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Research Article

Analysis of Factors Affecting Tourist Spot Revisitation After Natural Disaster Calamity: A Machine Learning Ensemble Approach

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Abstract: The tourism industry provides the Philippines with trillions of annual monetary incomes. However, being a country prone to natural disasters, many tourist attractions or destinations are damaged, which causes tourists to become hesitant. This study aimed to assess factors influencing tourist revisitation behavior towards disaster-stricken attractions by utilizing an extended version of the Theory of Planned Behavior, and by predicting human behavior through the Machine Learning Algorithms (MLA) such as Decision Tree (DT), Random Forest Classifier (RFC) and Artificial Neural Network (ANN). Through the use of MLA, this study was able to provide justification of its accurate results in identifying significant latent variables. From this study's findings, feature selection using correlation analysis was a good technique for data pre-processing. Moreover, it was proven that ANN help provided better insights from the RFC results. In addition, RFC overpowered the basic decision tree, having significant differences in the output. The discussion section is arranged from the most to the least important variable. A total of 1,008 Filipinos voluntarily answered an online questionnaire that consisted of 45 questions, leading to 45,360 datasets. With 97.86% and 96% accuracy rates for ANN and RFC, respectively, hedonic motivation was the most important factor affecting tourists' revisitation behavior. It may also be posited that the other significant contributing factors are intention, perceived behavioral control, and media. Interestingly, tourists' hedonic motivation relatively outweighed their disaster concern, and DT did not achieve accurate results as it only had an undesirable 56.97% accuracy rate. Finally, the managerial insights provided in this study could be applied and extended to tourism industries in different countries. Likewise, the MLA and its implications seen in the study may be considered for predicting other behavioral intention studies that aim to assess tourism for other tourist attractions.

Keywords: artificial neural network, behavioral intentions, decision tree, random forest classifier, revisitation, tourism

MSC: 03C45, 05C05, 62M45, 62M45

1. Introduction

Tourist spots are essential in the development of a country. According to Yehia [1], it provides increased monetary income and a steady source of employment, and it propagates cultural exchange between foreigners and natives. In an age

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where global competition is prominent, tourism gives the country an edge to keep up and remain economically stable. For instance, Yehia added that in Australia alone, around 22,000 people are employed in the tourism sector of a population of 4 million. This shows that tourism plays a huge role in a country's economic welfare. Aside from this, it is also essential in its sustainable development since it not only raises awareness but also encourages the conservation and enhancement of terrestrial ecosystems and biodiversity that people pay to visit [2]. Hence, tourism also directly or indirectly contributes to the Sustainable Development Goals (SDGs) the United Nations prescribed for its member nations. In particular, it has been listed as a target in Goals 8 (inclusive and sustainable economic growth), 12 (sustainable consumption and production), and 14 (sustainable use of oceans and marine resources) [2].

Approximately 80 million international visitors traveled to the United States, and 2 billion domestic trips were made in the country last 2019, contributing nearly $240 billion to the American economy and establishing the country as the global leader in revenue from international travel and tourism [3, 4]. Travel and tourism, the leading services export for the United States that year, generated a $53.4 billion trade surplus and supported 1 million employees in the United States. Similarly, it was also Australia's top services exports from 2017 to 2018, driving international travel spending to a new high of $42.5 billion [5]. Another country that significantly benefits from its tourism sector is Italy, which earned 162.6 billion euros from the 27 million international tourists and 37.2 million Italians who visited the various destination spots in the country last 2021 [6, 7]. That being said, the Philippines is another popular vacation destination known for its tourist spots [8].

The Philippines is widely known for its numerous tourist attractions that help its economy grow. The country is home to an estimated 240 national parks and landmarks, where at least 1.48 million international tourists flock yearly [2]. From recent reports, the country obtained Php 2.48 trillion just in Tourism Direct Gross Value Added (TDGVA) alone, which amounted to 12.7% of the country's gross domestic product (GDP) in 2019 [9]. However, being a country prone to natural disasters, many of these tourist spots have been at risk of being damaged. Ong et al. [10] and Kurata et al. [11] expounded on this issue-as they stated that the Philippines is centered around a ring of fire, which results in continuous damage due to natural disasters almost yearly. Thus, the exploration for tourist spot visitation should be considered-especially after natural disasters have hit it to help and continue the economic growth. This is especially important since the tourist gross value promotes and help the economy of the country. Evidenced in several studies [10, 11], it could be implicated that significant damage are seen on the different areas struck by natural disasters. Therefore, to continuously fix and promote this, one solution is to promote and highten the tourism aspect of the country. A part of which is the promotion of tourist spots even after a natural disaster, which can be connotated as unattractive after disastrous events [12]. Cahigas et al. [12] implicated that the socioeconomic status of people (for example, local tourists) affects their intention since recovery is still in progress. Moreover, cultural factors may also come into play, and that the thought of being recently struck by a natural disaster could be dangerous-affecting the psychological aspect of tourists [10].

Studies concerning tourism, visitation, and actual behavior have been covered. These studies have been focused on actual behavior, which is an individual's response to a stimulus given by their environment or intention [13, 14]. Verma and Chandra [15] considered the three variables related to young Indians' intentions to visit an eco-friendly hotel. Meanwhile, Pahrudin et al. [16] studied tourists' behavior and willingness to visit post-pandemic Indonesia. Both studies utilized the Theory of Planned Behavior (TPB), which is commonly used to assess person's intention to engage or participate in a specific behavior at a particular time and place. TPB is utilized to accurately predict and analyze how each behavioral variable relates to each other [17, 18]. Furthermore, the actual behavior in this framework is determined by attitude, subjective norms, and perceived behavioral control, which are defined as the degree of favor or disfavor of an individual's behavior, the individual's perceived difficulty or ease of acting, and the extent to which an individual believes a behavior can be controlled respectively [17, 19, 20].

