A SEM–Neural Network Approach to Predict Customers' Intention to Purchase Battery Electric Vehicles in China’s Zhejiang Province

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Abstract: As part of the increasing efforts toward the prevention and control of motor vehicle pollution, the Chinese government has practiced a range of policies to stimulate the purchase and use of battery electric vehicles (BEVs). Zhejiang Province, a key province in China, has proactively implemented and monitored an environmental protection plan. This study aims to contribute toward streamlining marketing and planning activities to introduce strategic policies that stimulate the purchase and use of BEVs. This study considers the nature of human behavior by extending the theory of planned behavior model to identify its predictors, as well as its non-linear relationship with customers’ purchase intention. To better understand the predictors, a substantial literature review was given to validate the hypotheses. A quantitative study using 382 surveys completed by customers in Zhejiang Province was conducted by integrating a structural equation model (SEM) and a neural network (NN). The initial analysis results from the SEM revealed five factors that have impacted the customers’ purchase intention of BEVs. In the second phase, the normalized importance among those five significant predictors was ranked using the NN. The findings have provided theoretical implications to scholars and academics, and managerial implications to enterprises, and are also helpful for decision makers to implement appropriate policies to promote the purchase intention of BEVs, thereby improving the air quality.

Keywords: battery electric vehicles; purchase intention; structural equation model; neural network; theory of planned behavior

1. Introduction

1.1. Background of Battery Electric Vehicle (BEV) Development in China

The increase in environmental concerns such as temperature change, air pollution, and the international energy crisis, and the problem of motor vehicle pollution has become more and more prominent globally [1]. The issue of vehicle pollution has attracted much attention and there have been many studies analyzing it due to its profound impact on the environment. The rapid growth in individual car ownership has led to the transportation sector becoming one of the vital energy consuming sectors in the world, in addition to being one of the primary contributors of greenhouse gases [2]. This poses serious challenges to energy security and environmental protection [3–5]. Based on China’s Vehicle Environmental Management 2018 Annual Report from the
Ministry of Ecology and Environment of the People’s Republic of China, the motor vehicles in China amounted to 310 million at the end of 2018 [5]. According to a forecast by the same report, China will experience an increase of more than 100 million motor vehicles in the next five years. This will result in a consequential increase in the consumption of gasoline and diesel from 100 million to 150 million tons, creating a heavier burden of air pollution. Motor vehicle pollution is one of the main causes for environmental air pollution in China; however, China has also been the largest producer as well as exporter of motor vehicles for nine consecutive years in the world [6,7].

Based on the above, it is recognized that the urgency for motor vehicle pollution intervention and control has become severely prominent [5]. New energy vehicles (NEVs) refer to the vehicles that are powered by new energy sources which are different from traditional energy sources, while the traditional vehicles are powered by traditional fossil energy [8]. The growth of NEVs has similarly become an important means to control greenhouse gas emissions, improve the atmospheric environment, ensure energy security, and attract the attention of governments around the world [2,9]. Un-Noor et al. [10] classified NEVs into battery electric vehicles (BEVs), hybrid electric vehicles, plug-in hybrid electric vehicles, and fuel cell electric vehicles. In addition, NEVs have some general features such as low emissions or zero-emission with water or oxygen [11]. Recently, the BEV has become particularly popular in the transportation sector. In this study, BEVs are defined as vehicles that are powered by electrical batteries and whose operation is entirely reliant on the energy stored in the battery packs [10].

Since 2014, both the local and central governments in China have issued a series of special policies to stimulate the development of NEVs [12]. These include fiscal subsidies, tax exemptions, industry access, electricity prices, infrastructure construction, subsidies for public transportation operations, and procurement of official vehicles. It is estimated that the total amount of various national and local subsidies for NEVs exceeds 1 trillion RMB [13]. Regarding the development of NEVs in China, sales reached 777,000 units in 2017, accounting for 54.7% of the sales of NEVs in major countries around the world, but only accounting for 2.69% of all car sales in China. Regarding vehicle use, passenger cars accounted for 74.4%, and commercial vehicles accounted for 25.5%. From the perspective of power supply type, BEVs accounted for 83.9%, while plug-in hybrid electric vehicles accounted for 16.1% [6,7]. Although China has issued a number of policies to encourage the development of the NEV industry, the market share of NEV is still small [14]. The most appropriate means to effectively promote NEV has become one of the hottest topics in China [15–17]. Therefore, research to understand consumer’s purchase intention concerning BEVs is an important issue in China.

Zhejiang Province is one of the key provinces in China with a beautiful natural environment. With the reform and opening for 40 years in China, Zhejiang Province has realized the historical leap from an agricultural province to a rapidly developing economic province [18]. It has become one of the fastest growing and most dynamic regions in the east coast of China, and also is known as the “Zhejiang economic miracle” and “Zhejiang economic phenomenon” [19]. At the end of 2017, there were 16.98 million motor vehicles in Zhejiang Province, placing it in sixth place of all the provinces in China concerning vehicle ownership. Of these, this amount number has seen an increase of 1.38 million motor vehicles from 2016 and is expected to continue experiencing at a rate of 11% year-on-year annual growth [20].

