IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received October 10, 2020, accepted November 6, 2020, date of publication November 16, 2020, date of current version December 8, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3037920

Autoencoder-Enabled Potential Buyer Identification and Purchase Intention Model of Vacation Homes

FAN LI[1], SOTARO KATSUMATA[2], CHING-HUNG LEE[3], QIONGWEI YE[4], WIRAWAN DONY DAHANA[2], RUNGTING TU[5], AND XI LI[5]

[1]Fraunhofer, Nanyang Technological University, Singapore 639798
[2]Graduate School of Economics, Osaka University, Suita 560-0043, Japan
[3]School of Public Policy and Administration, Xi'an Jiaotong University, Xi'an 170049, China
[4]Business School, Yunnan University of Finance and Economics, Kunming 650221, China
[5]College of Management, Shenzhen University, Shenzhen 518060, China

Corresponding authors: Qiongwei Ye (yeqiongwei@163.com) and Rungting Tu (rungting@szu.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 71772129, in part by the National Social Science Foundation of China under Grant 19BTJ048, in part by the Japan Society for the Promotion of Science (JSPS) KAKENHI under Grant 17H02573 and Grant 18K01875, in part by the Xi'an Jiaotong University Start-Up Funding under Grant 7121192301, in part by the Prominent Educator Program (Yunnan [2018]11), in part by the Yunnan Science and Technology Fund under Grant 2017FA034, in part by the Yunnan Province Young Academic and Technical Leader Candidate Program under Grant 2018HB027, in part by the China Ministry of Education Foundation for Humanities and Social Science under Grant 19YJC630219, and in part by the Natural Science Foundation of Hunan Province under Grant 2018JJ3038.

ABSTRACT A trend of purchasing a lakeside, seaside, or forest vacation home has been raised in China. However, such purchase behavior has received limited attention from the research community in emerging markets. This study aims at investigating the factors behind vacation home purchase behavior and helping identify potential buyers. Specifically, factors, such as air quality, enduring involvement, place attachment, and destination familiarity, are examined via a proposed integrative model, which links these factors to purchase intention. The total number of potential buyers of vacation homes is increasing but remains small, compared to the whole consumers' population, resulting in imbalanced purchase behavior data when validating a model. To address this problem, this study proposes an autoencoder-enabled and k-means clustering-based (AKMC) method to identify potential buyers. The proposed methods tested on a dataset of 309 samples, collected through a questionnaire-based survey, and achieves a model accuracy of 82% in identifying potential buyers, outperforming other traditional machine learning methods, such as decision trees and support vector machines. This study also provides explainable results for the vacation home purchase behavior and a decision-making tool to identify potential buyers.

INDEX TERMS Enduring involvement, identification, machine learning, place attachment, vacation home, potential buyers.

I. INTRODUCTION

Social and economic status is recognized as a strong determining factor for purchasing vacation homes. In Western countries, enjoying regular trips to vacation homes, such as weekend villas or holiday apartments in tourist destinations, has become an integral form of leisure [1]. Similarly, in China, with the rapid development of tourism, enjoying long-term vacations has become common [2], [3]. For example, tourists flock from the widespread smog and chilly weather in many northern cities of China to southern cities to enjoy the tropical climate, cleaner air, and bright sunshine [4]. In the recent decade, researchers have witnessed a great rise in the popularity of owning vacation homes at the lakeside, seaside, or forests for pursuing better-quality leisure or retirement life in China. Chinese provinces, such as Hainan and Yunnan, have become some of the popular destinations for Beijing residents to escape the smog [5]. While the permanent resident population of 2016 in Hainan province was officially 9.17 million, 1.13 million (i.e., 13%) of which was actually the ''migratory bird'' population [6]. Moreover, over 80% of the apartments in Sanya, a city in the Hainan province, were purchased by residents from other provinces [4].

The associate editor coordinating the review of this manuscript and approving it for publication was Mostafa M. Fouda.

Although there is no widely agreed definition of a vacation home, with other commonly used terms including "cabin," "holiday home," "recreational home," "summer house," "weekend home," and "vacation home," etc., a vacation home is generally regarded as being leisure- and recreation-oriented [7]. In this study, we adopt the term "vacation home" throughout the paper.

In addition to the climate factor mentioned above, the self-expression and hedonic dimensions of enduring involvement also play important roles in the decision-making process for purchasing a vacation home. Moreover, destination familiarity and place attachment can also influence the decision of purchasing a vacation home. Although various tourism and leisure studies have investigated the relationship between involvement and place attachment from several different perspectives, including resource planning, satisfaction, and revisiting behavior [8], [9], few have studied the relationships among enduring involvement, place attachment, destination familiarity, and purchase intentions towards vacation homes. However, understanding the demand of vacation homes is imperative for business planning, construction operations, and economic growth strategies.

To fill the current gap in research, this study aims at examining the relationships among destination familiarity, enduring involvement, place attachment, and purchase intentions. The total number of potential buyers of vacation homes is increasing but still remains small, compared to the whole consumers' population. As a result, data in purchase behavior is imbalanced and challenging to be analyzed using other traditional methods. Hence, a method that combines autoencoder and k-means clustering (AKMC) is proposed for identifying potential buyers. Data in this study were collected from over 300 tourists whose partial purpose of traveling was to buy a vacation home.

The remainder of the paper is structured as follows. In Section 2, we provide a summary of the previous studies on the impacting factors and moderators of vacation home purchase intention, such as place attachment, enduring involvement, and destination familiarity. In addition, the recent methods for identifying potential buyers are also reviewed. In Section 3, we describe the methodology of the current study. In Section 4, we examine the purchase intention model in detail and test the proposed method for potential buyer identification. Lastly, in Section 5, we discuss the findings and conclude the study.

II. LITERATURE REVIEW

In the following sections, we first review the impacting factors and moderators of vacation home purchase behavior and then provide a summary of the existing methods related to the identification of the potential buyers.

A. DRIVING FACTORS OF PURCHASE INTENTION

1) PLACE ATTACHMENT

Place attachment refers to the emotional tie between individuals and specific travel destinations [8], [9], and significantly influences tourists' travel destination loyalty and future revisit intention in tourism management and marketing [10]. Place dependence and place identity have been considered to be two main dimensions of place attachment [11] in earlier literature. However, more recently, an increasing number of researchers have begun to support the view that place attachment comprises three dimensions: place dependence, referring to the attachment to specific functions of a place; place identity, referring to the emotional symbolic meanings; and place affect, referring to the emotional bonds of an individual to a place [12]. Recent studies have indicated that place attachment has a strong impact on revisit intentions [13] and serves as an antecedent of destination loyalty [10].

2) ENDURING INVOLVEMENT

The involvement theory can be traced back to the idea of "ego-involvement," introduced in the field of social judgment theory [14]. In the consumer behavior literature, Krugman [15] makes the first attempt to apply involvement theory to measure the advertising effectiveness, whose view, contrary to the classical approach, claims that customers passively receive information. Later, Zaichkowsky [16] defines enduring involvement as the perceptual consequence of people grounded in unique needs, values, and interests. More specifically, involvement indicates the extent of the cognitive bond between individuals and objects, and sometimes related to situations. Higie and Feick [17] extend the concepts of pleasure involvement and self-expression involvement from the study of Zaichkowsky [16] and measure the extent of enduring involvement in computers and lawnmowers for undergraduates and MBA students. In the tourism literature, enduring involvement has been explored from the standpoint of leisure involvement, including the variables of "attraction, self-expression, and centrality to life" [8].

