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Application of machine learning to predict visitors' green behavior in marine protected areas: evidence from Cyprus

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ABSTRACT

Interpretive marine turtle tours in Cyprus yields an alluring ground to unfold the complex nature of pro-environmental behavior among travelers in nature-based destinations. Framing on Collins (2004) interaction ritual concept and the complexity theory, the current study proposes a configurational model and probes the interactional effect of visitors' memorable experiences with environmental passion and their demographics to identify the causal recipes leading to travelers' sustainable behaviors. Data was collected from tourists in the marine protected areas located in Cyprus. Such destinations are highly valuable not only for their function as an economic source for locals but also as a significant habitat for biodiversity preservation. Using fuzzy-set Qualitative Comparative Analysis (fsQCA), this empirical study revealed that three recipes predict the high score level of visitors' environmentally friendly behavior. Additionally, an adaptive neuro-fuzzy inference system (ANFIS) method was applied to train and test the patterns of visitors' pro-environmental behavior in a machine learning environment to come up with a model which can best predict the outcome variable. The unprecedented implications on the use of technology to simulate and encourage pro-environmental behaviors in sensitive protected areas are discussed accordingly.

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Machine learning; Fuzzy set qualitative comparative analysis; adaptive neuro-fuzzy inference system; pro-environmental behavior; memorable tourism experience; environmental passion

Introduction

There is a consensus among scholars that optimizing visitors' experience is the key to destinations' success and competitiveness (Ellis & Rossman, 2008; Loureiro, 2014, Ramkissoon & Uysal, 2014, 2018: Ramkissoon, 2020). Additionally, a shift in the global economy from service-based to experienced-based economy has triggered the focus on the creation and delivery of meaningful and memorable experiences in consumers' minds by service providers particularly in the tourism industry (Kelly, 2020; Kim & Chen, 2019; Sthapit et al., 2019). The pivotal role of visitors'

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experience in elucidating their behavioral intentions such as revisiting, positive word of mouth and recommendation has also exacerbated the attention to the study of memorable tourism experiences (MTE) recently (Chen & Rahman, 2018; Dewnarain et al., 2019; Gohary et al., 2020; Kim & Ritchie, 2014; Loureiro, 2014; Triantafillidou & Petala, 2016; Wong et al., 2019). The multidimensional concept of MTE is referred to as an experience that can be recalled and remembered easily after the event (Kim et al., 2012). Such emotional assessment of real experience during the travel can impact one's intention and behavior (e.g., Gohary et al., 2020; Sthapit et al., 2019).

Although literature evidences a range of studies on MTE (e.g., Akhshik et al., 2020; Wong et al., 2019), more clarification is required for conclusive results. Findings from previous research reflect that not all dimensions of tourism experience affect travelers in the same way at the post-experience stage (e.g. Kim & Ritchie, 2014; Triantafillidou & Petala, 2016). This issue highlights the necessity of understanding the mechanism through which various dimensions of MTE may influence visitor behavior.

Additionally, the contribution of MTE to visitors' behavior in nature-based tourism environments has comparatively received less attention in spite of scholars' recommendation for the exploration of MTE in new and novel contexts (Huang et al., 2019). Further, as indicated in the study of Kim and Chen (2019), revisit intentions and positive word of mouth have been two most likely observed outcomes of MTE research in the literature (e.g., Chen & Rahman, 2018; Gohary et al., 2020; Wong et al., 2019). The study of other significant variables such as travelers' pro-environmental behavior have received comparatively lesser attention in MTE studies (Lee et al., 2015).

Furthermore, an understanding of travellers' behaviours and intentions in protected areas in non-Western contexts and markets is relatively neglected and thus is highly momentous (Shi et al., 2019). To legitimatize the bipolarity of tourism development and the protection of nature, ecological modernization theory encourages a green sacrifice for economic gains in the short-term, with a vow to justify this paranoia through technological advancement (see Mol, 2006). Modernization of antiquated service experience with the recent advancement in technology, particularly artificial intelligence (AI) as an extension of human agency (Bryson & Kime, 2011) may partly facilitate the ambition to design meaningful experiences per capita that benefit visiting areas by elevating the user-centered design process to change human collective behavior (Hassan & Ramkissoon, 2021; Neuhofer et al., 2014). In other words, AI is able to train the data and generate a powerful ex-ante estimation of visitors' behavior which can be used to increase the propensity of pro-environmental behavior at the collective level. Encouraging collective pro-environmental behaviour has been highly recommended by researchers (e.g., Ramkissoon, 2020; Ramkissoon et al., 2018) as such adjustment may result in improvement of behaviors not only during a visit at the protected areas but also promote behavioural change long term. The use of artificial intelligence in contributing to a sustainable future has been outlined as one of the main research priorities in tourism. Researchers are invited to work on how AI in general and machine learning or deep learning in particular, can be utilized to achieve sustainable tourism (Tussyadiah, 2020).

Drawing on Collins' (2004) interaction ritual (IR) theory, which is an under-utilized concept in tourism literature (Sterchele, 2020) together with the tenets of complexity theory the present study integrates MTE and environmental passion (EP) to predict tourists' PEB (Figure 1). Although EP is known as an influential contributor to individuals' PEB (Afsar et al., 2016; Robertson & Barling, 2013), observing its interactional effect with MTE in a nature-based context to explain visitors' PEB is important and yet insufficiently studied. A series of configural models that simulate MTE, EP and visitors' demographics to predict visitors' PEB can be derived. This method enables researchers and practitioners to anticipate or manipulate visitors' experiences based on the recipes that achieve accurate prediction of outcomes per capita to produce patterns which are generalizable to all individuals in the sample (Woodside, 2018).

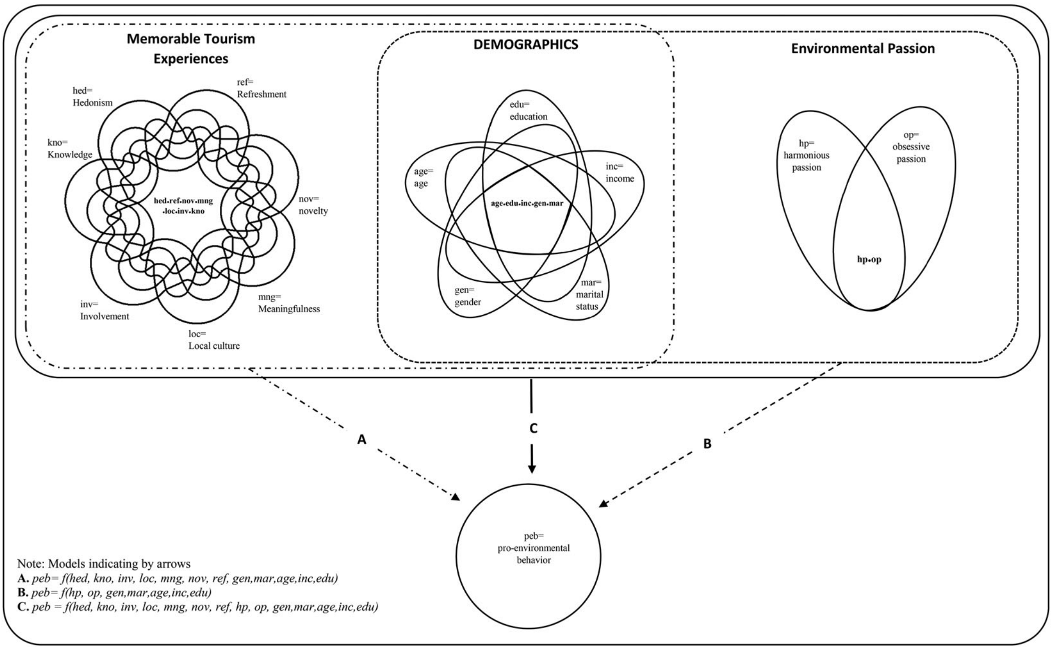


Figure 1. Asymmetrical and configurational model of the study.

The majority of existing studies in the literature have often used structural equation modelling, regression analysis and correlation testing to measure the effect of MTE on travellers' behavioural outcomes (Chen & Rahman, 2018; Coudounaris & Sthapit, 2017; Gohary et al., 2020; Sthapit et al., 2019; Tsai, 2016; Wong et al., 2019). However, non-linearity, disorder, and instability are inherent characteristics of systems, including behavioural studies in tourism (Boavida-Portugal et al., 2017) which mandates the application of deeper insights to reveal non-linearity of the antecedents and their associations with combination of outcomes. The current study uses an adaptive neuro-fuzzy inference system (ANFIS) method to train and test the patterns of visitors' PEB in a machine learning environment to come up with several compelling predictors that propel travellers' behavior upward. Although ANFIS modelling "can detect both non-linear and linear relationship between the variables to predict higher accuracy" (Yadegaridehkordi et al., 2018, p.370), its application in tourism is scarce. Our study applies machine learning to assist visitor management in ecologically fragile destinations through manipulation of the design process to foster long term behavior change. This is considered as 'the next evolutionary step in technology use and design' (Stankov & Gretzel, 2020).