Furthermore, there are 20.78 million registered motor vehicle drivers in Zhejiang Province, also ranked sixth in China [20]. The province plans to implement the “Plan to Win Blue Sky in Three Years in Zhejiang Province” that is aimed at improving the environmental air quality. This plan includes reducing the average PM2.5 concentration to 35 micrograms per cubic meter or less, having 82.6% days per year with good air quality, and reducing the days with heavy pollution by 25%. Moreover, the provincial government aims to reduce total emissions of sulfur dioxide and nitrogen oxides by more than 17%, compared to 2015 [6,7]. To realize the goal, large-scale promotion of BEVs and other measures are required.
1.2. Research Questions and Objectives

This study helps target and plan marketing and policy activities to promote the sale of BEVs, and this research will first identify and address the gap in existing literature concerning customers’ purchase intention of BEVs by extending the theory of planned behavior (TPB) model. However, in order to further explore the nature of human being behavior, the TPB can be developed by discussing new variables such as environmental performance, price value, non-monetary incentive policy (NMIP) and monetary incentive policy (MIP) measures which influence consumers’ purchase intention. In addition, considering that the existing studies concerning the promotion of BEVs were based on sampling consumers within a large domestic city, this research provides an in-depth empirical study involving consumers living in Zhejiang Province. As a result, the research provided reference for other large and medium-sized provinces in China to promote the purchase and use of BEVs, and also have referential value for other large and medium-sized regions in other countries. Furthermore, by using a consumer questionnaire survey, new factors influencing the promotion of BEVs can be explored to identify other factors that may influence consumers’ purchase behaviors. Having this knowledge will accelerate the growth and development of the BEV market and contribute toward alleviating the problems of energy supply and environmental pollution.

This study also combines the structural equation model (SEM) and neural network (NN) approach to perform hypothesis testing and a linear or non-linear regression model [21,22] to discover the factors affecting consumers’ purchase intention. The SEM will therefore identify the independent variables that have a significant influence on BEV purchase intention, while the significant predictors obtained from SEM will be used to rank their normalized importance through the NN. The strength of the combination of SEM with NN is that it helps to remedy the two critical “blackbox” weakness of oversimplifying the model in SEM and overfitting the model in the NN [23,24]. Consequently, the results of this research will be especially beneficial for decision makers to implement policies regarding the purchase and use of BEVs.

The remainder of this research is structured as follows: Section 2 introduces the literature review and related works of consumers’ purchase intention for BEVs, the TPB, and the NN. The conceptual framework and hypotheses are outlined in Section 3. Section 4 discusses the methodology, while Section 5 provides the results from the respective models. In addition, Section 6 presents the broader discussions with results of this research and compares with other studies as well. Finally, a conclusion is given in Section 7, including both managerial and social implications as well as limitations, and future research opportunities.

2. Literature Reviews and Related Works

2.1. Purchase Intentions for a Battery Electric Vehicle (BEV)

Taking into considering that technological factors and energy consumption matters are significant reasons that may determine consumers’ BEV purchase intention, one of the most noticeable results identified to expand the BEV market share is improving the batteries of BEVs. An improved battery is expected to have a longer life and increased efficiency [25]. Wu et al. [26] collected data concerning BEVs and their battery systems to measure energy consumption. They discovered that the BEV is more energy-efficient when driving in an urban setting (with many stops and slow traffic) than on continuous freeways. In our previous work [27], we also discussed the technical improvement of BEVs, considering both battery-related issues and the vehicle capacity of electric vehicles’ routing problems and extending the policy of classical recourse and preventive restocking.

However, rather than technology or energy attributes, the universal purchase intention concerning BEVs are mainly dependent on consumer perceptions [28]. In the social psychology field, intention refers to the related factors that may influence the actual behavior of an individual [29], which is an accurate indicator that could predict individual behavior [30]. As such, there is a large number of studies on consumer intention to purchase BEVs [17,31]. However, some of these studies use a rational
behavior framework (such as the rational choice theory) to determine positive and negative perceptions, while others inspect the perception effect, which is either positive or negative [17]. Furthermore, a large body of previous studies covers the industrial policy from the perspective of supply [32–36], rather than discussing consumers’ purchase behavior of BEVs from the perspective of demand. Table 1 presents the different opinions of major studies on the perceptions and experience of BEVs.

| Author                 | Research Aims                                                                 |
|------------------------|------------------------------------------------------------------------------|
| Mau et al. [35]        | To find the dynamics of consumer preferences by modeling the discrete choice, with the data collected from two national surveys related to new vehicle technologies in Canada. |
| Axsen et al. [32]      | To investigate the “neighbor effect” on hybrid-electric vehicles by using stated preference and revealed preference choice. |
| Bunce et al. [31]      | To evaluate the attitudes and experiences of 135 drivers after driving EV for 3 months trial in a UK Ultra Low Carbon Vehicle. |
| Egner and Trosvik [33] | Using panel data to test the influence of local policy measurements to encourage the electric vehicles’ adoption in Sweden. |
| Huang and Ge [5]       | To present the mechanism model of electric vehicles’ purchase intention under the theory of planned behavior, and analyze the factors using SEM. |

Therefore, this study takes a different approach to address BEV purchase intention based on TPB and its extension through positive utility. The positive utility includes attitude, perceived behavioral control, subject norm, environmental performance, price value, NMIP measures, and MIP measures.

2.2. Theory of Planned Behavior (TPB)

A person’s intention is thought to be a factor that can influence human behavior directly. Therefore, understanding an individual’s intention makes it highly possible to predict their consequent behaviors. In the area of social psychology, the TPB was developed by Ajzen in 1985 [37], who proved that attitudes toward behavior, subjective norms, and perceived behavioral control can be used to accurately predict the intention of various behaviors [29]. Moreover, crucial variances occur in actual behavior when these intentions are combined with perceived behavioral control [29].

In broad terms, the TPB model was designed to improve the explanatory power of a standard model and to predict behavioral intentions in real life. Previous researchers have claimed that the TPB model can improve the prediction of intentions significantly by using attitudes, subjective norms, perceptions of behavioral control, and individuals’ moral obligations [29,38]. For example, Yazdanpanah and Forouzani [39] used the model to predict Iranian students’ purchase intentions and found a relationship between their intentions. Yadav and Pathak [40] observed that the TPB model can help predict young consumers’ intention to buy green products and Paul et al. [41] measured consumers’ green product purchase intention in India by building the TPB model and extending it using the theory of reasoned action.

