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Exploring Ways to Improve Personalisation: The Influence of Tourist Context on Service Perception

The heterogeneity and dynamic nature of tourist needs requires an advanced understanding of their context. This study aims to investigate the effects of observable factors of internal and external contexts on tourist perceptions towards personalised information services performance. An exploratory approach is used to test measurement invariance and the moderating effects of personal, travel, technical and social parameters of the tourist context, when applicable. The findings demonstrate that contextual factors motivate tourists to attribute different meanings to the parameters of the service, that have already been personalised for them. Individually developed personalisation design solutions are required for each travel context.

Keywords: personalisation, information service, travel context, multi-group analysis

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Introduction

Personalisation has become a must-have of service-related industries, including tourism (Amadeus IT Group SA, 2019). Smart environments and a growing scope of real-time personal data and technology automation are revolutionising the opportunities to understand immediate tourist preferences and to deliver personalised services (Buhalis & Sinarta, 2019). Personalisation has high potential to improve tourist experiences. For this reason, it has triggered hot discussions in the industry and among academia (Angskun & Angskun, 2018; Boudet, Gregg, Rathje, Stein, & Vollhardt, 2019). Meanwhile, the problem of accurate recognition of tourist context and interpretation of their needs prevents the wide acceptance of personalisation technologies (Skift, 2018). Extensive research, aimed to improve personalisation methods and increase the relevance of provided services has been conducted (Glatzer, Neidhardt, & Werthner, 2018; Grün, Neidhardt, & Werthner, 2017; Massimo & Ricci, 2019). However, the context-dependent nature of tourist behaviour (Buhalis & Foerste, 2015; Choe, Fesenmaier, & Vogt, 2017) necessitates further exploration in this area.

This paper reports a portion of the results of a larger study. The study presumes that accurate personalisation leads to high individual perceptions on service performance. Differences in the assessment of a personalised service performance are caused by lack of service adaptation according to the factors of tourist internal and external context. The study aims to explore differences in tourist expectations and perception of personalised information services performance, co-created value, satisfaction and loyalty. The research applies a well-defined tourist satisfaction model (Song, Van der Veen, Li, & Chen, 2012), which is adjusted for the context of personalised information services (Volchek, 2019). The results identify factors that should be considered for tourist needs interpretation and designing personalised information services. In addition, the findings contribute to the literature on tourism management and user experience design by creating a background for further investigation.

Literature Review

Context-Dependent Nature of Tourist Needs

Consumer behaviour is driven by specific needs and motivations to satisfy such needs. Tourists needs and related trip planning, consumption and post-travel behaviour are shaped by the factors of individual travel context (Buhalis & Foerste, 2015). Contextual factors are those that describe tourist environment. Conceptually, it is common to distinguish between the factors of internal (e.g. age, gender, cultural and social belonginess, self-image and personality) and external (e.g. physical, social, task, temporal, informational, technical) context (Lamsfus, Xiang, Alzua-Sorzabal, & Martín, 2013; Neuhofer, Buhalis, & Ladkin, 2015; Tkalčič, De Carolis, De Gemmis, Odić, & Košir, 2016). Each of the factors has a potential to affect tourist behaviour. Importantly, a few of these factors can be observed a priori and used to explain differences in tourist behaviour. Certain factors and their combinations remain unobservable, thereby complicating possibilities to make inferences about tourist behaviour. Service personalisation, which is carried out by explaining the effect of individual context on tourist needs and adjusting the attributes of services accordingly, can co-create high value and satisfaction for tourists (Choi, Ryu, & Kim, 2019; Massimo & Ricci, 2019).