Our study aims to address the following research questions: a) Which aspects of MTE in case of marine protected areas are more effective to visitors' PEB? b) Are both types of generated emotional energy (obsessive environmental passion and harmonious environmental passion) effective in the prediction of participants' PEB? c) What are the main characteristics of those participants in interpretive marine turtle tours who engage in PEB? and d) In general, which conditions should be met to make tour participants more inclined to be environmentally friendly? These gaps are going to be elaborated utilizing newly emerged technological analysis techniques such as adaptive neuro-fuzzy inference system in the case of interpretive tours.

Nowadays, along with the enormous growth in leisure demand, a move from mass to special interest tourism such as interpretive experiences and education in marine wildlife tours has elevated in recent years where visitors expect more than only entertainment and relaxation (Lück, 2015; 2016). Interpretive experiences are complex forms of sustainable travel in which education and interpretation remain substantial segments of (eco) tours (Fennell, 2008). These tours chiefly aim to educate the significance of wildlife protection to visitors. Previous studies have asserted the considerable contribution of the learning with enjoyment (edutainment) through marine wildlife tourism experiences to the intended PEB (e.g., Pratt & Suntikul, 2016).

Theoretical discourse

Interaction ritual concept

Collins' (2004) interaction ritual (IR) theory has the merit of supporting the link between the social construction of MTE and the transformative effect (e.g., PEB) it brings to consumers of place through emotional erosion (e.g., EP) (Sterchele, 2020). Scholars argue that IR theory through its emphasis on interactions that form meanings, emotions and experiences provides a suitable ground for the functioning of rituals that have similar features to tourism practices (Bargeman & Richards, 2020; Sterchele, 2020; Weenink & Spaargaren, 2016). In fact, significant aspects of people's lives were treated as organized context-related activities in groups (e.g., interpretive tours) instead of occurring in the individualistic form (Bargeman & Richards, 2020).

The intellectual history of IR theory dates back to Durkheim's (1912) research on how emotional arousal emerges from religious rituals (Hausmann, Jonason, & Summers-Effler, 2011). Drawing on IR theory, future behavior and decisions are influenced by rituals (i.e. MTE) transforming individuals' feelings into longer-term emotional energy (Sterchele, 2020). The generated emotional energy from the experience of the interaction in rituals, acts as a moral constraint on individual behavior (Hausmann et al., 2011). Using Goffman's (1959) main characteristics for an effective interaction ritual, Collins (2004) delineates that the bodily co-presence of people is the first key ingredient which makes them become harmonized with each other. The second factor is the psychological or physical division between people in the group with outsiders. "Mutual focus of attention" and the "shared mood" are the third and fourth ingredients of a prosperous ritual interaction that altogether bring about a shared excitement that fills the participants with emotional energy (Simons, 2020). Collins (2004) articulates that these emotions create standards of morality and group solidarity.

Examining IR theory in case of interpretive marine turtle tours in which groups of travelers participate in the tours with the initial willingness to experience and acquire more knowledge about wildlife (Lück, 2015) could be expedient. These groups of visitors are often so passionate about nature that they voluntarily engage in releasing turtles into the Mediterranean Sea which is part of their tours (Olya & Akhshik, 2019). Moreover, promoting visitors' PEB is vital to protect the fragile ecosystem particularly in protected areas (Ramkissoon & Mavondo, 2015, 2017). Predicting the best recipes which can lead to active participation in environmentally friendly behaviors (Ramkissoon et al., 2013) is one of the major desired outcomes of these tours (Akhshik et al., 2020).

Memorable tourism experience

Experience is said to have a considerable impact on travellers' behavioural intention (Sthapit et al., 2017). On-site tourism experiences bring forth transitory feelings and have a prominent role in memory generation (Gohary et al., 2020). MTE is composed of several dimensions including the experience of interaction with community members (local culture), the experience of relaxation (refreshment), the experience of pleasure (hedonism), the experience of fulfilment by tourism (meaningfulness), the experience of novel information (knowledge), the experience of on-site activities (involvement), and the experience of something phenomenal (novelty) (Kim & Ritchie, 2014). Evidence in the literature has shown the positive influence of MTE on visitors' behavioral intentions in various tourism settings such as local food tourism (Tsai, 2016), authentic tourism (Coudounaris & Sthapit, 2017), cultural tourism (Chen & Rahman, 2018), ethnic minority tourism (Wong et al., 2019) and eco-tourism (Gohary et al., 2020).

Environmental passion

Environmental passion is described as a positive emotion which leads to individuals' willingness to participate in PEB (Robertson & Barling, 2013). Referring to the dualistic model of passion (Vallerand et al., 2003), there are two forms of passion that one may develop towards a valued activity. The first type is harmonious passion (HP) which refers to an autonomous internalisation of the favourable activity. Such a feeling generates the motivational energy to willingly participate in the task (Gousse-Lessard et al., 2013). The second one is obsessive passion (OP) that unlike the former is a controlled internalisation of the desired activity by which one cannot resist partaking the passionate activity (Vallerand, 2010). Although the empirical studies including environmental passion are limited in the literature, some evidence suggests a positive relationship between EP and people's PEB (Afsar et al., 2016; Gilal et al., 2019; Robertson & Barling, 2013). Moreover, the aforementioned previous studies have only investigated the effect of harmonious passion on the outcome variable. Thus, comprehensive research considering both types of environmental passion simultaneously will be important.

The complexity of human behaviour (PEB)

The development of interpretive experiences, which involves numerous interacting factors, per se is a complex phenomenon (Olya & Akhshik, 2019). Additionally, travellers' environmentally friendly behaviours in tourism destinations have always been an important discussion for managers, researchers and policymakers (Akhshik et al., 2020). This is evidenced by numerous studies on predictors of visitors' PEB across settings including highly valued ecological areas (Landon et al., 2018;Lee et al., 2019; Li & Wu, 2019; Li et al., 2020; Wu et al., 2020). Nevertheless, the complexities of tourism and individuals' environmental behaviours have been relatively neglected in the literature and need further elaboration (Akhshik et al., 2020; Akhshik et al., 2020; Lezak & Thibodeau, 2016; Olya & Akhshik, 2019; Ramkissoon et al., 2012). Although, human behaviour is best predicted when outcomes are extracted from non-linear antecedents that are not necessarily the 'sum of the separate effects' (Byrne, 1998, p. 20), often in the extant literature, visitors' PEB has been treated based on linear relationships (Byrne, 1998; Mackie, 1974; McDonald, 2009) using regression analysis or structural equation modelling (Nunkoo et al., 2013; Nunkoo & Ramkissoon, 2012). Correspondingly, the authors aim to address this deficiency and discuss the complex nature of visitors' environmentally friendly behavior. In their review paper on responsible behaviour of nature-based tourists, Lee et al. (2013, p. 102) stated that "scholars have adopted various terms to describe behavior that protects the environment" such as environmentally concerned behaviour, environmentally responsible behaviour or pro-environmental behaviour. Based on the literature, this study epitomized nature-based tourists' PEBs as behaviours that not only does not harm the environment but also benefit the environment of the destinations they visited as well. These behaviours can cover a wide range of activities such as the acquisition of knowledge about environmental protection, purchasing or donations in favour of ecological protection, picking up litter in the destination, persuading others to protect the nature, changing one's lifestyle after visitation to minimise negative impacts on the environment (Higham & Carr, 2002; Smith-Sebasto & D'Costa, 1995; Steg & Vlek, 2009).

Background, materials and tools

Tourism 4.0, AI and machine learning

Human is undergoing the 4th industrial revolution characterised by the advancement of emerging technologies such as AI (Schwab, 2016). AI was first presented in the 1950s by John McCarthy as "the science and engineering of making intelligent machines, especially intelligent computer programs" (McCarthy, 2007, n.p.). Machine learning (ML) which is known as a subset of AI, uses computational algorithms that learns (pattern recognition) and improve from experience of real-world data (training sets) to predict an outcome and to make decisions on its own (Bini, 2018). Such technology-based transformations have influenced the tourism industry by providing interconnected and phygital systems which are known as Tourism 4.0 (Stankov & Gretzel, 2020).

