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Purchasing Intentions Analysis of Hybrid Cars Using Random Forest Classifier and Deep Learning

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Abstract: In developed or first-world countries, hybrid cars are widely utilized and essential in technological development and reducing carbon emissions. Despite that, developing or third-world countries such as the Philippines have not yet fully adopted hybrid cars as a means of transportation. Hence, the Sustainability Theory of Planned Behavior (STPB) was developed and integrated with the UTAUT2 framework to predict the factors affecting the purchasing intentions of Filipino drivers toward hybrid cars. The study gathered 1048 valid responses using convenience and snowball sampling to holistically measure user acceptance through twelve latent variables. Machine Learning Algorithm (MLA) tools such as the Decision Tree (DT), Random Forest Classifier (RFC), and Deep Learning Neural Network (DLNN) were utilized to anticipate consumer behavior. The final results from RFC showed an accuracy of 94% and DLNN with an accuracy of 96.60%, which were able to prove the prediction of significant latent factors. Perceived Environmental Concerns (PENCs), Attitude (AT), Perceived Behavioral Control (PBC), and Performance Expectancy (PE) were observed to be the highest factors. This study is one of the first extensive studies utilizing the MLA approach to predict Filipino drivers' tendency to acquire hybrid vehicles. The study's results can be adapted by automakers or car companies for devising initiatives, tactics, and advertisements to promote the viability and utility of hybrid vehicles in the Philippines. Since all the factors were proven significant, future investigations can assess not only the behavioral component but also the sustainability aspect of an individual using the STPB framework.

Keywords: hybrid cars; machine learning algorithm; purchasing intentions; sustainability theory of planned behavior; UTAUT2

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1. Introduction

Greenhouse gases emitted by oil-powered and fossil-fueled vehicles have increased over the years. According to Tiseo [1], the global transportation sector is a significant polluter, producing approximately 7.3 billion tons of carbon dioxide emissions in 2020. In the same year, passenger cars were the most abundant source of emissions, accounting for 41% of global transportation emissions. In Wasiak's [2] study, internal combustion engines have two prominent drawbacks. The first is the relatively low efficiency of turning the energy contained in the fuel into valuable mechanical energy for propulsion, and the second is that the production of carbon dioxide and other components of the exhaust gas can contribute to global warming.

Hybrid cars are essential in technological development and in addressing carbon emission reduction. Furthermore, hybrid car production covers three of the United Nations' global Sustainable Development Goals (SDGs): the 7th SDG for affordable and clean energy, the 8th SDG for decent work and economic growth, and the 13th SDG for climate action. Since the introduction of the various SDGs, the usage of hybrid cars has been promoted [3].

The present generation is seeing an increase in the marketability of hybrid vehicles, but their utility is not widely acknowledged. Irawan et al. [4] estimated that roughly 18.20% of automobile owners have begun to consider switching from a conventional vehicle and becoming potential hybrid car users, while 81.22% of car buyers continue to reject getting a hybrid vehicle completely. Thus, consumer behavior should be investigated to understand purchasing behavior for sustainable transportation to be widely accepted.

One theory widely used to comprehensively assess consumers' behavior in the aspect of purchasing and marketing is the Theory of Planned Behavior (TPB) [5]. It is also proven to extensively measure the intention to purchase. It is applied to examine customers' behavioral aspects of buying while simultaneously proving some of the determinants of purchase intentions [6]. In line with the TPB framework, several studies have supported that TPB is commonly used in the field of purchasing cars due to its explanatory capacity to predict the adoption or purchasing intention of cars, specifically in Hybrid Electric Vehicles (HEVs) [7,8]. Similarly, a study by Javid et al. [9] stated that the determinants of TPB could also be applied to consumers' purchasing intention, even in Electric Vehicles (EVs). However, in the study of German et al. [10], TPB has limited variables that restrain the model for holistic measurements.

Another theory that can be used in assessing people's acceptance and behavioral intentions is the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Venkatesh et al. [11] explained how UTAUT2 comprehensively measures the behavioral aspect of technology usage. Studies such as that of Nordhoff et al. [12] employed the UTAUT2 model to explain the public acceptance of conditionally automated cars in European countries. According to their study's analysis, the UTAUT2 model can be applied to conditional automation, with hedonic motivation, social influence, and performance expectancy influencing the behavioral intention to purchase and utilize a conditionally automated car. Similarly, Prasetyo and Vallespin [13] used the UTAUT2 model to identify the factors influencing users' utility of mobile technology applications and services. In Malaysia, Khazaei and Tareq [14] examined consumers' usage of battery electric vehicles using the UTAUT2 since this model incorporated a broader scope of factors to measure consumers' usage intention. However, a limited number of studies have analyzed the purchasing intentions of hybrid cars, especially in the Philippines. Only that of Ong et al. [15] was seen to consider the purchasing intentions of hybrid cars in the Philippines.

In the Philippines, hybrid cars are available in the market. With only leading car brands such as Cherry, Geely, Hyundai, Mitsubishi, Nissan, and Toyota selling the product, limited access and popularity are observed. There were 11,851,192 registered motor vehicles and fossil-fueled cars in the Philippines as of December 2020 [16]. Unlike other countries, the hybrid car vehicle market in the Philippines only caters to the extreme upper class, which accounts for only less than 0.1% of the market—with about 7000 hybrid cars registered in 2018 [17]. A recent report by Canivel [18] presented how Kia Philippines showed a steady increase in the purchase of hybrid cars due to increase in fuel costs. The once affordable diesel fuel is now relatively not that cheap in the market. It was reported that Kia was able to increase its sales by 14.6% in 5 months' time of the same year. Kampi also expected a rise in sales of 17% in 2021. A report by Statista research department [19] summarized the hybrid/electric cars sold from 2020–2022. From 378 in 2020 to 843 in 2021, a significant increase was seen in 2022 with 1013 units being sold. One reason why hybrid cars are not highly popularized in the country is their maturity in the Philippine car market, leading to low adoption rates of hybrid cars [20]. As reported by the news [21], only recently (2023) has there been any plans to put up charging stations. It was reported that 200 charging stations are planned to be established and 500 more by 2025. Therefore, the need to explore the purchasing intentions of consumers with this relatively new technology for the country is needed. The slow progression of movement in purchase may be capitalized by the governing units since the establishment of charging stations and business are still on the rise. The determination of purchasing intention surrounding these hybrid cars would be beneficial for the literature and business owners alike.

This paper aimed to determine what factors influence drivers' preferences for future use and purchase intentions of hybrid vehicles (HVs) in the Philippines. Through the integration of the extended pro-environmental theory of planned behavior (PEPB) of German et al. [22] and the extended unified theory of acceptance and use of technology (UTAUT2) on hybrid car purchase and usage intention, this study is one of the first few that examined the MLA approach to behavioral intention. Since the current study extended the established purchasing intention of hybrid cars in the Philippines [15], this study wanted to add to the literature on closing the gap between the use of machine learning and analyzing human behavior. Structural equation modeling was considered by the previous study [15], which suggested the use of machine learning to better analyze the nonlinear relationship among latent variables. In accordance, the literature, such as that of Fan et al. [23], explained that some latent variables when mediating factors are present may cause little to no significance. In accordance, the study of Woody [24] also presented similar findings and explained that large nonlinear relationship models may be unreliable when SEM is used as Heywood cases might be present which may cause wrong parameter estimates [23,25]. Therefore, this study contributes to a more thorough evaluation of the Philippines' capability to sustain smart technology—eventually developing into a smart and sustainable city.

2. Conceptual Framework

2.1. Theories and Related Studies

Venkatesh et al. [11] extended the existing UTAUT by incorporating three latent variables, namely hedonic motivation, price value, and habit, thus developing the UTAUT2 model. The extensions proposed in the UTAUT2 produced a significant improvement in the variance explained in behavioral intention and technology use compared to its predecessor, the UTAUT. Although the UTAUT2 model comprehensively analyzes the constructs for the adoption of new technology, the scope of the model only evaluates the intention to use new technologies, making it insufficient in terms of holistically measuring the human behavior attributes and aspects [26]. LaRose et al. [27] suggested that the UTAUT2 model employs generic measures of the latent variables so that the same operational standards can be used across different studies. This approach improved the model's generalizability but compromised the actionable information gathered. In addition, Ong et al. [26] stated that the UTAUT2 model was not able to analyze the actual behavior of adopting technology. Their study recommended incorporating other factors in order to obtain a more accurate depiction of the viewpoint of the general population in light of these minor informational gaps in the research. Subsequently, their study also showed that demographic factors as mediating effects might not be considered in an analysis.

