inbound tourist perspective to analyse cultural distance. Given that Hong Kong is only one country, generalisability is limited. Future studies can use a similar set of inbound tourists to examine multiple destinations. In particular, the invariance analysis of cultural distance's impact on tourist arrivals, attitudes or behaviours can be analysed, and thus, enhance the generalisability of the findings. This idea is in line with the conduct of cross-cultural studies with the aim of enhancing the external validity or generalisability of the findings (Milfont, Duckitt & Wagner, 2010). Fifthly, our analysis assumes the direct effect between cultural distance and tourist (1) arrivals, (2) attitudes and (3) behaviours. Occasionally, focusing on the direct effect can miss information in between. For example, we investigate the impact of cultural distance on tourist revisit intention and satisfaction. Theoretically, satisfaction can engender revisit intention (Jang & Feng, 2007; T. T. Kim, Kim & Kim, 2009). In this regard, researchers can understand the role of cultural distance in enhancing tourist revisit intention in terms of a mechanism, which is deeper than the association between cultural distance and this construct. Future research can apply this mediator analysis to gain further insights into the underlying mechanism of cultural distance's impact.

Sixthly, this study suffers from the ceiling effect of certain items, such as overall satisfaction. With a ceiling of 10 points, the score of overall satisfaction ranges from 7 to 9.5 since 2002. In this situation, if analysts fail to factor in the ceiling effect, then an insignificant relationship can be easily drawn from the analysis because the effect exerts downward pressure on the variation of dependent variables; this situation makes the effect difficult to capture (Cramer & Howitt, 2005). Another problem of the ceiling effect is that we can occasionally obtain false significance (Austin & Brunner, 2003). Future studies should consider this factor when evaluating the effect of cultural distance on overall satisfaction. Finally, this study investigates the effect of cultural distance on the aggregate national level. However, we cannot make an inference from our results at the individual level. Future studies can apply the CVSCALE, which can capture the variance explained from the exploratory factor analysis (EFA) settings at approximately 66% (Ahn & McKercher, 2019) to capture the effect of cultural distance at the individual level.

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