Adaptive Neuro Fuzzy Inference System (ANFIS) which is known as a machine learning technique consists of a combination of artificial neural networks and fuzzy inference system (Karaboga & Kaya, 2020) which has been recently adopted in the tourism and hospitality industry to predict various variables. For example, Sun et al. (2019) used ML to accurately forecast tourist arrivals for popular destinations in China. Using ANFIS, Atsalakis et al. (2018) forecasted the success of a newly launched service in tourism. Recommender systems in tourism, an example of AI, have been the focus of research in recent years (Nilashi et al., 2017). Another recent application of ML models was to forecast hotel room prices in the Gulf Cooperation Council (GCC) countries (Al Shehhi & Karathanasopoulos, 2020). ML was used as a technique to predict travellers' choice preferences of eco-friendly hotels (Nilashi et al., 2019) and as a means for searching query data for tourism and hospitality forecasting (Li et al., 2020). ML methods were also utilized to predict potential situations of over-tourism in destinations (Perles-Ribes et al., 2020). In their review paper, Jiao and Chen (2019) reported that AI-based models are becoming a new trend in tourism demand forecasting studies. In sum, ML and deep learning have attracted growing interest in tourism to refine predictions in recent years and especially, ML techniques have been found to be suitable for long-term and mid-term forecasting (Claveria et al., 2016).

There is also considerable evidence in literature suggesting how ML may contribute to environmental issues (e.g., Froemelt et al., 2020; Grant et al., 2020). ML creates a mathematical model to predict or make decisions without human interventions. The application of this approach in environmental studies has shown that it can accurately predict potential human behaviour and provide valuable contribution to tackle ecological and conservational challenges. For example, the exact tracking of the spatial distribution of fisheries' impacts on remote areas and high seas has been a difficult task for many years for scientists (de Souza et al., 2016). In order to understand the global behaviour of fisheries, ML was able to locate a large fraction of the likely fishing events successfully to support the conservational management programs (de Souza et al., 2016). Within the context of our daily lives, ML can be used to predict households' consumption behavior by providing a comprehensive information base for policymakers to derive environmental strategies that may reduce consumers' ecological footprints accordingly (Froemelt et al., 2020). Machine learning algorithm was used in several other studies to predict individuals' various environmental behaviours such as outdoor water conservation (Grant et al., 2020), electric vehicle purchase behavior (de Rubens, 2019) and green consumption behaviour of college students (Tang et al., 2020) among others.

Methodology

Study area

Alagadi Beach in Northern Cyprus is one of the few sites in the Mediterranean where two globally categorized as endangered turtles namely loggerheads (Caretta caretta) and green (Chelonia mydas) turtles nest. Sadly, human recreational activities and their consequences are among the main anthropogenic threatening factors that affect marine turtle nesting areas (Camiñas & De Málaga, 2004). As the economic resources generated by tourism are inevitable, the protection of these endangered species at the same time mandates the presence of strict environmental management. To promote ecological well-being, the conservational plan for the marine protected area of the study site is administrated by the "society for the protection of turtles" in Northern Cyprus. The members of the tours whose number do not exceed 20 people per visit are booked in advance and the visitors participate in a video-based educational programme followed by a comprehensive introduction about the area and turtles. The final stage in the tour is a guided activity of baby turtle release into the sea. These practices as one of the forms of alternative tourism enhance travelers' interest in nature which is undoubtedly a significant factor in managing protected areas (Kim et al., 2020). Protected areas are generally highly precious for ecosystem services, tourism, preserving biodiversity, and also generating economic benefits for indigenous people (Afifi et al., 2017; Maldonado-Oré & Custodio, 2020) contributing to sustainable tourism development.

Measurement scales

Well-established scales from the relevant literature feed the data for this study. In this regard, the dualistic model of passion i.e. obsessive passion (6 items) and harmonious passion (6 items) was measured based on items adapted from Marsh et al. (2013) and Vallerand et al. (2003). The multidimensionality of memorable tourism experience (MTE) composed of hedonism (4 items), refreshment (4 items), local culture (3 items), meaningfulness (3 items), new knowledge (3 items), involvement (3 items), and novelty (4 items) which was adopted from Kim and Ritchie (2014). In line with studies of Su et al. (2018) and Thapa (2010), pro-environmental behaviour has been adapted from Smith-Sebasto and D'Costa (1995). All items were gauged by 5-point Likert scale ranging from 'strongly disagree' (1) to 'strongly agree' (5), except PEB, HP and OP that ranged from 'strongly disagree' (1) to 'strongly agree' (7).

Reliability, readability, timing and clarity of the items were assessed by conducting a pilot study (Karatepe et al., 2020a) with 20 participants and 10 academics in the field. No modifications were required. Table A1 (appendix) presents the measurement tools and items.

Sampling and procedure

After obtaining the necessary permissions from the Society for the protection of turtles, the research team referred to the site during the hatchling summer season of 2018. The data was collected in two phases: pre-visit and post-visit. The latter is believed to convey a structural shift in the behaviour of marine-watching visitors (Forestell & Kaufman, 1990). In the first phase, the research team contacted the visitors face to face. The visitors who agreed to participate in the survey were provided with the consent form, purpose of the study and questions about their demographic information and their email address inquiry. Additionally, the respondents were assured about their anonymity and informed that they would be contacted via email. In total, out of 520 visitors who visited Alagadi beach during the study time, 438 people agreed to participate in this research. A follow-up questionnaire was sent by email to the participants after 4 months to capture their MTE, EP and their PEB. A total 332 (75.79%) filled questionnaires were returned for the analysis. Moreover, remedies such as temporal, proximal and methodological separation of measurement items such as counterbalancing question order and reversing coded items were considered to reduce the potential common method bias (MacKenzie & Podsakoff, 2012). The distribution of gender, age, education, marital status, income and nationality is presented in Table 1.

Table 1. Respondents' profile ($n = 332$).

Characteristics	Frequency	Percentage
Gender		
Male	140	42.2
Female	192	57.5
Age		
18–29	26	7.8
30–49	104	31.3
50–64	127	38.3
Over 65	75	22.6
Education level		
No schooling completed	36	10.5
Some high school	98	29.5
Associate degree/diploma	95	28.6
Trade/technical/Vocational training	64	19.3
Bachelor's degree	29	8.7
Graduate and higher degree	10	3
Marital status		
Married	206	62
Single	126	38
Income		
Less than 1000 USD	72	21.7
1000 – 2999 USD	83	24.4
3000 – 5999 USD	152	45.8
More than 6000 USD	25	7.5
Nationality		
British	115	34.6
Cypriot	30	8.7
German	27	8.1
Swedish	22	6.6
Norwegian	21	6.3
Turkish	18	5.4
Others	99	29.8
Total	332	100%

Data analysis

After the assessment of psychometric properties, correlation coefficient of the variables was calculated using cross-tabulation and Cramér's V test to determine the extent of the relationship between the antecedent and the outcome (Olya et al., 2020). Cross-tabulation reveals the existence of contrarian cases in the data set. Therefore, the associations among antecedents and outcome of PEB are asymmetrical. As a result, the study pursues configural and non-linear models to address the inherent heterogeneity of PEB using fsQCA (Ragin, 2014). In this phase, the data were calibrated to fuzzy membership scores, and then, the fuzzy truth table was crafted using Boolean algebra by minimization of Boolean function (Quine-McCluskey method). This step produces a list of all possible conditions resulting in high and low scores of PEB. Finally, to refine the relatively important recipe from this list, counterfactual analysis was performed. Consistency and coverage are two probabilistic criteria in this step (Ragin, 2009). The formulas to calculate these are as follows:

$$\text{Coverage} : (X_i \le Y_i) = \frac{\sum\{min(X_i, Y_i)\}}{\sum Y_i}$$

$$Consistency : (X_i \le Y_i) = \frac{\sum\{min(X_i, \ Y_i)\}}{\sum X_i}$$

Where X_i, indicates case i's membership score in set X and Y_i, presents case i's membership score in set Y in the outcome condition (Ragin, 2008). A threshold value beyond 1 and 8 is commonly accepted for coverage and consistency, respectively.

The study further investigates predictive validity of the model by fairly dividing the sample into two sub-samples; a causal recipe from sub-sample 1 was then compared with the holdout sample (see Gigerenzer & Brighton, 2009). Further, to simulate the behavior of visitors, ANFIS was used to portray the possibility of the prediction of these behaviors in a machine learning environment to identify and rank critical factors that contribute to the high PEB of the visitors. In this phase, the data was split to sub-sample (75% of the total sample), and holdout sample (35% of the total sample). Then, the subsample was used as an input to train the data while the hold-out sample was an input for testing data. The in-depth clarification of each step is presented below.