3) DESTINATION FAMILIARITY

In the marketing field, the concepts of product familiarity have been widely examined. Product familiarity refers to the extent of customers' product-related experiences in terms of three aspects: advertising exposure, information searching, and product experience [18]. Similarly, destination familiarity refers to the extent of destination-related experience, built up through information search, previous visiting experiences, destination involvement, and internal information [19]. Destination familiarity notably affects satisfaction and leads to destination loyalty [20]. Tourists' destination familiarity strongly influences their behaviors [21]. For instance, tourists with a higher extent level of destination familiarity to a travel destination tend to show higher destination loyalty and show higher desires to visit the specific destination [22].

4) AIR QUALITY INDEX

Additionally, air quality is another important driving factor in purchasing a vacation home [23]. Dong *et al.* [24] indicate that air quality could potentially influence travel destination selection of the inbound tourists. For example, the primary purpose of holding a vacation home is often to pursue a suitable climate, health improvement, and a comfortable lifestyle [25]. We expect that the worse the air quality index of the tourists resident, the higher likelihood of purchasing a vacation home.

B. POTENTIAL BUYER IDENTIFICATION

By analyzing the factors impacting purchase intention, it is possible to identify consumers with higher willingness-to-buy [26]–[28]. Previous studies have found that the behaviors and trust of potential buyers are different from repeat consumers and indifferent consumers [29], [30]. Hence, it is possible to identify potential buyers from a group of people [31], [32]. For example, one recent study facilitates cross-selling in a mobile telecom market by identifying potential buyers for new services and products [33]. Various data mining techniques used in pattern recognition, such as logistic regression, artificial neural networks, and decision trees [34], [35], can be applied to predict purchase intention based on demographic and behavior data [33], [36]. The problem of identifying potential buyers can typically be treated as a classification problem [26] but the challenge is the imbalanced training data [37]. For example, only one out of a thousand people may intend to purchase a vacation home, consisting of a small percentage of the whole consumers' population. As such, the machine learning algorithms mentioned do not generally perform well in identifying potential buyers from a large group of people.

The challenge of imbalanced data may be solved by combining multiple classifiers [26], [38]. Hence, we propose a method that combines an autoencoder and k-means clustering techniques. The autoencoder is a state-of-art method [39], [40], which performs well in anomaly detection and can be improved by leveraging the advantages of the k-means cluster. In this study, "enthusiastic consumers" are considered as anomalies of "indifferent consumers". Merely using an autoencoder for anomaly detection would create the problem of needing to determine an appropriate threshold. Hence, we combine the autoencoder with k-means clustering. K-means clustering is similar to k-nearest neighbor search, which is a widely used method in consumer classification [41]. Moreover, it is an unsupervised method, making it more suitable for identifying potential buyers.

III. RESEARCH METHODOLOGY

Our method includes two main parts, namely, the purchase behavior analysis and the potential buyer identification, as presented in Figure 1. In the first part, the correlations between driving factors and purchase intention are analyzed, and a conceptual model of purchase intention is established. In the second part, the AKMC method is used to identify potential buyers. Specifically, the AKMC classifies consumers into generic consumers and enthusiastic consumers. Enthusiastic consumers refer to consumers with great willingness-to-buy and are defined as potential buyers.

A. PHASE 1: PURCHASE INTENTION ANALYSIS

1) DRIVING FACTORS ANALYSIS

Place attachment interacts with affective aspects, expertise level, and behaviors towards a particular place [9]. Thus, we revise the definition of Tsai [12] and classify place attachment as an emotional, cognitive, and functional assessment to tourist destinations. For enduring involvement, we adapt the scales from the study of Higie and Feick [17], which includes both hedonic factors (e.g., interesting, fun, fascinating, exciting, and appealing) and self-expression factors (e.g., "portraying an image of me to others," "forming my self-image, tells me about a person"). Destination familiarity measures are adapted from Sun *et al.* [20].

2) THEORY MODEL AND HYPOTHESIS DEVELOPMENT

Hypotheses are generated to link all these impacting factors and moderators together. Kyle *et al.* [11] indicate that each dimension of involvement (including attraction, self-expression, and centrality) have strong positive effects on place attachment (place identity, affective attachment, and place dependence). Thus, the first hypothesis is proposed as follows:

H1: For the potential buyers, the greater their extent of enduring involvement, the stronger their place attachment to the destination is.

In marketing literature, brand attachment has consistently been found to positively affect the intent to purchase a product. Accordingly, the level of tourists' place attachment can be hypothesized as a mediating function to the relationships of enduring involvement and willingness-to-buy of a vacation home. Thus, the following hypotheses are proposed:

H2: For the potential buyers, the greater their extent of enduring involvement, the higher their purchase intention of vacation homes in the destination is.

H3: For the potential buyers, the greater their extent of place attachment, the higher their purchase intention in the destination is.

H4: Place attachment mediates the relationship between enduring involvement and purchase intention.

Destination familiarity and involvement have significant impacts on destination perception [19]. In the context of this study, destination familiarity has a potential moderating role between vacation home involvement and destination attachment. Thus, the following hypotheses are proposed:

H5: For the potential buyers, the greater their extent of destination familiarity, the stronger their place attachment to the destination is.

H6: Tourists' destination familiarity moderates the relationship between enduring involvement and place attachment.

Additionally, Li and Katsumata [42] show that geographic attributes significantly affect the purchase behaviors of international tourists. Additionally, Dong *et al.* [24] indicate that air quality could potentially influence the travel

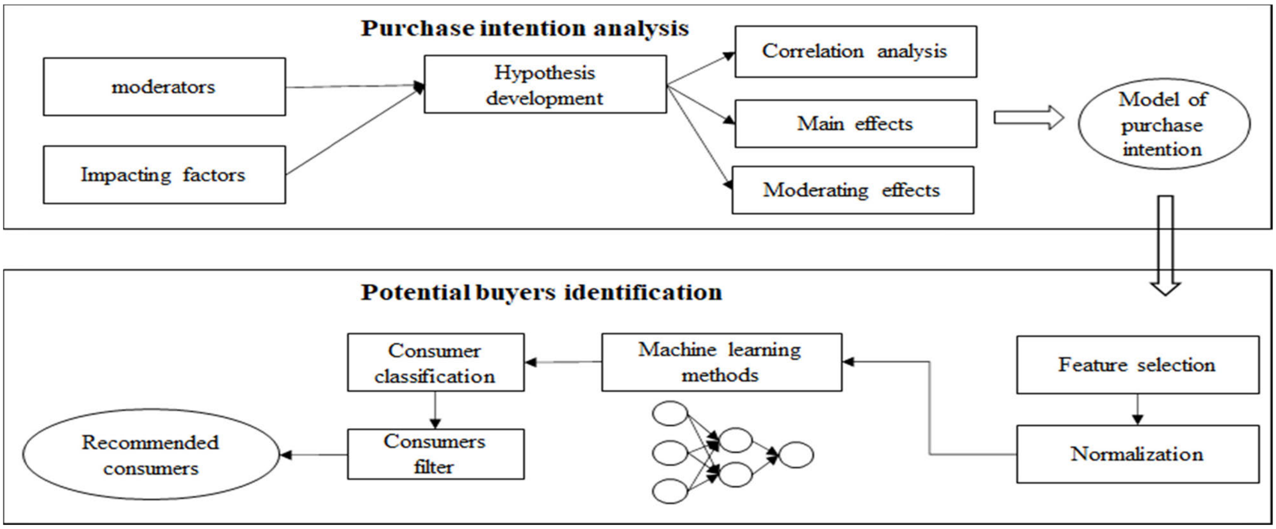

FIGURE 1. Framework of Data-driven purchase behavior analysis.

destination selection of inbound tourists. Therefore, the following hypotheses are proposed:

H7: Air quality index moderates the relationship between enduring involvement and place attachment.

Considering the relationships among these driving factors (e.g. place attachment, enduring involvement, destination familiarity) and the vacation home purchase intentions, the research framework of this study is developed, as shown in Figure 2.

