Public Intentions to Purchase Electric Vehicles in Pakistan

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Abstract: Electric vehicles (EVs) have the potential to lead the transition in road transportation from traditional petroleum mobility to electric mobility. Despite many environmental benefits, the market penetration rate of EVs is still low in most developing countries. Recently, Pakistan formulated its first EV policy for 2020–2025 to accelerate EV adoption. This study aims to explore the factors, including environmental concerns, perceived ease of use, effort expectancy, social influence, and perceived facilitating conditions, affecting individuals’ behavioral intentions to purchase EVs in Pakistan. The hypotheses were developed based on the literature, and an online questionnaire survey was conducted in Lahore, Pakistan, to collect the relevant data. The partial least square path modeling approach of structural equation modeling was used to test the hypothesis. The results confirmed that the environmental concerns, perceived ease of use, and effort expectancy positively affect the public’s intentions to use EVs in the future. However, social influence and facilitating conditions did not significantly contribute to EV adoption in the present study. The findings suggest that the EV manufacturers aiming to accelerate EV adoption should develop marketing strategies to disseminate information regarding the environmental benefits of EVs and enhance clarity about EVs’ performance and usage.

Keywords: electric mobility; sustainable transportation; public perceptions; environmental concerns; marketing strategies

1. Introduction

Environmental problems and climate change have been recognized as global issues [1,2]. The transportation sector has been considered a significant contributor to escalating environmental issues because it is responsible for 23% of global CO₂ emissions via fuel combustion [3]. To combat the arising transportation-related environmental problems, such as traffic noise, air pollution, and CO₂ emission, it is necessary to pursue technological development in vehicles [2,4]. Advancement in the vehicle technology has been shifting vehicles’ engines from traditional internal combustion to electric ones [5–7]. The worldwide sales of EVs have been increasing dramatically, underpinned by the supported transportation policies [8]. In 2019, global EV sales reached a record number of 2.1 million, surpassing past years’ sales records [9]. Despite the remarkable growth in EV sales, the uptake of EVs is still very limited due to its uneven market share across countries. For example, electric mobility was expanding at a fast pace in a few developed countries, including Norway (55.93%), Iceland (22.6%), the Netherlands (15.14%), and Sweden (11.43%). However, the penetration rate of EVs in the rest of the world was no more than 7% [9].

The global passenger car fleet is projected to be doubled by the end of 2050, with most of its expected growth in developing countries. The United Nations Environment’s Electric Mobility Program has been initiated to support the developing and transitional countries to shift from fossil fuels to electric vehicles [10]. Pakistan and India have set a
30% electric mobility target for 2030, but electric vehicle sales, including two and three-wheeler, remain low [11]. Despite continuous growth in the EV sales volume in China, the market share of electric vehicles was only 2.7% in 2017 [2,12]. Likewise, Malaysia is also struggling to promote the adoption of EVs and their market penetration [13]. Considering the low market penetration rate of EVs in developing countries, it is essential to explore the public intentions to adopt EVs to develop market strategies of promoting the EVs’ penetration. However, most relevant studies have focused on high-income and middle-income countries [4,12,14–17].

Being the seventh most vulnerable country to climate change, Pakistan must consider sustainable energy solutions [18]. Road transportation in Pakistan relies on non-renewable energy resources and contributes 18% of the total CO₂ emissions [19]. The country has been facing 310,000 deaths annually due to air pollution, indicating the extremely severe environmental conditions for public living [20]. Increasing air pollution issues and its connection with road transportation brought government attention to EVs as an environmentally friendly solution [21]. Recent media reports indicated the Pakistani Government’s interest in e-mobility and converting 90% of the vehicle fleet into electric-powered vehicles by 2040 [22]. Under the China Pakistan Economic Corridor project, a policy framework has also been developed to identify the challenges in the uptake of e-mobility in the context of Pakistan [18,23]. However, the influencing factors to predict the people’s intentions to purchase EVs remain poorly understood. The recently introduced monetary benefits by the Government of Pakistan to EV manufacturers, buyers, and importers brought public interest towards EVs. With the Government’s support, it is expected that there will be a boom in EV production in Pakistan in the near future [24]. Given this, there is an essential need to explore the public acceptance of electric vehicles through various factors that may guide the policymakers and EV manufacturers to predict the population’s intentions to purchase EVs.

Thus, this paper aims to explore the public behavioral intentions to purchase EVs in an area with an early stage of EV induction, i.e., Lahore, Pakistan. This paper proposed a hypothesis model to identify the influential factors of public behavioral intentions to purchase EVs, including environmental concerns, performance expectancy, effort expectancy, social influence, and facilitating conditions. Environmental concerns refer to public awareness of environmental problems that indicate the willingness to contribute personally to environmental issues [4,25–27]. Performance expectancy refers to the degree to which an individual believes that using the vehicle will help them in attaining gains in their job performance [28,29]. Effort expectancy is the degree of ease associated with the use of EVs [26,30]. Facilitating conditions refer to the (perceived) external influences that relate to the technical, social, or organizational factors that support (or obstruct) the use of specific technology, such as EVs [7]. Social influence is the degree to which individuals perceive the importance of vehicles via others’ beliefs that they should use EVs (new technology) [26,29]. Public behavioral intentions refer to public willingness to purchase EVs [27,30].