Results and discussion

Psychometric properties

Table A1 (appendix) reports the descriptive statistics, normality test, and exploratory factor analysis (EFA) results using the principal components analysis (PCA) and the varimax rotation method. Skewness and Kurtosis test provides evidence of normality of data distribution that falls in the commonly accepted values of ± 3 (Bowen, 2006). EFA reveals the items accurately loaded under their measuring scales at an acceptable level ($\lambda > 0.64$). Moreover, the eigenvalue for all of the scales was higher than 1.00.

The reliability of the constructs was assessed using Cronbach's alpha (α>.70) (see Table 2). Internal consistency was validated using composite reliability (CR) which is greater than the commonly accepted 0.70 cut-off level (Bagozzi & Yi, 1988). Table 2 provides evidence of convergent validity by illustrating the average variance extracted (AVE) > .50 and greater than maximum shared squared variance (MSV) for each construct (Fornell & Larcker, 1981). A CFA has been performed with acceptable loadings of items under desired factors (standardized factor loading > .50; $p < .001$) (see Table 2). Table A3 (appendix) provides evidence of discriminant validity by comparing the factor correlations with square roots of the AVEs (Fornell & Larcker, 1981).

Results of Cross-Tabulation analyses

To further pursue the most appropriate approach to study PEB, cross-tabulation of an antecedent (OP) and the outcome (PEB) was conducted to reveal the existence of contrarian cases in the dataset. Consequently, linear approaches may not adequately explain the behavior of these individuals that runs counter to the main effect (Woodside, 2014, 2018). As an example, the results in Table 3 reveal that 70 individuals (21% of the sample) were not passionate about the environment but behaved pro-environmentally. Moreover, the negation of these relations presents 15 individuals (4.5% of the sample) who were passionate about the environment but failed to behave pro-environmentally. Consequently, despite the positive correlation between OP and PEB, there is a heterogeneity in the relationships that is hidden in the data not accurately addressed by conventional methods. Therefore, the study of PEB as a complex phenomenon demands further exploration (Ramkissoon et al., 2013c) which needs to consider the complex relationships using configural and non-linear modelling (Woodside, 2018).

Results of model testing

To further pursue the asymmetrical and configural model of the study (Figure 1), fsQCA was applied to provide unprecedented results to determine high/low scores of PEB. Arrow A in Figure 1 indicates that the confluence of MTE and demographics on PEB [peb = f(hed, kno, inv, loc, mng, nov, ref, gen,mar,age,inc,edu] results in four unique recipes (A: M1-M4; solution

Table 2. Result of CFA, CR, AVE, MSV and α.

Variable		*SFL*	CR	AVE	MSV	α
Obsessive Passion (Marsh et al., 2013; Vallerand et al., 2003***)***			***.914***	***.64***	***.068***	***.800***
OP3	My environmental activities are the only thing that really turns me on.	.827				
OP4	If I could, I would only do environmentally friendly activities.	.849				
OP6	I have the impression that my passion toward the environment controls me.	.797				
OP2	I have almost an obsessive feeling for the environment.	.787				
OP1	I have difficulties controlling my urge to do environmentally friendly activities.	.769				
OP5	My environmental activities are so exciting that I sometimes lose control over them.	.769				
Harmonious Passion (Marsh et al., 2013; Vallerand et al., 2003***)***			***.888***	***.57***	***.068***	***.755***
HP2	The new things that I discover in the environment allow me to appreciate it even more.	.819				
HP6	Taking care of the environment is in harmony with other things that are part of me.	.767				
HP4	Helping the environment allows me to live a variety of experiences.	.803				
HP3	Behaving environmentally friendly reflect the qualities I like about myself.	.766				
HP5	My environmental activates are well integrated in my life.	.734				
HP1	My environmentally friendly practices are in harmony with the other activities in my life.	.626				
Pro-environmental Behaviour (Smith-Sebasto & D'Costa, 1995; Su et al., 2018; Thapa, 2010***)***			***.879***	***.548***	***.044***	***.741***
PEB3	When I see garbage, tree branches etc., I will put them in the trash bin.	.803				
PEB5	I try to convince partners to protect the natural environment.	.786				
PEB4	If there are environment cleaning activities, I am willing to attend.	.769				
PEB2	I report to the destination administration on any environmental pollution or destruction.	.713				
PEB1	I comply with relevant regulations to not destroy the environment.	.696				
PEB6	I try to not disrupt the fauna and flora during my visit.	.666				
Hedonism (Kim & Ritchie, 2014***)***			***.883***	***.654***	***.391***	***.809***
Hed3	Really enjoyed this tourism experience	.799				
Hed2	Indulged in the activities	.914				
Hed4	Exciting	.711				
Hed1	Thrilled about having a new experience	.799				
Knowledge (Kim & Ritchie, 2014***)***			***.924***	***.802***	***.034***	***.895***
Kno2	Knowledge	.928				
Kno1	Exploratory	.887				
Kno3	New culture	.871				
Novelty(Kim & Ritchie, 2014***)***			***.924***	***.527***	***.025***	***.726***
Nov2	Unique	.736				
Nov3	Different from previous experiences	.803				
Nov4	Experienced something new	.757				
Nov1	Once-in-a lifetime experience	.588				
Refreshment (Kim & Ritchie, 2014***)***			***.81***	***.523***	***.034***	***.723***
Ref2	Enjoyed sense of freedom	.826				
Ref1	Liberating	.777				
Ref3	Refreshing	.735				
Ref4	Revitalized	.515				
Involvement (Kim & Ritchie, 2014***)***			***.905***	***.763***	***.03***	***.873***
Inv2	I enjoyed activities which I really wanted to do	.963				
Inv3	I was interested in the main activities of this tourism experience	.882				

(*continued*)

Table 2. Continued.

Variable		*SFL*	CR	AVE	MSV	α
Inv1	I visited a place where I really wanted to go	.762				
Local culture (Kim & Ritchie, 2014)			***.892***	***.735***	***.087***	***.857***
Loc3	Local people in a destination were friendly	.944				
Loc1	Good impressions about the local people	.828				
Loc2	Closely experienced the local culture	.793				
Meaningfulness (Kim & Ritchie, 2014)			***.805***	***.583***	***.391***	***.764***
Mng2	I did something important	.833				
Mng1	I did something meaningful	.815				
Mng3	Learned about myself	.626				

Note: SFL: standardized factor loading; SFL is significant at the .001 level; AVE: average variance extracted; MSV: maximum shared squared variance; CR: composite reliability; α: Chronbach's Alpha; hp = Harmonious passion; op = Obsessive Passion; peb = Pro-environmental behaviour; hed = Hedonism; kno = Knowledge; inv = Involvement; loc = Local culture, mng = Meaningfulness; nov = Novelty; ref = Refreshment.

Table 3. Cross-Tabulation Analysis of Obsessive Passion* Pro-environmental Behaviour.

			Peb							
			1	2	3	4	5	6	7	Total
Op	1	Count	0	0	0	2	**2**	**0**	**0**	4
		% within op	0.0%	0.0%	0.0%	50.0%	**50.0%**	**0.0%**	**0.0%**	100.0%
		% within peb	0.0%	0.0%	0.0%	3.3%	**1.6%**	**0.0%**	**0.0%**	1.2%
		% of Total	0.0%	0.0%	0.0%	0.6%	**0.6%**	**0.0%**	**0.0%**	1.2%
	2	Count	0	2	9	6	**12**	**6**	**1**	36
		% within op	0.0%	5.6%	25.0%	16.7%	**33.3%**	**16.7%**	**2.8%**	100.0%
		% within peb	0.0%	15.4%	17.6%	10.0%	**9.7%**	**7.4%**	**100.0%**	10.8%
		% of Total	0.0%	0.6%	2.7%	1.8%	**3.6%**	**1.8%**	**0.3%**	10.8%
	3	Count	1	3	15	18	**37**	**12**	**0**	86
		% within op	1.2%	3.5%	17.4%	20.9%	**43.0%**	**14.0%**	**0.0%**	100.0%
		% within peb	50.0%	23.1%	29.4%	30.0%	**29.8%**	**14.8%**	**0.0%**	25.9%
		% of Total	0.3%	0.9%	4.5%	5.4%	**11.1%**	**3.6%**	**0.0%**	25.9%
	4	Count	1	3	17	23	44	22	0	110
		% within op	0.9%	2.7%	15.5%	20.9%	40.0%	20.0%	0.0%	100.0%
		% within peb	50.0%	23.1%	33.3%	38.3%	35.5%	27.2%	0.0%	33.1%
		% of Total	0.3%	0.9%	5.1%	6.9%	13.3%	6.6%	0.0%	33.1%
	5	Count	**0**	**3**	**7**	11	24	26	0	71
		% within op	**0.0%**	**4.2%**	**9.9%**	15.5%	33.8%	36.6%	0.0%	100.0%
		% within peb	**0.0%**	**23.1%**	**13.7%**	18.3%	19.4%	32.1%	0.0%	21.4%
		% of Total	**0.0%**	**0.9%**	**2.1%**	3.3%	7.2%	7.8%	0.0%	21.4%
	6	Count	**0**	**2**	**2**	0	5	14	0	23
		% within op	**0.0%**	**8.7%**	**8.7%**	0.0%	21.7%	60.9%	0.0%	100.0%
		% within peb	**0.0%**	**15.4%**	**3.9%**	0.0%	4.0%	17.3%	0.0%	6.9%
		% of Total	**0.0%**	**0.6%**	**0.6%**	0.0%	1.5%	4.2%	0.0%	6.9%
	7	Count	**0**	**0**	**1**	0	0	1	0	2
		% within op	**0.0%**	**0.0%**	**50.0%**	0.0%	0.0%	50.0%	0.0%	100.0%
		% within peb	**0.0%**	**0.0%**	**2.0%**	0.0%	0.0%	1.2%	0.0%	0.6%
		% of Total	**0.0%**	**0.0%**	**0.3%**	0.0%	0.0%	0.3%	0.0%	0.6%
Total		Count	2	13	51	60	124	81	1	332
		% within op	0.6%	3.9%	15.4%	18.1%	37.3%	24.4%	0.3%	100.0%
		% within peb	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	0.6%	3.9%	15.4%	18.1%	37.3%	24.4%	0.3%	100.0%