Several studies have integrated the UTAUT2 model with other theories to evaluate innovative solutions and technology. Yuduang et al. [28] considered the integration of Protection Motivation Theory (PMT) and UTAUT2 to assess the actual usage and intention to use new technologies, specifically mobile applications. Their study stated that this integration could be interpreted as a model that can comprehensively assess the intention and actual usage of a mobile application. Hassan et al. [29] integrated the Privacy Calculus Model (PMC) and UTAUT2 by adding four constructs: privacy concern, perceived risk, trust, and perceived credibility. Their study validated that the addition of these constructs thoroughly measured the consumers' perspectives in relation to the adoption of new technologies. Chang et al. [30] extended the UTAUT2 model, which assimilates the existing constructs from the UTAUT2 along with age, gender, and experience as moderators. Their study highlighted three findings: (1) age and experience reduce the impact of habit on usage behavior, (2) age affects the influence of facilitating conditions on usage behavior, and (3) the moderating effect of experience reduced the direct impact of behavioral intention on usage behavior, making it irrelevant.

The Theory of Planned Behavior (TPB) was established to anticipate human behavior. According to the TPB, behavioral intention is influenced by three factors: attitude (AT), subjective norm (SN), and perceived behavioral control (PEC) [31]. In the study of Chau and Shiau [32], six well-known theoretical models were used to have a better understanding of terms of behavioral intention, including the TPB and five other models, namely Service Quality (SQ), Self-Efficacy (SE), Motivational Model (MM), Technology Acceptance Model (TAM), and Innovation Diffusion Theory (IDT); thus, the united model gave a thorough grasp of the aspects that have a significant impact on behavioral intention. With that, the TPB is to be proven effective when combined with other models. It provides a more comprehensive review of a person's behavioral intention concerning hybrid cars with reference to the said study. In the paper of Sentosa [33], the TPB, along with Technology Acceptance Modeling (TAM), was integrated. In fulfillment of the paper, it was implied that a person's conduct is influenced by the desire to execute the activity, which is determined by one's attitude toward the behavior and subjective norm.

Kim and Hwang [34] used a research model that combined the TPB and Norm Activation Model (NAM) into a single theoretical framework to analyze eco-friendly behavioral intentions to employ drone food delivery services. Furthermore, the moderating influence of product knowledge was investigated in this study, as the amount of product knowledge has a major impact on customer behaviors. PEPB and SERVQUAL models were integrated to further determine Filipino consumers' behavioral intention in the paper of German et al. [22], particularly during the COVID-19 pandemic. In reliance on the said study, since it was mentioned that the PEPB places emphasis on environmental concerns and authority, variables from the TPB play a role in determining an individual's behavioral intention towards a particular situation or activity. Additionally, the two models also indicated a higher level of investigation. They can be used in developing countries like the Philippines because the said country strongly encourages the emergence of more sustainable smart technology.

The PEPB model was developed as an extension of the theory of planned behavior (TPB) since it could not address all factors relevant to this study [22]. Perceived authority support (PAS), perceived environmental concern (PEC), perceived behavioral control (PBC), subjective norm (SN), attitude (AT), and behavior intention (BI) were important in determining the consumer's intention to purchase products. Furthermore, other variables under the three sustainability domains, namely economic, environmental, and social, are covered in this study [35].

From the PEPB model [22], no economic aspects were covered. In line with the objective of this study, natural resources such as oil cannot be replenished rapidly enough, which impacts the economy [36]. Fossil-fueled cars are known for producing large amounts of toxic air pollutants in the atmosphere [37]. This increase in CO2 in the atmosphere will raise the average temperature of the earth's surface [38]. In order to reduce air pollution, an alternative must be used. Asim et al. [39] found that hybrid cars are less harmful to the environment because they use less gasoline. This shows that hybrid cars are much cleaner and better for the environment; nevertheless, a consumer's interest does not include economic or environmental concerns [40]. An individual's choice of hybrid cars may vary depending on their social environment perspective. For instance, a consumer's decision to buy a hybrid car may possibly be influenced by their family, relatives, or friends [41].

The researchers utilized the Unified Theory of Technology Acceptance and Use of Technology 2 (UTAUT2), the Pro-environmental Theory of Planned Behavior (PEPB), and sustainability domains while incorporating an additional factor which is perceived economic concerns (PECCs) to measure human behavior and technology acceptance. Turoń and Kubik [42] studied the economic considerations of adopting autonomous vehicles compared to the traditional automobile fleet acquired by individual consumers in car-sharing systems. In a different scope, Nisa et al. [43] revealed that perceived economic risk consistently predicted mitigation behavior and policy support, and economic considerations positively predicted all outcomes. Hence, the added factor, perceived economic concerns

(PECCs), relates to a sense of social responsibility, extensive societal and commercial consideration, and voluntary company involvement.

2.2. Conceptual Framework

The Sustainability Theory of Planned Behavior (STPB) framework used in this study (Figure 1) encompasses the combination of the TPB and the PEPB with the UTAUT2 and the extension of the economic factor. Several variables, including habit (HB), price value (PV), hedonic motivation (HM), performance expectancy (PE), effort expectancy (EE), facilitating conditions (FCs), perceived authority support (PAS), perceived environmental concern (PENC), perceived behavioral control (PBC), perceived economic concern (PECC), subjective norm (SN), attitude (AT), and behavioral intention (BI) were taken into account to comprehensively analyze the intention to use and actual purchase intention of consumers' toward hybrid cars. This framework was adopted from the study of Ong et al. [15].

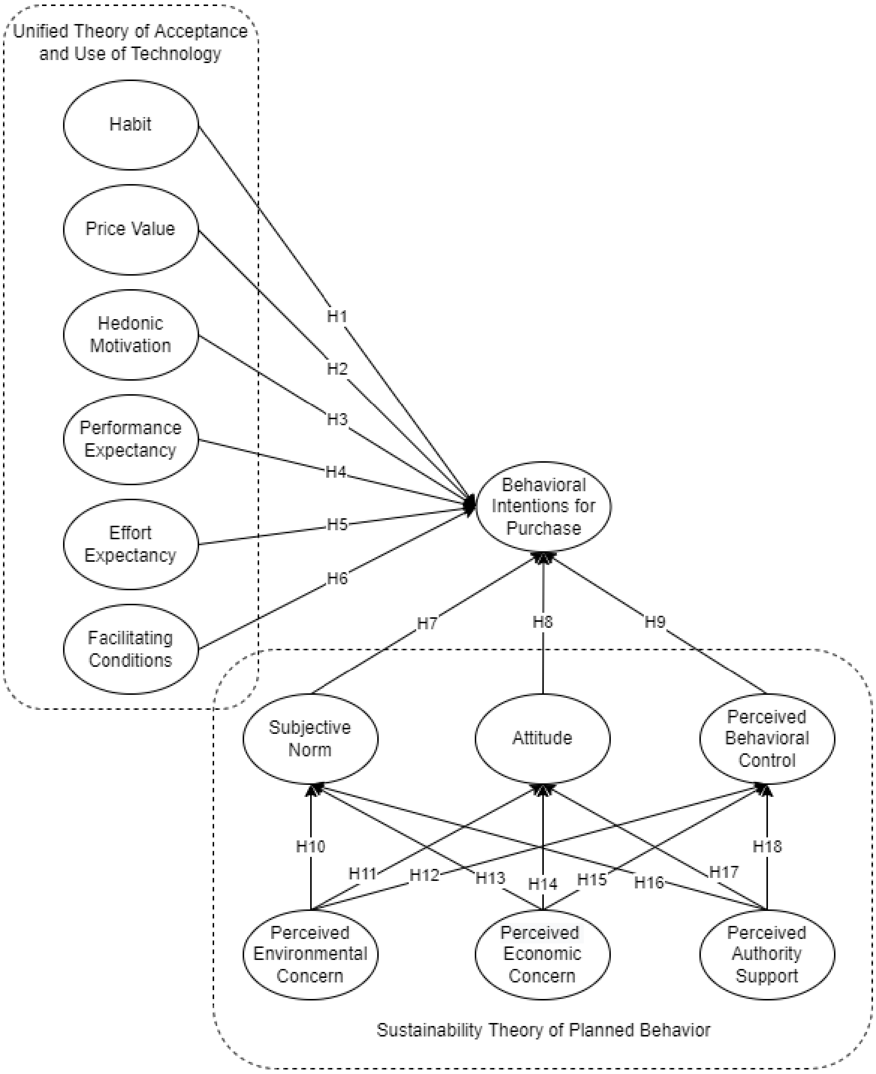


Figure 1. Sustainability theory of planned behavior framework with UTAUT2.