However, the studies utilized an extended version of this theory while analyzing actual behavior toward tourism or visitation. Researchers usually resort to this process, as the theory is heavily criticized for having limited variables that describe behavior influences [21]. Verma and Chandra [15] added the variables of moral reflectiveness and consciousness to supplement why eco-friendly attitudes are developed among their respondents. Meanwhile, Pahrudin et al. [16] included specific factors such as intention to visit, perception of COVID-19, non-pharmaceutical intervention, health consciousness, and health-related change intention, which the researchers claimed to affect visitation behavior. The studies employed questionnaires to gather data from their respondents, which were analyzed using covariance-based Structural Equation Modeling (SEM) and Structural Equation Model-Partial Least Squares (SEM-PLS), respectively.

Structural Equation Modeling (SEM) refers to a set of methodologies that utilize smaller numbers of structural parameters defined by a theoretical model in representing hypotheses regarding the means, variances, and covariances of gathered data [22]. Because of this, it is usually employed in social and behavioral sciences, where testing models usually involve numerous variables. However, hypothesized relationships between personal benefits from tourism, development, perceived negative impacts, and overall tourism satisfaction were all rejected [23]. Studies such as Hwang et al. [24], Pourmand et al. [25], and Verma and Chandra [15] did not utilize this, since they claimed that SEM provides nearly similar results every time [26]. Consolidating the related studies, the research gap is highlighted on studies solely using the TPB model in assessing actual behavior. Therefore, there is a need to extend this for holistic assessment. In accordance, the tool used are limited with the calculation, path analysis, and some implicated that larger models may results to lower accurate output. Thus, the need to assess the complexities using machine learning could result to better estimation and calculation.

The objective of this study was to assess factors influencing tourist revisitation behavior towards areas recently struck by natural disasters considering an extended TPB. Specifically, factors such as response of government, disaster effect concern, media, and hedonic motivation were analyzed simultaneously using Machine Learning Algorithms. Random forest classifiers and artificial neural networks were considered tools to analyze the non-linear relationship of the different latent variables. Ong [27] indicated how these two algorithms might be capitalized on when assessing factors affecting human behavior. It was identified how these different tools might support the analysis and findings of human behavior with much better accuracy as compared to the traditional multivariate tool like Structural Equation Modeling (SEM). In accordance, related studies have also proven that the use of classification techniques under machine learning algorithms enables the analysis of nonlinear relationships, multiple path analysis, and larger models with higher accuracy rates. Specifically, this study wanted to answer several research questions:

1. Does the extended TPB provide a more holistic and comprehensive analysis of revisiting behavior?
2. What are the main contributing factors affecting revisition behavior?
3. Would random forest classifier provide higher accuracy rate than the basic decision tree?
4. Can the neural network analysis classify the different variables considered?
5. What implications could be suggested, both on the theoretical and pracitcal standpoint, in relation to the study output?

Numerous studies have examined the disadvantages of using SEM. One such disadvantage when using SEM is that the model should fit the analysis and be represented by proper data collection to give a meaningful interpretation [27]. The researchers may address this issue by testing the model each round, yet, the approach is model generating rather than model testing. It is convenient for studies that call for the addition of variables, such as the case in the extended TPB of the current study. Although SEM is criticized as a poor tool in explanatory cases that have numerous variables and non-existing or weak substantive theory [28]; indeed, Tomarken and Waller [29] stated that simultaneously including numerous relationships in SEM models is computationally intensive due to iterative algorithms (i.e., testing the model each round). This may lead to estimation problems, such as the Heywood case, wherein parameter estimates do not make sense. Aside from that, Al-Emran et al. and Fan et al. [30, 31] also expounded on the possibility of SEM presenting an insignificant and limitable latent result as a product of its path and indirect effects. It was added that the outcome may present low to no significance by how the latent variables are connected. As outlined by Woody [32], the impairment of the multivariate analysis may be due to the mediating factors present in the model. With that, Al-Emran et al. [30] have explained that simplification of the model is a decision researchers could make to have an acceptable model. However, this scenario may not always be applicable if an extended analysis is the objective of the study. In line with this, Kheirollahpour et al. [33] provided further justifications for adopting neural networks and other machine learning algorithm (MLA) methods to address the aforementioned limitations of SEM and accurately predict and analyze human behavior [10, 34].

This study's outcome will reveal what affects tourists' intent and behavior to visit a tourist attraction (such as Taal Volcano) that was recently struck by a natural disaster. Hence, it will provide the opportunity for the tourism industry to palliate its losses through promotional efforts aligned with the study's findings. This may serve as the theoretical framework for future research studies for improving marketing and post-recovery tactics aimed at increasing tourism rates in tourist destinations that were recently stricken by a natural disaster.

This paper is organized as follows: (1) the first section presents the introduction, highlighting the background and problem, research gap and need for study, and the objectives and significance of study, (2) conceptual framework and related studies, (3) methodology and algorithms, (4) results and interpretation, (5) discussion, implications, and limitations for consideration of future works, and (6) conclusion.

2. Conceptual framework

Since this study is aimed at evaluating people's intention to revisit tourist spots after a natural disaster, the Theory of Planned Behavior (TPB) is used. The TPB's purpose is to understand and foresee human behavior [19]. It is used to measure an individual's intention, which leads to the development or manifestation of actual behavior. The theory proposes that people's actions are determined by three domains: attitude, subjective norms, and perceived behavior control, which affect a person's intention and actual behavior [17].

In the tourism industry, the TPB has been utilized to predict people's intentions of visiting a particular place. Pahrudin et al. [16] investigated tourists' behavior and their willingness to revisit post-pandemic Indonesia. However, the authors claimed that the theory in itself is insufficient in explaining the willingness of the tourists surveyed. Hence, to accommodate more specific influences, their study extended the TPB framework, which hypothesized that the perception of COVID-19, non-pharmaceutical intervention, health consciousness, and health-related change intention play a role in tourist behavior.

Moreover, Tommasetti et al. [21] analyzed customers' perceptions of restaurants' sustainability using the TPB. However, the TPB has gained criticism because of its poor predictive efficacy because of the limited number of variables explaining why an individual participates in a given behavior. Because of this, the study extended the TPB with more variables influencing behavior, such as perceived usefulness and curiosity. Likewise, Verma and Chandra [15] also extended TPB to predict Indian adolescent consumers' ecohotel visit intentions. The addition of moral reflectiveness and conscientiousness as latent variables were used as an antecedent to attitudes, subjective norms, and perceived behavior as it supplements the development of eco-friendly behavior. Furthermore, the study reported that the extension is a more dominating factor between the two antecedents, allowing them to conclude that favorable attitude among Indian youths and moral reflectiveness influenced their visitation behavior.