This paper employed a partial least square-based structural equation modeling (SEM) approach to confirm the hypothesis model [31,32], in line with past studies [33,34]. The multi-group analysis was also performed to capture sociodemographic heterogeneity. The suggestions and implications are prepared based on study findings, which can help automobile manufacturers to form efficient marketing strategies for EVs. This study also provides recommendations to policymakers to promote EV purchase intentions among locals. The literature was also briefly reviewed to develop a hypothesized model for the present study. Following the review segment, a detailed description of the study methods is given, followed by questionnaire design, data collection, respondent details, and the analytical instrument used to analyze the data. After the methodology, the study’s findings are presented, which were determined by executing a measurement model, structural model, and multi-group comparisons. Then, the discussion and implications are presented, and lastly, the conclusions, limitations, and future research directions are presented to illuminate the significance of this study.
2. Hypothesis Development

The consumption of fossil fuels by road transportation with internal combustion engines harms the environment [2]. Considering the interlinkages of energy and transportation, worldwide induction of EVs is important to achieve the United Nations’ Sustainable Development Goals 2030 [1,35]. Previous studies [36–38] have been discussing various strategies to explore EV adoption in different countries. Rafique and Town [36] explored the potential of EV adoption in South Wales, Australia, where most of the inner-city vehicle trips were less than 30 km. This study mapped the average state of the charge distribution of electric vehicles during daytime and suggested the high feasibility of EV adoption and its potential impacts, such as reducing CO$_2$ emissions. A study from Portugal suggested increasing tax applied to fossil fuel consumption and conventional vehicle sales as an efficient solution to increase EVs’ diffusion [37]. In Brazil, a SWOT analysis was conducted by Costa et al. [38] to explore the stakeholders’ perspectives regarding EV adoption. The study analyzed the opportunities and challenges to adopting the EVs and suggested the market diffusion of light-duty electric vehicles as a first option. However, they argued that the EVs’ expansion requires market regulation, incentive policies, and adequate charging infrastructure.

Besides incentives and technological development, the diffusion of EVs in a society largely depends on the stakeholders’ perceptions of EVs [39]. A recent meta-analysis of 211 peer-reviewed research papers by Singh et al. [40] explored the psychological factors that influence the public perceptions to purchase EVs, such as social influence, performance expectancy, effort expectancy, environmental concerns, subjective norms, attitudes, and sociodemographic variables. They highlighted some prominent theories, including a theory of reasoned action [41], the theory of planned behavior [42], technology acceptance model [43], and unified theory of acceptance and use of technology [28], which have been extensively used in the previous literature to explore public intentions to purchase EVs. Meanwhile, Singh et al. [40] confirmed that the significance of psychological factors varies from one country to another country. Moreover, the theories and factors used to predict EV adoption vary from one study to another [39,40,44].

In Pakistan, EVs are in their early stage, and government organizations are trying to accelerate the market penetration of EVs to meet the target of 30% electric mobility by 2030 [11,24]. Furthermore, the air pollution in Lahore, Pakistan, has been rising continuously and causing deaths [20,23]. Alvi et al. [45] revealed that Pakistanis who have a higher income and education level are sensitive to climate change and willing to adopt mitigation measures. Considering the environmental benefits of EVs and electric mobility targets of Pakistan [24], this study considered environmental concerns, performance expectancy, effort expectancy, social influence, and facilitating conditions as the factors affecting individuals’ behavioral intentions to purchase EVs.

2.1. Environmental Concerns (EC)

Environmental concerns (EC) refer to public awareness of environmental problems that indicate the willingness to contribute personally to environmental issues [4,25–27]. A study from Hong Kong considered the influence of environmental concerns together with the perceived value, trust in EV, responsive efficacy, and willingness to pay on public intentions to purchase EVs [27]. However, EC was not found to contribute to the public’s intentions to adopt EVs in their study. In contrast, Degirmenci and Breitner [46] proposed that EC was a stronger predictor of attitudes towards purchase intentions to buy EVs than price value and range confidence. Thus, EC was found to have significant effects on the purchase intentions to buy EVs. Concurrently, a study from Saudi Arabia [14] applied the theory of reasoned action [41] to explore consumers’ intentions to adopt hybrid electric vehicles. Utilizing the SEM approach, they found that EC, subjective norms, and attitudes were significant predictors of behavioral intentions to adopt hybrid electric vehicles. Consistently, an anecdotal study from Malaysia also found that EC significantly affects public acceptance of electric vehicles [26]. Besides EC, they have also
considered other factors such as social influences, performance attributes, financial benefits, demographics, infrastructure readiness, and government interventions to apply multiple regression analysis to uncover the significant factors to predict EV purchase intentions. Another study from Malaysia [47] used partial least squares structural equation modeling to uncover the purchase intentions of hybrid vehicles by a combination of norm activation theory [48] and theory of planned behavior [42]. The research findings confirm that the pro-environmental attitude and the social norms and perceived behavioral control positively influence the hybrid vehicle purchase intentions. From the above-mentioned studies, it is clear that EC is an important factor impacting the public intentions to purchase EVs. Considering that air pollution is the highest in Lahore, Pakistan, it is expected that the population are more concerned about the environment. Given this, we proposed the following hypothesis.