The UTAUT2 model can measure the individual's intention to use hybrid cars. In this study, a new framework was established in which the social influence (SI) was transferred to the PEPB model as subjective norm (SN). This is due to the PEPB having a subjective norm (SN) variable, where they offered the same behavioral aspect based on the influence of other people.

Habit is repeatedly described as a result of earlier experiences with numerous factors, which becomes a beneficial choice [11]. It is also considered a potential factor in decision making [44]. Positive feelings associated with the habitual product experience of driving a car strengthens the habit and discourages consumers from embracing a new means of transportation, such as hybrid cars [45,46]. Additionally, the adoption of a new car may be influenced by previous experience with similar cars [47]. Thus, it was hypothesized that:

H1. *Habit has a significant direct effect on behavioral intention.*

The term price value (PV) refers to consumers' cognitive trade-off between the perceived advantages of the applications and the financial expense of utilizing them [11]. Moreover, the advantages and associated expenses of purchasing hybrid cars were assessed and contrasted [48]. Irawan et al. [4] observed that gas price and supply affected the utility of hybrid cars significantly; this suggests that consumers are more likely to acquire a hybrid car depending on the fuel cost and supply. Thus, it was hypothesized that:

H2. *Price value has a significant direct effect on behavioral intention.*

Venkatesh et al. [11] defined hedonic motivation as the fun or pleasure derived from using technology. It also makes an individual feel better since it is a crucial factor in consumer choice to purchase hybrid cars [49–51]. Thus, it was hypothesized that:

H3. *Hedonic motivation has a significant direct effect on behavioral intention.*

According to Venkatesh et al. [11], performance expectancy (PE) is the degree of personal belief that employing collaborative technology would increase work efficiency and result in operational success. Additionally, if customers find a simple system to be used, it will be more accepted [52]. This could be a factor in encouraging people to purchase [53]. Thus, it was hypothesized that:

H4. *Performance expectancy has a significant direct effect on behavioral intention.*

Effort Expectancy (EE) relates to the level of ease connected with the use of the system. The definition of EE discusses the effort required to become skillful when utilizing technology. This method is comparable to the idea of Davis [54] of perceived ease of use, which addresses the extent to which people think utilizing technology does not involve much effort [55]. Ombach [56] concluded that developed technologies are efficiently integrated with several vehicles. Thus, it was hypothesized that:

H5. *Effort expectancy has a significant direct effect on behavioral intention.*

Facilitating Conditions (FCs) are said to be the degree to which a person feels that a technological and organizational infrastructure exists to enable the usage of the system [57]. FC affects people's perception of infrastructures, technical support, and other facilities when they utilize technology, products, and services. In the previous UTAUT models, FC was theorized as an operator of user behavior. This means that users are more likely to use new technology if there are available resources, expertise, and support [58]. Due to this, national policy actions are required to promote the commercialization of low-carbon technology (i.e., hybrid cars) in both advanced and especially developing nations like the Philippines [53]. In addition, FC is presumed to be an essential variable influencing behavioral intention in the UTAUT2 framework [11,59]. Thus, it was hypothesized that:

H6. *Facilitating conditions has a significant direct effect on behavioral intention.*

A study by Wang et al. [8] revealed that the theory of planned behavior (TPB), together with its primary constructs, was found to predict behavioral intentions accurately. Attitude is characterized as the positive or negative evaluation of the adoption behavior. Social influence or subjective norm refers to the perceived social pressure an individual feels from others. Perceived behavioral control was defined as the level of perceived ease or difficulty with regard to engaging in the behavior. Hybrid electric vehicles have been regarded as a potential solution to the pressure of lowering carbon emissions in the transportation industry—affecting consumers' behavioral intentions on adopting hybrid cars. Tanwir and Hamzah [7] integrated the theory of planned behavior with environmental knowledge as the foundation of their research model to examine the factors influencing people's intention to buy a hybrid car. They found that people's perceptions of their ability to manage resources are the most significant predictors of their intention to purchase hybrid vehicles. Thus, it was hypothesized that:

H7. *Subjective norm has a significant direct effect on behavioral intentions.*

H8. *Attitude has a significant direct effect on behavioral intentions.*

H9. *Perceived behavioral control has a significant direct effect on behavioral intentions.*

According to Lin et al. [60], the perceived environmental concerns (PENCs) latent variable functions as the antecedent of the subjective norm (SN), attitude (AT), and perceived behavioral control (PBC) variables in the PEPB model of German et al. [22]. Car emissions raise quantities of carbon dioxide and other greenhouse gases while trapping the sun's heat in the Earth's atmosphere, which causes global warming. In the year 2020, transportation passenger cars contribute to around 41% of worldwide carbon emissions [1]. There is an apparent need for alternatives or modifications that would better sustain the means of transportation and automotive industry productions nationwide, such as developing an electric car, but more open and accessible to the general public and more ethically priced, particularly hybrid cars [61]. Racz et al. [62] conducted a study on the ecological perspective of hybrid cars. Their results revealed that the modern concept of an eco-friendly car is a strong start for a healthier environment, but at the same time, battery recycling requires greater focus because the advantages of electric batteries are generally acknowledged, while the drawbacks of recycling are frequently ignored. Thus, it was hypothesized that:

H10. *Perceived environmental concerns have a significant direct effect on subjective norm.*

H11. *Perceived environmental concern has a significant direct effect on attitude.*

H12. *Perceived environmental concerns have a significant direct effect on perceived behavioral control.*

To thoroughly examine the adoption potential of hybrid cars, the researchers established the STPB model in accordance with the sustainability domains. The latent variable perceived economic concerns (PECCs) was added. Barbosa Junior et al. [63] presented the economic dimension of the financial viability of providing production continuity with economic resources obtained through sustainable practices. Their research identified three barriers: low financial return, financial incentive, and financial viability. Social factors are strongly related to survey respondents' adoption of sustainable practices. Similarly, economic concerns or perceived economic concerns directly impact subjective norm and attitude. Economic efficiency was used as an independent variable in a study by Saif et al. [64] to predict the intention to adopt digital-only technology. It was defined as customers' perceptions of being able to save time, effort, and financial resources by using the services. According to their findings, perceived convenience and perceived economic efficiency have a significant positive effect on the usage intention, which would suffice the significant direct effect PECC has on perceived behavioral control. Thus, the following were hypothesized:

H13. *Perceived economic concerns have a significant direct effect on subjective norm.*

H14. *Perceived economic concerns have a significant direct effect on attitude.*

H15. *Perceived economic concerns have a significant direct effect on perceived behavioral control.*

In a study by German et al. [22] utilizing the pro-environmental theory of planned behavior (PEPB) model, perceived authority support (PAS) refers to an individual's perception of any resources, regulations, processes, or actions delivered by a government or authority organization that can assist people in carrying out a particular activity. The Philippines' policies and programs are aimed at preventing the depletion of environmental resources, which involves reducing energy use, chlorofluorocarbons, and carbon dioxide emissions [65]. The government's initiative to supervise the transition from fossil-fueled cars to hybrid cars is expected to have an impact on consumers' purchase intention toward hybrid cars [66]. According to Lin et al. [60], support from the government has a positive and substantial effect on subjective norm, attitude, and perceived behavioral control, demonstrating that the government has a significant impact on its population. Thus, it was hypothesized that:

H16. *Perceived authority support has a significant direct effect on subjective norm.*

H17. *Perceived authority support has a significant direct effect on attitude.*

H18. *Perceived authority support has a significant direct effect on perceived behavioral control.*

3. Methodology

3.1. Participants

The researchers conducted an online survey to predict Filipinos' purchasing intentions for hybrid cars. Non-probability sampling methods were utilized to gather the respondents for the study. According to Galloway [67], convenience sampling can help gather a variety of attitudes and opinions as well as identify tentative ideas. That being so, the convenience sampling method was used. Meanwhile, snowball sampling was also employed to reach the targeted number of participants with the help of each one's social network [68]. The researchers obtained more than 500 respondents, generalizing the study's results [69]. Since the self-administered survey was open to the general public, the respondents answered at their discretion. A total of 1149 responses were accumulated (Table 1), but 1048 was the number of responses considered since 101 participants did not possess a driver's license—the instrument's primary qualification. This resulted in a 91.21% valid response rate with no missing data—similar to the adopted data from Ong et al. [15].

Table 1. Respondents' descriptive characteristics (n = 1048).

Characteristics	Category	N	%
Gender	Female	146	13.9
	Male	902	86.1
Age	17–22	5	0.48
	23–29	341	32.54
	30–36	365	34.83
	37–43	192	18.32
	44–50	97	9.26
	51–60	48	4.58
Monthly Income/Salary	Less than 20,000	42	4.01
	20,000–30,000	310	29.58
	30,000–40,000	495	47.23
	40,000–50,000	113	10.78
	50,000–60,000	52	4.96
	Greater than 60,000	34	3.24
	Others	2	0.19
Occupation	Employed	1035	98.76
	Self-employed	8	0.76
	Unemployed	1	0.1
	Retired	0	0.0
	Student	4	0.38
Marital Status	Married	553	52.77
	Single	487	46.47
	Widowed	4	0.38
	Separated	4	0.38

Table 1. *Cont.*

Characteristics	Category	N	%
Educational Attainment	Elementary graduate	2	0.19
	Junior high school graduate	1	0.1
	Senior high school graduate	4	0.38
	Technical–Vocational Graduate	2	0.19
	College Graduate	992	94.66
	Master Graduate	45	4.29
	PhD Graduate	2	0.19
Residence	Urban	866	82.63
	Rural	182	17.37
Type of Residential Home	Owned house and lot	566	54.01
	Owned an apartment	25	2.39
	Owned a condominium	10	0.95
	Rental	395	37.69
	Others	52	4.96
Do you have car insurance?	Yes	636	60.69
	No	412	39.31

3.2. Questionnaire

A questionnaire with 13 distinct portions and four items each was adapted from the related literature [15]. Participants were asked to rate how much they agreed or disagreed with the given statement on a 5-point Likert scale to gather information for this study.

Data preprocessing was performed prior to integrate the Machine Learning Algorithm (MLA). SPSS 25 was utilized to examine the missing data. For the data cleaning process, nonsignificant indicators with a p-value more significant than 0.05 were removed from the data using correlation analysis. Similarly, for the MLA optimization, only the indicators with a value higher than 0.20 correlation coefficient were considered. Since none of the indications were removed, all proposed indicators were deemed significant.

To represent the input for the MLA, the various indicators were averaged through data aggregation. The implications in the questionnaire portray the latent factors that were unobserved variables and were taken into account in this study for the MLA utilizing Python 3.8, specifically Spyder 3—an integrated development environment. Other algorithms, such as the decision tree (DT), the random forest classifier (RFC), and the deep learning neural network (DLNN) were used after data normalization to predict the factors affecting the acceptance of hybrid cars among Filipino drivers.

3.3. Decision Tree

A decision tree is a structure and classification approach with regression capacity applied as a prediction factor in a cluster of independent variables [70]. This structure is labeled as a primary classifier of decision nodes organized in a tree pattern [71]. They are easily interpretable and visually portrayed as hierarchical structures [72]. Additionally, decision trees are often employed in model classification in data mining [73]. Milani et al. [74] also stated that DT is widely recognized as one of the most effective methods for dealing with nonlinear datasets. Since decision trees study a nonlinear dataset for understanding human features and behavior [75], this approach can be applied to the current study.

Based on the study of Topîrceanu and Grosseck [76], MLA recognizes decision trees as one of its classification tools. It categorizes relevant latent variables that impact a dependent factor by evaluating the relationship between factors represented by tree branches. Their study also stated that DTs are a predictive model for human behavior regardless of the target variable's quantity. Furthermore, DTs are utilized to develop a prediction model for multiple class (dependent factor) labels in domains such as healthcare, human factors, manufacturing, and other fields [77].

In conjunction with establishing the Entropy and Gini index values alongside best and random splitters, various testing and training ratios were applied to the DT classification process, such as the 40:60, 50:50, 60:40, 70:30, 80:20, and 90:10 training-to-testing ratios. Following the study of Chen et al. [78] the tree depth was evaluated, spanning from four to seven. The ideal decision tree was determined by running each combination 100 times for a total of 9600 runs. The splitter (Random or Best), training and testing ratios, tree depth, and the criterion (Gini or Entropy) were all determined using the analysis of variance (ANOVA) to evaluate the ideal decision tree.

3.4. Random Forest Classifier

The random forest classifier is a supervised classification algorithm that categorizes data by creating several classifiers to attain greater prediction accuracy [79]. The basic decision tree generates a large number of branches; therefore, RFC classifies the most satisfactory decision tree using several characteristics and creates the best branch split among the decision trees [80]. The primary goal of employing the RFC as MLA is to locate the best tree with a high accuracy rate. The random forest classifier evaluates the best tree for each iteration, whereas the standard DT generates a random tree for each run. Chen et al. [81] supported the claim that the random forest classifier is the best among other decision trees. According to the study of Rodriguez-Galano et al. [82], RFCs are far more accurate and resistant to noise than single classifiers (i.e., basic decision trees); hence, ensemble learning algorithms like random forest, bagging, and boosting are gaining popularity. In the paper of Elhenawy et al. [83] and Ermagun et al. [84], the RFC was used to predict human behavior, specifically driving behavior. Thus, the same classification tool was applied in the current investigation. Similar optimization parameters were utilized in the study, as presented in the DT sections.

3.5. Deep Learning Neural Network

Compared to other machine learning and artificial intelligence applications, the deep learning neural network (DLNN) is recognized as the best model for predicting parameters or identifying patterns because of its capacity to assess and calculate many perceptions [26]. Cassini [85] stated that this algorithm has significant advantages over conventional machine learning algorithms (MLAs) in extracting features at various levels of abstraction and thereby learning more complex patterns. Furthermore, deep learning neural networks are artificial neural networks with additional hidden layers between the input and output layers, wherein Ong et al. [26] explained how these can assess nonlinear relationships among frameworks developed. According to Sturman et al. [86], the variation between and among human annotators is eliminated by the deep neural network, which outperforms commercial systems at a lower cost and contributes to the enhancement of behavioral data quality and accuracy. Luceri et al. [87] affirmed that the deep learning neural network effectively evaluates the psychological behavior, behavioral intention, and psychology of consumers. In this study, the results obtained from the random forest classifier would be supported by use of the deep learning neural network since this method can predict and categorize the most influential factors affecting the behavioral intention of consumers in purchasing hybrid cars.

Similar to the set conditions with a random forest classifier, the deep learning neural network preprocessing incorporated correlation analysis for data cleaning. Following data normalization, various activation functions for the hidden layer (sigmoid, tanh, and swish), output layer (sigmoid), and optimizer (Adam, SGD, RMSProp) were taken into consideration [80]. Additionally, the number of nodes for the 80:20 training and testing ratio was also included using a feed-forward neural network process. A total of 6480 runs were conducted, set with 150 epochs per iteration [88].