With the different studies, an extended TPB was utilized in this study to assess factors affecting the revisitation of tourist spots after a natural disaster. Presented in Figure 1 is the extended theoretical framework considering the main domains of TPB, response of government, disaster effect concern, media, and hedonic motivation. The theory is significant to this study as it maps how different factors may influence an individual's decision or behavior toward revisitation.

Response of the government pertains to the various actions and measures taken by local and national government units to influence the operation of an industry. In the case of natural disasters, government agencies usually are tasked to intervene and aid-stricken locations. This can be seen through the allocation of resources, training of individuals, distribution of monetary subsidies, and others [35]. Ganzon-Ozaeta [36] reported that the Batangas local government developed promotional plans to reignite visitor interest in Taal Volcano tourism following the eruption; capability-building programs and skills enhancement were also implemented to speed up the area's post-disaster rehabilitation. Additionally, Javier and Elazigue [37] stated that activities similar to the mentioned projects are required by law, as stated by Section 17 of Republic Act No. 7160. Ong et al. [10] expounded on the need among governing units and the community to initiate efforts on mitigation for disaster-risks. Hence, it was interpreted that government response could affect people's disaster effect concerns, as these activities can be directly experienced or witnessed by the public. From this, it was hypothesized that:

H1: *Response of the government affected disaster effect concerns which may lead to actual revisitation.*

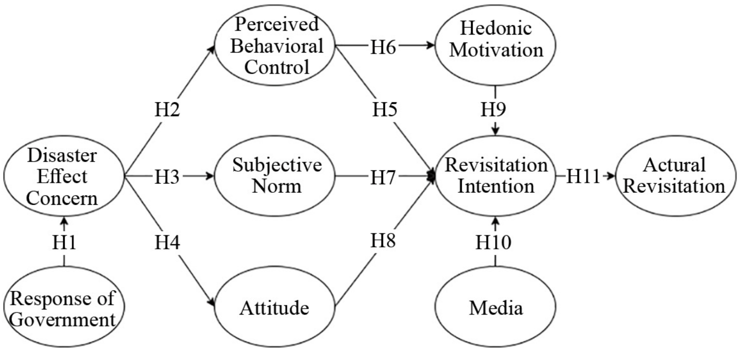

Figure 1. Theoretical framework of the study (* Legend: H-hypothesis)

Since the efforts exerted by the government may strengthen the positive evaluation of tourists visiting an establish tourist spot [36], it can be inferred that perceived behavioral control may be involved. Perceived behavioral control is the extent to which an individual believes a behavior can be controlled [19]. In an integrative medicine study by Shamblen et al. [38], the intention of an individual are preceded by the perceived behavioral control. Moreover, established TPB studies have also presented how this latent affects a person's intention and actual behavior. Hence, it can be proposed that perceived behavioral control is capable of affecting the intention of an individual to perform a behavior, even in precarious situations [10, 39]. This study therefore hypothesized:

H2: *Disaster effect concern affects perceived behavioral control, which may lead to actual revisitation*.

An established vital concept regarding how an individual's post-disaster intention to visit a specific location has been proven to be an essential initiator of the decision-making process for revisiting a particular tourist destination [40]. On the other hand, attitude is defined as a cognitive aspect that considers the degree of favor or disfavor of an individual's behavior [17]. According to Cherry [41], it has a stalwart influence over behavior and how people act in particular situations. Now, when disaster concerns are addressed by the government, for instance, the restoration of infrastructures and rehabilitation of tourist areas or facilities in an area, which possibly affects attitude of individuals related to their geographic location. Given that these interventions are actual events one can witness, disaster effect concerns can be attributed to their individual attitudes. In accordance, the awareness of an individual for intervention of post-disaster have been explained to provide significant effect on subjective norm. According to Zou and Yu [42], tourists consider destination safety and security when visiting areas, especially overseas. Lai et al. [43] stated a similar idea where it is observed that tourists tend to consider locations that guarantee personal safety. Thus, it could be hypothesized that:

H3: *Disaster effect concern affects subjective norm, which may lead to actual revisitation*.

H4: *Disaster effect concern affects attitude, which may lead to actual revisitation*.

Ajzen [17] and Liu et al. [20] referred to perceived behavioral control as the individual's perceived difficulty or ease of performing an action. Similar to the variable attitude, much literature discovered that perceived behavioral control has a significant and positive direct effect on individuals' intentions [20, 44]. To support this, Joo et al. [45] assessed important factors that affected the potential behavior of rural tourism tourists by expanding the TPB model. It was discovered that perceived behavioral control influenced the intent of the tourist concerning rural tourism. Hence, it was hypothesized that:

H5: *Perceived Behavioral Control affects revisitation behavior, which may lead to actual revisitation*.

Hedonic motivation is the willingness to engage in acts that increase pleasurable or positive experiences and lessen unpleasant or negative experiences. Hedonic motivation also plays a huge role in online communities; for instance, some individuals who do not know each other tend to post an excessive amount of information and advice compared to other individuals in online communities [46]. By connecting with like-minded people and exchanging information and experiences, online communities can satisfy hedonic needs by offering amusement and enjoyment value [47]. Moreover, people intending to utilize various components of the online environment might be influenced by the satisfaction they believe they can derive from certain online acts that can motivate others to do what others desire [48]. Therefore, it was expressed that:

H6: *Perceived Behavioral Control affects hedonic motivation, which may lead to actual revisitation.*

According to Abbasi et al. [49] study, which aims to find factors that influence tourists' revisit intention, an individual's negative or positive attitude can affect the intention to perform the behavior. Moreover, in terms of tourism, they added that many studies had found a notable positive relationship between attitudes toward a visitation of a specific destination and intentions to visit the said destination [49–52]. It was highlighted by Ong et al. [10] that attitude toward the behavior affects a person's negative intention for self-protection. Similarly, German et al. [53, 54] and Kurata et al. [11] presented similar findings. Likewise, Ham et al. [55] defined subjective norms as being determined by the perceived social pressure from, in this case, the tourist's peers or family for the tourists to behave in a particular manner to comply with the views of their peers or family. According to Mohammed et al. [56], subjective norms may judge the social pressures on individuals, whether they will perform or not to perform a behavior, which is considered the intention. The following hypotheses were therefore created as:

H7: *Subjective norm affects revisitation behavior, which may lead to actual revisitation.*

H8: *Attitude affects revisitation behavior, which may lead to actual revisitation.*

This study represented media as everything from printed paper to digital data, such as art, news, educational content, phones, television, the Internet, and anything that can reach or influence people [57]. According to Tarannum [58], the presence of media is able to influence an individual's perception of engaging in a particular behavior related to consumerism and tourism, as marketing strategies employ e-marketing or e-advertisments evident nowadays. Javed et al. [59], which explored the media's effect on Czech Republic tourism showed how media as a latent variable affects behavioral intention and actual behavior. From Liu et al. [20], it was found that the extensive utilization of social media has subsequently allowed tourists to refer to these sources for their travel choices regarding destination, accommodation, and budget, among others. Moreover, in the scope of destination safety, media further contributes to an individual's positive perceptions of the location [42]. This suggests that the presence of media can influence an individual's intention to visit. While hedonic motivation refers to an individual's aim to experience pleasure, it is also defined as the willingness to display behaviors that enhance a positive experience and behaviors that decrease a negative experience [60]. Shanmugavel and Solayan [61] found that motivation directly influences an individual's intention to purchase eco-friendly products, which led to the development of:

H9: *Hedonic motivation affects revisitation behavior, which may lead to actual revisitation.*

H10: *Media affects revisitation behavior, which may lead to actual revisitation.*

According to Ajzen [17], intentions are thought to reflect the motivating variables that influence behavior. They demonstrated people's willingness to try or how much effort they plan to exert to do the behavior. Generally, the higher the desire to engage in an activity, the more likely its performance. Actual revisitaton in this study is the actual behavior reflecting the study of Ajzen [17]. That is, whether people would actually visit the place after the natural disaster, assured they will go if they would want to, have the resources and means, and would consider the place because if its tourist destination tag. Studies such as that of German et al. [53] presented that an individual's intention positively and directly affects their actual behavior. It was explained that green behavior affected the high positive aspects of actual behavior among individuals upon considering packaging-which was also related to buying behavior, buying activities, and green activities. Therefore, this study was able to suggest that:

H11: *Revisitation intention affects actual revisitation.*

3. Methodology

3.1 *Participants*

For this study, an online questionnaire was developed which was distributed through different Filipinos using Google forms among different available social media platforms. The slow progression of health restrictions for the COVID-19 in the Philippines led to the online distribution in this study. However, such a data collection method is still sufficient, as shown by similar behavioral studies conducted online, such as that of Ong et al. [10] and Pourmand et al. [25].

To obtain respondents for the study, the non-probability sampling method was utilized [62]. To be more specific, the researchers used convenience and snowball sampling techniques, as they are often used in a broad spectrum of research due to their cost-effectiveness, with respondents chosen because they are "in the right place at the right time" [63]. Furthermore, the techniques' advantage of being able to gather more respondents was considered for generalizability (since there was no quota set for the number of respondents and the population variability could not be determined), as suggested by Memon et al. [64]. This study was approved by the Mapua University Ethics Committee (FM-RC-23-01-81). In addition, consent form was obtained among respondents (FM-RC-23-02-81).

Most of the respondents were between 25-34 years old (38.5%) with 63.2% high school degrees or 20.3% with college degrees, while the rest were graduates (16.5%). The rest of the age group represented 21.6% between 35-44 years old, 7.04% for 46-64 years old, 0.30% for older than 64 years old, and the rest were 24 years old and below (32.56%). The data presented that most respondents were unemployed (68.0%), while 6.09% were employed, 25.09% were students, and the rest were unemployed (0.82%). However, evidently, 92.14% were considered as they were the ones able to revisit travelled destination which are attributed to the needed respondents of this study. The data was collected from December 2021 until April 2022, during the time when the abrupt volcanic eruption in the Philippines happened. The questionnaire considered was adapted from Laws [65] and Kurata et al. [11] for the response by the government. Disaster effect concern considered the studies of Genç [66] and Kurata et al. [11], while TPB domains were from the established study done by Ajzen [17] in the study of Kurata et al. [11]. The hedonic motivation latent variable was adapted from Seabra et al. [67] and media from Ong et al. [10], considering five items each.

3.2 *Data pre-processing*

The first step was scanning for missing data utilizing SPSS 25 prior to the MLA application. No missing data was found following the assessment and considered the dataset as ordinal types. A correlational analysis was then conducted to remove insignificant indicators as the feature selection technique following related studies [27, 53]. All items were deemed to be significant with their coefficient within 0.20 and 0.05 p-values [53]. Data aggregation was utilized by researchers to collect data and gain relevant insights. There were a total of eight main attributes created to represent the MLA input (hedonic motivation, revisitation intention, perceived behavioral control, attitude, media, subjective norm, disaster effect concern, and response of government). In accordance, the data was done by overseeing the average of different variables. The measure items in actual revisiting behavior was re-scaled to represent the class, the output variable of the MLA. After which, data normalization was performed using Python's Spyder 3.8 using the min_max_scalar and various MLAs were implemented to classify and examine the factors affecting the revisitation behavior of tourists; for ANN implementation, MATLAB was considered. The min_max_scaler data normalization was employed to make sure that the dataset considered in running the MLA creates an equal contribution representing each feature [68]. A total of 45,360 data points from 1,008 respondents and 455 measure items were considered in the analysis of this study.

3.3 *Decision tree*

The researchers utilized a tree-based classification model, which are decision trees (DT), to classify determinants of variables [69]. In this study, revisitation behavior served as the dependent variables which was considered as the DT's class. In an attempt to evaluate the outcomes, the different indexes for the output were used (i.e., entropy and Gini). The Gini (Equation (1)) measures impurities and determines the coherence of nodes generated in the DT model [70].

$$\mathrm{Gini}(t) = 1 - \sum_{j}^{t} [p(j|t)]^2 \tag{1}$$

where p in $p(j|t)$ is the proportion probablity of data points taking a value in the node, j, belonging to t.