Note: peb = pro-environmental behavior, op = obsessive passion; Cramer's V = .354, phi = 1.938, p < 0.000 indicating association between variables; Bold marks indicates 70 cases for ∼ Obssessive Passion → pro-environmental behavior and 15 cases for Obssessive Passion → ∼pro-environmental behavior; 1 represent Strongly disagree, 7 represents agree.

coverage: .23, Solution consistency: .98) (see Table 4). To clarify the recipes, an example of A: M1 (age*gen*mar*inc*∼edu*hed*mng*loc*∼nov*kno*ref) reveals that older married females with high incomes and less education who scored high on hedonism, meaningfulness, local culture, knowledge and refreshment, but lacked novelty achieved a high pro-environmental behavior score. This is in line with the studies of Olya and Akhshik (2019) and Olya and Gavilyan (2017) who found that these characteristics result in higher intention to behave pro-environmentally and support sustainable tourism development, respectively. The study further investigates the negation of PEB (Table 4. ∼A: M1-M4). To clarify with an example, ∼A:M1 (age*∼gen*mar*inc*∼edu*hed*mng*loc*nov*inv*∼kno*ref), reveals a recipe towards a low score of pro-environmental behavior of visitors through older married and uneducated males with higher incomes who score high on hedonism, meaningfulness, local culture, novelty, involvement and refreshment, but didn't have sufficient knowledge of the area. Therefore, contrary to the assumption of the conventional and symmetrical approaches, a low score of PEB is not the mirror opposite of a high score in PEB. However, fsQCA facilitates crafting different recipes for the negation of the same outcome. More recipes regarding Arrow B [peb = f(hp, op, gen,mar,age,inc,edu)] and ∼ B are illustrated in Table 4.

Table 5 presents the configural models of high and low scores of PEB (Arrow C in Figure 1) with all the antecedents [peb and ∼ peb: f(hed, kno, inv, loc, mng, nov, ref, hp, op, gen, mar,

Table 4. Configural Models of high and low scores of Peb (model A, B and their negations).

A. *peb = f(hed, kno, inv, loc, mng, nov, ref, gen,mar,age,inc,edu)*				**~A.** *~peb = f(hed, kno, inv, loc, mng, nov, ref, gen,mar,age,inc,edu)*			
Models for predicting high score of peb	**RC**	**UC**	**C**	**Models for predicting low score of peb**	**RC**	**UC**	**C**
M1. age*gen*mar*inc*~edu*hed*mng*loc*~nov*kno*ref	.16	.09	.98	M1. age*~gen*mar*inc*~edu*hed*mng*loc*nov*inv*~kno*ref	.21	.01	.91
M2. age*~gen*mar*inc*~edu*hed*mng*loc*nov*inv*~kno*ref	.10	.01	1	M2. age*gen*mar*inc*~edu*hed*mng*loc*~nov*~inv*kno*ref	.22	.06	.88
M3. age*~gen*~mar*inc*edu*hed*mng*loc*~nov*inv*kno*ref	.09	.01	.99	M3. age*~gen*~mar*inc*edu*hed*mng*loc*~nov*inv*kno*ref	.19	.02	.91
M4. age*~gen*mar*inc*edu*hed*mng*loc*nov*inv*kno*~ref	.11	.02	.98	M4. age*~gen*mar*inc*edu*hed*mng*loc*nov*inv*kno*~ref	.22	.02	.86
solution coverage: .23				*solution coverage: .33*			
solution consistency: .98				*solution consistency: .76*			
B. *peb = f(hp, op, gen,mar,age,inc,edu)*				**~B.** *~ peb = f(hp, op, gen,mar,age,inc,edu)*			
Models for predicting high score of peb	**RC**	**UC**	**C**	**Models for predicting low score of peb**	**RC**	**UC**	**C**
M1. op*hp*age*inc	.50	.09	.93	M1. ~hp*~op*age*~gen*edu	.36	.01	.70
M2. ~op*~hp*age*~gen*edu	.21	.01	.95	M2. ~hp*~op*age*~gen*mar*inc	.29	.02	.73
M3. ~op*~hp*age*mar*inc	.29	.01	.94	M3. ~hp*~op*age*~mar*inc*edu	.29	.007	.74
M4. ~op*~hp*age*inc*edu	.31	.01	.95	M4. hp*op*age*~gen*~mar*inc	.23	.01	.74
M5. op*hp*age*gen*mar	.32	.04	.94	M5. hp*op*age*~mar*inc*edu	.28	.009	.72
M6. ~op*~hp*age*~gen*~mar*~inc	.13	.01	.94	M6. hp*op*age*gen*mar*~inc*edu	.29	.13	.80
M7. ~op*~hp*gen*mar*inc*~edu	.19	.01	.96				
solution coverage: .68				*solution coverage: .64*			
solution consistency: .91				*solution consistency: .60*			

Note: RC: raw coverage; C: consistency; UC: unique coverage; *: and; ~ : negation; Peb: Pro-environmental behaviour; age : respondents' age; gen: gender; mar: marital status; inc: income; edu: education; hed: Hedonism; kno: Knowledge; inv: Involvement; loc: Local culture, mng: Meaningfulness; nov: Novelty; ref: Refreshment; hp: harmonious passion; op: obsessive passion; marital status and gender are dummy variables: 0 indicates: single and men, while 1 indicates: married, women respectively.

Table 5. Configural models of high and low scores of Peb with all the antecedents (model C and its negation).

C. *peb : f(hed, kno, inv, loc, mng, nov, ref, hp, op, gen, mar, age, inc, edu)*	RC	UC	C
Models for predicting high scores Peb			
M1. age*~gen*mar*inc*~edu*hed*mng*loc*nov*inv*~kno*ref*~op*~hp	.09	.01	1
M2. age*~gen*mar*inc*edu*hed*mng*loc*nov*inv*kno*~ref*op*hp	.10	.02	.98
M3. age*gen*mar*inc*~edu*hed*mng*loc*~nov*inv*kno*ref*op*hp	.14	.07	.99
solution coverage: 0.19			
solution consistency: 0.98			
~C. ~ *peb : f(hed, kno, inv, loc, mng, nov, ref, hp, op, gen, mar, age, inc, edu)*	**RC**	**UC**	**C**
Models for predicting low scores Peb			
M1. age*~gen*mar*inc*~edu*hed*mng*loc*nov*inv*~kno*ref*~op*~hp	0.21	0.01	0.92
M2. age*~gen*mar*inc*edu*hed*mng*loc*nov*inv*kno*~ref*op*hp	0.22	0.02	0.87
solution coverage: 0.24			
solution consistency: 0.84			

Note: RC : raw coverage; C : consistency; UC: unique coverage; ~ : negation; Peb: Pro-environmental behaviour; age: respondents' age; gen: gender; mar: marital status; inc: income; edu: education; hed: Hedonism; kno: Knowledge; inv: Involvement; loc: Local culture, mng: Meaningfulness; nov: Novelty; ref: Refreshment; hp: harmonious passion; op: obsessive passion; marital status and gender are dummy variables: 0 indicates: single and men, while 1 indicates: married, women respectively.

age, inc, edu)]. Accordingly, three recipes for high score peb and two recipes for low score PEB sufficiently describe PEB and its negation (Table 5). As an example, Table 5. C: M1. (age*~gen*mar*inc*~edu*hed*mng*loc*nov*inv*~kno*ref*~op*~hp) reveals that older, uneducated, married and wealthy males who scored high on memorable tourism experience dimensions except for knowledge but lacked obsessive and harmonious passion achieved high score of PEB. This finding is contrary to results of previous studies dominated by findings on passion having a positive effect on PEB. This is majorly due to the misinterpretations of symmetric models based on conventional methods (e.g. Afsar et al., 2016). However, in line with the results of the current study, Junot et al. (2017) report that obsessive passion negatively correlates with environmental behaviors. What is evident, however, is that passion may not be sufficient or necessary to adjust PEB. It means that people who lack obsessive passion are not necessarily opposed to behaving pro-environmentally.