A broad range of intentions and behaviors in various research areas have been explained by using the TPB model, including existing green research pertaining to the use of BEVs (e.g., Huang and Ge [5]; Paul et al. [41]; Degirmenci and Breitner [42]; Ritter et al. [43]; Jing et al. [44]).

2.3. Neural Network (NN)

NN is currently one of the most popular artificial intelligence techniques. It was developed by Haykin [45], who defined it as a massively parallel and distributed processor composed of simple processing units, which have a neural propensity to store data and knowledge from the experiment and ensure the availability of its usage.

The shortcomings of using conventional linear statistical techniques is clear, since only linear relationships can be detected, which may oversimplify the sophisticated decision-making processes [22].
Compared with traditional statistical methods, such as multiple regression analysis and SEM, NN has some obvious advantages. First of all, to solve the proposed research problem, the NN method was suggested, which can discover both linear and non-linear relationships, allowing the process inspection of non-compensatory decision [24]. Secondly, NN is superior to traditional compensatory models including multiple, logistic, and discriminant regression analyses in various aspects [46]. More specifically, NN cannot only promote the effectiveness of a linear relationship, but also save training time due to a large training set [47]. The testing and training data—that include input patterns and expected output results—should have a representativeness to include the different characteristics of the problems [48]. Finally, NN provides more accurate predictions, and the accuracy of NN can be further improved by “learning” from the input data, meaning that situations can be generalized to the NN without being taught [23].

There are many types of multiple-analytic approaches that combine NN and SEM. For instance, SEM can be used to analyze part of the question responses, while the rest of the responses can be predicted by the NN [22]. However, Scott and Walczak [49] suggested that the efficiency of the causal relationship in the research model should be tested first by checking the model’s goodness of fit before predicting the factors by using NN among SEM’s supported relationships. Using the output result of NN as SEM’s input is also a common approach [24]. Although there are existing research that applied NN, such as economic and financial studies [50,51], these studies leave gaps in the application of NN concerning customer relationship management and customer satisfaction. Therefore, to further develop the existing research field, this study aims to determine BEV purchase intention from a customer perspective by combining the SEM and NN approaches, which is a different method from previous studies.

Based on the above, a two-stage approach was be applied in this study. First, the SEM was first employed to test the variables that have significant relationships with BEV purchase intention. Next, the non-compensatory NN model was used to predict the BEV purchase intention considering the significant intention factors. Finally, the results were analyzed for accuracy.

3. Conceptual Framework and Hypotheses Justification

3.1. Attitude, Perceived Behavioral Control, and Subject Norm

A major contribution of the TPB is its high explanatory power, which can link behavioral intention with social psychological constructs [52]. The explaining attitude concerning perceived behavioral control and subject norm can predict different types of behavioral intention. Attitude can be defined as the positive or negative evaluation of a psychological emotion, which is the outcome of rational-choice-based evaluation [29]. Perceived behavioral control is understood as a human being’s belief that she/he can complete a certain behavior of inherent difficulty. It can further be stated that the decision was not made on impulse but was under their volitional control [41]. Generally speaking, an individual’s outcome can be determined by her/his own behaviors and internal locus of control, but a low perceived behavioral control may make an individual feel that the chances are slim [29]. Subject norm mentioned in the TPB includes the strength of the belief and corresponding motivations.

In this study, attitude refers to the consumers’ positive or negative evaluation of the purchase of BEVs. Perceived behavioral control is defined as consumers’ ability to purchase BEVs. Subject norm represents the perception of important people (such as family and friends or influential people like celebrities) who may or may not influence them to purchase BEVs. Therefore, the following hypotheses are proposed:

**H1:** Consumers’ attitude has a significant and positive effect on their intention to purchase BEV.

**H2:** Perceived behavioral control has a significant and positive effect on their intention to purchase BEV.

**H3:** Subject norm has a significant and positive effect on their intention to purchase BEV.
3.2. Environmental Performance

In China, pro-environmental behaviors such as a “low carbon lifestyle” and “environmental protection” are becoming more and more popular [15]. Pro-environmental behaviors are considered as either direct or indirect behaviors that benefit environmental sustainability and conservation. These may include perceptions towards geographic locations and environmental value [53]. BEVs have two main features that contribute to environmental protection: energy-saving and environment-friendly features. These features are becoming popular around the world [16].

The majority of Chinese people realize that environmental pollution, deteriorating air quality, and increasing frequency and intensity of extreme weather calls for increased awareness of the need for environmental protection [16]. Environmental performance refers to people’s awareness and their contribution towards environmental protection by purchasing and using BEVs. The impact of environmental performance is considered to be very important when purchasing a BEV. Therefore, the following hypothesis is proposed:

**H4:** Environmental performance has a significant and positive effect on the intention to purchase BEV.

3.3. Price Value

Many factors can influence BEV purchase intention. However, previous research shows that the price of a vehicle is the key driver for customers to purchase a BEV. Price signals can also change customers’ purchase behavior [2]. Generally, the BEV is considered to be a “green” product and the effect of influence on purchasing decisions is associated with price as well as other costs [54]. Mostly, prices of green products—such as BEVs and solar panels—tend to be higher than non-green products. While some consumers prefer to pay more to use green products, there are also those who do not [55]. Since, the price value may affect the customer’s intention to buy a BEV, in this study, the price value will be considered as the consumer’s perception of a “reasonable price” for a BEV. Thus, the following hypothesis is proposed:

**H5:** Price value has significant and positive effect on the intention to purchase BEV.

3.4. Government Incentive Policy Measures

Earlier empirical research has already examined the influence of incentive policy instruments to promote BEV. Langbroek et al. [34] used a stated choice experiment and argued that policy instruments have a significant and positive effect on the purchase of BEV. The research further stated that non-financial incentive policy instruments—such as providing permission to drive along bus-only lanes and free parking—are an effective choice. Chandra et al. [4] elaborated on a Canadian province and argued that consumers chose BEVs mainly due to the tax rebate incentives, which saves BEV users a great deal of money. Similarly, Beresteanu and Li [3] carried out a survey on BEV owners and figured out that federal incentives have positive influence on the purchase and use of BEV. The measure of incentive policy is one of the key factors influencing consumers’ intention to buy BEVs.