On the other hand, the Entropy index was calculated, which is used to predict the optimal hierarchical DT structure-similiar with Gini. According to Milani et al. [71], the result would represent the variable which helps predict human behavior that is highly accurate. This is because this type of DT does not require assumptions or setup upon subjecting to machine learning.

$$\text{Entropy}(t) = -\sum_{j}^{t} p(j|t) \log p(j|t) \tag{2}$$

where: p in $p(j|t)$ is the proportion probablity of data points taking a value in the node, j, belonging to t.

According to Topîrceanu and Grosseck [72], the classification tools under MLA, which are DTs, consider the pattern linked between different factors to classify only the variables that are significant correlating to the dependent variable. Moreover, DTs have been utilized to assess taget variable in terms of assessing human behavior. It was presented how this algorithm provides a simple yet powerful optimum output in classifying human behavior [27, 53, 71]. Aside from the criterion utilized, the splitter of tree (random or best) and testing ratios were determined to provide the suboptimal DT with RFC output. From the optimization process, 100 iterations for every combination was done. As suggested by Aning and Pryzbyla-Kasperek [73], the utilization of criterion (entropy or Gini) could be employed and the output would be based on majority voting. That is, either of the criterion could be considered and is dependent on the dataset available for accuracy rate. Therefore, there needs to be an iterative process for the optimum classifier output to results, which coders could determine from each run [27]. Moreover, standard splitting of training and testing ratios and depths were considered, avoiding under(over)fitting; and that splitters (best or random) were adopted from scikitlearn algorithms of DT and RFC.

3.4 *Random forest classifier*

RFC is employed to display the DT that has higher accuracy rate of prediction and classification model as it creates ranges of branches, determining the best output every iteration compared to the basic DT [74, 75]. Therefore, RFC could be utilized as a better predictive model [75]. As evident from the mentioned study, RFC provides higher accuracy rate therefore, the applicability of RFC in the present study was considered. Since this was set to be a bechmark study, the comparison between the implicated algorithms were tested. That is, if RFC accuracy is really higher than DT among tourist behavior activity analysis. Following the study of Ong [27], the parameter optimization from the basic DT were similar for this MLA.

3.5 *Artificial neural network*

Artificial neural network is an algorithm that simulates how biological neurons process information and deliver the signaling message to the human brain [76]. The inspiration of this brought about mathematical function for optimized analysis [77], leading to the development of the machine learning algorithm for (but not limited to) pattern recognition, classification, forecasting, and robotics control. This was utilized as a predictive machine learning algorithm tool in the studies of Liébana-Cabanillas et al. [78] and Kalinić et al. [79]. Specifically, the two aforesaid studies utilized this to predict human behavior. Moreover, Kheirollahpour et al. [33] also elaborated on how nonlinear and complex relationship models may be easily identified when artificial neural network is used-presenting lower error rates and high classification model accuracy outputs.

This study employed a feed-forward process with activation functions, and the optimizers used for the optimization of the artificial neural network were specifically considered through different works of literature. Subsequently, an initial run was conducted to determine which among the activation functions would fit the data. MATLAB R2021a using the Levenberg-Marquardt Algorithm was considered to run the neural network [80]. This was said to have higher predictive power and accuracy compared to other ANN algorithms (e.g., Bayesian Regularization and Scale Conjugate Gradient). In accordance, several iterative runs using different training, validation, and testing ratios of 75 : 10: 15, 80 : 10 : 10, and 90 : 5 : 5 were employed with 30 iterations each. All output were considered and the best would present the optimum ANN [80].

4. Results

4.1 *Decision tree*

Performing initial optimization for the basic decision tree, all combinations of parameters were iterated. From the results in Table 1, the highest accuracy rates were evident in the best splitter and Gini criterion at 7 tree depth. However, a 56.97% accuracy rate would still be regarded as undesirable as other classification techniques, or ensembles can provide higher accuracy rates [54].

Table 1. Decision tree summarized accuracy results

Train/Test split	60 : 40	70 : 30	80 : 20	90 : 10
Random				
Entropy accuracy score	47.53	46.98	49.94	48.56
Standard deviation	3.492	4.398	4.387	5.976
Gini accuracy score	48.56	48.24	50.03	48.29
Standard deviation	3.698	4.741	4.776	5.807
Best				
Entropy accuracy score	45.88	45.13	43.71	30.74
Standard deviation	3.089	2.209	1.385	1.672
Gini accuracy score	51.94	51.86	56.97	54.22
Standard deviation	0.835	1.560	2.782	1.776

4.2 *Random forest classifier*

With the 56.97% highest accuracy rate produced by the basic decision tree, this study opted to consider the random forest classifier to provide the optimum classification model. As presented in Table 2, the consistent parameters of best and Gini are seen. From the output, 96% had the highest accuracy rate. However, depth 5 presented the optimum tree compared to depth 7 of the basic decision tree. In accordance, this combination provided the best output at any training and testing ratios. Presented in Figure 2 is the optimum decision tree utilizing a random forest classifier.

Table 2. Random forest classifier summarized accuracy results

Train/Test split	60 : 40	70 : 30	80 : 20	90 : 10
Random				
Entropy accuracy score	82.00	79.42	82.71	85.60
Standard deviation	5.313	6.512	7.032	5.074
Gini accuracy score	82.65	80.15	82.06	84.12
Standard deviation	4.124	4.032	6.302	5.897
Best				
Entropy accuracy score	83.18	84.97	89.43	92.00
Standard deviation	1.224	0.710	0.497	0.000
Gini accuracy score	88.63	84.06	92.45	96.00
Standard deviation	0.998	1.003	0.500	0.000

From the results, it could be deduced that Hedonic Motivation, Media, and Disaster Effect Concern influenced a person's Perceived Behavioral Control for Actual Revisitation in the revisitation of a tourist spot after a natural disaster. To further validate the findings and classify other influential factors, an artificial neural network was employed. German et al. [53] and Ong [27] suggested that other MLAs should be considered to support random forest classifiers as this only produces the most influential factors and neglects other latent variables.