Tenets of complexity theory

Woodside (2017) proposes 6 tenets to evaluate complexity theory based on the empirical data. Accordingly, a single antecedent rarely suffices to predict the desired outcome (tenet 1). Moreover, a complex interaction of the antecedents describes high/low scores of the outcome. As seen in Table 5. C: M1. (age*~gen*mar*inc*~edu*hed*mng*loc*nov*inv*~kno*ref*~op*~hp), a complex interaction of memorable tourism experience and passion predict the high score in PEB.

Tenet 3, known as Equifinality principle proposes that a recipe that sufficiently predicts the outcome, is not necessary by itself, as there are other paths to predict the same result. Accordingly, in this study, a number of recipes described the high/low scores in PEB.

Tenet 4, known as the causal asymmetry principle, proposes that the rejected outcome is unique. In this study the negation of PEB is not the mirror opposite of the high score PEB (Tables 4, 5).

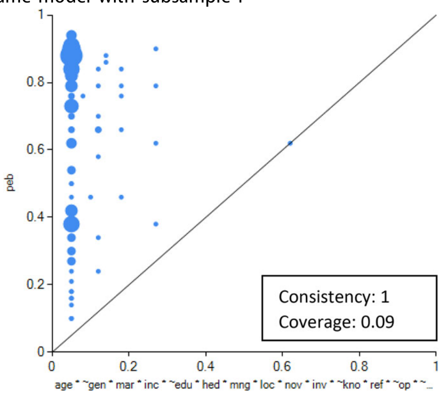
Tenet 5 propose that a single antecedent can contribute positively or negatively to predict the outcome, that depends on the other ingredients in the model. The results of the study on the other side revealed that the dualistic dimension of passion contributed to the high PEB scores both positively and negatively (Table 5).

Tenet 6 proposes that a given recipe is relevant for some, but not all cases and the coverage is less than 1. This is evident in Table 6 illustrated by the fuzzy XY plot. Therefore, as predicted

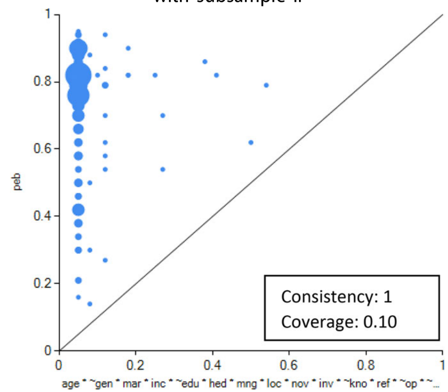
Table 6. Evidence of predictive validity on two subsamples.

Configural model		Raw coverage	Consistency		
age*∼gen*mar*inc*∼edu*hed*mng*loc *nov*inv*∼kno*ref*∼op*∼hp	0.09	1	.09	.01	1

Test of the same model with subsample I



Test of the same model
with subsample II

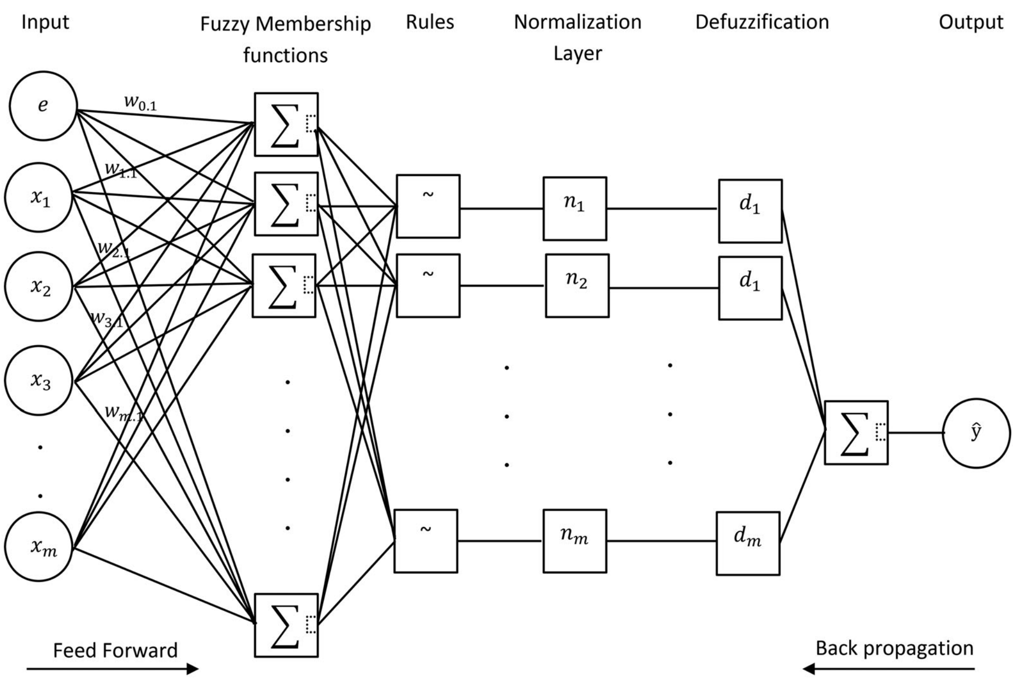


Note: The fuzzy XY plot unveils the asymmetric relationship of the causal model and provides the predictive validity.

Table 7. ANFIS sensitivity analysis results

Model	Absent	Input	Output	RMSE
Model 1	–	Hed, Mng, Loc, Nov, Inv, Kno, Ref, Hp, Op	Peb	2.0922
Model 2	Hed	Mng, Loc, Nov, Inv, Kno, Ref, Hp, Op	Peb	5.5279
Model 3	Mng	Hed, Loc, Nov, Inv, Kno, Ref, Hp, Op	Peb	6.6864
Model 4	Loc	Hed, Mng, Nov, Inv, Kno, Ref, Hp, Op	Peb	5.0278
Model 5	Nov	Hed, Mng, Loc, Inv, Kno, Ref, Hp, Op	Peb	3.3427
Model 6	Inv	Hed, Mng, Loc, Nov, Kno, Ref, Hp, Op	Peb	5.7577
Model 7	Kno	Hed, Mng, Loc, Nov, Inv, Ref, Hp, Op	Peb	2.9652
Model 8	Ref	Hed, Mng, Loc, Nov, Inv, Kno, Hp, Op	Peb	3.7893
Model 9	Op	Hed, Mng, Loc, Nov, Inv, Kno, Ref, Hp	Peb	3.4022
Model 10	Hp	Hed, Mng, Loc, Nov, Inv, Kno, Ref, Op	Peb	3.4223

Note: RMSE = root mean square error.



Note: e: error tolerance; $w_{0.1}$: weights assign by ANFIS; $x_{1,m}$: antecedents of the study, i.e. constructs of memorable tourism experience and passion; $\hat{y}$: Pro-environmental behaviour

Figure 2. ANFIS model structure.

by Kollmuss and Agyeman (2002), PEB is extremely complex and overly simplistic models may not fully predict the PEB of the visitors (Ramkissoon et al., 2012; Siegel et al., 2018).

Predictive validity

The result of the predictive validity provides further insights on the ex-ante power of the proposed model and configurations. As illustrated in Table 6, we have divided the sample to a sub-sample and holdout sample. Drawing on an instance from the result of fsQCA (Table 5), a fuzzy XY plot has been portrayed with the recipes on X-axis and PEB on Y-axis with the sub-sample (Consistency: 1; Coverage: 0.09). Later, the same configural model was portrayed using the holdout sample (Consistency: 1; Coverage: 0.10). The comparisons of the models on different samples provide evidence for predictive validity of the proposed configural model (Olya et. al., 2020).