3) MODEL VALIDATION

To test the conceptual model, we conducted several analyses in R (version 3.6.0), using the packages "lavaan," a useful tool for examining a variety of latent variable models, including confirmatory factor analysis, structural equation modeling, and latent growth curve models (https://cran.r-project.org/web/packages/). We examined the hypotheses by a two-stage estimation. The measurement equation (confirmatory factor analysis) in the first stage was used to examine the reliability and validity of the constructs. Our model incorporated five constructs, (1) PA, place attachment of tourists, (2) DF, tourists' destination familiarity of a specific location, (3) EDV, enduring involvement of a vacation home, (4) PI, purchase intention of a vacation home at a tourist destination, and (5) AQID, air quality index difference between a travel destination and the resident city of a tourist. The second model is the structural equation model, which was used to examine the hypotheses with interaction terms included. The second model was based on mediating moderation analysis [43]. In the second model, we estimated a model without interaction to compare the result of the hypothetical model.

B. PHASE 2: POTENTIAL BUYER IDENTIFICATION

In section III-A, we analyzed the driving factors of purchase intentions. If a factor was found to be a significant driving factor, it could be a potential indicator of purchase intention and would be used as the input to the machine learning method proposed in this section. This process provided explainable results for selecting features. We proposed a two-process machine learning method to classify consumers, which includes an autoencoder-based model for enthusiastic consumers and a k-means-based consumer classifier, as shown in Figure 3. The model was based primarily on data from enthusiastic consumers, rather than indifferent ones, as data from enthusiastic consumers could be more easily and directly acquired by real estate managers. The factors verified in Section III-A and demographic information were used as inputs. The categorical variables were encoded as numerical vectors using one-hot encoding, which enabled the "binarization" of a category. Numerical variables were first normalized and then scaled from 0 to 1.

1) AUTOENCODER-ENABLED MODEL

Instead of using the traditional feature selection algorithms, the autoencoder was adopted to automatically generate low-dimension hidden features, which could effectively represent high-dimensional features [44], [45]. The original inputs x belong to an m-dimensional space and the hidden layer h belongs to a five-dimensional space. The output y has the same dimensions as the input x. J is the reconstruction error:

$$J(W, b; x, h) = \frac{1}{2} \|y - x\|^2 \tag{1}$$

where W is the weight matrix of nodes and b is the bias vector. The encode transfer function is a positive saturating linear transfer function:

$$f(z) = \begin{cases} 0, & \text{if } z \leq 0 \\ z, & \text{if } 0 < z < 1 \\ 1, & \text{if } z \geq 1. \end{cases} \tag{2}$$

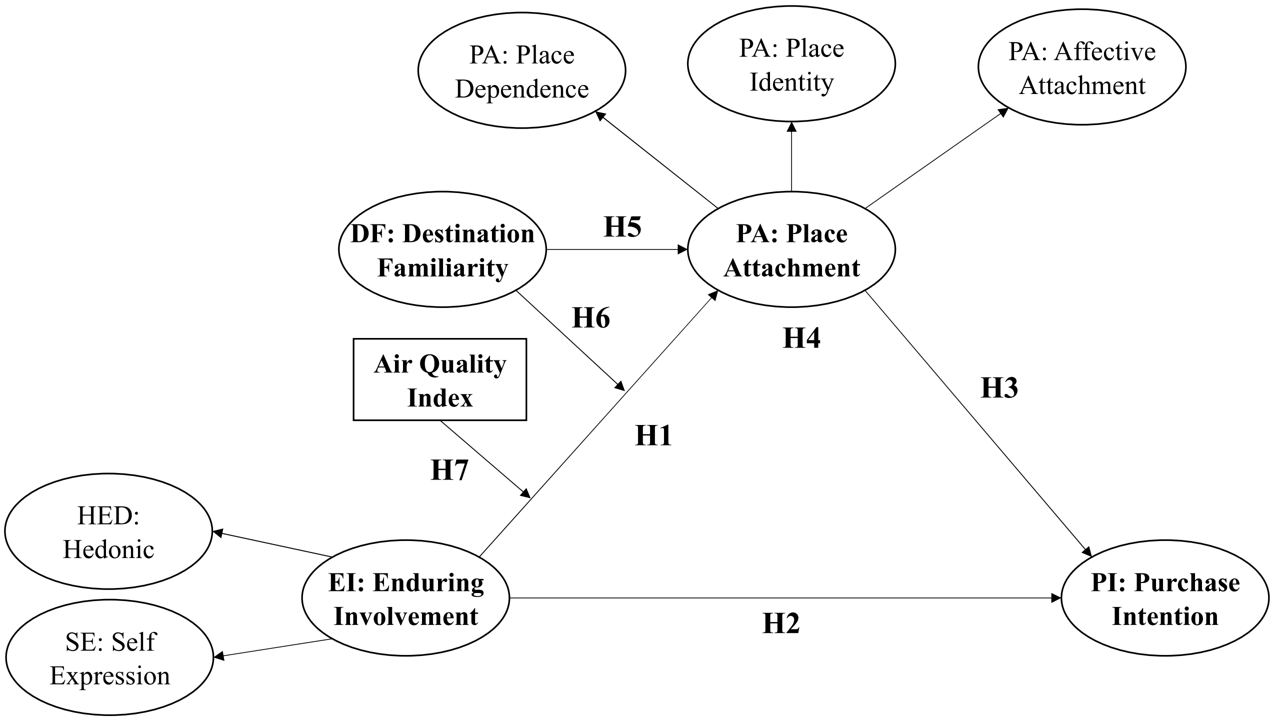

FIGURE 2. Assumed conceptual model of purchase intention.

The decoder transfer function is a linear function:

$$f(z) = z \tag{3}$$

The loss function used for training is the mean squared error function, as follows:

$$L = \frac{1}{N}\sum_{n=1}^{N}(x_n - y_n)^2 + \lambda \times \Omega_{weights}, \tag{4}$$

where $\Omega_{weights}$ is the regularization term on the weights (W), and λ is the coefficient for the regularization term.

2) K-MEANS CLUSTERING-BASED CLASSIFICATION

The proposed k-means-based consumer classifier included the traditional k-means clustering using reconstruction errors as inputs and a labeling process. The testing data ($X1$) were processed by the enthusiastic consumers model, resulting in reconstruction errors and hidden node values. The reconstruction errors were combined with raw features and used as the inputs for k-means clustering. K-means clustering divided data into k clusters and treats each observation ($x1$) as an object [46]. Specifically, the distances between each observation and centroids of clusters were calculated. The observations were then assigned to their nearest respective clusters. The squared Euclidean distance was calculated as follows:

$$d(x1, c) = (x1 - c)(x1 - c)' \tag{5}$$

where $x1$ is an observation belonging to $X1$, and c is the centroid of a cluster. The initial centroids are randomly selected from $X1$. After all observations were analyzed and assigned, a new cluster consisting of one point furthest from its centroid was generated.

Though k-means clustering can divide data into several clusters, it cannot directly label the clusters [47]. The proposed method compared the centroid of the cluster with the hidden features of the enthusiastic consumers model. The distance was calculated as a squared Euclidean distance. The cluster closest to the enthusiastic consumers model was labeled as the "enthusiastic consumers" and the others were labeled as the "indifferent consumers."

