An Empirical Study of the Outcomes of Luxury Hotel Personalization - Utilizing Structural Equation Modeling and Machine Learning (SEM-ML) for Explanation and Prediction.

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Abstract:

The personalization of products and services has received considerable attention due to the proliferation of technology and marketing information systems and the growth of interest in one-to-one marketing. This study explores the luxury hotel personalization outcomes of lifestyle congruence, loyalty, and willingness to pay more (WTPM). By employing both structural equation modeling (SEM) and machine learning (ML), explanatory and predictive models are created. SHAP, an explainable AI method, is used alongside various machine learning methods to turn their "black box" nature into a "glass box" by illuminating the feature importance of each variable. The relationship between personalization and WTPM was found to be stronger for males and Gen Xers. The serial mediating role of lifestyle congruence and loyalty was also significant in the relationship between personalization and WTPM. The study results indicate a congruence between the explanatory and predictive models regarding the hierarchical significance of the variables - personalization, loyalty, and lifestyle congruence - in determining the willingness to pay more. Both models consistently rank the importance of these variables in *the same order, thereby affirming their robustness in explaining and predicting willingness to pay more.*

Key Words:

Personalization, Willingness to Pay More, Loyalty, Lifestyle Congruity, Machine Learning, Explainable AI

Introduction

Marketers are increasingly adopting personalized marketing strategies in a dynamic and competitive market to enhance customer service and gain a competitive edge. The personalization of products and services has received considerable attention due to the growth of interest in one-to-one marketing and has been studied in various fields and disciplines, such as consumer behavior and marketing, management, computer science, and information systems, to name a few (Ball et al., 2006; Kwon & Kim, 2012). Personalization is company-initiated and offered by firms based on collected customer data to decide the most suitable marketing mix for an individual customer (Desai, 2016; Kwon & Kim, 2012; Indeed Editorial Team, 2023).

Chandra et al. (2022) conducted a bibliometric study through a comprehensive review of 383 publications. One of the major knowledge gaps identified was exploring personalized marketing in offline environments, as most studies have been conducted in the online context. They also recommended that future research investigates personalized marketing practices across various cultural contexts, generational groups, and product categories to identify potential areas of convergence for personalized marketing strategies.

Crafting experiences based on individual preferences has become an essential element of luxury travel. While practitioners and scholars acknowledge the potential effectiveness of personalization as a management tool, the hotel industry has yet to explore this area. Hotel companies now have a greater ability to personalize their offerings. In luxury hotels, this could include personalized greetings, room amenities, concierge services, dining options, pricing, and even recreational activities (Thornell, 2022). Also, the proliferation of hotel brands and intense competition calls for a greater understanding of the outcomes of personalization and how it drives loyalty and willingness to pay more (WTPM hereafter).

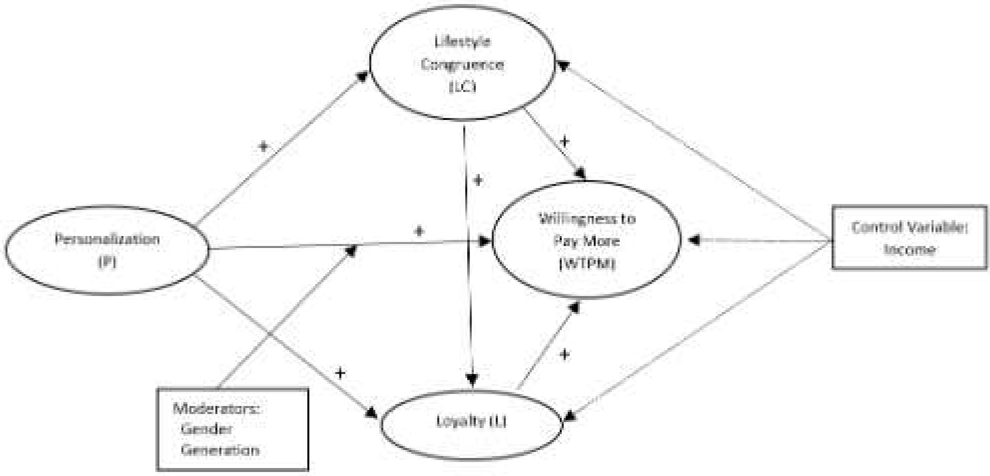
As suggested by Dawn (2014) and Chandra et al. (2022), there is a significant gap in our understanding of the role of personalization in achieving customer loyalty and strengthening service relationships. The expected positive outcomes of personalization are assumed rather than empirically studied and validated. This paper argues that personalization influences willingness to pay more through several routes (brand lifestyle congruity and loyalty). The study develops a model and empirically investigates the nature of relationships among four constructs, perceived personalization, brand-lifestyle congruence, loyalty, and WTPM, to delineate the path from personalization to WTPM in a model. This study contributes to general and hospitality marketing literature in the following ways: First, while using income as a control variable, this research reveals the pivotal role of perceived personalization in developing and improving a willingness to pay more directly and via mediating variables of lifestyle congruence and behavioral loyalty. Second, it proposes and empirically tests a model involving psychological paths from personalization to WTPM for luxury hotels and provides initial empirical evidence for the impact of perceived personalization on lifestyle congruence, loyalty, and WTPM. This makes it possible to examine the mediation, the interrelationships among the outcomes, and the direct and indirect effects of personalization on those focal outcomes to understand personalization's efficacy better. Third, the model incorporates gender and generational cohorts (Gen Y and Gen X) as moderating variables to assess their impact on the relationship between personalization and WTPM. Finally, the study utilizes both explanation and prediction tools to test the model: structural equation modeling (CB-SEM) and multiple machine learning algorithms.