Different provinces and cities in China have adopted different incentive policies for BEVs, which is currently in use. In Zhejiang Province, BEVs bear special green colored vehicle license plates, certain traffic restrictions for BEVs were abolished, purchase subsidies are available when purchasing BEVs, loan limits for purchasing BEVs were increased, and tax exemption and preferential insurance policies were implemented as part of BEVs’ policy incentives. Inspired by the work of Huang and Ge [5], the government’s incentive policy measures are also divided into two parts: MIP and NMIP. Thus, the following hypotheses are proposed:

**H6:** Non-monetary incentive policy measures have a significant and positive effect on the intention to purchase BEV.

**H7:** Monetary incentive policy measures have a significant and positive effect on the intention to purchase BEV.
3.5. Research Model Development

According to the hypotheses stated above, the research model for the research is developed as presented in Figure 1.

![Research Model](image)

**Figure 1.** Research model.

The research model hypothesizes that the intention factors of attitude, perceived behavioral control, subject norm, environmental performance, price value, and two government incentive policy measures (NMIP and MIP) will have significant and positive relationship with consumer intention to purchase a BEV.

4. Methodology

4.1. Sample and Procedure

An online survey was conducted in Zhejiang Province, China in December 2018 and January 2019. The initial English survey questionnaire was translated into Chinese, and disseminated using “Questionnaire Star (https://www.wjx.cn)”, China’s largest online survey portal. To encourage response rate and quality, respondents were given an option to participate in a lottery draw or to receive 2 RMB in cash credits for completing the survey. The respondents took an average of 10 mins to complete the 2-page survey. A total of 460 Zhejiang residents older than eighteen took part in the survey questionnaire and 382 valid and completed responses were analyzed. The total response rate was 83.04%. Table 2 shows the results of respondent profiles.
Table 2. Respondent profile.

| Respondents' Characteristics | Item                        | Frequency (n = 382) | Percentage (%) |
|------------------------------|-----------------------------|---------------------|----------------|
| Gender                       | Male                        | 179                 | 46.90          |
|                              | Female                      | 203                 | 53.10          |
| Age                          | 18–25                       | 105                 | 27.50          |
|                              | 26–33                       | 115                 | 30.10          |
|                              | 34–41                       | 54                  | 14.10          |
|                              | 42–49                       | 62                  | 16.20          |
|                              | 50–57                       | 39                  | 10.20          |
|                              | Older than 58               | 7                   | 1.80           |
| Family size                  | 1 person                    | 6                   | 1.60           |
|                              | 2–3 persons                 | 211                 | 55.20          |
|                              | 4–5 persons                 | 129                 | 33.80          |
|                              | More than 5 persons         | 36                  | 9.40           |
| Education level              | High school and below       | 31                  | 8.10           |
|                              | Technical secondary school  | 10                  | 2.60           |
|                              | Junior college              | 54                  | 14.10          |
|                              | Undergraduate course        | 199                 | 52.10          |
|                              | Master                      | 72                  | 18.80          |
|                              | Doctor                      | 16                  | 4.20           |
| The total family income from | ¥100,000 and below          | 76                  | 19.90          |
| all sources before taxes     | ¥110,000–200,000            | 142                 | 37.20          |
|                              | ¥210,000–400,000            | 103                 | 27.00          |
|                              | ¥410,000–600,000            | 26                  | 6.80           |
|                              | ¥610,000 and above          | 35                  | 9.20           |
| BEVs owned in the household  | Yes                         | 13                  | 3.40           |
|                              | No                          | 369                 | 96.60          |
| Willing to pay for a BEV     | ¥100,000 and below          | 125                 | 32.70          |
|                              | ¥110,000–200,000            | 162                 | 42.40          |
|                              | ¥210,000–300,000            | 64                  | 16.80          |
|                              | ¥310,000–400,000            | 17                  | 4.50           |
|                              | ¥410,000–500,000            | 6                   | 1.60           |
|                              | ¥510,000 and above          | 8                   | 2.10           |
| Planning to buy a BEV in the | Yes                         | 98                  | 25.70          |
| coming 2 or 3 years          | No                          | 284                 | 74.30          |

4.2. Partial Least Squares (PLS)-SEM and NN Approach

A multi-analytical approach that combines partial least squares structural equation modeling (PLS-SEM) with NN was applied in this research. PLS-SEM can be considered as a complete SEM approach, which is a statistical framework to deal with a factors model that includes substantive or theoretical models, unobserved or observe variables, and observed data of model testing [56]. This means that PLS-SEM is used to figure the relationship among observed variables by using different types [57]. On the one hand, SEM can explore the relationships among multiple variables. To be specific, SEM can deal with two kinds of variables, which are measurement variables and potential variables. On the other hand, SEM allows measurement errors in both dependent variables and independent variables, because errors always exist in measurement of behavior. For instance, it is difficult for traditional analysis methods to solve the problem involving complicated relationships, but SEM can be used to analyze the structure of the relationships among latent variables for calculating correlation coefficients [39]. However, when considering the customer’s intention to purchase BEV, linear models like PLS-SEM tend to oversimplify the complexities. To solve the problem of oversimplification, the NN can be combined with PLS-SEM to identify non-linear relationships [21,22]. Although the application
of NN is an extremely suitable approach for prediction, it still has its limitations. The biggest limitation lies in it being a “blackbox” method, which makes it inappropriate to test hypotheses and examine causal relationships [23]. Thus, to balance these two methods and to take full advantage of both PLS-SEM and NN, this study first examined the research model and hypotheses using PLS-SEM, of which the results were used for further ranking analysis using NN. This approach solves the problem of overfitting the model, which is the biggest disadvantage of NN. Although PLS-SEM has often been used to verify hypothesized relationships in social and behavioral science, there are few studies on integrating it with other artificial intelligence algorithms and even fewer pertaining to purchase intention studies on BEVs. Therefore, this research fills the blank in the literature concerning the above.