IV. EXPERIMENTS

A. DATA COLLECTION

The majority of studies on vacation homes and related tourist behavioral intentions were conducted at international destinations or developed Western countries; therefore, their implications might not have been directly applicable to the Asian and emerging markets. As such, we studied domestic tourists in four popular resort destinations in China, including Hainan, Xiamen, Beihai, and Fangchengguang. Data for this study were collected between February 1st and March 28th., 2019 through a self-administered questionnaire. The target group included domestic tourists above 18 years old who had traveled to at least one of the four cities within the previous six months with the partial purpose of purchasing a vacation home. After removing unqualify samples that missing permanent address or the time to participate in the survey is less than 10 minutes, acquired with a 92% response rate

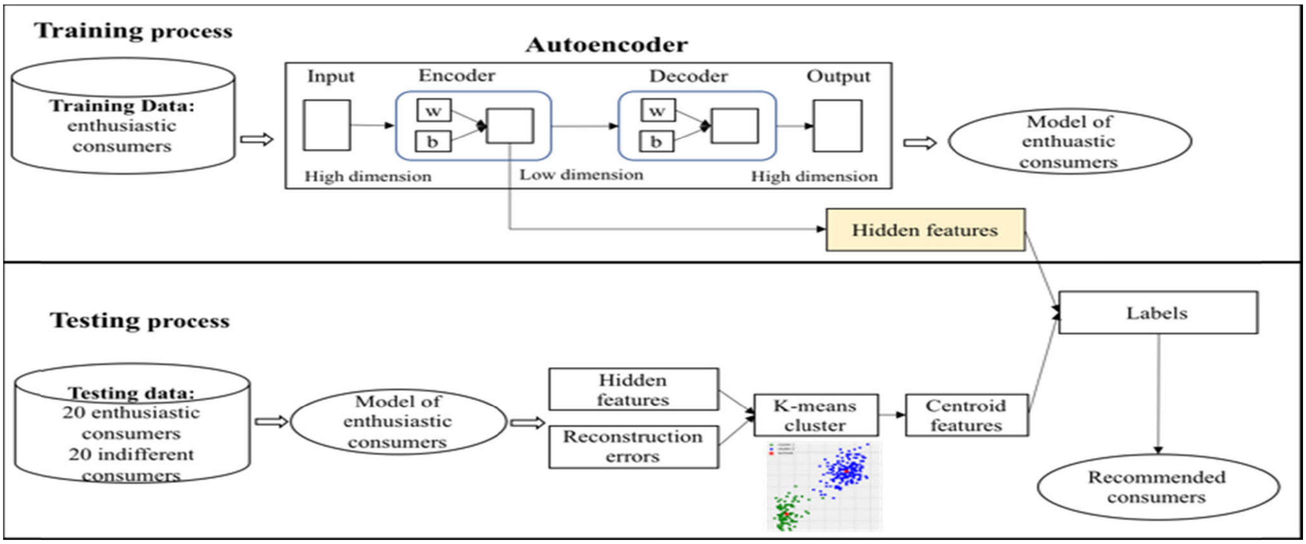

FIGURE 3. Autoencoder and K-means-based method for identifying potential buyers.

and remaining 309 (female=194, 62.8%) valid samples and for further analysis. All the materials initially utilized in this study were presented in Chinese. Following the procedures of back-translation, the measures were translated from English into Chinese to retain all the meanings of these items [48] and some wordings were adjusted to ensure clarity. The main variables of place attachment, enduring involvement, destination familiarity, and purchase intention were responded on a 7-point Likert scale (7 = strongly agree, 1 = strongly disagree). And descriptive statistics are presented in Table 1.

B. PURCHASE INTENTION MODE

1) MEASUREMENT EQUATION

The results of the measurement equation are shown in Table 2. Previous studies have consistently suggested the Cronbach's Alpha Coefficients above 0.7 to be considered as acceptable, CR (Composite Reliability) to be higher than 0.6, and AVE (Average Variance Extracted) to be above 0.5 [43]. All indices of the four constructs in the result were above the suggested thresholds. We also checked the discriminant validity for constructs. We adopted the general rule that the squared covariances should be lower than AVE of each construct to suggest proper discriminant validity. The result showed that the minimum value of AVEs exceeded the maximum value of squared covariances. In the following analysis, we incorporated the average scores of the constructs into the structural model. The correlations of constructs and control variables are presented in Table 3. All variables are standardized because the hypothetical model includes an interaction term.

2) STRUCTURAL EQUATION

Structural regression analysis was conducted to examine the seven hypotheses. The results are presented in Table 3 and Table 4. AIC (akaike information criterion) and BIC (Bayesian information criterion) imply the overall fitting of Model 2 (Interaction model) is better than Model 1 (without interaction model), therefore, the interaction terms are necessary to explain place attachment (PA).

Model 1 (without interaction model) was designed to test H1, H2, H3, and H5. The results of Model 1 testing have shown that enduring involvement was positively associated with place attachment ($\beta = 0.344$, $p < 0.001$), supporting H1. Similarly, enduring involvement was positively associated with purchase intention ($\beta = 0.149$, $p < 0.01$), supporting H2. Place attachment was positively associated with purchase intention ($\beta = 0.433$, $p < 0.001$), and thus supporting H3. H5 was supported also as destination familiarity was positively associated with place attachment ($\beta = 0.566$, $p < 0.001$).

Model 2 (Interaction model) was conducted to test H6 and H7. H6 suggests that destination familiarity moderates the relationship between enduring involvement and place attachment. To test H6, the interaction effects of enduring involvement and place attachment were determined by the levels of destination familiarity. A significant interaction term was known from the results of Model 2 ($\beta = -0.157, p < 0.001$), and therefore H6 was supported. Additionally, the AQID (Air Quality Index Difference) between a destination and the tourists' homes affected the relationship between enduring involvement and place attachment ($\beta = -0.079$, $p < 0.05$). Accordingly, H7 was also supported. Finally, the results from Model 3 presented in Table 4 showed that place attachment partially mediated the relationships between enduring involvement and purchase intention. Thus, H4 was supported. As such, all seven hypotheses were supported.

C. POTENTIAL BUYER IDENTIFICATION

Section IV-B indicates that the driving factors of enduring involvement, destination familiarity, place attachment, and air quality can directly or indirectly affect purchase intention.

TABLE 1. Correlation matrix.

	EI	DF	PA	PI	AQID	AGE	GEN	EDU	INC	PT	FAM	FRI	COL
EI: Enduring Involvement													
DF: Destination familiarity	**0.56**												
PA: Place Attachment	**0.66**	**0.75**											
PI: Purchase Intention	**0.56**	**0.69**	**0.66**										
AQID: Air Quality	0.00	-0.05	0.07	-0.05									
AGE: Age	**0.29**	**0.34**	**0.36**	**0.36**	**-0.18**								
GEN: Gender	-0.05	-0.09	-0.06	-0.04	0.01	0.08							
EDU: Education	**-0.21**	-0.10	**-0.19**	-0.08	-0.01	**-0.23**	0.08						
INC: Income	**0.16**	**0.18**	**0.13**	**0.24**	-0.10	0.09	**0.11**	**0.42**					
PT: Package Tour	**0.30**	**0.38**	**0.30**	**0.45**	-0.04	**0.20**	0.00	-0.03	**0.20**				
FAM: Family	0.07	0.07	0.08	0.07	0.02	0.08	0.02	0.00	**0.18**	**0.12**			
FRI: Friend	-0.09	-0.09	**-0.11**	**-0.18**	-0.03	**-0.24**	0.04	0.04	**-0.19**	-0.06	**-0.34**		
COL: Colleague	-0.01	-0.01	-0.04	0.05	-0.05	-0.04	-0.01	0.05	0.03	-0.02	-0.02	**0.17**	
TE: Travel Experience	**0.40**	**0.44**	**0.31**	**0.39**	-0.10	**0.31**	-0.08	-0.09	**0.17**	**0.29**	0.10	**-0.23**	-0.01

TABLE 2. Summary of measurement equation.