Literature Review

The concept of personalization is fundamental to marketing; however, it is also multidisciplinary and has been studied across fields and disciplines across management, computer science, decision science, information systems (IS), and psychology (Chandra et al., 2022). Drawing on relationship marketing theory, a model of personalization outcomes was developed including hypothesized relationships and moderating and control variables based on a thorough review of literature in consumer behavior, marketing, psychology, computer science, and hospitality (Mehmood, Verleye, De Keyser, & Larivière, 2022; Lei, Chan, Tang & Ye, 2022; Sarkar et al., 2021; Pérez-Troncoso, Epstein & Castañeda-García, 2021; Li, 2016; Morosan & DeFranco, 2016; Alnawas & Altarifi, 2016; Dawn, 2014; Kuo and Cranage, 2012; Li, Li, & Kambele, 2012; Kwon &

Kim, 2012; Srinivasan et al., 2002; Kuo & Cranage, 2012; Pérez-Troncoso, Epstein, & Castañeda-García, 2021).

Figure 1. Conceptual Model



A conceptual framework of personalization offered by Vesanen (2007) proposed that the benefits of personalization for a company would include a higher price paid by customers for products/services, customer loyalty, customer satisfaction, and differentiation from competitors. Personalization has great potential to develop intimate customer relationships and is associated with attitude and behavior (Mehmood, Verleye, De Keyser, & Larivière, 2022). Li (2016) empirically demonstrated that perceived personalization, instead of actual personalization, is the underlying psychological mechanism of message effectiveness. Perceived personalization was found to have a significant and positive effect on attitudes, purchase intention, or behavioral intention (Lei, Chan, Tang & Ye, 2022; Li, 2016). Smink et al. (2020) studied the impact of perceived personalization on product and brand responses and found it leads to more positive attitudinal and behavioral outcomes. Brand-lifestyle or identity congruence refers to the extent to which the brand matches the consumer's lifestyle or the degree of overlap between a consumer's self-identity and the retailer's brand identity (Nam, Ekinci & Whyatt, 2011; Roggeveen et al., 2021). Personalized customer experience was believed to generate strong affective relationships between the customer and company and increase loyalty and purchasing behavior (Monk & Blom, 2007; Liang et al., 2012; Baloglu & Bai, 2023).

Consumers' WTPM is defined as the maximum price a buyer is willing to pay for a given quantity of a good (Kuo & Cranage, 2012). Sarkar et al. (2021) examined how self-brand connection leads to consumer willingness to pay a premium (WPP) through the mediation of brand attitudes. The findings showed a strong positive indirect effect of self-brand connection on WPP. However, the study has not investigated the direct effect of the self-brand connection on WPP. The conceptual framework developed by Roggeveen et al. (2021) suggested that brand congruence leads to positive outcomes such as increased customer engagement, brand loyalty, and higher willingness to pay.