4.3. Evaluation of the Measurement Model

The survey questionnaire included seven independent variables and one dependent variable through four parts. The first part measured 13 demographic variables that included gender, age, marital status, family size, education level, city, convenience level of public transportation, job specification, family income, car ownership, BEV ownership, and future plans to purchase a BEV. The second part of the survey contained questions concerning attitude and perceived behavioral control that were adapted from the work of Paul et al. [41], while questions about subject norm were adopted from Nayum and Klöckner [58]. McCarty and Shrum [59] provided a good survey question on environmental performance. Questions on price value were taken from the work of Venkatesh and Goyal [21]. In the third part, questions concerning NMIP and MIP measures were adopted from Zhang et al. [15], which reviewed the respondents’ satisfaction with incentive policy measures of BEVs in Hangzhou City, the capital of Zhejiang Province. Lastly, questions on purchase intention were reviewed by referencing the work of Nayum and Klöckner [58]. Apart from demographic variables, a five points Likert-type scale was adopted in the survey questionnaire, ranging from 1 to 5, where 1 referred to strongly disagree and 5 referred to strongly agree. The questionnaire used for this paper is provided in the Appendix A. Table 2 represents the results of the demographic profile of the respondents.

5. Analytical of Results

5.1. Assessment of the Measurement Model

A three-step statistical data analysis was performed as suggested by Liébana-Cabanillas et al. [60] and Chong [61]. First, to evaluate the validity of the conceptualized research model, the value of the Cronbach’s alpha coefficient was applied to determine the reliability of model variables. Furthermore, a factor confirmatory analysis was used to determine the convergent and discriminant validity and composite reliability. Secondly, the hypotheses were verified with the PLS-SEM path modeling estimation by applying SmartPLS 3, which also determined the significant hypothesized predictors. The main reason to apply PLS-SEM is that it can manage the factor models and the models composed of estimating constructs, measure the structural models, and conduct the model’s adjustment trials [62]. In the last step of the analysis, the strength of the influence of exogenous variables on the endogenous variables were verified by using NN and the significance of endogenous variables were verified by PLS-SEM. In other words, analyzing the results of PLS-SEM through the NN determined the importance of each predictor variable. In summary, inspired by Scott and Walczak [49], the hypotheses, reliability, and validity were examined by PLS-SEM, while the strength of the influence of antecedents as predictors on BEV purchase intention was verified by NN. Social Sciences (SPSS v20) and SmartPLS 3 software were used to conduct the data analysis.

5.2. Factor Analysis and Construct Reliability

This paper employed a principal component analysis to conduct a factor analysis and thereby ensure the construct validity. As shown in Table 3, the factor loadings of all factors in this research were higher than 0.50, confirming the validity of the constructs.
Table 3. Reliability and validity.

|                      | Factor Loadings | \( \alpha \) | CR   | AVE  | \( R^2 \) |
|----------------------|-----------------|--------------|------|------|---------|
| Attitude (ATT)       | 0.911–0.935     | 0.915        | 0.947| 0.856|         |
| Perceived behavioral control (PBC) | 0.762–0.882     | 0.786        | 0.875| 0.701|         |
| Subject norm (SN)    | 0.816–0.896     | 0.826        | 0.900| 0.750|         |
| Purchase intention (PI) | 0.823–0.850     | 0.784        | 0.879| 0.707| 0.694   |
| Environmental performance (EP) | 0.937–0.965     | 0.945        | 0.965| 0.901|         |
| Price value (PV)     | 0.846–0.917     | 0.857        | 0.914| 0.779|         |
| Non-monetary incentive policy (NMIP) | 0.823–0.918     | 0.856        | 0.912| 0.777|         |
| Monetary incentive policy measures (MIP) | 0.847–0.955     | 0.939        | 0.957| 0.847|         |

Note: CR = composite reliability, \( \alpha \) = Cronbach’s alpha, AVE = average variance extracted, \( R^2 \) = coefficient of determination.

Hair et al. [63] suggested adopting three criteria to examine convergent validity: Cronbach’s alpha, composite reliability (CR), and average variance extracted (AVE). Cronbach’s alpha is applied to measure the reliability, which should ideally fall between 0.60 and 0.70, requiring a reliability of 0.70 or higher and that 0.60 is the lower acceptable limit [64]. CR must be examined before assessing construct validity. The values above 0.60 reflect a latent construct that extends the measured variables’ reliability and internal consistency [63]. AVE is a brief measure that reflects the convergence among a set of items in a latent construct. The value of AVE should be greater than 0.50 [65]. All the constructs shown in Table 3 met the three criteria. The values of the Cronbach’s alpha of all the factors were greater than 0.70, the CR’s values were greater than 0.60, and the AVE values were greater than 0.50. The value of CR was higher than that of AVE, which confirmed the convergent validity. However, the value of \( R^2 \) was 0.694 (higher than 0.670), indicating the endogenous value has forceful explanatory power in practice.

Table 4 shows the results of the discriminant validity measures, while the diagonal values indicate that the average variance is obligated to each variable. Given the results shown in Table 4, all diagonal values are higher than non-diagonal lines, which indicate the goodness of fit of the measurement methods in this research [66]. Particularly, the value of the correlation coefficients of the model between the variables ranged between 0.269 and 0.727.