4. Results

4.1. Decision Tree

Iterations of the different combinations of parameters in the basic decision tree were accomplished to generate the best output. Presented in Table 2 are the summarized results. It could be posited that at depth 5, the most consistent tree output based on standard deviation was produced with Gini and best as splitter and criterion. Though entropy and best had higher accuracy rates, a significant difference was not evident. In addition, the accuracy rates under Gini and best had higher accuracy rates.

Table 2. Decision Tree Summarized Results.

Category	60:40	70:30	80:20	90:10
Random				
Gini Standard Deviation	65.54 2.051	67.16 2.214	65.16 2.344	67.20 3.117
Entropy Standard Deviation	65.42 1.962	67.00 2.168	65.29 2.384	67.61 3.512
Best				
Gini Standard Deviation	70.18 0.389	68.15 0.642	67.06 0.639	72.00 0.000
Entropy Standard Deviation	67.00 0.000	69.49 0.503	68.00 0.000	72.32 0.471

The study of German et al. [22] presented that these low accuracy rates from the basic decision tree were due to the fact that it generates random trees every iteration. It was proposed that a random forest classifier be used. In this case, the random forest classifier finds the best tree output every iteration, which in turn considers a higher accuracy rate. Studies such as that of Ong [80] and Chen et al. [81] presented the same discussion and justified how the random forest classifier can present the optimum tree output.

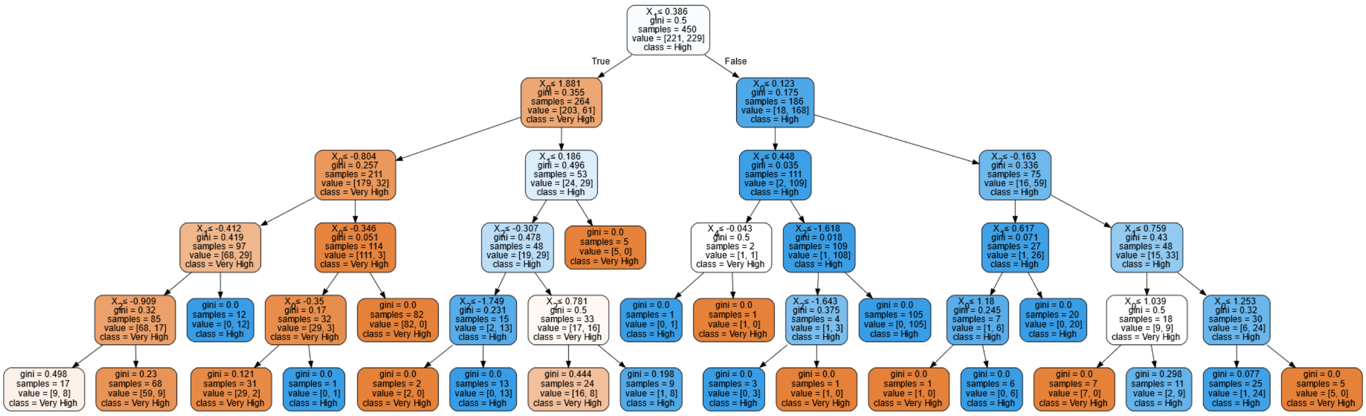
4.2. Random Forest Classifier

Presented in Table 3 are the summarized results of the random forest classifier. Following related studies [22,80,81], higher accuracy rates were evident in the random forest classifier output compared to the basic decision tree. Similar to the basic decision tree, depth 5 presented the most consistent output with Gini and best as the parameters.

Table 3. Random Forest Classifier Summarized Results.

Category	60:40	70:30	80:20	90:10
Random				
Gini Standard Deviation	81.82 4.896	80.69 3.668	83.22 5.904	85.38 4.582
Entropy Standard Deviation	82.85 3.300	80.36 3.976	84.43 5.028	83.69 6.238
Best				
Gini Standard Deviation	88.74 0.7115	84.06 1.003	92.55 0.500	94.00 0.000
Entropy Standard Deviation	83.63 1.120	84.98 0.642	89.37 1.077	92.00 0.000

It could be seen from the results that the 90:10 training testing ratio produced the most consistent tree with 94% accuracy and a standard deviation value of 0.000. Thus, this tree output was considered the optimum classification model. Figure 2 represents the optimum tree with a random forest classifier.



Legends:
X_0—Attitude (AT)
X_1—Perceived Environmental Concerns (PENC)
X_2—Perceived Behavioral Control (PBC)
X_4—Performance Expectancy (PE)

Figure 2. Optimum Tree with Random Forest Classifier.

From the output, PENC (X_1) dictated the behavioral intentions for acceptance of hybrid cars. The tree will consider AT (X_0) for the first node. Then, it will consider X_0, X_1 (≤ -0.412), and PBC (X_2) with a value less than or equal to -0.909. Satisfying this condition, people will have very high behavioral intentions. If the X_1 (≤ -0.412) condition is not satisfied, only a high behavioral intention is seen. This indicates that PENC should be highlighted for people to have a very high or positive behavioral intention. A similar output is evident if the first child node conditions are not satisfied.

If the parent node with a value less than or equal to 0.386 is not satisfied, a 0.123 condition for X_0 first child node is considered. Satisfying this will consider X_1 and then PE (X_4) with a value less than or equal to -0.043, which will lead to a high behavioral intention. This posits that as PENC is influential to the control of an individual to accept hybrid cars, its performance should also be highlighted as utilization for transportation. Lastly, if the child node conditions are not satisfied, it will consider X_2, then X_1, and X_0, which will lead to very high behavioral intentions.

From the findings, it could be deduced that PENC and AT are the top significant factors that affected people's PBC and PE to have very high behavioral intentions for hybrid cars. This dictates that PBC and PE are significant factors as well that would influence users' acceptance of hybrid cars. However, with varied factors still present, the random forest classifier needs further assistance from other MLAs to provide a distinct classification of latent variables affecting behavioral intentions. Chen et al. [81] considered other tools in support of the findings of the random forest classifier to deduce significant latent variables.

4.3. Deep Learning Neural Network

Following the study of Ong et al. [75], deep learning neural network parameter optimization was conducted to provide the optimum classification model. From the different parameters tested, tanh, as the activation function for the different hidden layers, presented the best output. Using sigmoid as the activation function in the output layer and adam as the optimizer, the summarized training and testing average results are presented in Table 4.

Table 4. Summarized results for deep learning neural network.

Factor	Average Training	Standard Deviation	Average Testing	Standard Deviation
PENC	91.41	1.630	93.14	1.681
AT	90.71	0.928	93.06	1.807
PBC	80.95	1.663	89.84	2.631
SN	80.70	0.143	87.29	2.997
PE	81.12	1.071	83.14	2.285
PAS	80.01	7.850	80.62	1.943
FC	77.21	1.473	79.14	2.491
HM	74.72	0.800	77.29	2.860
EE	67.80	2.769	75.76	1.993
PECC	68.67	3.343	70.35	1.226
PV	65.78	7.093	70.43	3.210
HB	60.50	2.211	68.52	3.761

Tanh is an activation function that is considered to be an extension of the sigmoid function. Gudivada [89] explained that a stretched and shifted sigmoid calculation is seen in the tanh activation function. This is usually considered for nonlinear relationship models, which can present high accuracy rates when used in the hidden layers. As explained by Walrave et al. [90], tanh is an activation function with stronger complexity to update weights in neural network models, which results in faster optimization and higher accuracy rates. The equation of tanh is presented in Equation (1) adopted from de Ryck et al. [91].

$$\tanh(x) = \frac{2}{1+e^{-2x}} - 1 \tag{1}$$

For sigmoid, Costarelli [92] explained that this activation function is mostly utilized in the output layer as it calculates nonlinear relationships with smaller ranges. Since tanh was considered with several hidden layers in this study, bounded values would be evident after the process, which can be computed using sigmoid [93]. It is also argued to be efficient despite its simple calculation, which is commonly utilized when probabilities are considered. Equation (2) represents the sigmoid activation function adopted from Narayan [94].

$$sigmoid(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The final deep learning neural network classification model is presented in Figure 3. A total of three hidden layers with 50, 50, and 20 nodes, respectively, provided the optimum model. With a 96.60% accuracy, the score of importance using SPSS 25 was used to verify the output of consecutive ranking of factors affecting the acceptance of hybrid cars. Presented in Table 5 is the normalized score of the importance of the resulting parameters.