The fundamental goal of personalization is to increase customer retention and profitability. Kwon and Kim (2012) investigated the effects of personalization on customer satisfaction and loyalty and found that the optimal level of personalization increases customer loyalty and retention. Morosan and DeFranco (2016) found that the perceived personalization of hotel apps positively influences behavioral intentions toward using them. Srinivasan et al. (2002) examined the antecedents and consequences of customer loyalty in an e-commerce setting and found that personalization is a significant antecedent of e-loyalty and revealed that e-loyalty significantly and indirectly influences WTPM. However, they did not investigate the direct impact of personalization on WTPM.

Pérez-Troncoso et al. (2021) found that personalization had varying impacts on WTPM for different segments. A similar call has been made by Chandra et al. (2022). Kuo and Cranage (2012) found a significant gender effect that males are more likely to pay more for personalized products under the extensive choice variety. According to a Bain & Company study, Gen X consumers make up a significant portion of global luxury spending for travel and entertainment. Millennials and Gen Xers value personalization, but Gen Xers have significant buying power and disposable income, and they spend more on luxury brands and trips globally than any other age group. (D'Arpizio, et al.,2023; Degn, 2024). Therefore, gender and generational cohorts were proposed to moderate the relationship between personalization and WTPM.

Methodology

A survey questionnaire composed of scales used by other studies and demographic questions was developed and sent to a Qualtrics Panel. Personalization was measured using six items adapted from Ball et al. (2006) and Nath and Mukherjee (2012), lifestyle congruence using three items (Nam et al., 2011), loyalty using five items (Hwang et al., 2019), and

WTPM using four items (Netemeyer et al., 2004). All items were measured on a 7-point Likert scale. The study's target demographic is Americans aged 25 to 54 who have recently stayed at a luxury hotel in the United States. This age range was chosen because it represents around 75% of U.S. tourists (Peter, 2019), and Millennials will soon overtake Baby Boomers as the major generational market category for hotels (Bowen & McCain, 2015).

The sample size for 4 constructs, 17 observed variables, medium effect size, 0.80 minimum power level, and 0.05 probability level resulted in 91-137 respondents. Considering the moderation and 10 respondents per observed variable, data were collected from 220 respondents. The sample size also met the minimum requirements of 5 respondents per parameter to be estimated (NPAR=42) (Soper, 2024; Hair et al., 2010; Kline, 2011).

Procedural guidelines and practices (Podsakoff et al., 2003; Podsakoff et al., 2012; Min et al., 2016) to reduce common method bias were used before data collection. To assess the common method bias statistically, Harman's single construct test, confirmatory factor analyses of competing models - hypothesized four-factor model and one-factor model - were used (Korsgaard & Roberson, 1995; Podsakoff et al., 2012; Serrano et al., 2018). The hypothesized model significantly fit the data better than the model including all items loading on one latent construct (Normed $\chi2$ ($\chi2$/df)=5.37 (628.8, 117 df); CFI=.78; TLI=.74; RMSEA=0.15). Moreover, the chi-square statistics between the two models were statistically significant ($\Delta\chi2 = 389.6$, df=6, $p < .00001$), which provided some support that common method variance is not a serious issue in this study.

The bias-corrected bootstrapping method available through AMOS 27 based on 5000 bootstrap samples was used for mediation analyses. The study also performed 500 randomized permutation tests to show whether an equivalent of a better-fitting model could be found. The probability was 0.0002 (1/500) to get a model as good as the proposed.

A novel SEM-machine learning approach was used in this study and closely follows the methodology of Zobair et al. (2021), where the authors utilized structural equation modeling (SEM), machine learning (ML), and LIME (an Explainable AI method similar to SHAP). Structural equation modeling tests mediation, moderation, and indirect effects of latent constructs and is intended to provide explanations. Machine learning is used to showcase the model's predictive power and model non-linear relationships as ML incorporates black-box algorithms (Sharma et al., 2021) that do not have the interpretability of SEM. SHapley Additive exPlanations (SHAP) enables more interpretability for machine learning methods by showing both local and global feature importance (Liu et al., 2023). Leo Breiman (2001), one of the pioneers of the Random Forest algorithm, discussed two cultures of statistical modeling, the "data modeling" and "algorithmic modeling" cultures, where the data modeling culture essentially focuses on knowledge creation through theory-guided data analysis (e.g., inferential statistics), while the algorithmic modeling culture focuses on solving specific problems through pure prediction (e.g., ML). Later, a third culture, termed the "hybrid modeling culture," was introduced by Daoud and Dubhashi (2023), who advocated combining predictive and inferential statistics. Furthermore, machine learning can be used on survey data (Buskirk et al., 2018; Kern et al., 2019) and is not only reserved for "Big Data." Additionally, it has been argued that methods prominent in psychology (i.e., social sciences) should focus on ML instead of traditional methods to promote psychology as more of a predictive science (Yarkoni & Westfall, 2017).