Table 4. Result of discriminant validity measures.

|                | ATT  | PBC  | SN   | PI   | EP   | PV   | NMIP | MIP  |
|----------------|------|------|------|------|------|------|------|------|
| Attitude (ATT) | 0.925|      |      |      |      |      |      |      |
| Perceived behavioral control (PBC) | 0.727 *** | 0.837|      |      |      |      |      |      |
| Subject norm (SN) | 0.647 *** | 0.644 *** | 0.866|      |      |      |      |      |
| Purchase intention (PI) | 0.705 *** | 0.761 *** | 0.635 *** | 0.841|      |      |      |      |
| Environmental performance (EP) | 0.505 *** | 0.479 *** | 0.457 *** | 0.599 *** | 0.949|      |      |      |
| Price value (PV) | 0.539 *** | 0.513 *** | 0.542 *** | 0.552 *** | 0.459 *** | 0.883|      |      |
| Non-monetary inc. policy (NMIP) | 0.269 *** | 0.273 *** | 0.270 *** | 0.323 *** | 0.440 *** | 0.296 *** | 0.881|      |
| Monetary inc. policy measures (MIP) | 0.454 *** | 0.353 *** | 0.363 *** | 0.464 *** | 0.419 *** | 0.457 *** | 0.675 *** | 0.920|

Note: *** Correlation is significant at the 0.01 level (two-tailed). The data bold on the diagonal represent the square root of each latent variable (AVE). “inc.” is the abbreviation of “incentive”.

As a result, the measurement methods of convergence and discriminant validity in this research were within acceptable limits. This confirms that the research was valid for further analysis and discussions.

5.3. Structural Model PLS Results

Table 5 presents the results of the discriminant validity measures tests. Based on these results, perceived behavioral control was the most important variable that influences consumers’ decision to purchase BEVs, followed by environmental performance, MIP measures, attitude, and subject norm. Nonetheless, all of these variables had a significant impact on customers’ intention to buy
BEVs. However, the results also indicate that price value and NMIP measures do not have a significant influence on customers’ intention to purchase BEVs.

Table 5. Structural model results.

| Hypothesis                                  | Mean   | T-Statistics | Standard Deviation | Remarks |
|---------------------------------------------|--------|--------------|--------------------|---------|
| H1: Attitude -> Purchase intention         | 0.135  | 2.394        | 0.055              | **      |
| H2: Perceived behavioral control -> Purchase intention | 0.447  | 9.777        | 0.046              | ***     |
| H3: Subject norm -> Purchase intention     | 0.098  | 2.374        | 0.043              | **      |
| H4: Environmental performance -> Purchase intention | 0.199  | 4.776        | 0.042              | ***     |
| H5: Price value -> Purchase intention      | 0.050  | 1.452        | 0.034              | n.s.    |
| H6: Non-monetary inc. policy measures -> Purchase intention | −0.011 | 0.326        | 0.034              | n.s.    |
| H7: Monetary inc. policy measures -> Purchase intention | 0.102  | 2.655        | 0.039              | ***     |

Note: *** T-statistics >2.58 of significance at 1%, ** T-statistics >1.9 of significance at 5%, * T-statistics >1.78 of significance at 10%, n.s. means not significant.

5.4. Neural Network Analysis

This study used SPSS v20 to build the NN model, which plays an important branch of modern artificial intelligence techniques and was trained by a multilayer perception training algorithm. Several hierarchical layers such as one input, one or more hidden, and one output layer comprise a typical NN [22]. Furthermore, the input layer of this research consisted of five independent significant variables, which was the output from PLS-SEM (e.g., perceived behavioral control, environmental performance, MIP measures, attitude, and subject norm), while the output layer was composed of one output variable (e.g., purchase intention). The analysis examined the network with one to ten hidden nodes, as there is no heuristic method to identify the number of hidden nodes in a NN [67]. The nodes’ number in one hidden layer was set to 2, and the activation function was set to sigmoid function in both hidden and output layers, following recommendations of Chong et al. [22] and Liebana-Cabanillas et al. [60]. As for increasing the effectiveness of training, both inputs and outputs were normalized to the range [0, 1] [60]. Figure 2 shows the NN architecture for this study.

The NN was validated by computing the root mean square error (RMSE) in both the training and testing datasets. Following Hyndman and Koehler’s [68] suggestions, accuracy can be measured by RMSE—as RMSE is a scale-dependent measure of forecast accuracy—by comparing specific datasets to predict errors. RMSE is always positive and the value of 0—indicating a perfect fit—has virtually never happened in practice. In other words, lower values of RMSE are preferred and the value of RMSE can be calculated as follows:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{n} (X_{\text{Obs},i} - X_{\text{true},i})^2},
\]

where \(X_{\text{Obs},i}\) is the observed value, and \(X_{\text{model},i}\) is the true value.

The averages and standard deviations were also calculated and are presented in Table 6. As mentioned earlier, to avoid over-fitting, a ten-fold cross validation was implemented where 90% of the data were used to train the NN, while the remaining 10% of the data were applied to measure the trained network’s prediction accuracy. The results of RMSE values for the NN is shown in Table 6 as well.
Figure 2. The map of neural network architecture. Note: X1 = attitude, X2 = perceived behavioral control, X3 = subject norm, X4 = environmental performance, X5 = monetary incentive policy measures.

Table 6. Root mean square error (RMSE) values for the neural network.

| Neural Network | Training | Testing |
|----------------|----------|---------|
| ANN1           | 0.074    | 0.076   |
| ANN2           | 0.085    | 0.104   |
| ANN3           | 0.071    | 0.087   |
| ANN4           | 0.068    | 0.078   |
| ANN5           | 0.086    | 0.096   |
| ANN6           | 0.067    | 0.108   |
| ANN7           | 0.081    | 0.104   |
| ANN8           | 0.072    | 0.102   |
| ANN9           | 0.078    | 0.062   |
| ANN10          | 0.079    | 0.088   |
| Average        | 0.018    | 0.022   |
| Standard deviation | 0.002 | 0.004 |

Note: RMSE = root mean square error.