					Cov^2 (squared covariances)		
	# of items	Alpha	CR	AVE	EI	DF	PA
EI: Enduring Involvement	10	0.936	0.936	0.597			
DF: Destination Familiarity	4	0.919	0.920	0.742	0.360		
PA: Place Attachment	4	0.940	0.940	0.637	0.486	0.591	
PI: Purchase Intention	3	0.860	0.871	0.695	0.375	0.566	0.508

Notes: Alpha: Cronbach's alpha coefficients, CR: composite reliability, AVE: Average variance extracted.

Hence, all these variables should be the potential indicators of the vacation home purchase intention. This study applies a classical feature selection method, namely the correlation-based feature selection for machine learning [49]. Hence, only factors that show significant correlations with purchase intention are selected. According to the results presented in Table 3, the control variables of travel companion and travel experience significantly influenced purchase intention, whereas other control variables, such as education, income, package style, had no significant correlations with purchase intention. The significant factors were selected according to the statistical analysis in Section IV-B. According to the multiple regression analysis of Model 1-3, if a factor's p value of any of these models was lower than 0.05, the factor was considered as a potential indicator. A detailed description of all these variables can be found in Appendix1 and Appendix 3.

Considering the results of purchase intention analysis, all driving factors and part of the control variables were selected as inputs, resulting in 54-dimensional inputs. The autoencoder was developed to perform feature transformation, which transformed these 54 features into 5 new super features. The experiments were performed on the MATLAB R2019b platform with a dual processor. The subjects were classified into ''indifferent consumers'' and ''enthusiastic consumers'' according to their response to Questions E1, E2, E3, as displayed in Appendix 2. Specifically, the average scores of E1, E2, E3 were calculated for each subject and compared with a threshold, which was predefined as ''4'' in this study. As the purchase intention ranges from 1 to 7, ''4'' was the median value and reflected consumers' purchase intention. If the score was greater than ''4'', the subject was considered to be ''enthusiastic consumers''. The analysis resulted in 39 ''indifferent consumers'' and 270 ''enthusiastic consumers''. The Bayesian optimization was used to preliminarily select optimal hyperparameters for the autoencoder. After a preliminary study, the size of the hidden layer was set as 5 and the coefficient of the regularization term was set as 0.0001. We adopted L2 regularization term, namely the Ridge Regression in this study. The k for k-means clustering was set to 2. The proposed method was tested on twenty samples of ''indifferent consumers'' and twenty samples of ''enthusiastic consumers''. To evaluate the model's performance in identifying the potential buyers, accuracy, precision, recall, and F1 of the model were calculated and compared with the performance of other traditional methods. Accuracy referred to the percentage of consumers that were accurately classified. Recall, also known sensitivity, was the percentage of correctly identified ''enthusiastic consumers''. Precision was the positive predictive value of ''enthusiastic consumers''. F1-score conveyed the balance between precision and recall.

Tables 5 shows the performances of AKMC, a decision tree, a support vector machine, and a k-nearest neighbor search. The results of linear regression were similar

TABLE 3. Result of estimation.

Model	Model 1						Model 2					
Dependent Variables	Place Attachment			Purchase Intention			Place Attachment			Purchase Intention		
	Estimates	SE		Estimates	SE		Estimates	SE		Estimates	SE	
Direct Effect												
EI: Enduring Involvement	0.344	0.042	***	0.149	0.054	**	0.303	0.040	***	0.149	0.054	**
DF: Destination Familiarity	0.566	0.043	***				0.520	0.041	***			
PA: Place Attachment				0.433	0.052	***				0.433	0.052	***
AQID: Air Quality	0.103	0.034	**				0.083	0.032	**			
Interaction												
EI*DF							-0.157	0.027	***			
EI*AQID							-0.079	0.037	*			
CV: Control Variables												
AGE: Age	0.105	0.038	**	0.077	0.044	+	0.150	0.037	***	0.077	0.044	+
GEN: Gender	-0.009	0.033		-0.008	0.039		-0.008	0.032		-0.008	0.039	
EDU: Education	-0.045	0.039		0.034	0.045		-0.087	0.038	*	0.034	0.045	
INC: Income	0.007	0.040		0.071	0.046		0.043	0.038		0.071	0.046	
PT: Package Tour	-0.005	0.036		0.218	0.042	***	-0.010	0.034		0.218	0.042	***
FAM: Family	0.011	0.035		-0.059	0.041		-0.007	0.033		-0.059	0.041	
FRI: Friend	-0.02	0.037		-0.086	0.043	*	-0.008	0.035		-0.086	0.043	*
COL: Colleague	-0.012	0.033		0.083	0.039	*	-0.025	0.031		0.083	0.039	*
TE: Travel Experience	-0.111	0.039	**	0.085	0.044	+	-0.062	0.037	+	0.085	0.044	+
AIC: Akaike Information Criterion	1206.4						1173.5					
BIC: Bayesian Information Criterion	1299.4						1274.3					

Notes: $^{+}$p<10%; * p<5%;* p<5%; ** p<1%; ***p<0.1%

TABLE 4. Indirect and total effect of enduring involvement (EI) for purchase intention (PI).

	Model 3							
	DF: Destination familiarity	PA: Place Attachment	Indirect Estimates	SE		Total Estimates	SE	
1	High	High	0.029	0.027		0.178	0.058	**
2	High	Low	0.165	0.032	***	0.314	0.052	***
3	Low	High	0.097	0.031	**	0.247	0.056	***
4	Low	Low	0.233	0.038	***	0.383	0.051	***

Notes: $^{+}$p<10%; * p<5%;* p<5%; ** p<1%; ***p<0.1%

TABLE 5. Classification results of four methods.

Method	Accuracy	Precision	Recall	F1-score
AKMC	0.82	0.85	0.80	0.824
Decision tree	0.58	0.54	0.95	0.69
Support vector machine	0.53	0.52	1.00	0.68
K-nearest neighbor	0.53	0.52	1.00	0.68

to a decision tree and support vector machine; therefore, the results were not presented here. It is shown that AKMC had the highest accuracy, precision, and F1-score. We could deduce that the other three methods tend to classify all consumers as the "enthusiastic consumers," so they offered high recall and low precision, resulting in a low F1-score. Although the recall of AKMC was lower than other methods, we could still conclude that the AKMC strategy proposed in this study showed the best performance in identifying the potential buyers of vacation homes. It is also worth noting that the decision tree provided higher accuracy, recall, and precision than the other two methods (i.e., support vector machine and k-nearest neighbor). This suggested that the decision tree performed better than the support vector machine and k-nearest neighbor in dealing with imbalanced data.

V. DISCUSSION

Based on the previous research in consumer behavior, our study examined the antecedents of tourists' purchase intentions using the case study of vacation homes. Both direct and indirect effects of tourists' destination familiarity and enduring involvement on place attachment and purchase intentions of vacation homes were examined. Based on the enduring involvement theory [17], the place attachment theory [12], and the destination familiarity theory [18], [20], a theoretical model was designed in Section III-A-(2).

Despite the increase in demand for vacation homes in both developed and developing countries, there is still a lack of understanding of the determinants and associated mechanisms of the decision-making process of buying a vacation home. As such, this study explored the relationships between enduring involvement, destination familiarity, and place attachment, as well as their roles as the antecedents of the vacation home purchase intentions in tourist destinations. First, we identified the indirect effect of the tourists' destination familiarity on enduring involvement and place attachment when it came to the durable luxury products of vacation homes. In addition, our findings confirmed that the air quality index positively moderated the relationship between enduring involvement and place attachment. Finally, this study contributes to the literature by examining the moderating effect of destination familiarity on the relationship between enduring involvement and place attachment, and further identified the mediating effect of place attachment between enduring involvement and purchase intention.