A specific feature of the tourist context and its influence on travel service consumption is the dynamic influence such context has on tourist behaviour. Some of those factors form consistent consumer preferences. For example, different cultures or age groups perceive the importance of such factors as information usefulness and efficiency differently, paying attention to different information characteristics, such as visual design and interface aesthetics (Ji, Wong, Eves, & Scarles, 2016; Lala, 2014). However, aiming to acquiring new, unique and memorable experiences (Cohen, Prayag, & Moital, 2013), tourists can switch to liminal behaviour, which is distinct from their daily preferences (Pritchard & Morgan, 2006). Moreover, destination type, tourism activities, location, weather conditions, social environment, availability of travel time as well as available personal devices and the Internet can lead to immediate changes in tourist needs. Those factors can trigger alternative requirements towards service parameters, including those related to interactions with digital information. Thus, tourist information needs constitute functional, hedonic, aesthetic, innovation and sign components (Choe et al., 2017). Regardless of whether or not tourists have a planned itinerary, a change in weather forecast can trigger a change in travel behaviour. This, in turn can affect the tourist information need and information search behaviour. Tourists can introduce new information requirements depending on real-time situation. For instance, they can prioritise functional information parameters over hedonic ones and switch to a targeted information search of indoor points of interest rather than browsing destination-related information (Choe et al., 2017). A combination of tourist internal and destination-specific factors is believed to be among the important determinants of tourist needs (Gavalas, Konstantopoulos, Mastakas, & Pantziou, 2014; Lamsfus et al., 2013). However, the satisfaction of immediate tourist needs requires real-time service personalisation (Buhalis & Sinarta, 2019).

Information Services Consumption in the Travel Context of Use

To satisfy heterogenous tourist information needs, service providers have introduced multiple information services aimed to facilitate information exchange while delivering distinct functionality and content to different tourists. Value from tourist interactions with such services and subsequent satisfaction and loyalty is formed under the influence of tourist expectations and their perceptions on these services performance (Song et al., 2012; Volchek, 2019). To enable relevant personalisation, understanding whether a contextual factor affects the strength of the relationships within the decision-making process and the nature of such effect are important.

Moreover, service intangibility and the complexity of personalisation processes restrict tourists from using objective criteria to assess the performance of such services. Thus, representatives of different religions and cultures may interpret the same event through distinct concepts. Furthermore, interactions with external environment, including received information and acquired service-related experiences, can transform tourist expectations and modify their ability to perceive the service characteristics (Parasuraman, Zeithaml, & Berry, 1985). For instance, awareness of personalisation, which applies tourists' personal data to recognise their context and filter out information, irrelevant for this context, motivates those tourists to pay attention to the information service privacy and security settings (Powers, 2017). Heterogeneity of tourist perceptions results in measurement invariance of individual perceptions (Hair Jr, Sarstedt, Ringle, & Gudergan, 2017). Therefore, effective personalisation necessitates not only recognition of the needs that tourists aim to satisfy but also understanding the exact meanings that tourists attribute to personalised services parameters and the desired level of these parameters' performance.

Methodology

Research Context

Google Trips belonged under the umbrella of Google services. The application was developed as a travel planner and was available for Android users via Google Play. Whilst corresponding to the global requirements of UI design, this application functionality was distinctive owing to the incorporated personalisation capabilities. Specifically, the application had the capacity to track tourists' personal data independently and from other Google services, such as the Google search engine, Gmail, Google Maps and Google Calendar (Google, 2017). Given the availability of data, this application had advanced capabilities to recognise tourist needs and personalise services in real time.

Data Collection

This study used a quantitative approach to understand the differences in tourist perceptions on personalised information services. The reflective indicators for the latent constructs of expectations, satisfaction and loyalty were borrowed from the existing studies (Dickinger & Stangl, 2013; Song et al., 2012). The formative indicators for co-created personalised information service performance and value were proposed based on the studies related to the performance of personalised information services (Volchek, Law, Buhalis, & Song, 2019) and tourist information needs (Choe et al., 2017), accordingly. The resulting survey included a 5-point Likert scale and a semantic differential scale.