In training the model, the average value of RMSE in the NN was 0.018, while the value of the testing model was 0.022. Conversely, the standard deviation of training model was 0.002, while the standard deviation of the testing model was 0.004. The value of RMSE was low, indicating that it is an accurate and reliable prediction [22,60,69].

Table 7 presents the sensitivity analysis performance. The sensitivity analysis provided information concerning the importance of each predictor, whereas the importance of each independent variable was an extent of how much the value predicted by the network model varies with diverse values of the independent variable [24]. The normalized importance value was the rate obtained by dividing the importance values of each predictor by the largest importance value, presented as a percentage.
Table 7. Normalized variable importance.

| Predictors                                | Normalized Importance (%) |
|-------------------------------------------|---------------------------|
| Attitude                                  | 76.10                     |
| Perceived behavioral control              | 100                       |
| Subject norm                              | 84.69                     |
| Environmental performance                 | 77.80                     |
| Monetary incentive policy measures        | 50                        |

According to the sensitivity analysis performance, it is clear that perceived behavioral control was the most significant predictor of BEV purchase intention, followed by subject norm, environmental performance, attitude, and MIP measures.

6. Discussions

The broader discussions with results of other studies are given below.

On the one hand, consistent with previous purchase intention studies of BEV, attitude, perceived behavioral control, and MIP measures were found to be significant when consumers consider purchasing a BEV [5,15], which support H1, H2, and H7. Moreover, it was found that price value and NMIP do not have significant impact on the customer’s purchase intention, which rejects H5 and H6. In this case, since the results are same as previous studies, the research therefore helps to validate the research model from a customer’s perspective for BEV market and policy decision makers.

However, on the other hand, it is also worth noting how partial results of this experiment differed from other studies such as Huang and Ge [5], Zhang et al. [15], and He et al. [17]. The results showed that the subject norm (H3) and environmental performance (H4) have a significant influence on the intention to purchase BEVs. In this sense, the difference can be interpreted that the penetration rate of BEVs is not very high and is not enough to influence the decision-making behavior of buyers using social pressure in China. However, in Chinese traditional culture, the subject norm of consumers is affected by image value, which implies that it is very necessary to consider whether their purchase behavior will help them retain a good impression in their social circle. There are a few studies on BEV purchase intention from the perspective of environmental performance. Since the environmentally friendly and energy conservation characteristics of BEV are related to consumers’ perception of green consumption, purchasing behavior is also affected by environmental performance. It is obvious that consumers have a strong perception of the crucial role BEVs play in mitigating environmental pollution pressure and improving air quality.

As the main result of this paper, the research model emphasizes the importance of perceived behavioral control, subject norm, environmental performance, attitude, and MIP measures (from high to low) in consumer’s purchase intention. Although environmental performance, attitude, and MIP measures had significantly positive effects on the intention to purchase BEVs, perceived behavioral control was the most important factor. In other words, the higher the consumer’s perceived behavioral control concerning BEVs, the stronger their willingness to purchase BEVs. Furthermore, if customers have a positive attitude towards BEVs, and the MIP measures are superior, it can significantly enhance customers’ willingness to purchase BEVs. The results also suggest that consumers with high education level (above undergraduate course) and high-income level (above 400k RMB annually) were more likely to accept the purchase and use of BEVs. Therefore, the future market of BEVs is still optimistic.

7. Conclusions

This research was implemented in Zhejiang Province, China and collected data through a questionnaire survey. It extended previous research by providing better insights in understanding the intention to purchase BEVs from a customer’s perspective. This study developed a research model using theoretical supports from literature relating to purchase intention of BEVs, TPB, and NN studies.
To stimulate the private consumption market is the key factor to promote BEV effectively, hence, it is important to know consumers’ purchase behaviors. This research presents and tests a novel research model that processes seven potential predictors of behavioral intention from the perspective of consumers, as a complement to the traditional research method from the perspective of industry and technological improvement. Therefore, it provides helpful theoretical implications to scholars and academics, managerial implications to the automobile industry, and social implication to governmental policy makers. It also provides decision-making support, especially for government and relevant departments to modify existing policy. Moreover, a multi-analytical approach that integrates the PLS-SEM and NN was applied in this research to examine the research model, which provides a new approach to solve the analytical problems in other relevant research fields.

7.1. Managerial Implications

The results play a positive role in relevant enterprises, especially for managers and decision-makers. Consumers have a high dependency on brands. As most of BEVs are more expensive than gasoline vehicles, it may affect the consumers’ willingness to purchase BEVs. The majority of consumers evaluate the quality of vehicles through the popularity of manufacturers, brands of enterprises or product, and technical capability. Hence, the consumers’ trust to the brand can reduce the psychological risk of BEV purchasing behavior, and the BEV industry should improve attitude, perceived behavioral control and subject norm in various aspects. Meanwhile, more and more entrepreneurs have realized that the higher education environment can provide more valuable sources [70], therefore, BEV enterprises can cooperate with universities or research institutes deeply to design the strategy for brand building. Besides, since social media and advertising media enterprises have indispensable psychological stimulation effects on the recognition and acceptance of BEV, the managers and decision-makers need to reinforce cooperation with media enterprises to strengthen the efforts on publicity of BEV through the Internet.

7.2. Practical/Social Implications

The results from the research provide practical/social implications that are especially very helpful for policy implementation by the government.

7.2.1. Demonstrate, Promote, and Strengthen the Role of BEVs in Environmental Protection

Based on the results of the survey, environmental performance is one of the critical factors in customers’ purchase intention. Customers want to protect the environment, improve environmental cleanliness, and reduce air pollution by purchasing and using BEVs. Therefore, the government should address the benefits of using BEVs over traditional petrol vehicles, which include reduced emissions, usage of new energy, and how driving BEVs can contribute to the environmental protection. This information should be publicized on authoritative platforms such as WeChat, China’s most popular social media application, to promote the effectiveness of BEVs in alleviating harmful emissions and protecting the environment.