Considering the importance of vacation homes to firms and economies, the findings of this study could contribute to the development of innovative and practical understandings of tourist behaviors. Our findings also provide several managerial implications for the sustainable development of travel destinations. In addition, our findings provide references for policymakers to develop appropriate schemes to attract potential buyers. For example, we found that the extent of enduring involvement could significantly enhance place preferences. Holding cultural events could induce a high level of enduring involvement and further enhance the tourist intention of vacation home purchase.

The proposed AKMC can identify potential buyers with a high willingness-to-buy from a number of indifferent consumers. Hence, advertisements can be sent to these correctly identified potential buyers to reduce the potential problems of advertisement fatigue. In summary, the empirical study can provide explainable results of the driving factors behind the purchase intention and the machine learning-based method can provide a practical tool to identify potential buyers. This study, compared to methods simply using the empirical study results or the machine learning-based methods, provides a more systematic way to investigate consumer behaviors.

The management of negative perceptions represents one of the major challenges for tourism planners and marketers in a destination affected by disasters (e.g. hurricanes, floods, snowstorms) or pandemics (e.g. COVID-19 pandemic). Previous studies attempt to identify the relationship between pandemics and panic consumption [50]–[52]). For example, Prentice *et al.* [50] report that panic consumption is identified as one major "side effect" of timed intervention in pandemics by the government. In the context of tourism, ownership of vacation homes influences the way tourists respond to the post-COVID-19 pandemic in travel and tourism worldwide. Tourists' risk perception significantly influences their travel decisions [52]. Moreover, Tourists' past travel experiences, specifically, their travel frequency, destination familiarity, and personal affiliations to the destination, positively influence their revisit intention [53]. In particular, place attachment enables tourists to reduce risks and enhance familiarity with tourism destinations [13]. The holders of vacation homes are much more likely to have higher visiting frequency, destination familiarity, and place attachment than those without a vacation home at the destination. Thus, holders tend to have a stronger sense of security and trust to the destinations of their vacation home and may have a higher tendency to revisit the destination post-COVID-19 pandemic. Accordingly, maintaining contact with holders of vacation homes is a vital way for destination marketing authorities to encourage visits following an epidemic. Moreover, with more explanation and patient persuasion, tourists from areas severely stricken by pandemics may be attracted to purchase vacation homes at sheltered destinations. Destination marketing authorities need to recognize the demographic differences in response to pandemic-related safety procedures when serving their customers for a safe and enjoyable traveling experience.

VI. CONCLUSION

There is a growing trend in purchasing vacation homes in China. To assess the potential impacts of the vacation homes as a crucial tourism destination attraction, and to contribute to the development of local tourism, this study develops an integrated purchase intention model based on destination familiarity, enduring involvement, and place attachment. In addition, a machine learning method AKMC is proposed to help identify potential buyers.

This study makes three main contributions. First, the study shows the relationships between destination familiarity, enduring involvement, place attachment, and purchase intention of vacation homes. In addition, destination familiarity and air quality are suggested to serve as the moderators between enduring involvement and place attachment. Second, an integrated method is developed for identifying the potential buyers of vacation homes. The proposed method effectively handles the imbalanced data and achieves a high accuracy of identifying potential buyers. Lastly, an integrated purchase intention model is generated. This study can serve as a reference to policymakers in developing cross-city or cross-region tourism.

A few limitations should be taken into consideration when applying the findings of the study to practical cases. First, the small sample size might potentially affect the

TABLE 6. Sample Characteristics (n = 309).

Variable	Frequency (%)	Variable	Frequency (%)
Gender		**Household structure**	
Male	115 (37.2)	Single	121 (39.2)
Female	194 (62.8)	Married with children	123 (39.8)
Age		Married without children	25 (8.1)
18-29	138 (44.7)	**Travel arrangement**	
30-39	115 (37.2)	Package tour	33 (10.7)
40-49	35 (11.3)	Non-package tour	276 (89.3)
50-59	16 (5.2)	**Travel companion**	
60 or above	6 (1.9)	Friend	140 (45.3)
Education		Family	242 (78.3)
Junior high school	18 (5.8)	Colleague	34 (11)
Senior high school	14 (4.5)	Solo	21 (6.8)
College	50 (16.2)	**Previous trips to the destination**	
University	178 (57.6)	1	124 (40.1)
Master or above	49 (15.9)	2	87 (28.2)
Monthly disposable income (RMB)		3	42 (13.6)
Less than 5000	76 (24.6)	4	20 (6.5)
5001-8000	85 (27.5)	5	14 (4.5)
8001-10000	45 (14.6)	6 or more	22 (7.1)
10001-15000	48 (15.5)	**Holding vacation homes**	
15001-20000	19 (6.1)	Yes	121 (39.2)
20001-30000	22 (7.1)	No	188 (60.8)
30001-50000	8 (2.6)	**Purpose of holding vacation homes**	
above 50001	6 (1.9)	Relax	188(60.8)
Residency of seaside		Invest	167(54)
Yes	101(33.3)	Preretiment	186(60.2)
No	208(66.7)	Retirement	106(34.6)

generalizability of the model. In addition, data in this study was collected using questionnaires, which might lack qualitative support. Future studies can adopt user-generated media data to further analyse consumers' behaviour. Another limitation of the study is that the data was only collected in the context of vacation homes. Despite the limitations, the theoretical framework in this study can be applied in future studies to investigate the effects of purchasing other products, such as entertainment activities, tea, cuisine, and alcohol.

APPENDIX A
See Table 6.

APPENDIX B
SUPPLEMENTARY QUESTIONNAIRE
A. PLACE ATTACHMENT MEASUREMENT
1) PLACE DEPENDENCE

PA1 I do not find any other destination capable of serving my needs better than the travel destination (Hainan/Xiamen/Beihai/ Fangchengguang).
此地旅游体验不可替代（海南岛/厦门/北海/防城港）

PA2 The settings and facilities provided by the travel destination are beyond compare
此地提供的设置和设施是其他地方无法比的

PA3 I enjoy the environment of the travel destination more than in any other destination
我最喜欢此地的环境

2) PLACE IDENTITY

PA4 The travel destination (e.g. Hainan) seems to be a part of me
此地（比如：海南）仿佛是我的一部分

PA5 Visiting the travel destination enriches meaning of my life
此地旅游对我意义重大

PA6 I identify with the image represented by the travel destination
我对此地所塑造的形象有共鸣

3) AFFECTIVE ATTACHMENT

PA7 I miss the travel destination (e.g. Hainan) a lot when I am leaving it

TABLE 7. Descriptive Statistics.

Variables	Mean	SD	Variables	Mean	SD
PA1	5.21	2.15	SE1	4.61	2.78
PA2	4.89	2.35	SE2	4.64	2.91
PA3	5.32	2.64	SE3	4.61	3.08
PA4	4.69	2.67	SE4	4.45	3.18
PA5	5.01	2.48	SE5	4.43	3.06
PA6	5.37	2.25	DF1	4.62	2.48
PA7	5.40	2.24	DF2	4.51	2.98
PA8	5.16	2.50	DF3	4.44	3.09
PA9	5.37	2.17	FI1	4.66	2.50
HED1	5.33	2.26	FI2	4.58	2.83
HED2	5.05	2.56	FI3	4.54	3.00
HED3	5.03	2.59	PI1	5.69	2.12
HED4	4.93	2.98	PI2	5.12	2.69
HED5	5.27	2.45	PI3	4.49	3.53
Temperature	12.15	68.97	AQID	36.67	1051.21