Tourist responses on the survey questions were collected with a help of an online data-capturing company using a nonprobability self-selected sampling method. The study targeted Hong Kong residents who travelled abroad and used the Google Trips personalised travel planner to support their travel arrangements. The study targeted n = 250 responses, with a minimum sample size of n = 220, which was determined by the ad-hoc power test (Hair Jr, Hult, Ringle, & Sarstedt, 2016). A total of 244 responses was retained for analysis after validity was verified. Table 1 summarises the acquired data in relation to the factors of tourist internal and external context. The mean values for all the variables fell within the interval of $3.6 < m < 4.1$, with a standard deviation of $SD < 0.85$.

Data Analysis

Considering the complexity of the model, the presence of a formative hierarchical latent construct and the impossibility of ensuring data normality for all groups, the analysis was carried out using PLS SEM. Specifically, assessment of the outer model was conducted to validate and partially refine the proposed measurement scales. Assessment of the inner model ensured its predictive relevance and accuracy. Given the presence of a second-order hierarchical latent construct of co-created service performance, the model was estimated following a two-stage approach (Hair Jr et al., 2017).

Table 1. Tourist Context

Personal Context	N	%	Technical Context	N	%
Place of birth			**Awareness of Personalisation**		
Hong Kong	224	91.80	*Aware*	200	81.97
China	17	6.97	*Unaware*	44	18.03
Australia	3	1.23	**Awareness of Data being tracked**		
Gender			*Aware*	142	58.20
Male	114	46.72	*Unaware*	102	41.80
Female	130	53.28	**Previous experience with travel planners**		
Unspecified	0	0.00	*With Google Trips*	199	81.56
Age			*With Other Trip Planners*	85	34.84
18–24 years (Gen Z)	30	12.30	*No Experience*	30	12.30
25–34 years (Gen Y)	59	24.18	**Operating System used for survey completion**		
35–54 years (Gen X)	100	40.98	*Windows (desktop/mobile)*	156	63.93
55-64 years (Baby Boomer)	55	22.54	*Mac/iOS*	42	17.21
Unspecified	0	0.00	*Other*	46	18.85
Completed Education			**Device used for survey completion**		
None	106	43.44	*Desktop PC*	170	69.67
Undergraduate (Degree)	138	56.56	*Mobile (all types)*	74	30.33
Unspecified	0	0.00	Social-Economic Context		
Travel Context			**Income (KHD)**	**Quant**	
Travel Experience		0.00	*Less than 9,999*	3	1.23
Frequent traveller (>3 trips per year)	33	13.52	*10,000–19,999*	7	2.87
Regular Traveller (2–3 trips per year)	141	57.79	*20,000–29,999*	41	16.80
Infrequent traveller (once a year or less)	70	28.69	*30,000–59,999*	130	53.28
Destination			*More than 60,000*	63	25.82
Short haul	190	77.87	*Unspecified*	0	0.00
Long Haul	54	22.13	**Family Status**		0.00
Social Environment			*Single*	81	33.20
Alone	11	4.51	*Married/live with partner*	160	65.57
With a spouse	105	43.03	*Separated/divorced*	3	1.23
With family members	37	15.16	*Widowed*	0	0.00

With a group of friends	51	20.90	*Prefer not to say*	0	0.00
Other	40	16.39	*Single*	0	0.00

Observed heterogeneity can be identified by testing the moderating effects within a model (Hair Jr et al., 2017). Measurement invariance of composite models (MICOM) can be used to ensure the equivalence of meanings, which different individuals attribute to the same phenomenon under investigation (Sinkovics, Henseler, Ringle, & Sarstedt, 2016). This method includes three tests, namely, identification of configural invariance, compositional invariance and equality of composite mean value and variances. The establishment of full invariance allows testing of differences between path coefficients. Significant differences indicate the presence of a moderating effect by another factor. If data validity was ensured, the absence of compositional invariance and the presence of inequality of means indicates that tourists attribute different meanings, use different interpretations of services parameters and tend to apply different principles when accessing these services performance. The absence of full invariance makes comparing path coefficients irrelevant (Hair Jr et al., 2017).