7.2.2. Strengthen the NMIP Measures of BEVs

Although the results revealed that NMIP do not have a significant influence on customers’ purchase intention, the government can use this opportunity to review their strategy to encourage consumers to purchase and drive BEVs. Additionally, the general public may not be aware of the non-environment related benefits of driving a BEV as opposed to a traditional petrol vehicle. It is therefore important for government to improve the convenience of driving BEVs for users to make it attractive for people to switch to driving BEVs. In a city with a vehicle limit line such as Hangzhou, authorities can consider relaxing the peak hours restrictions, weekend restrictions, and parking fees for BEVs with relevant local city licenses. Furthermore, as part of the benefit of driving BEVs, the BEV can be considered to be allowed to drive along bus-only lanes. Consequently, BEV license plates
continue to be colored differently—in green—so as to differentiate it from other car types. Under these circumstances, citizens driving BEVs can enjoy the preferential treatment offered by NMIP policy measures everywhere, which will encourage consumers to purchase BEVs.

7.2.3. Establish an Elastic System of MIP Measures

Based on the historical experience of developed countries and other emerging BEV markets, MIP measures—including fiscal subsidy policies, increasing the loan limits for purchasing BEVs, tax exemption policies, and preferential insurance policies—need to be addressed and revised appropriately. MIP measures rely on fiscal subsidies to reduce the cost of vehicle purchases and increase the income of automobile manufacturing enterprises effectively. Therefore, governments should proactively establish elastic MIP measures with flexible design based on different subjects, development levels, markets, and other actual situations. Furthermore, the government should communicate and cooperate with automobile manufacturing enterprises actively, explore fiscal subsidy policies, and innovate a new commerce cooperation model.

7.3. Limitations and Future Research

This research has several limitations that should be noted. First, as shown in Figure 1, attitude, perceived behavioral control, subject norm, environmental performance, price value, NMIP, and MIP have a positive influence on customer’s purchase intention, but there are many other factors that may affect consumers’ intention to purchase BEVs, which are not discussed in this research. Different consumer behavior theories have different opinions concerning influencing factors. Future studies should expand the independent variables to explore and establish a model that is more applicable for real-world decision-making. Secondly, this study only considered consumers in Zhejiang Province. Therefore, the empirical results are based on a particular region and may not be generalizable and representative of all the people in China. Furthermore, different geographical locations (coastal and inland) and market conditions (mature, developing, and undeveloped) may influence the implementation effect of the policy. Future studies should be extended to different provinces or cities concerning data acquisition and empirical analysis to derive a robust understanding, thereby helping policy makers design appropriate policies.

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## Appendix A

### Table A1. Questionnaire items.

| Constructs                        | Item                                                                 | References                      |
|-----------------------------------|----------------------------------------------------------------------|---------------------------------|
| **Attitude (ATT)**                | Purchasing a battery electric vehicle (BEV) is a good idea. (ATT1)  | Paul et al. [41]                |
|                                   | I think it is very necessary to use BEVs. (ATT2)                    |                                 |
|                                   | I think purchasing a BEV is wise. (ATT3)                             |                                 |
| **Perceived behavioral control (PBC)** | If I wanted, I could have purchased an energy conservation and environmentally friendly BEV. (PBC1) | Paul et al. [41]                |
|                                   | If it were entirely up to me, I am confident that I will choose a BEV for my next purchase. (PBC2) |                                 |
|                                   | I will have the ability to purchase an energy conservation and environmentally friendly BEV in the near future. (PBC3) |                                 |
| **Subject norm (SN)**             | Most people who are important to me (such as family members and friends) think I should purchase a BEV when buying a new vehicle. (SN1) | Nayum and Klöckner [58]        |
|                                   | Many of the people who are important to me (such as family members and friends) like to own a BEV. (SN2) |                                 |
|                                   | If people around me (such as family members and friends) use BEVs, this will encourage me to buy. (SN3) |                                 |
| **Environmental performance (EP)**| BEVs will contribute to environmental sustainability. (EP1)          | McCarty and Shrum [59]          |
|                                   | BEVs will promote to reduce environmental pollution. (EP2)           |                                 |
|                                   | BEVs are important to save natural resources. (EP3)                  |                                 |
| **Price value (PV)**              | BEVs are reasonably priced. (PV1)                                   | Venkatesh and Goyal [21]        |
|                                   | BEVs are a good value for the money. (PV2)                          |                                 |
|                                   | At the current price, BEVs provide a good value. (PV3)              |                                 |
| **Non-monetary incentives policy (NMIP)** | Separate allocations of BEVs license plates. (NMIP1)               | Zhang et al. [15]               |
|                                   | Abolish traffic restrictions on BEVs. (NMIP2)                       |                                 |
|                                   | Implement the right to use bus lanes (The policy had not been implemented in Zhejiang Province, China yet, but some municipalities in China, such as Beijing City, have already put it into practice). (NMIP3) |                                 |
| **Monetary incentive policy measures (MIP)** | Implement purchase subsidy for BEVs. (MIP1)                         | Zhang et al. [15]               |
|                                   | Increase the allowable loan amounts for purchasing BEVs. (MIP2)      |                                 |
|                                   | Implement tax exemption policy for the purchase of BEVs. (MIP3)      |                                 |
|                                   | Provide preferential insurance policy for the purchase of BEVs. (MIP4) |                                 |
| **Purchase intention (PI)**       | If BEVs are beneficial, I would recommend them to my friends. (PI1)  | Nayum and Klöckner [58]        |
|                                   | I expect more brands and models of BEVs to be introduced to the market. (PI2) |                                 |
|                                   | When I purchased a new vehicle, I planned to purchase an environmentally friendly BEV. (PI3) |                                 |
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