Notes: SD = standard deviation

当我要离开时，我很留恋此地（比如：海南）

PA8 I am emotionally attached to the travel destination
我非常迷恋此地

PA9 I am passionate about visiting the travel destination
我对到此一游充满了热情

B. ENDURING INVOLVEMENT MEASUREMENT

1) HEDONIC COMPONENTS

HED1 I am interested in purchasing vacation homes
我对买度假房感兴趣

HED2 Purchasing vacation home is fun
买度假房是很有趣的事情

HED3 Purchasing vacation home is fascinating
买度假房产是一件很令人着迷的事情

HED4 I feel exciting when thinking about owning a vacation home
想到买度假房能让我兴奋

HED5 Purchasing vacation home is appealing
度假房对我来说很有吸引力

2) SELF-EXPRESSION COMPONENTS

SE1 Vacation home can portray an image of me to others
度假房能在别人面前体现出我的形象

SE2 Vacation home is part of my self-image
房产是自我形象的一部分

SE3 I can use vacation home tells others about me
可以通过房产把自己展现给他人

SE4 Others can use my vacation home to judge me
其他人可以通过我的度假房来评判我

SE5 Vacation home tells me about a person
我能通过别人的房产去了解一个人

3) DESTINATION FAMILIARITY MEASUREMENT

DF1 I am more familiar with the destination (e.g. Hainan) than other tourists
我比其他游客更了解该目的地（比如：海南）

DF2 I am more familiar with the travel destination than my friends
我比我的朋友们更了解该旅游目的地

DF3 I am more familiar with the destination than those who travel frequently
我比那些经常去的人更了解该目的地

4) FUTURE INTENTION MEASUREMENT

F11 I will visit the travel destination (e.g. Hainan) within two years
我会在 2 年以内再来该旅游目的地（比如：海南）

F12 I will recommend the travel destination to others
我会把该地作为旅游目的地推荐给我的朋友

F13 I will post positive word-of -mouth to others about the destination
我会发布一些该旅游目的地的正面的信息给其他人

5) PURCHASE INTENTION MEASUREMENT

P11 I would like to purchase vacation home at the travel destination
我想在该旅游目的地买度假房。

P12 To purchase vacation home at the destination, I actively obtain multiple information
为了在该旅游目的地买度假房，我积极的获取信息。

P13 Ian viewing house at the destination
我在该旅游目的地看了很多度假房楼盘。

APPENDIX C

See Table 7.

REFERENCES

[1] M. Nouza, R. Ólafsdóttir, and A. D. Sæþórsdóttir, "Motives and behaviour of second home owners in iceland reflected by place attachment," *Current Issues Tourism*, vol. 21, no. 2, pp. 225–242, Jan. 2018.
[2] İ. Topal and M. K. Ucar, "Hybrid artificial intelligence based automatic determination of travel preferences of chinese tourists," *IEEE Access*, vol. 7, pp. 162530–162548, 2019.
[3] L. Tang, Y. Zhao, Z. Duan, and J. Chen, "Efficient similarity search for travel behavior," *IEEE Access*, vol. 6, pp. 68760–68772, 2018.
[4] Z. Ma. (2017). *A Winter Refuge From the Cold and Smog*. China Daily. [Online]. Available: http://www.chinadaily.com.cn/kindle/2017-01/27 content_28065989.htm
[5] S. Cheng. (2018).*Beijing Residents Heading South to Escape Winter Smog and Cold*. China Daily. [Online]. Available: http://www.chi nadaily.com.cn/m/guangxi/fangchenggang/2015-04/27 content_20554438.htm
[6] Hainan Provincial Bureau of Statistics. (2017). *Hainan Statistical Yearbook 2017*. [Online]. Available: http://stats.hainan.gov.cn/tjsu/ndsj/
[7] C. M. Hall, "Second home tourism: An international review," *Tourism Rev. Int.*, vol. 18, no. 3, pp. 115–135, Nov. 2014.
[8] G. Prayag and C. Ryan, "Antecedents of tourists' loyalty to Mauritius: The role and influence of destination image, place attachment, personal involvement, and satisfaction," *J. Travel Res.*, vol. 51, no. 3, pp. 342–356, 2012.
[9] I. Altman and S. M. Low, *Place Attachment*. New York, NY, USA: Springer, 2012.

[10] S. Vada, C. Prentice, and A. Hsiao, "The influence of tourism experience and well-being on place attachment," *J. Retailing Consum. Services*, vol. 47, pp. 322–330, Mar. 2019.

[11] G. Kyle, A. Graefe, R. Manning, and J. Bacon, "Effect of activity involvement and place attachment on Recreationists' perceptions of setting density," *J. Leisure Res.*, vol. 36, no. 2, pp. 209–231, Jun. 2004.

[12] S.-P. Tsai, "Place attachment and tourism marketing: Investigating international tourists in singapore," *Int. J. Tourism Res.*, vol. 14, no. 2, pp. 139–152, Mar. 2012.

[13] M. Kim and D. W. Koo, "Visitors' pro-environmental behavior and the underlying motivations for natural environment: Merging dual concern theory and attachment theory," *J. Retailing Consum. Services*, vol. 56, Sep. 2020, Sep. 102147.

[14] M. Sherif and C. Hadley, *The Psychology of Ego Involvement*. New York, NY, USA: Wiley, 1947.

[15] H. E. Krugman, "The impact of television advertising: Learning without involvement," *Public Opinion Quart.*, vol. 29, no. 3, pp. 349–356, 1965.

[16] J. L. Zaichkowsky, "Measuring the Involvement Construct in Marketing," *J. Consum. Res.*, vol. 12, pp. 341–352, May 1985.

[17] R. A. Higie and L. F. Feick, "Enduring involvement: Conceptual and measurement issues," *ACR North Amer. Adv.*, vol. 16, pp. 690–696, 1989.

[18] J. W. Alba and J. W. Hutchinson, "Dimensions of consumer expertise," *J. Consum. Res.*, vol. 13, no. 4, pp. 411–454, 1987.

[19] H. K. Chi, K. C. Huang, and H. M. Nguyen, "Elements of destination brand equity and destination familiarity regarding travel intention," *J. Retailing Consum. Services*, vol. 52, Jan. 2020, Art. no. 101728.

[20] X. Sun, C. Geng-Qing Chi, and H. Xu, "Developing destination loyalty: The case of hainan island," *Ann. Tourism Res.*, vol. 43, pp. 547–577, Oct. 2013.

[21] A. Milman and A. Pizam, "The role of awareness and familiarity with a destination: The central florida case," *J. Travel Res.*, vol. 33, no. 3, pp. 21–27, Jan. 1995.

[22] P. Mechinda, S. Serirat, and N. Gulid, "An examination of tourists' attitudinal and behavioral loyalty: Comparison between domestic and international tourists," *J. Vacation Marketing*, vol. 15, no. 2, pp. 129–148, Apr. 2009.

[23] G. I. Crouch, "Destination competitiveness: An analysis of determinant attributes," *J. Travel Res.*, vol. 50, no. 1, pp. 27–45, Jan. 2011.

[24] D. Dong, X. Xu, and Y. Wong, "Estimating the impact of air pollution on inbound tourism in China: An analysis based on regression discontinuity design," *Sustainability*, vol. 11, no. 6, p. 1682, Mar. 2019.

[25] K. M. Wong and G. Musa, "International second home retirement motives in malaysia: Comparing british and japanese retirees," *Asia Pacific J. Tourism Res.*, vol. 20, no. 9, pp. 1041–1062, Sep. 2015.

[26] J. Xiao, L. Xie, C. He, and X. Jiang, "Dynamic classifier ensemble model for customer classification with imbalanced class distribution," *Expert Syst. Appl.*, vol. 39, no. 3, pp. 3668–3675, Feb. 2012.

[27] S. P. Besemer, "To buy or not to buy: Predicting the willingness to buy from creative product variables," *Int. J. Creativity Problem Solving*, vol. 10, no. 2, pp. 5–18, 2000.

[28] H. Chen, L. Zhang, X. Chu, and B. Yan, "Smartphone customer segmentation based on the usage pattern," *Adv. Eng. Informat.*, vol. 42, Oct. 2019, Art. no. 101000.