This study first tested a hypothesis on the presence of full measurement variance to identify differences in perceptions resulting from travel contextual factors by applying MICOM procedures. It further compared the path coefficients between the groups. If full measurement invariance of the latent constructs was confirmed, the study proceeded to comparison of the path coefficients between the groups. It applied a multi-group analysis (i.e. PLS-MGA) and an omnibus test of group differences (i.e. PLS-OTG) to compare the differences between two groups and between three and more groups, respectively. If full measurement invariance of the latent constructs was unconfirmed, the study did not produce the model estimates separately, as the exact value of the path coefficients of each model separately was beyond the scope of the study.

Findings

Outer and Inner Model Assessment

The validity and reliability of the outer model were established. In the reflective latent constructs, all indicators loadings exceeded the threshold of 0.70. The average variance explained of the latent constructs met the threshold (AVE > 0.50). The composite reliability was mainly within the desirable interval of 0.60 < CR < 0.90. The 95% bias-corrected confidence intervals of the heterotrait-monotrait (HTMT) ratio of correlations excluded 1 (Hair Jr et al., 2017). In the formative latent constructs, one of the proposed indicators was deleted, as its contribution to the construct was unconfirmed. Other indicators met the requirements for validity and demonstrated a desirable variance inflation factor (VIF < 3). The outer weights exceeded the threshold of w > 0.20 and were significant. In the single case of a nonsignificant outer weight, its loading exceeded the minimum required threshold of l > 0.50. Considering this fact and the belonginess of the indicators to a well-defined usability scale; thus, it was retained in the formative scale. Lastly, redundancy analysis demonstrated path coefficients as $\beta > 0.70$ and $R^2 > 0.60$, thereby reconfirming that the acquired definitions were relevant to interpret the meanings of the constructs.

The inner model assessment demonstrated a moderate predictive power and relevance. The standardised root mean square residuals did not reach the conservative border of 0.08 ($SRMR_{Sat} = 0.045$ and $SRMRE_{st} = 0.045$), whilst the normed fit indices exceeded it ($NFI_{Sat} = 0.881$ and $NFI_{Est} = 0.88$). The squared Euclidean distance and the geodesic distance values fell within the 95% $BCaCI_{SRMR}$ both for the saturated and estimated models. Assessment of the explained variance and effect sizes for the latent constructs reconfirmed the relevance of the predictors. The predictive relevance of each construct is confirmed as $Q^2_{incl} > 0$. Unfortunately, the $Q^2_{predict}$ ratios were negative for three out of four constructs. However, the result in this case may be biased owing to the model complexity (Hair Jr et al., 2017).

Figure 1 summarises the model estimates based on the entire sample. The identified path coefficients accorded with previously observed trends (Song et al., 2012; Volchek, 2019).