Table 5. Normalized scores of importance.

Factor	Importance	Normalized Importance
PENC	0.107	100%
AT	0.103	96.32%
PBC	0.101	94.50%
SN	0.099	92.12%
PE	0.097	90.20%
PAS	0.090	84.50%
FC	0.087	81.20%
HM	0.084	79.00%
EE	0.083	77.60%
PECC	0.082	76.70%
PV	0.081	76.20%
HB	0.076	70.90%

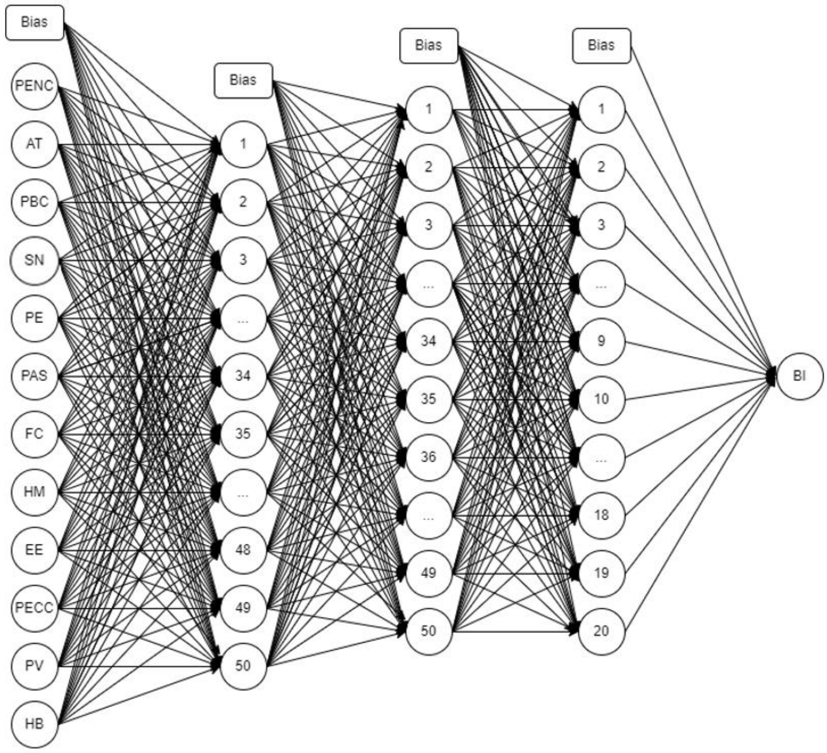


Figure 3. Deep learning neural network model.

4.4. Validation

To validate the different MLA accuracy outputs, a Taylor Diagram was generated. Following the study of German et al. [22] and Ong [23], the root mean square error should be within 20% and the accepted correlation value at 90% for significant factors. Setting the threshold of 1.00 for the standard deviation, Figure 4 represents the Taylor Diagram for this study. It could be seen that the output of different MLAs used in this study is acceptable. Moreover, the basic decision tree cannot be utilized due to the low output at 0. In addition, the least significant factors, such as HM, EE, PECC, PV, and HB, can still be considered but are less influential latent variables.

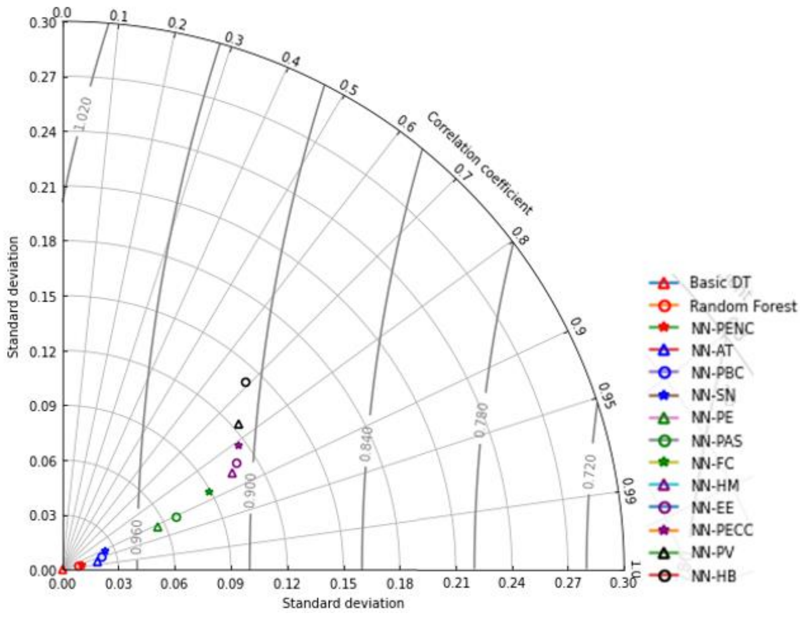


Figure 4. Taylor Diagram.

5. Discussion

Hybrid cars promote sustainable transportation, which is essential for both technological advancement and reducing carbon emissions; therefore, it is crucial to study the role of behavioral intention in determining how Filipino drivers adapt and transition to eco-friendly vehicles. The study aimed to examine the factors influencing Filipinos' acceptance or purchasing intentions toward hybrid cars using the Pro-environmental Theory of Planned Behavior (PEPB) and Sustainability Domains. These were combined into the Sustainability Theory of Planned Behavior, along with the integrated the Unified Theory of Acceptance and the Use of Technology 2 (UTAUT2). From the results, both the random forest classifier (RFC) and the deep learning neural network (DLNN) were utilized to evaluate the different significant factors affecting purchasing intentions of hybrid cars.

This study was able to justify the limitations of SEM as discussed by related studies [23–25]. As seen, PENC was deemed to be the most important latent variable, followed by AT, PBC, SN, and PE. Compared to the SEM result [15], it was seen that these were ranked fifth, third, seventh, second, and fourth, respectively. Clear distinctions were seen within the indirect effects among sustainability domains, which were mediated by the TPB domains. From the current study, PENC was deemed highly significant, while PAS ranked sixth, and PECC ranked tenth–compared to its SEM counterpart results being fifth, third, and first, respectively. Since the presence of mediating factors are seen among the STPB model, the justification of hindrance among mediating factors played a role [23–25].

In addition, the MLA results proved that the FC, EE, and HB were significant while the SEM results deemed them insignificant. As explained by Li et al. [95] who compared the SEM with the MLA, it was presented that the MLA has more predictive capabilities, generated higher accuracy rates, and could better present the model output rather than the final model SEM considers. It was added that the MLA can provide better explanation of the model based on the mutual understanding of machines and humans. Hadiyat [96] also provided the same justification. However, not all output may be different like that of Ong et al. [75] when analyzing telemedicine acceptance in the Philippines where both the SEM and the ANN provided the same output. Their explanation in the paper was that their study only utilized a direct relationship from the UTAUT2. Thus, this small model compared to the current study has distinct differences. Summarized in Table 6 are the different ranked scores of the latent variables. The discussion of the succeeding section is based on the highest significant effect from MLA.

Table 6. MLA versus SEM Results.