Various scholars in the social sciences have realized the importance of both explanation and prediction through hybrid methods such as SEM-ANN, which combines the explanatory power of SEM with the predictive power of artificial neural networks (ANN), an ML method. Papers using SEM-ANN have been recently published in hospitality journals (e.g., Xia & Zhang, 2022; Chen et al., 2023) and general business journals (e.g., Lee et al., 2020), showcasing the relevance of this type of dichotomous methodology. However, one flaw of the SEM-ANN method is that it only incorporates one type of ML algorithm, which is the ANN. This is problematic due to the "No-Free-Lunch-Theorem" introduced by Wolpert and Macready (1997), which essentially posits that there is no guarantee that one ML method will outperform the others due to each dataset and method having its own inherent biases. This is why Martinez-Torres and Toral (2019) utilized multiple ML classifiers regarding deceptive hotel reviews in their study. Accordingly, an SEM-ML method will be used as this research aims to establish an empirical model with both explanatory and predictive power. The performance of classical ML regression methods, such as support vector machines, random forests, boosted trees, and neural networks, will be compared.

Results

Most respondents are Caucasian (84%), have Bachelor's Degrees (35%), have a household income between \$100K and \$150K (30%), are married (71%), and are company-employed (77%).

The measurement model involving 4 latent constructs and 17 variables produced a moderate model fit based on the initial Confirmatory Factor Analysis (CFA) (Normed $\chi2$ ($\chi2$/df)=2.61 (294.9, 129 df); CFI=.90; TLI=.88; RMSEA=.095). After closely examining modification indices and standardized factor weights, two modifications were made to improve the model fit and enhance the reliability and validity of the measurement model. First, an error correlation was added between two items of loyalty "I say positive things about this hotel to other people" and "I would recommend this hotel to someone who seeks my advice." As both items were related to word-of-mouth behavior, it was deemed justifiable on conceptual grounds. Second, an error correlation was added to the items "If I changed hotels, I wouldn't obtain products and services as personalized as I have now" and "The hotel offers products and services that I could not find in another hotel." Those two items were related to comparative or switching costs for personalized services. After the modifications, the model showed significantly improved fit measures (Normed $\chi2$ ($\chi2$/df)=2.15 (239.1, 111 df); CFI=.94; TLI=.93; RMSEA=.075).

Table 1. Measurement model: Factor loadings, mean and standard deviation

Model Variables	Factor loading	Mean	Std. Dev.
Personalization (CR=0.86; AVE=0.51)		5.02	1.99
If I changed hotels, I wouldn't obtain products and services as personalized as I have now.	0.64		
The hotel offers products and services that I could not find in another hotel.	0.59		
Being a regular guest, the hotel offers me special treatment.	0.72		
The hotel sends me greeting cards or gifts on special occasions.	0.75		
The hotel sometimes offers services to me that they do not offer to other guests.	0.67		

The hotel provides customized products/services to meet my needs.	0.82		
Lifestyle Congruence (CR=0.92; AVE=0.80)		5.40	1.22
This hotel reflects my personal lifestyle.	0.89		
This hotel is totally in line with my lifestyle.	0.92		
Staying in this hotel supports my lifestyle.	0.86		
Loyalty (CR=0.88; AVE=0.59)		4.644	1.62
I say positive things about this hotel to other people.	0.75		
I would recommend this hotel to someone who seeks my advice.	0.69		
I encourage my friends to visit this hotel.	0.78		
I consider this hotel to be my first choice in lodging accommodation.	0.84		
I intend to visit this hotel more often in the future.	0.79		
Willingness to Pay More (WTPM) (CR=0.85; AVE=0.68)		5.88	1.39
I am willing to pay a higher price for this hotel than for other hotels.	0.88		
I am willing to pay a lot more for this hotel than other hotels.	0.87		
I am willing to pay __% more for this hotel over other hotels*.	0.67		

Note: The items were measured on a 7-point Likert scale, 1 being "Strongly Disagree" and 7 being "Strongly Agree" except for the WTPM item denoted by "*" where the scale used 7 points ranging from 0% to 30% or more, 5% intervals.