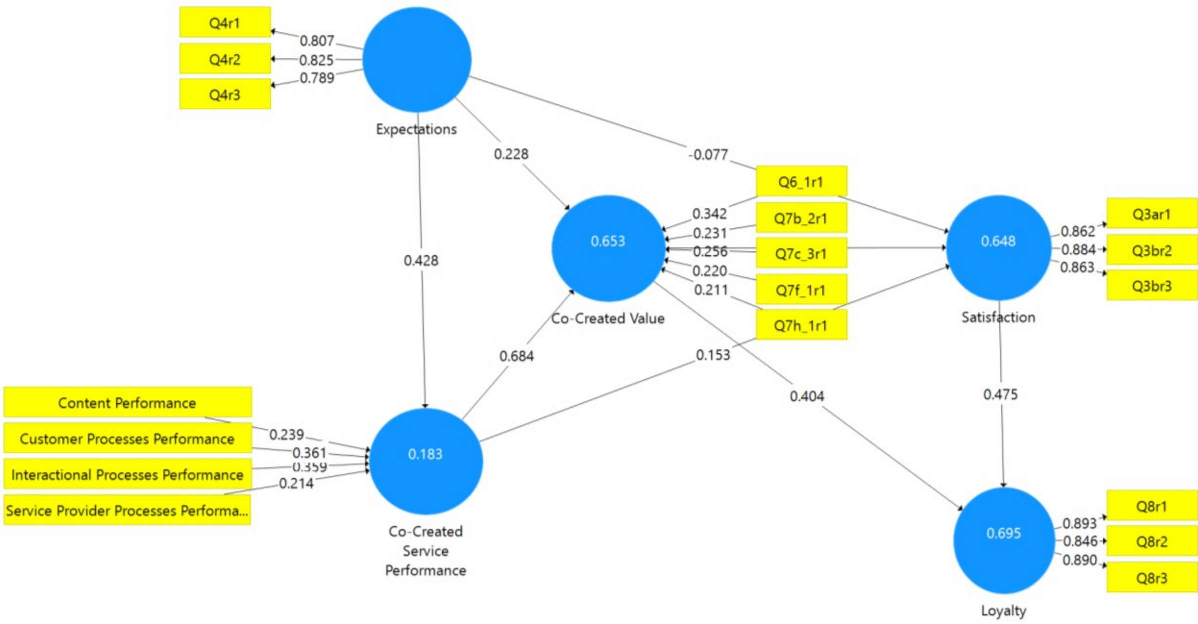

Figure 1. Estimated Inner Model (2 – Stage Approach)

Measurement Invariance and Path Coefficients Difference resulting from the Tourist Context

Assessment of measurement invariance and the comparison of the relationships between the constructs demonstrated that the factors of personal, travel, technical and social contexts largely affected tourist perceptions. Specifically, configural invariance was established for all variables as the same measurement scale, and the same questionnaire was used to collect data from all the participants. However, the MICOM procedures demonstrated that full compositional invariance could not be established for several cases, thereby making the comparison of the path coefficients between the groups irrelevant.

Among the personal context factors, gender played a moderating role in the relationships between expectations and co-created service performance ($\beta_{F\text{-}M} = 0.367^{**}$) and between co-created service performance and satisfaction ($\beta_{F\text{-}M} = 0.260^{**}$). The male tourists had higher expectations and higher perceptions of co-created value, satisfaction and loyalty than the female tourists. However, the male tourists assessed co-created service performance lower than the female tourists. Interestingly, in both cases, the relationships between the latent constructs were not significant for the females but significant for the male tourists. *Age groups* exhibited the absence of equal composite mean values. The absence of compositional variance was confirmed in the case of the large age differences between the members of Generations Z and Generations X and between the members of Generation Z and the Baby Boomer. In most cases the tourist perceptions of loyalty were the cause of those differences. The older generation indicated a significantly higher intention to use the service again. In the case of *education*, the analysis demonstrated identical trends in the expression of expectations and perceptions towards the personalised mobile application, as no significant differences were identified.

In the case of social-economic context, measurement invariance was not established for the representatives of different *income* groups and for *married and single tourists*. This finding indicated that tourists can attribute different meanings to the proposed parameters. Interestingly, tourists who were single had significantly higher expectations towards personalised information services than married couples ($M_{Sngl\text{-}Married} = 0.370^{**}$).

Among the factors of technical context, neither *awareness of personalisation* nor *awareness of data being tracked* demonstrated the presence of full invariance. Surprisingly, compositional invariance was established for awareness of the personalisation technologies used. However, the composite mean difference for this factor differed significantly between the tourists who were aware of personalisation and those who were unaware. In the cases of *awareness of personalisation* and *the absence of awareness of data being tracked,* the results demonstrated the correlation between the scores for loyalty ($C_l = 0.999^{**}$) as significantly lower than 1. This result prevented the establishment of compositional invariance. In the case of previous experience with travel planners, the tourists with and without experience with Google Trips had similar expectations towards the service ($M_{NoExperience\text{-}Experienced} = 0.285$).