Latent Variable	MLA	SEM
PENC	1st	5th
AT	2nd	3rd
PBC	3rd	7th
SN	4th	2nd
PE	5th	4th
PAS	6th	3rd
FC	7th	Insignificant
HM	8th	6th
EE	9th	Insignificant
PECC	10th	1st
PV	11th	8th
HB	12th	insignificant

From the findings, the highest contributing factor to consumer acceptance was the perceived environmental concern (PENC) (100%) latent, having a significant direct effect on subjective norm (SN), attitude (AT), and perceived behavioral control (PBC). Based on the indicators, Filipino drivers or general respondents recognized that humankind is severely abusing and polluting the environment, causing them to be worried about its future status and avoiding more disastrous consequences. They felt compelled to adopt more ecologically friendly products, such as hybrid cars, which are both handy and beneficial to the existing environmental conditions. Rossi and Rivetti [97] mentioned that younger people, notably millennials and post-millennials (ages 23–29 and 30–36), are more concerned with sustainability, have a collective purchasing power, and are becoming an increasingly crucial consumer demographic. Because they are more inclined to environmental activism and engaging through platforms where these eco-labeled items and ideologies are promoted—in this study, obtaining hybrid cars—millennials are more likely to utilize eco-friendly manufactured products [98]. Thus, it could be deduced that hybrid cars could be viable as a highly efficient form of transportation due to their positive environmental effects.

Attitude (AT) (96.32%) was also deemed to have a highly significant direct effect on behavioral intention (BI). This shows that the positive or negative evaluation of the adoption behavior of hybrid cars will particularly influence a person's intention to purchase them. Respondents were more likely to believe that purchasing a hybrid car is a wise and pleasant decision, and they trusted the notion of purchasing a hybrid car since learning to utilize it may be a fulfilling experience. In addition, this finding is substantiated by the study of Chen et al. [78], which proves how products that may make customers feel joyful, thrilled, or cheerful can lead to more acceptance and a higher loyalty attitude. In addition, the study of Nadlifatin et al. [99] validated the correlation between AT and BI as the greatest value among all correlation results regarding the use of eco-label products. Therefore, these can be obtained through the associated emotional and known sustainable benefits that green products actively elicit. In accordance, PBC and PE were proved to have a highly significant and direct effect on BI.

PBC (94.50%) and PE (90.20%) were shown to have a highly significant and direct effect on BI. Although lower than that of the AT latent, it suggests that drivers can still sense the ease of operation of a hybrid car compared to a conventional vehicle and that it comes with more excellent resources and opportunities or anticipation that it is less vulnerable to impediments [100]. This finding was supported by Cahigas et al. [101], which found that PBC significantly and positively affected the intention to use in the transportation setting. Based on the two sets of indicators, it is up to the consumer's discretion to confidently select a hybrid car for his/her future purchase by determining that driving a hybrid car would be safer, more comfortable, and more productive. Furthermore, PE has been proven by Chong et al. [102] to have a strong, positive association with behavioral intention in adopting new technology, similar to the study conducted by Foroughi et al. [103] in the area of autonomous transportation. These are vital aspects, especially when a high percentage of respondents were working individuals who require efficiency in transportation and fewer hindrances in using a different type of vehicle.

Concerning the significant factors, SN (92.12%) latent had a significant direct effect on BI. Filipinos believed that the people they trusted who influenced and had a good impression on them would also recommend that they purchase or use a hybrid car. Similarly, it was indicated that hybrid cars would come off as more prestigious than traditional fossil-fueled vehicles. This result aligned with a study by Yang [104], wherein consumers' buying intentions were impacted by peer trust and reciprocity. They were eager to take advice and suggestions from trustworthy peers. Consequently, the moderate influence SI has on BI may be because only the experience of social interactions that have created close relationships among peers would impact customers' buying intentions more significantly [10,101].

Along with SN, perceived authority support (PAS) (84.50%) had a significant direct effect on SN, AT, and PBC. The indicators reveal that the government is active in setting up facilities for hybrid cars, enacts regulations that allow Filipinos to use these vehicles, and encourages or endorses the usage of them through these same regulations. Although the Philippine Statistics Authority [65] has acknowledged that there are policies and programs in place to enable the acquisition and handling of hybrid vehicles, they still need to be promoted on par with conventional vehicles in the market. A study by Yazdanpanah and Hadji Hosseinlou [105] suggested that policymakers seek to modify habits by providing relevant information to enhance the intention-behavior relationship. With that, there is a need for eco-labeled cars in the country, which is gradually being addressed by the authorities. Especially in the Philippines, the government is taking small steps, such as setting up some places for charging electric cars. However, the promotion of the usage is still underrepresented in the country.

Facilitating conditions (FCs) (81.20%) also proved to be a significant factor affecting BI. The indicators delineated that Filipino drivers have the necessary resources to operate a hybrid car, are knowledgeable in driving, and can ask questions and find solutions if any problems are identified. This finding is similar to the study of Lallmahomed et al. [106], wherein they presented how FC significantly affects usage intention. Yuduang et al. [28] also mentioned how consumers prefer using applications that are beneficial and easily accessible. The resources that are accessible for continuous usage of new technologies, such as hybrid cars, are considered by the current generation. Hedonic motivation (HM) (79%) was also seen to be a significant factor affecting BI. Based on the indicators, using a hybrid car is more fun, entertaining, enjoyable, and satisfying than driving a fossil-fueled car. It has been demonstrated that hedonic motivation, defined as the enjoyment or pleasure consumers derive from adopting new technology, is crucial in influencing technology acceptance and use [107]. The results of the analysis of the hedonic motivation construct were in line with the results of previous studies by Venkatesh et al. [11] and Palau-Saumell et al. [108], as both their results substantiated the fact that hedonic motivation is a significant predictor of intention to use.

Effort expectancy (EE) (77.60%) also proved to be a significant factor affecting BI. The indicators that led to the importance were that hybrid cars provide clear and understandable interactions that are easy to operate, adapt, and adept. This result is quite similar to the findings of Nordhoff et al. [12]: since EE is a substantial positive predictor of behavioral intention, individuals who imply that using conditionally autonomous cars is simple are more likely to want to utilize them. Aligned with this, perceived economic concern (PECC) (76.70%) was also proved to be a significant factor affecting BI, SN, AT, and PBC. The study found that hybrid cars have good warranties and economic incentives, can generate more savings which improve an individual's economic standing in the long run, drive more efficiently, and are easily acquirable in the market. This added latent, which completes the sustainability theory of planned behavior (STPB), is related to an individual's voluntary involvement, comprehensive societal and commercial consideration, and sense of social responsibility.

This is supported by the study of Saif et al. [64], which proved that consumers' intention to adopt has a positive relationship with perceived economic efficiency. According to their findings, practitioners should provide clients with financial benefits, such as charge-free, new, or unique services, and competitive prices, to further promote user acceptance. It has been established by Lane and Potter [109] that economic instruments point to a strategy of promoting the use of cleaner fuels and vehicles through the use of financial incentives, an approach based on the concept of ecological taxation reform. This indicates substantial evidence that economic factors can effectively encourage cleaner options such as hybrid cars.

Interestingly, despite the positive remarks of the latent price value (PV) (76.20%) indicators that hybrid cars are reasonably priced, good value for money, and a valuable purchase, it was still considered the second least significant factor affecting BI. Chaveesuk et al. [110] explained that price value, which is defined as consumers' cognitive trade-offs between the perceived costs and benefits of adopting a specific system, has a significant direct effect on behavioral intention. Concerning the demographic factors, most of the respondents have a monthly salary of 20,000 pesos to 50,000 pesos which means that they belong to the lower middle class to the middle class as stated on the indicative range of monthly family income in the study of Albert et al. [111]. However, consumers may purchase or are willing to invest in hybrid cars instead of fossil-fueled cars, regardless of the added amount, since they are considered cost-effective. This study figured that consumers are willing to pay the extra amount for the efficiency, environmental, and economic benefits that hybrid cars offer.

The least significant out of all the latent affecting behavioral intention was Habit (HB) (70.90%). Based on the indicators, using a hybrid car became a habit, an addiction for which consumers are willing to pay more, and serves as a daily utility. The utility of hybrid cars remains unrecognized and unfamiliar to many since the Philippine market for hybrid cars is currently sparse, which is why HB has not been established and is the least significant factor. Similarly, Nordfjaern et al. [112] discovered that the car habit factor negatively predicts intention and is not as significant as other behavioral factors. It was found that to predict better user intention, user personality traits must be assessed in line with TPB domains. As a result, consumers still need to develop the habit of using this mode of transportation. Eventually, it is expected that habit will soon develop if the hybrid car market in the Philippines becomes saturated, building strong familiarity with Filipino drivers.