Simulation analysis with ANFIS

Conventional methods may oversimplify the human agency process (Yadegaridehkordi et al., 2018); many researchers have thus recommended soft computing techniques (Ahani et al., 2017; Liébana-Cabanillas et al., 2017, Yadegaridehkordi et al., 2018). ANFIS integrates the cognitive dimension of human intelligence and the mechanism of reasoning with the empirical examination of the collected evidence, which allows the in-depth prediction of the future outcome. However, ANFIS was used as a complementary method in this study as it is not designed for casual relationships or conventional hypothesis testing due to its 'Black Box' operations (Liébana-Cabanillas et al., 2017). In the current study, ANFIS is performed in two ways. First, it is used to determine the most critical factor contributing to PEB. ANFIS is capable of identifying the relationships between optimal input and the output; therefore, a sensitivity analysis can identify the most relevant and critical antecedents to predict PEB (see Table 7). Second, it is used to simulate and forecast pro-environmental behavior with the sufficient antecedents retrieved from fsQCA. In this regard, the output from fsQCA was input for ANFIS further analysis.

As an information processing system ANFIS combines the power of artificial network and fuzzy inference system with a multilayer feed-forward network. The fundamental building block of the ANFIS is a single neuron known as a 'Perceptron'. Forward propagation of a perceptron in a neural network is illustrated in Figure 2.

Each input (x_m) has a corresponding weight (w_m), and the inputs have an error (e) tolerance (w_0) as well. Multiplication of each of the inputs proceeds by membership functions that provide a sum ($\sum$), then Fuzzy If-Then rules formulate the conditional statements that contain fuzzy logic. Then, through a normalization layer ANFIS defuzzifies (L) the weights and estimated errors and the final output ($\hat{y}$) is produced. By comparing the errors from the actual output, the testing data predicts the best possible solution from training data in a process called "back-propagation" where the network feed backwards in each perceptron by calculating root mean square error (RMSE). To test the performance criteria, the RMSE of predicted values of ANFIS output are compared (Karaboga & Kaya, 2019).

Therefore, the operation of ANFIS is based on nodes that are arranged in different layers. The first layer is usually the input. Then, these inputs are merged in other nodes and layers based on the membership functions. Each node is regarded as a mathematical function that performs operations on its incoming input and processes it into and generates a corresponding output. This technique facilitates various fuzzy membership function categories. To obtain the optimal category, we generated the variables with different FIS in different categories (see Table A2, appendix). Gaussian curve membership function (gaussmf) with three categories (low, medium, and high) was deemed adequate among the existing FIS to further pursue the process (RMSE = 2.0922). In the next step, the data was split into 75:25 ratios for training and testing, respectively (Abubakar et al., 2019). Ten epochs with the error tolerance of 0.05 for all the 9 inputs and one output were defined. Figure 3a illustrates the data set index for training data (O) and FIS output (*) of PEB and all antecedents.

Moreover, by excluding variables from the equation, ANFIS sensitivity analysis (Table 7) revealed that by eliminating meaningfulness (Model 2) from the equation, RMSE is significantly increasing. It indicates the importance of meaningfulness in predicting PEB. On the other hand, the model that lacks knowledge (Model 7) has the minimum change on RMSE. This means that knowledge contributes less to the overall prediction of PEB. The surface view of the highest and lowest contributor to PEB is displayed in Figure 3b.

Moreover, our comparison of different models that were extracted from fsQCA outputs demonstrates the ex-ante power of ANFIS to adequately train and predict the behaviors of visitors. It, therefore facilitates the selection of models with the best performance derived from the real-life experience in a machine learning area. To explain further, the ANFIS was tuned and run for each model derived from Table 5. The first model (C: M1) has the smallest training and testing RMSE

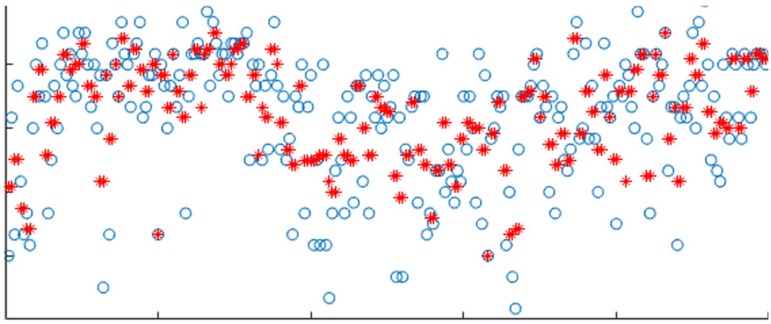


Figure 3a. Plot representing training data (O) and FIS output (*) of outcome (Peb) and all the antecedents.

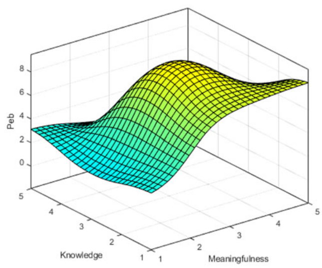


Figure 3b. Surface view of the highest and lowest scored antecedents with Peb.

compared to other models and overall performs better (training RMSE = 0.72415, testing RMSE = 1.5536) (See Table 7).

Conclusion and implications

The management of human impacts on fragile and sensitive ecological resources needs a comprehensive understanding of behaviours and their influential antecedents. Meanwhile, the study of individuals' discretionary environmentally friendly behaviours or pro-environmental behaviours continue to attract considerable attention in tourism and hospitality and other disciplines (e.g., Ari et al., 2020; Karatepe et al., 2020b; Ramkissoon, 2020; Rezapouraghdam et al., 2018). However, the majority of the studies in the tourism and hospitality literature did not use ML approach which creates a mathematical model to predict the future behavior of individuals. The trained data prepared by ML, provides a valuable information base for destination managers and policymakers to derive appropriate context-based environmental strategies that may mitigate the future environmental hazards to the environment.

Using ML to identify the combination of factors that can lead to visitors' pro-environmentally friendly behaviours in a tourism destination, the present study brings forth several methodological, theoretical and practical implications in the context of marine protected areas. Theoretically, our proposed model was designed based on the interaction ritual concept and confirmed by tenets of complexity theory. Complexity theory asserts that the interaction of tour members' MTE, EP and their demographics revive their PEB. This finding may further contribute to the body of knowledge. Although the interaction ritual (IR) concept along with its emotional energy notion provides a worthwhile tool to analyze and understand visitors' behaviors affected by their travel experiences and interactions during tours, it is an underutilized framework in tourism literature. Our study advances the application of this theory by explicating tourists' environmentally friendly behaviors in destinations and thus contributing to sustainable development goals (Ramkissoon, 2020; Ramkissoon et al., 2020). Secondly, the affirmation of our proposed conceptual model by complexity theory is an attempt to focus on the complexities of visitors' behavior in relation with environmental phenomena which have been extensively neglected in the literature because of treating such complexities through linear approaches. Our study concludes that relying on the IR concept, the interaction of members during the interpretive marine turtle tours are effective in fostering environmental passion which may promote their responsible behavior toward the environment. However, as asserted by complexity theory, the level of such environmentally friendly behaviors varies (e.g. high, low, and medium) among the members due to the interaction between their demographics and other two variables (EP & MTE).

Our study may also contribute to the application of artificial intelligence which has been identified as one of the research priorities in sustainable tourism field (Tussyadiah, 2020). Our research has attempted to advance the knowledge in the field by using AI, specifically ML techniques to predict, interpret and analyze the complexity of tourists' behaviors. Although it has been long since these technologies have been introduced (McCarthy, 2007), their application in the tourism and hospitality industry is still in its infancy and scholars have only recently started to utilize them for various predictive purposes (e.g. Al Shehhi & Karathanasopoulos, 2020; Li et al., 2020; Nilashi et al., 2019; Sun et al., 2019). Instead of fencing off visitors from ecologically valuable sites, alternative tourism with the aid of technology provides insights to manage visitors accordingly.

Destination managers can benefit from our findings in several ways. Our findings suggest the importance of optimizing the quality of tourists' experiences and make them memorable. This can be achieved through increasing the meaningfulness of their travel by emphasizing their presence as a helping factor for saving the lives of baby turtles. Professional tour guides can provide further information and enhance participants' knowledge which is an important factor in creating a memorable tourism experience. Arranging tours is a way through which tourists may experience the local culture and unique local food will be beneficial for hedonism and novelty. Moreover, the IR concept used in this study also provides implications for managers. In order to achieve a successful ritual interaction, the destination managers can increase the time participants spend together on site. Besides, the participants can be given some unique symbols such as badges, shirts or hats so that they can identify themselves as being different from other visitors. Finally, to enhance the mutual focus of attention and the shared mood the professional tour guides can be trained with a number of meditation techniques to share with the tour members before starting their turtle rescuing activities. These practices together can help the members experience more excitement and fill them with the desired emotional energy that creates standards of morality (Collins, 2004).