[29] H.-W. Kim, Y. Xu, and J. Koh, "A comparison of online trust building factors between potential customers and repeat customers," *J. Assoc. Inf. Syst.*, vol. 5, no. 10, p. 13, 2004.

[30] A. Greenstein-Messica and L. Rokach, "Personal price aware multi-seller recommender system: Evidence from eBay," *Knowl.-Based Syst.*, vol. 150, pp. 14–26, Jun. 2018.

[31] H. Jiang, C. K. Kwong, G. E. Okudan Kremer, and W.-Y. Park, "Dynamic modelling of customer preferences for product design using DENFIS and opinion mining," *Adv. Eng. Informat.*, vol. 42, Oct. 2019, Art. no. 100969.

[32] S. H. Ha, "Applying knowledge engineering techniques to customer analysis in the service industry," *Adv. Eng. Informat.*, vol. 21, no. 3, pp. 293–301, Jul. 2007.

[33] H. Ahn, J. J. Ahn, K. J. Oh, and D. H. Kim, "Facilitating cross-selling in a mobile telecom market to develop customer classification model based on hybrid data mining techniques," *Expert Syst. Appl.*, vol. 38, no. 5, pp. 5005–5012, May 2011.

[34] F. Li, C.-H. Chen, G. Xu, L. P. Khoo, and Y. Liu, "Proactive mental fatigue detection of traffic control operators using bagged trees and gaze-bin analysis," *Adv. Eng. Informat.*, vol. 42, Oct. 2019, Art. no. 100987.

[35] C.-H. Chen, L. P. Khoo, and W. Yan, "A strategy for acquiring customer requirement patterns using laddering technique and ART2 neural network," *Adv. Eng. Informat.*, vol. 16, no. 3, pp. 229–240, Jul. 2002.

[36] E. Suh, S. Lim, H. Hwang, and S. Kim, "A prediction model for the purchase probability of anonymous customers to support real time Web marketing: A case study," *Expert Syst. Appl.*, vol. 27, no. 2, pp. 245–255, Aug. 2004.

[37] Y. Xie, X. Li, E. W. T. Ngai, and W. Ying, "Customer churn prediction using improved balanced random forests," *Expert Syst. Appl.*, vol. 36, no. 3, pp. 5445–5449, Apr. 2009.

[38] E. Kim, W. Kim, and Y. Lee, "Combination of multiple classifiers for the customer's purchase behavior prediction," *Decis. Support Syst.*, vol. 34, no. 2, pp. 167–175, Jan. 2003.

[39] S. Park, S. Yu, M. Kim, K. Park, and J. Paik, "Dual autoencoder network for retinex-based low-light image enhancement," *IEEE Access*, vol. 6, pp. 22084–22093, 2018.

[40] X. Wu, G. Jiang, X. Wang, P. Xie, and X. Li, "A Multi-Level-Denoising autoencoder approach for wind turbine fault detection," *IEEE Access*, vol. 7, pp. 59376–59387, 2019.

[41] T. K. Das, "A customer classification prediction model based on machine learning techniques," in *Proc. Int. Conf. Appl. Theor. Comput. Commun. Technol. (iCATccT)*, Oct. 2015, pp. 321–326.

[42] X. Li and S. Katsumata, "The impact of multidimensional country distances on consumption of specialty products: A case study of inbound tourists to japan," *J. Vacation Marketing*, vol. 26, no. 1, pp. 18–32, Jan. 2020.

[43] J. F. Hair, W. C. Black, B. J. Babin, and R. E., Anderson, *Multivariate Data Analysis*, 8th ed. Harlow, U.K.: Pearson, 2018.

[44] C. Zhang, Y. Liu, and H. Fu, "AE2-nets: Autoencoder in autoencoder networks," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2019, pp. 2577–2585.

[45] J.-C. Kim and K. Chung, "Multi-modal stacked denoising autoencoder for handling missing data in healthcare big data," *IEEE Access*, vol. 8, pp. 104933–104943, 2020.

[46] S. Shankar, B. D. Sarkar, S. Sabitha, and D. Mehrotra, "Performance analysis of student learning metric using K-mean clustering approach K-mean cluster," in *Proc. 6th Int. Conf.-Cloud Syst. Big Data Eng. (Confluence)*, Jan. 2016, pp. 341–345.

[47] K. Wagstaff, C. Cardie, S. Rogers, and S. Schrödl, "Constrained k-means clustering with background knowledge," in *Proc. ICML*, vol. 1, 2001, pp. 577–584.

[48] R. W. Brislin, W. J. Lonner, and R. M. Thorndike, *Cross-Cultural Research Methods*. New York, NY, USA: Wiley, 1973.

[49] M. A. Hall, *Correlation-Based Feature Selection for Machine Learning*. 1999.

[50] C. Prentice, J. Chen, and B. Stantic, "Timed intervention in COVID-19 and panic buying," *J. Retailing Consum. Services*, vol. 57, Nov. 2020, Art. no. 102203.

[51] L. T. T. Tran, "Managing the effectiveness of e-commerce platforms in a pandemic," *J. Retailing Consum. Services*, vol. 58, Jan. 2021, Art. no. 102287.

[52] M. Caber, M. R. González-Rodríguez, T. Albayrak, and B. Simonetti, "Does perceived risk really matter in travel behaviour?" *J. Vacation Marketing*, vol. 26, no. 3, pp. 334–353, Jul. 2020.

[53] G. Walters, J. Mair, and W. andB Ritchie, "Understanding the tourist's response to natural disasters: The case of the 2011 Queensland floods," *J. Vacation Marketing*, vol. 21, no. 1, pp. 101–113, 2015.

FAN LI received the B.S. degree from the School of Aeronautic Science and Engineering, Beihang University, China, in 2013, and the M.Sc. and Ph.D. degrees in mechanical engineering from the School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore, in 2015 and 2020, respectively. She is currently a Research Fellow with Fraunhofer, Singapore.

SOTARO KATSUMATA received the M.Sc. and Ph.D. degrees from the School of Economics, The University of Tokyo, Japan, in 2007 and 2011, respectively. He is currently an Associate Professor with the Graduate School of Economics, Osaka University, Japan. His research interests include product innovation, consumer behavior, and advertising.

CHING-HUNG LEE received the M.B.A. degree from National Cheng Kung University and the Ph.D. degree in business administration from the National Taipei University of Technology. He was a Postdoctoral Research Fellow with Nanyang Technological University. He is currently an Associate Professor with the School of Public Policy and Administration, Xi'an Jiaotong University. His research interests include digital transformation and service science.

QIONGWEI YE is currently a Professor and the Vice Dean of the Business School, Yunnan University of Finance and Economics, Kunming, China. His research interests include e-business, business intelligence and analytics, and information and experience economics. He was the Vice President of the China Information Economics Society.

WIRAWAN DONY DAHANA received the M.Sc. and Ph.D. degrees from the School of Economics, Tohoku University, Japan, in 2006 and 2009, respectively. He is currently a Professor of marketing with the Graduate School of Economics, Osaka University. His research interests include marketing decisions, consumer behavior, and electronic commerce.

RUNGTING TU received the M.Sc. degree in operation research from Stanford University, USA, in 1996, and the Ph.D. degree in business administration from the University of North Carolina at Chapel Hill, in 2004. He is currently the Director of the Center for Brand Relationships, College of Management, Shenzhen University. His research interests include service marketing, brand management, and social media.

XI LI received the B.S. degree from the School of Business, Kansai University, Japan, in 2014, and the M.Sc. and Ph.D. degrees from the School of Economics, Osaka University, in 2016 and 2019, respectively. She is currently a Research Fellow with the College of Management, Shenzhen University. Her research interests include marketing decisions and P2P platforms.