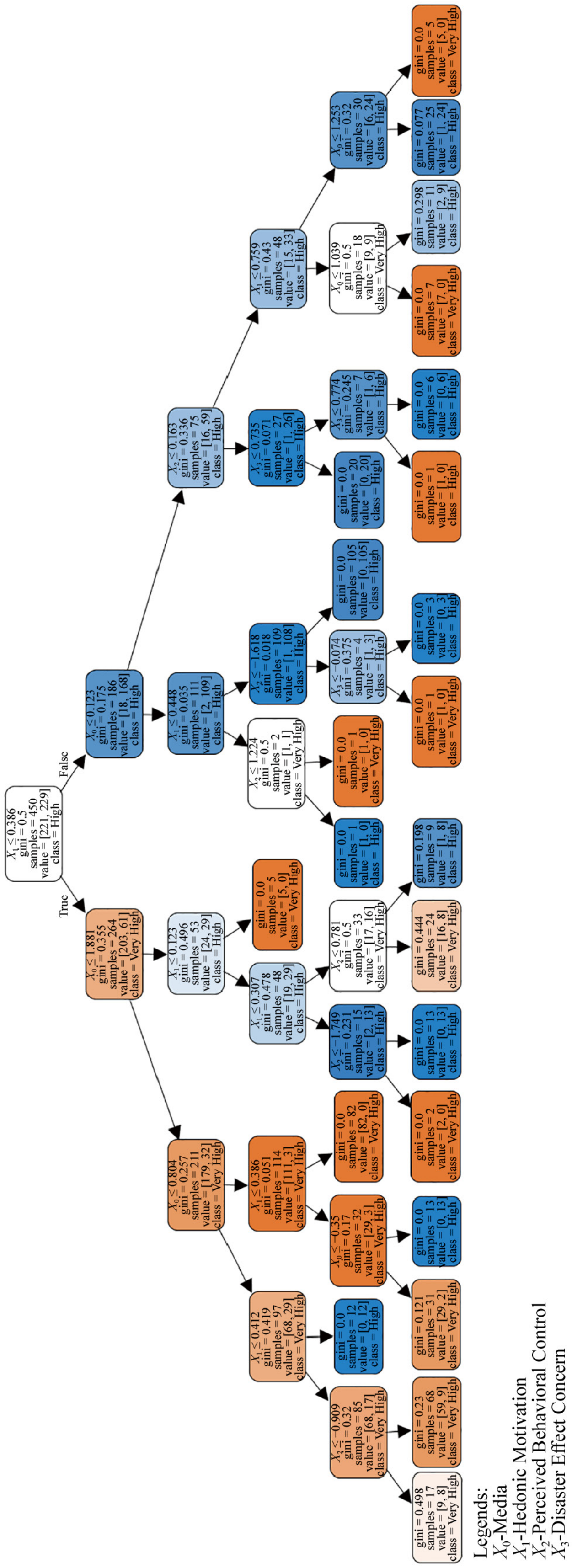

Figure 2. Optimum decision tree with random forest classifier

4.3 *Artificial neural network*

For the artificial neural network, the parameters that presented the best output are 75% training, 10% validation, and 15% training datasets. At 30 nodes in the hidden layer from the 8 input variables and 1 output layer node-all connected on each node, low MSE scores were obtained as 0.372826 on the training, 0.129818 on the validation, and 0.537293 on the testing results. It could be deduced that the high *r*-squared value obtained deemed the analysis as highly acceptable. Presented in Figure 3 is the optimum neural network, followed by Figure 4-the *r*-squared results.

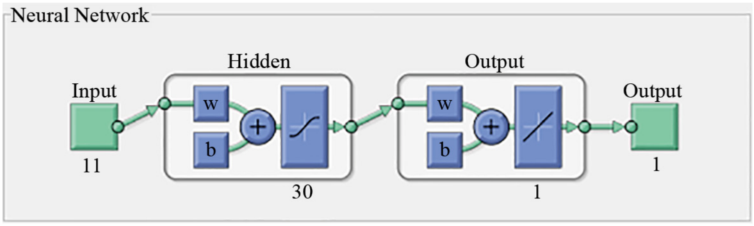

Figure 3. Optimum ANN model

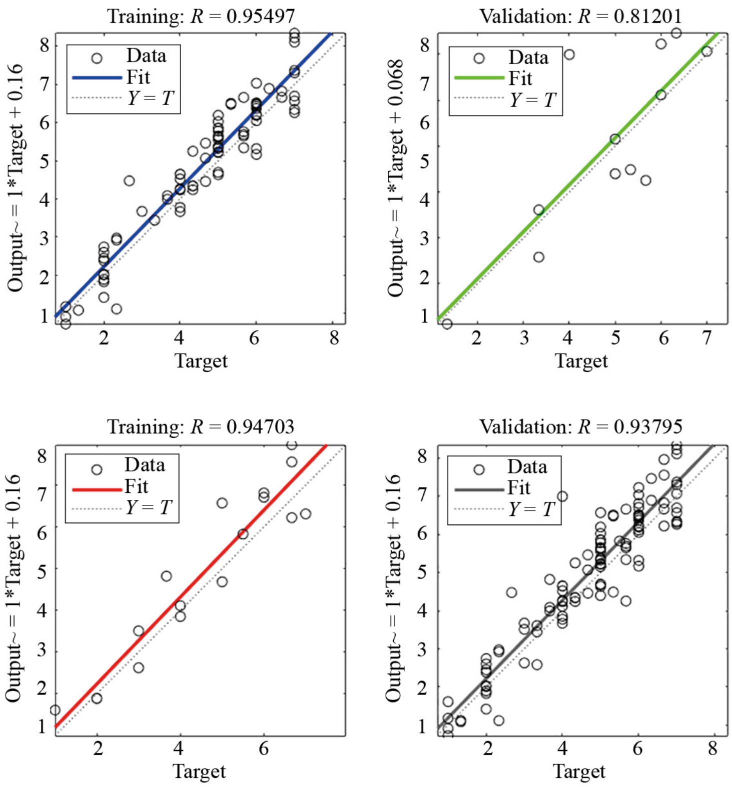

Figure 4. Validation result

From the results, similar findings of highly significant factors from the random forest classifier are seen. Hedonic Motivation, Intention, and Media played significant factors that affected Perceived Behavioral Control towards people's actual behavior to revisiting a tourist destination after a natural disaster. Other factors were also deemed significant, which was verified using the normalized score of importance. Disaster Concern, Attitude, and Subjective Norm, with Government Response as the least significant latent variable, were evident from the result. Presented in Table 3 are the summarized score of importance using the Shapley Additive Explanations (SHAP) Package [53]. This was utilized as a python package since it presents the optimal credit allocation (normalized importance) and their local extension of allocation (importance score) through game theoretic approach. Further discussion of the significant findings is explained in the succeeding section.