However, they formed rather distinct perceptions of the personalised information service ($M_{NoExperience\text{-}Experienced}$ = 0.715**), co-created value ($M_{NoExperience\text{-}Experienced}$ = 0.806**), satisfaction ($M_{NoExperience\text{-}Experienced}$ = 0.829**) and loyalty ($M_{NoExperience\text{-}Experienced}$ = 0.955*). Application of *operating systems used for survey completion* exhibited partial composite invariance, as the comparison between groups indicated the absence of equal composite mean variance. Interestingly, Windows users gave higher scores for co-created value ($M_{Win\text{-}other}$ = 0.461**), satisfaction ($M_{Win\text{-}other}$ = 0.439**) and loyalty ($M_{Win\text{-}other}$ = 0.479**) compared with other OS users, whereas Mac users only perceived co-created value as higher compared with other OS users ($M_{Win\text{-}other}$ = 0.486*). Lastly, the MGA did not identify any significant differences between the users who completed the survey using mobile devices or desktop PCs.

In terms of the travel context, *frequency of travel* demonstrated that people with different travel experience attributed different meanings to the explored constructs, as the composite scores means of all constructs differed significantly. By contrast, *travel distance* did not change tourist perceptions. The MGA analysis demonstrated the existence of only one path coefficient, which was moderated by the type of destination, that is, expectations->co-created value ($\beta_{LH\text{-}SH}$ = 0.237*). Whilst short-haul and long-haul destinations exhibited positive relationships between expectations and co-created value, the relationship was nonsignificant in the case of long-haul and significant for short-haul locations (β_{LH} = 0.010; β_{SH} = 0.247***). Another trend involved the relationships for co-created service performance->satisfaction. The path coefficient was nonsignificant for long-haul destinations but significant for short-haul locations (β_{LH} = 0.122; β_{SH} = 0.161**). Lastly, the study compared the *travel social context* of tourists who travelled with their spouse, with their family members and with their friends. In this case, full measurement variance was not established, as the variance ratio for the satisfaction differed significantly for the tourists who travelled with their spouse and with their family members.

Conclusion

The study explored the effects of factors of personal, travel, sociodemographic and technical contexts on tourist perceptions towards personalised information services. The findings demonstrated that these factors could moderate the structural relationships between tourist expectations, perceptions of co-created service performance, co-created value and satisfaction. Context may trigger distinct interpretations of experienced interactions with personalised information services in distinctive ways. Therefore, a more comprehensive service design strategy is required to maximise co-created value and satisfaction and to motivate tourists to use the service again.

The findings contributed to consumer behaviour and service design domains. Despite being context-dependent, they reconfirmed the complexity and dynamic nature of tourist perceptions. The findings also deepened our understanding of the process of tourists' reasoning towards personalised information services. Specifically, research in the tourism domain generally accepts the unidimensional approach of comparing the outcome of personalised information services with their standardised versions. Accurate tourist context recognition and relevant information personalisation are assumed to increase tourist satisfaction. All tourists regardless of the context are expected to be similarly highly satisfied with the personalised service. Therefore, the comparison between personalised and non-personalised services allows researchers to identify whether a designed solution demonstrates high performance. However, it restricts understanding of the relevance of personalisation to individual contexts. Based on the case of advanced personalisation, this study identified differences in tourists' interpretations of personalised information service. By doing so, it demonstrated the importance of further specifying the concept of personalisation in relation to the relevance of the designed service to in-context tourist needs satisfaction and value maximisation.

This study likewise has practical implications, as the presence of measurement variance indirectly suggested that core services should be personalised, and the entire personalisation strategy should be adapted to specific contexts.

Finally, this study has several limitations, the main one involving the absence of unobserved heterogeneity in the analysis. Multiple factors and their combined effects on the core factors were unexplored. Moreover, the applied sample size was insufficient to test several target factors as potential moderators. Thus, an explanatory study, which would provide an in-depth interpretation of each groups' perceptions and reasonings, would prove beneficial.

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