The technology-based prediction has the potential to reform the experience design through the information gathered from the visitors. This technique can record different aspects of an experience to offer potential benefits to managing bodies, visitors, and visiting areas. Practitioners can use ML-empowered software at destinations to predict and provide services in a way that desired and expected outcomes may best be achieved.

In other words, AI could address the heterogeneity nature of service experiences per capita to encourage predictable outcomes. Planners can produce AI-based apps to predict or calibrate pro-environmental behaviors on site. On the other hand, PEB itself is a complex phenomenon that could be reached through the interaction of different antecedents. Nevertheless, the combination of these antecedents may not be the same for different demographics. Inclusion of demographic data in the prediction of PEB unfolds unprecedented implications for managerial bodies in order to design possible personas. Moreover, an experience design with the aim of elevating PEB of visitors may be achieved through different combination of antecedents, and unless these combinations reach a certain tipping point level, self-transformation may not occur (Gladwell, 2006). This study addresses this issue by applying a state-of-the-art method i.e. fsQCA and ANFIS. Our study found three unique recipes (Table 5. C. M1-M3) addressing significant gaps in theory and practice. It is of the highest concern for tourism stakeholders to understand the underlying patterns shaping the high/low pro-environmental behavior of visitors, particularly at sensitive ecological sites. Additionally, the combination of memorable tourism experience and passion for the environment provides a unique solution to provoke tourists' PEB which has rarely been investigated in the tourism literature.

Limitations and future research

The study was limited to self-report data collected from visitors; future studies may use other psychophysical approaches in managing visitors' experience. The majority of the travellers to North Cyprus were from Britain and Germany at the time of data collection (Ataoğlu, 2019). Considering the importance of cultural backgrounds in shaping attitudes and behaviours, future research can consider including the influence of culture in promoting PEB.

Also, since the study site in the present study was limited to Alagadi beach, different study settings may provide a better understanding of managing tourism in protected areas. The equifinality principle emphasizes the existence of various recipes towards the desired outcome. Our study, however, was limited to two constructs (i.e. passion and memorable experiences). A combination of different antecedents provides more recipes to predict PEB. Future studies may include different antecedents of PEB. Moreover, measuring PEB using actual consumption patterns, or dividing the outcome to high-effort, low-effort PEB may add unprecedented value to future research. Our study was limited to data collected from visitors. Future studies would benefit from integrating other stakeholders. Finally, the limited spatio-temporal data used in this study opens an avenue to future studies to replicate the findings of our research.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

Table A.1. Results of EFA, and descriptive statistics of scale items (n = 332)

Factor	λ	Mean	Std. Deviation	Eigenvalues	% of Variance	Skewness Statistic	Std. Error	Kurtosis Statistic	Std. Error
				5.865	13.963				
OP3	.792	3.98	1.767			.004	.134	−1.056	.267
OP4	.822	4.05	1.763			.006	.134	−1.055	.267
OP6	.841	4.11	1.825			−.014	.134	−1.110	.267
OP2	.795	4.03	1.798			.003	.134	−1.067	.267
OP1	.682	3.95	1.832			.051	.134	−1.128	.267
OP5	.832	4.11	1.691			.009	.134	−.890	.267
				4.213	10.030				
HP2	.810	4.24	1.310			−.058	.134	−.269	.267
HP6	.812	4.37	1.362			−.143	.134	−.241	.267
HP4	.769	4.29	1.369			−.063	.134	−.386	.267
HP3	.815	4.27	1.422			.045	.134	−.563	.267
HP5	.869	4.31	1.406			.078	.134	−.350	.267
HP1	.938	4.29	1.384			−.029	.134	−.316	.267
				3.588	8.543				
PEB3	.906	4.98	1.288			−.533	.134	−.020	.267
PEB5	.909	4.99	1.424			−.540	.134	−.239	.267
PEB4	.931	5.04	1.339			−.423	.134	−.546	.267
PEB2	.909	4.86	1.569			−.321	.134	−.937	.267
PEB1	.875	5.07	1.284			−.432	.134	−.224	.267
PEB6	.863	5.23	1.541			−.788	.134	−.200	.267
				3.387	8.063				
Hed3	.923	4.02	.851			−.951	.134	1.198	.267
Hed2	.791	3.71	.986			−.485	.134	−.288	.267
Hed4	.839	3.81	1.012			−.615	.134	−.253	.267
Hed1	.701	3.76	.997			−.791	.134	.291	.267
				2.973	7.079				
Kno2	.744	3.49	1.070			−.408	.134	−.581	.267
Kno1	.838	3.42	1.047			−.323	.134	−.566	.267
Kno3	.824	2.90	1.027			.076	.134	−.450	.267
				2.813	6.698				
Nov2	.775	3.91	1.052			−.878	.134	.252	.267
Nov3	.813	3.56	1.209			−.443	.134	−.746	.267
Nov4	.824	3.85	1.093			−.768	.134	−.152	.267
Nov1	.850	3.24	.817			−.035	.134	.210	.267
				2.247	5.350				
Ref2	.848	3.26	.800			.141	.134	.241	.267
Ref1	.788	3.31	.878			.107	.134	.015	.267
Ref3	.838	3.29	.952			−.016	.134	−.379	.267
Ref4	.759	3.59	1.408			−.623	.134	−.996	.267
				2.114	5.034				
Inv2	.771	3.55	1.432			−.589	.134	−1.060	.267
Inv3	.826	3.58	1.358			−.605	.134	−.945	.267
Inv1	.798	3.76	1.383			−.989	.134	−.329	.267
				1.801	4.289				
Loc3	.804	3.80	1.286			−.999	.134	−.119	.267
Loc1	.735	3.87	1.304			−1.146	.134	.161	.267
Loc2	.818	3.36	.924			−1.380	.134	.891	.267
				1.139	2.713				
Mng2	.837	3.45	.910			−1.000	.134	.250	.267
Mng1	.816	3.57	1.065			−.824	.134	.119	.267
Mng3	.649	3.34	.907			−.303	.134	−.225	.267

Note: λ is factor loading coefficient; Std. Deviation is standard deviation. pebi = Pro-environmental behaviour intention; hp = Harmonious passion; op = Obsessive passion; hed = Hedonism; kno = Knowledge; inv = Involvement; loc = Local culture, mng = Meaningfulness; nov = Novelty; ref = Refreshment; All items gauged by 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5) except peb, hp and op that are ranging from Strongly disagree (1) to Strongly agree (7). Kaiser-Meyer-Olkin (KMO): .793; Bartlett's Test of Sphericity: Approx. Chi-Square: 8169.053, df: 861; Sig.: 0.000; All Eigen-values > 1; Skewness and Kurtosis provide evidence for normality.

Table A2. ANFIS best configuration for Peb according to membership function type and its category.

		Category of Membership Function	
	Member Function	2	3
RMSE Values	trimf	5.5107	2.2728
	trapmf	11.2922	9.4735
	gbellmf	7.3679	2.1002
	gussmf	5.2425	2.0922
	guss2mf	17.0251	3.0516
	pimf	39.6398	11.6474
	desigmf	47.9745	3.9697
	psigmf	47.9745	3.9697

Note: Abbreviations of member functions: Difference between two sigmoid functions membership function (dsigmf); gaussian combination membership function (gauss2mf); Gaussian curve membership function (gaussmf); generalized bell membership function (gbellmf); p-shaped membership function (pimf); product of two sigmoidal membership function (psigmf); trapezoidal membership function (trapmf); triangular membership function (trimf).

Table A3. Result of discriminant validity analysis.

	1	2	3	4	5	6	7	8	9	10
(1) Obsessive passion	**0.800**									
(2) Harmonious passion	0.260***	**0.755**								
(3) Pro-environmental Behaviour	0.163**	0.209**	**0.741**							
(4) Hedonism	0.123*	0.183**	0.076	**0.809**						
(5) Knowledge	0.080	0.027	−0.041	0.125*	**0.895**					
(6) Novelty	0.022	0.000	0.018	0.041	−0.122	**0.726**				
(7) Refreshment	−0.060	−0.065	−0.135*	0.048	−0.184**	−0.159*	**0.723**			
(8) Involvement	0.043	−0.084	−0.012	−0.037	0.174**	0.022	−0.139*	**0.873**		
(9) Local culture	−0.002	0.027	0.041	0.294***	0.014	0.042	−0.119	0.022	**0.857**	
(10) Meaningfulness	−0.012	0.082	0.061	0.625***	0.009	0.046	0.043	0.111	0.201**	**0.764**

Note: The non-diagonal elements are the correlations of the constructs along with their p-value indication while the diagonal elements (in bold) are the square roots of the Average Variance Extracted (AVE);.
***$p < 0.001$.
**$p < 0.010$.
*$p < 0.050$.