Table 3. Normalized score of importance

Factor	Abbreviation	Importance	Normalized importance
Hedonic motivation	HM	0.202	100.0%
Revisitation intention	I	0.198	97.8%
Perceived behavioral control	PBC	0.192	95.2%
Media	M	0.186	92.3%
Disaster effect concern	DC	0.182	90.1%
Attitude	A	0.175	86.7%
Subjective norm	SN	0.170	84.2%
Response of government	GR	0.143	70.6%

5. Discussion

The results showed that the highest contributing factor to tourists' actual revisitation behavior (AB) for revisiting a tourist spot after a natural disaster was HM (100%). From its indicators, the tourists thought revisiting the stickened tourist area would be an enjoyable and effective stress-relieving experience. They also thought that the activities they could do would emotionally stimulate their well-being and evoke enjoyment and relaxation. Based on the findings, the tourists are highly motivated to revisit an area, which affects their AB towards revisiting the said tourist spot. Indeed, Soebandhi et al. [81] found that an individual's hedonic motivation plays a role in determining their intention to purchase a product on the social media platform Instagram. In line with this study, Cahigas et al. [82] stated that HM has the highest direct effect on travel intentions, which affects AB since I has a significant effect on AB during the COVID-19 pandemic among Indonesian tourists. This finding is also supported by the study of Luo et al. [83], which showed a direct and positive relationship between hedonism and revisit intention among tourists in Macau. According to Sørensen and Jensen [84], tourists always look for a pleasurable experience, making tourism experience-intensive despite circumstances as long as safety is available.

As for I, it was also seen to be a highly significant latent variable (97.8%) that affects tourists' AB toward revisiting a tourist spot that was severely affected by a natural disaster. It indicates that the tourists intended to visit the tourist spot, spend their vacation touring, showcase the beauty of the tourist spot to their colleagues, and invite their friends and family to visit it someday despite the natural disaster. It also indicates that the tourists planned to visit the tourist destination to help rebuild the tourism industry in the area. The finding of this study showed that tourists have the intention to visit disaster-sticken tourist spots for varying reasons that make them want to revisit, affecting their PBC. Generating intentions leads to actual visits toward their desired destination [85], and travel intentions directly influence actual visitation (which serves as their AB).

PBC was also seen to be a significant variable (95.2%) that determines AB. Based on its indicators, tourists knew the protocols and precautionary measures necessary to handle the risks of visiting a tourist spot after a natural disaster calamity. Thus, they were confident in their decision and ability to visit the tourist destination safely. Indeed, results showed that the surveyed population is willing to revisit and is aware of the risks and protocols to be exposed to and followed upon visiting the area. Moreover, the variable was shown to significantly affect I, similar to the results gathered in the study of Verma and Chandra [15], which proved that PBC was positively and significantly related to young consumers' green hotel visit intention. This is due to the tourists' positive perceptions of the location and its activities, reinforcing that they will visit the area. In AL Ziadat [86], PBC was also found to impact intention regarding tourist revisitation in Jordan directly, and according to the study, this would subsequently affect AB.

M was also a significant factor (92.3%) affecting the AB of tourists toward revisitation of a disaster-stricken tourist destination. Its indicators show that tourists have seen social media advertising materials showcasing and promoting post-disaster stickened tourist spots and its numerous activities and attractions. For that reason, it also incites the tourists' desire to share their experiences on social media, affecting their AB to revisit. This affirms Javed et al. [59] findings that using social media for searching tourist-related information predicts the behavioral intention of the tourists' choice of destination, affecting their AB toward visiting their desired destination. In contrast, Saurabh's [87] study shows that media does not affect human behavior significantly. However, the study states that the resulting behavioral effect is based on the duration of media use. In Cahigas et al. [82], the specific media variable 'social media' was found to be insignificant in affecting actual behavior regarding Bali visitation amidst the COVID 19 pandemic. According to the researchers, social media posts, digital marketing campaigns, and even verbal recounts did not strengthen their participant's intention to visit the location.

On the other hand, DC, A, SN, and GR are found to be significant (90.1%, 86.7%, 84.2%, and 70.6%, respectively) toward tourists' AB of revisiting a tourist spot after a natural disaster. However, the results are contrary to German et al. [54] study for DC, A, and GR, stating that perceived environmental concern (i.e., DC) and perceived authority support (i.e., GR) had significant positive relationships to perceived behavioral control (PBC). On the other hand, A had a strong positive relationship to behavioral intention, which affects AB. As for SN, the result aligns with Pahrudin et al. [16], which stated that the variable has an insignificant impact towards I to visit a post-disaster destination (post-COVID Indonesia), affecting AB. That means that tourists take marginal concern over potential disasters (DC), self-evaluation (A), word-of-mouth (SN/M), and government activities taking place within the area (GR). Instead, they are seen to be more focused on what the destination offers to them.

5.1 *Theoretical contributions*

The study extended the theory of planned behavior (TPB) formulated by Ajzen [17] which has been widely utilized in the area of tourism and actual visitation behavior. For this study, an extension was made for the revisitation behavior, specifically in disaster-stricken tourist spots. Moreover, the model can also be utilized for other tourist destinations severely affected by a disaster. Aside from this, Pahrudin et al. [16] also stated that the extended framework, as long as proven effective, can be employed to investigate different natural disaster-related behavior worldwide. Strategies to strengthen tourist-related businesses may also be evaluated using the study's extended model of the theory of planned behavior through the significant latent variables. Lastly, as Harwati and Sudiya [88] claimed, the machine learning algorithms artificial neural network (ANN), decision tree (DT), and random forest classifier (RFC) may be utilized to create a classification model in different fields of tourism and intention behavior. To which, it can also analyze the non-linear relationship of different latent variables that may be included in future studies [27].