The measures of convergent and discriminant validity were satisfactory based on composite reliability coefficients and validity properties, and heterotrait-monotrait (HTMT) ratio of correlations (Fornell & Larcker, 1981; Hair et al., 2010; Henseler, Ringle & Sarstedt, 2015).

Table 2: Reliability and validity results

Model	CR	P	LC	L	WTPM
Personalization	.857	.709			
Lifestyle Congruency	.922	.687	.893		
Loyalty	.880	.708	.768	.770	
Willingness to Pay	.851	.693	.656	.672	.811
The Heterotrait-Monotrait (HTMT) Ratios		P	LC	L	WTPM
Personalization					
Lifestyle Congruency		.698			
Loyalty		.680	.749		
Willingness to Pay		.711	.646	.621	

Note: CR =composite reliability. The diagonal values are the square root of the average variance extracted (AVE) value. The values below the diagonal are correlations (all $p < 0.001$), which all are lower than their associated AVE value(s).

The results fully supported the hypotheses proposed in the study. The SEM model, while controlling income for all variables in the model, presented good fit indices (normed $\chi 2 = 2.07$; CFI = 0.94; TLI=0.93; RMSEA = 0.072; SRMR = 0.055). Standardized regression weights showed that personalization had positive impacts on lifestyle congruency (.64, $p < .001$), loyalty (.34, $p<.001$), and WTPM (.35, $p<.001$). Lifestyle congruency was positively affecting loyalty (.53, $p<.001$) and WTPM (.19, $p<.05$). Finally, loyalty was also positively related to WTPM (.24, $p<0.05$).

The findings demonstrate that personalization is the most influential variable on both loyalty intentions and WTPM. Bias-corrected bootstrapping methods based on 5000 bootstrap samples indicated that, after considering the indirect effects, personalization influenced loyalty intentions more strongly than lifestyle congruence, creating a domino effect in the model as well as total effects on WTPM through lifestyle congruence and loyalty intentions.

The study assessed the mediating roles of lifestyle congruence and loyalty in the relationship between personalization and WTPM, including serial mediation (Table 3). The serial mediation was significant at a 0.05 probability level. Lifestyle congruence was a partial mediator between personalization and loyalty but not between personalization and WTPM. Loyalty was a partial mediator between lifestyle congruence and WTPM, as well as personalization and WTPM.

Table 3: Mediation Analysis

Relationship	Direct Effect	Indirect Effect	Bias-Corrected Confidence Interval		P-value	Conclusion
			Lower Bound	Upper Bound		
P→LC→L	.320 (0.001)	.267	.175	.396	0.001	LC is a partial mediator
LC→L→WTPM	.214 (0.034)	.141	.006	.276	0.044	L is a partial mediator
P→LC→WTPM	.507 (0.001	.178	-.018	.384	0.065	LC is not a mediator
P→L→WTMP	.507 (0.001)	.118	.016	.272	0.033	L is a partial mediator
P→LC→L→WTMP	.507 (0.001)	.120	.007	.277	0.042	Serial mediation

Note: P=Personality; LC=Lifestyle Congruence; L=Loyalty; Willingness to Pay More=WTPM. The coefficients are unstandardized.

The moderating effect of gender on the relationship between personalization and WTPM was significant at a 0.01 probability level. The relationship was significantly stronger for males (.94) than females (.05). The moderating effect of generation was also significant ($p<0.01$). The path coefficient from personalization and WTPM was stronger for Generation X (.90) than for Millennials (.15).

The study evaluated the performance of various machine learning models using a leave-one-out cross-validation method. This technique is particularly rigorous as it involves using a single observation from the original sample as the validation data and the remaining observations as the training data. This process is repeated so that each observation in the sample is used once as validation data. The machine learning models used in this study are Random Forest, Neural Network, AdaBoost, kNN (k-Nearest Neighbors), XGBoost (Extreme Gradient Boosting), and SVM (Support Vector Machine).

The performance of the models was measured using five different metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The results show that SVM was the most robust model as it has the lowest MSE (1.238), RMSE (1.113), MAE (0.892), and MAPE (0.283), along with the highest R^2 (0.391) (Table 4). This study's order from best to worst performing machine learning methods are SVM, neural network, kNN, Random Forest, XGBoost, and AdaBoost.