To better provide insights among readers, Table 7 lists all the abbreviations used throughout the study.

Table 7. List of abbreviations used throughout the paper.

Abbreviations	Meaning
ANN	Artificial Neural Network
AT	Attitude
BI	Behavioral Intentions
DLNN	Deep Learning Neural Network
DT	Decision Tree
HB	Habit
HM	Hedonic Motivation
HV	Hybrid Vehicle
IDT	Innovation Diffusion Theory
MLA	Machine Learning Algorithm
MM	Motivational Model
NAM	Norm Activation Model
PE	Performance Expectancy
PECC	Perceived Economic Concern
PEPB	Pro-Environmental Theory of Planned Behavior
PENC	Perceived Environmental Concern
PV	Price Value
RFC	Random Forest Classifier
SE	Self-Efficacy
SI	Social Influence
SN	Subjective Norm
SQ	Service Quality
EE	Effort Expectancy

Table 7. *Cont.*

Abbreviations	Meaning
FC	Facilitating Conditions
PAS	Perceived Authority Support
STPB	Sustainability Theory of Planned Behavior
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
UTAUT2	Unified Theory of Acceptance and Use of Technology

5.1. Theoretical Contributions

According to the study by Agaton et al. [113], air pollution and greenhouse gas emissions from the combustion of fossil fuels are one of the main drivers of why governments and regions seek more sustainable means of transportation. With that, PEPB was used to analyze the environmental impact on consumers' behavioral intention and supports the other latent variables of the sustainability domains [22]. Alongside the PEPB framework, the sustainability domains, such as social, environmental, and economic, were considered, while the UTAUT2 addressed the technological aspect. In the study of Yuriev et al. [114], the TPB, or the theory of planned behavior, is the most extensively used model in studying individuals' behavior and is stated to encompass all environmental behavior variables. However, it lacks the necessary sustainability latent construct [102,115].

In measuring the acceptance entirely or holistically, the frameworks mentioned above were combined with integrating the economic aspect into the proposed sustainability theory of planned behavior (STPB). It can be applied when evaluating the current generation's behavioral intention and acceptance of newly emerging or current smart technologies such as the hybrid car. According to the study of Zadjafar and Gholamian [116], consumers nowadays are more conscious of obtaining and purchasing sustainable products. In this case, it was suggested that manufacturers and industries focus more on developing and selling products that attest to the demand of green consumers. Since all the factors in the study were proven significant, the developed framework could be used by future researchers to measure not only the behavioral aspect but also the sustainability aspect of an individual utilizing the STPB.

5.2. Practical and Managerial Implications

The findings of this study have demonstrated the importance of predicting consumers' acceptance of hybrid cars in the Philippines. Filipino drivers tend to consider hybrid cars when aware of the environmental and economic benefits. The result of the study proved that it is essential for the younger generation to adapt to a more sustainable lifestyle, with the high demand for greener transportation. Given that there is currently a limited market for hybrid cars in the Philippines, consumers are still unaware of the utility of these vehicles. Fortunately, this condition might improve with increased government reinforcement by adopting incentives to promote their utility. Hybrid cars cost more than fossil-fueled cars, which makes the marketing aspect challenging. In line with this, car companies and manufacturers can also use the result of this study as a framework for designing and implementing programs, strategies, and advertisements to propagate the marketability and utility of hybrid cars. It is suggested that car companies should consider millennials as the primary target for eco-friendly manufactured products such as hybrid cars, as projected in the study's demographic results. The advertisement and strategies may revolve around sustainability, target generation, and the development and usage of hybrid cars to engage purchasing intentions. Lastly, considering the technological aspect, companies can also disseminate information about the ecological and economic advantages of hybrid cars through social media platforms and in-app advertisements such as Facebook and YouTube ads that can be capitalized by marketing firms.

5.3. Limitations

Although there are positive findings in this study, there are also several limitations to be noted. First, due to the adapted questionnaire, there were limited constructs. The instrument was a self-administered online survey, which presents a constraint in terms of the modality of the dissemination and follows the second point, the consideration of the respondents. Having more constructs and items of measure may develop response efficiency. In addition, considering interviewers may identify drivers for purchasing hybrid cars among residents in the Philippines that other studies may consider.

Second, the primary criteria of a driver's license and the modality narrowed the respondents to those drivers who were active on social media. It is recommended that the data collection be more diversified and not be inclined to only a particular generation, specifically the millennials. A balance of each variation would emerge if the study could expound on other generations, such as Generation Z or baby boomers, and would also make studying the acceptance of each generation toward hybrid cars possible. It would be more profound to gather more respondents outside the current study's sample, such as public utility vehicles or public utility jeepney drivers, separately to reassess the different perspectives, behavior, and experiences of drivers toward hybrid cars.

Third, it is suggested that the study conduct interviews with these individuals to provide a qualitative and quantitative analysis of those who intend to purchase hybrid cars. Allowing the study to have a qualitative aspect would provide more flexibility. The insights from the interview results may be considered for additional latent variables and items of measure, even presenting a qualitative-quantitative study.

Fourth, this study only considered two machine learning algorithms: the random forest classifier and the deep learning neural network. To maximize the utility of related analysis techniques, other machine learning algorithm tools such as the Naïve Bayes classifier, K-Nearest neighbor, vector machine, or even C-Means clustering may be incorporated to capture different areas of the result and identify factors based on probability and similarities aside from the individual findings found in this study. Lastly, other tools such as K-Means clustering could be utilized after gathering respondents from different generations to assess the demographic characteristics of drivers who intend to purchase hybrid cars from the lowest to the highest valued customers, which would allow the researchers to formulate strategies with the market to support the economic aspect further. Simultaneous analysis of the various factors may be reanalyzed using multivariate analysis tools to justify the study's findings since the indirect effect found on each latent may provide a significant relationship among the factors considered when it comes to the behavioral, sustainable, and technological aspects of consumers' purchasing intentions toward hybrid cars.

6. Conclusions

There are not enough studies on the purchasing intentions regarding hybrid cars in developing countries like the Philippines. This necessitated the formulation of the Sustainability Theory of Planned Behavior (STPB). The framework was constructed using the Pro-environmental Theory of Planned Behavior (PEPB) and sustainability domains, as well as integration of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to predict the adoption of hybrid cars in the country. It was utilized to fully assess the acceptance of smart and green technology, emphasizing sustainability—a vital aspect when addressing climate change. A total of 1048 participants completed the self-administered survey, disseminated using non-probability sampling methods, including convenience and snowball sampling.

This study utilized a Machine Learning Algorithm (MLA) ensemble comprising a Decision Tree (DT), Random Forest Classifier (RFC), and Deep Learning Neural Network (DLNN), which proved that PENC, AT, PBC, and PE were the most influential factors that significantly affect user acceptance of hybrid cars in the Philippines. This implies that MLA is advantageous in analyzing the antecedents of human behavior, particularly sustainability behavior. Comparing the results of both SEM and MLA, this study identified that MLA provided better and more accurate results since this study was able to consider an expanded and large framework for analysis. However, based on other studies, a smaller model may provide similar output. Therefore, this study concludes that using MLA may be applicable and better suited for analyzing nonlinear relationships among large and extended models. Moreover, it should be noted that this study was not able to guarantee that it represents an unbiased cross section of the target audience since a convenience sampling approach was used due to the limitations discussed. In addition, this study only focused on those who are capable and have drivers' licenses. This means that the output may be biased in the aspect of capable purchasers.

From this study output, perceived environmental concerns have the highest significant direct effect on behavioral intention, suggesting that the environmental benefits that come with utilizing green technology increase Filipino drivers' tendency to purchase hybrid cars. It is recommended that car companies consider the study's results and demographics in propagating the marketability of hybrid cars. Other researchers could use the STPB framework established by the study's constructs and model to contextualize and emphasize technological sustainability, which further validates the objectives of the United Nations' Sustainable Development Goals (SDGs) to expedite the decarbonization of the overall market and the entire economy.

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