5.2 *Practical and managerial implications*

Natural disasters are very prominent in the country due to its geographical location. Hence, the tourism industry is becoming increasingly concerned with how they can encourage tourists to revisit tourist destinations, which was severely affected by natural disasters and deemed a threat to people's health. As evident in the tourism industries, the Philippines is one of the countries that has a lot of natural attractions and tourist spots. Thus, action is needed to boost the tourism rates in disaster-stricken tourist spots that were temporarily shut down. This study's significant findings shed light on tourist visitation behavior, as the results illustrate the factors that may affect tourists' intention to visit disaster-stricken areas.

Recognizing such factors can help local authorities and tourism businesses adjust existing or develop new strategies to revitalize tourism-dependent areas following a calamity. As such, the study's results give the government and private sector the opportunity to invest in programs that will improve tourist destination enjoyment (HM, I, M) and safety (PBC, M) to fortify revisitation behavior. For instance, they may have promotional projects that will increase the publicity of the Taal Volcano (a recently sticken natural disaster in the Philippines) and create a series of videos that showcase the tourist spot's natural beauty and the area's numerous fun activities, to be highlighted and promoted in different social media sites, which are highly utilized by the current generation. It was also seen that 48% of people often use it as a basis to choose where they will go on their next vacation [89]. Such projects are centered on using media, could be done, to influence potential tourists to visit the disaster-stricken tourist spot. Indeed, it also increases individuals' hedonic motivation as it projects the place where people can have fun and have positive experiences.

Another example that both the private and public sectors may do to increase tourists' hedonic motivation-the most significant factor affecting revisitation behavior, is to have development programs that aim to increase the variety of activities that tourists may engage in the area. The government may also lend loans to small tourist-related businesses to fund new activities they may have in mind, such as taking tourists out on the lake to catch fish, for instance. Such a setup may also encourage businesses to improve existing projects, such as buying bigger boats for boat riding or supplying tourists with hiking equipment for their convenience when trekking.

5.3 *Limitations*

Though the study resulted in positive results, it nonetheless has several limitations. First, the research paper is a quantitative study that utilizes a multiple-choice survey questionnaire to take the factors that affect the respondents' visiting attitude towards post-disaster tourist locations. Hence, the in-depth reasoning behind their answers cannot be explored and analyzed. It may be critical to developing other strategies necessary for tourism-dependent areas, such as Batangas, to palliate their losses after a disaster. It is therefore suggested to conduct interviews and interactions among tourists to identify further different factors affecting AB.

Second, the study does not consider cultural differences in behaviors and attitudes toward natural disaster tourism behavior and tourism in genreal since all the respondents were Filipinos from different regions of the country. Moreover, socioeconomic and demographic factors were not directly related as moderators of the factor analysis which future researchers could consider. Lastly, since the researchers used an extended version of TPB (in which the additional factors of response of government, disaster effect concern, media, and hedonic motivation were considered alongside TPB's traditional factors), the study does not consider other possible variables that may influence revisiting behavior, such as emotional and cognitive factors. Hence, future studies may further extend the paper's TPB model by adding other factors that may affect the tourists' revisitation behavior in other aforementioned aspects.

For the algorithm, it could be suggested that future research may consider integration and development of combined classification algorithms. For example, the study of Salazar et al. [90] combined two algorithms-nonlinear and linear regularized alpha integration. Comparing with with other classification tools such as Naive Bayes, RFC, and linear and quadratic discriminant analyses. It presented positive and accurate outcome, but data should undergo deep pre-processing and cleaning for better outcome. Similarly, it could be deduced that since this study proved RFC to be better than DT, and ANN provided support on the RFC significant output, it could be integrated to reduce the optimization process. For implementation, the output of RFC may be the input for the neural network algorithm to provide higher predictive outcome. Moreover, other tools such as SEM from multivariate analysis could be considered as a data cleaning process and could be subjected to the neural network for better significant dataset determination [91].

6. Conclusions

The lack of studies on revisitation behavior following a natural disaster prompted researchers to investigate this issue since the Philippines is located in the Pacific Ring of Fire, characterized by a higher frequency of natural disasters such as active volcanoes, typhoons causing floodings, and frequent earthquakes. The Extended Theory of Planned Behavior was utilized as an instrument of this study because it has been widely used to predict individuals' behavioral intentions to visit a tourist spot.

From the study's results, both machine learning provided high accuracy rates of 96% and 97.86% on RFC and ANN, accordingly, whereas DT did not have good outcome. The accuracy of the ANN was obtained from the average iterative output of the 75 : 15 : 10 training : testing : validation output. This displayed the prediction of significant latent variables affecting the revisitation behavior of tourists toward a tourist spot after a natural disaster calamity. As for DT, it showed an accuracy of 56.97%, which is considered undesirable. Thus, MLA could be used to assess revisitation behavior toward a post-disaster tourist spot because the results of this study were able to highlight how each factor contributed towards revisitation behavior after a natural disaster calamity.

Based on the study's main findings, the most influential factors that affect revisiting behavior are media, which pertains to social media and online reviews; hedonic motivation, which refers to the pleasure or enjoyment derived from the experience; perceived behavioral control, which refers to a person's belief in their ability to control the outcome of their actions; and disaster concern, which refers to a person's level of concern about potential disasters or safety issues. In addition, promotion from tourism sectors could highlight the positive aspects of a location, such as the hedonic experiences it offers, and highlighting the safety measures they have in place to alleviate disaster effect concerns. Finally, utilizing social media and online review platforms can effectively reach potential visitors and influence their revisiting behavior.

Future research may opt to consider in-depth identification of revisitation behavior through group or individual open-ended question interviews. This way, future studies may acquire several factors that could affect tourism behavior. In addition, development of strategies may be considered based on the responses once done. In addition, cultural factors may differ among tourists, therefore behaviors and attitudes may be assessed for other countries. Lastly, other frameworks and analytical tools may be considered by future researchers to cover cognitive and/or tourism behavior.

Data availability

The data utilized in this study is available upon request.

Conflict of interest

The authors declare no competing financial interest.

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