Table 4. Machine Learning Performance by Method

Method	MSE	RMSE	MAE	MAPE	R^2
Random Forest	1.459	1.208	0.962	0.291	0.282
Neural Network	1.337	1.156	0.931	0.287	0.342
AdaBoost	1.737	1.318	1.029	0.307	0.145
kNN	1.369	1.170	0.935	0.297	0.327
XGBoost	1.656	1.287	1.020	0.306	0.185
SVM	1.238	1.113	0.892	0.283	0.391

SHAP values were utilized to understand the impact of various features on the predictive model's output (Table 5). Feature importance was measured based on the R^2 score, with a permutation of 5 to account for random error. Regarding feature importance, personalization showed the highest impact on the R^2 score, suggesting it is the most significant predictor in the model. Loyalty also demonstrated substantial influence, followed by lifestyle congruence. Income and gender, while still important, had a relatively lower impact than the other features.

The results show congruency between explanation (SEM) and prediction (ML) regarding the direct effects between the independent variables personalization, lifestyle congruence, and loyalty with the dependent variable willingness to pay more. The beta coefficients of the SEM model and the SHAP feature importance means are ranked the same (personalization ranked the highest, loyalty ranked in the middle, and lifestyle congruence ranked the lowest).

Table 5. Global Feature Importance of SVM Using SHAP

Feature	*Mean*
Personalization	*0.35*
Loyalty	*0.18*
Lifestyle Congruence	*0.13*
Gender	*0.11*
Generation	*0.09*
Income	*0.07*

Discussion and Conclusion

The hotel industry continually seeks ways to enhance the guest experience and loyalty. Personalization is one way to accomplish this, and it will help hotels cultivate more meaningful relationships with guests, boost their loyalty, and increase revenue. Hoteliers are interested in the impact of personalization on customer-brand relationships, the bottom line, and how it influences focal marketing variables. Our present research investigates the interrelationships between personalization, lifestyle congruence, behavioral loyalty, and willingness to pay more in a luxury hotel context. The study provides insights for hotel managers' empirical support and implications for the efficacy of personalization for customer loyalty and willingness to spend more for hotel offerings. Hotels providing personalized offerings are more likely to be rewarded with higher behavioral loyalty and increased customer spending. Hotel managers can use personalization as an actionable and controllable element to increase loyalty and profitability.

The results elucidate that personalization influences willingness to pay more directly and indirectly through lifestyle congruence and behavioral loyalty intention. Personalization had a significant impact on all outcome variables included in the study. The study contributes to the existing body of knowledge by revealing potential outcomes of perceived personalization and psychological path to WTPM and revealing that the effect of personalization on WTPM is mediated by lifestyle congruence and behavioral loyalty (serial mediation and/or partial mediation). In addition, it reveals some key moderators, such as gender and generational cohorts, affecting the personalization and WTPM relationships for luxury hotels.

The findings offer several practical implications for luxury hotel practitioners aiming to enhance customer loyalty, align with guests' lifestyles, and increase their willingness to pay more (WTPM). Personalization may not be for everybody, and certain demographic groups would value it more than others. Our study found a stronger relationship between personalization WTPM for males and the Generation X cohort. So, hotels that consider personalization must begin with the guest type. Hotels could target critical demographics and develop marketing campaigns and personalized offerings that specifically appeal to these demographics. By focusing on personalized services in line with guests' lifestyles and loyalty enhancement, hotels could ensure that the hotel's brand and services reflect the target clientele's personal lifestyles, as they directly impacted WTPM. Hotels should leverage guest data and utilize customer relationship management (CRM) systems to collect and analyze guest preferences, enabling more accurate personalization and establishing metrics to evaluate the effectiveness of personalization strategies on loyalty and WTPM.

Luxury hotel managers would integrate personalization into their core business strategies, leveraging technology and data analytics to significantly enhance guests' willingness to pay more for improved profitability. Artificial intelligence (AI) and machine learning (ML) are becoming increasingly vital in marketing strategies, enabling more effective targeting and personalization efforts. These technologies can uncover hidden patterns and customer segments, or even at the individual level, in personalization data and accurately predict future behaviors. Moreover, AI-powered chatbots and virtual assistants are being utilized to interact with guests, offering personalized recommendations and support based on individual preferences and past interactions, including customized room amenities, tailored concierge services, and individualized dining options and recreational activities.

Future research can examine hotel personalization practices across cultures, micro-segments, and other hotel classes. Specifically, different levels of personalization can be studied using an experimental design to compare the different levels of personalization on focal outcomes.

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