**Hypothesis 1 (H1):** Environmental concerns positively affect individuals’ behavioral intentions to purchase EVs.

### 2.2. Performance Expectancy (PE)

Performance expectancy (PE) is the degree to which an individual believes that using new technology can improve his/her job performance [28]. It is an important construct that has been widely discussed in the literature related to the unified theory of acceptance and use of technology [28,30,40]. In the context of EVs, PE refers to the degree to which EVs will provide benefits to users in performing particular daily activities [49]. Previous studies have found that PE significantly affects the behavioral intentions to adopt new technology [7,28,30,50,51]. For example, Zhou et al. [50] found that PE positively affects the behavioral intentions to adopt electric trucks in China. Likewise, Tran et al. [30] support the positive influence of PE on behavioral intentions in the context of electric car-sharing systems in China. An Australian study also confirmed that the early E-bike adoption was significantly influenced by perceived performance expectancy and supportive social environment and personal ecological norms [7]. In Pakistan, EE was found to positively influence the acceptance of public cloud technology [51]. Thus, we proposed the following hypothesis.

**Hypothesis 2 (H2):** Performance expectancy (PE) positively affects individuals’ behavioral intentions to purchase EVs.

### 2.3. Effort Expectancy (EE)

Effort expectancy (EE) is the perceived degree of ease associated with the use of technology [6,28]. It is also referred to as ease of use in the technology acceptance model [43]. In general, most of the previous studies [29,30,49,52] have confirmed the relevance of EE in predicting individuals’ behavioral intentions. For example, Ali et al. [51] confirmed EE’s positive influence on users’ adoption of public cloud technology in Pakistan. Similarly, positive effects of EE on the acceptance of automated road transport systems were observed in a study conducted on European cities [29]. In Pakistan, EVs are considered a new technology to transform the road transportation fossil fuel consumption to electricity [18,24]. Given this, it is expected that EE will have positive effects on individuals’ intentions to purchase EVs in Pakistan. Therefore, we proposed the following hypothesis.

**Hypothesis 3 (H3):** Effort expectancy (EE) positively affects individuals’ behavioral intentions to purchase EVs.

### 2.4. Facilitating Conditions (FC)

Facilitating conditions (FC) means the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system [6,28]. In the context of EVs, FC refers to the availability of organizations and infrastructure required in the future to use EVs smoothly for daily travel activities. In a German study,
FC was found to have a positive influence on the individuals’ intentions to adopt battery electric vehicles. Similar findings were observed in China for the acceptance of driverless buses [30]. In the Pakistani context, a study confirmed the positive effects of FC on behavioral intentions to adopt public cloud technology [51]. As the EV infrastructure, including charging stations and EV repair shops, is not widely available in Pakistan [21], it will be interesting to explore the FC effects on individuals’ intentions to adopt EVs in the future. In line with the aforementioned studies, we proposed the following hypothesis.

**Hypothesis 4 (H4):** Facilitating conditions (FC) positively affect individuals’ behavioral intentions to purchase EVs.

### 2.5. Social Influence (SI)

Social influence (SI) is the degree to which individuals perceive the importance of vehicles via others’ beliefs that they should use new technology [26,29]. SI is an important factor affecting individuals’ intentions to purchase EVs, as confirmed in a Malaysian study [26]. Moreover, the positive relationship of SI with behavioral intentions was supported for the acceptance of automated road transport systems in European cities [29]. However, the positive influence of SI on individuals’ intentions was not supported in a few studies from China (acceptance of electric car-sharing system) [30] and Germany (users’ intentions to adopt battery electric vehicles) [53]. It is obvious that SI’s influence on behavioral intentions to adopt technology is sensitive to the study context and the region. Ali et al. [51] confirmed the positive influence of SI to adopt public cloud technology in the Pakistani context. Therefore, we assumed that SI would have a positive influence on individuals’ intentions to purchase EVs. Given this, we proposed the following hypothesis.

**Hypothesis 5 (H5):** Social influence (SI) positively affects individuals’ behavioral intentions to purchase EVs.

From the above discussion, it is clear that public intentions to purchase EVs rely on the psychological factors affecting such behavior. Past studies have mentioned using a better understanding of behavioral aspects of purchase intentions in managing the marketing strategies and promotion to enhance EVs’ market penetration [8,40]. In a previous discussion, we postulated five hypotheses consistent with previous studies, which can also be seen in the conceptual model presented in Figure 1.

![Conceptual model](image)
3. Methods

3.1. Questionnaire Design

A questionnaire was prepared under the supervision of experts in the transportation field to test the hypothesis explained previously in Figure 1. At the beginning of the questionnaire, it was declared that the information collected was only for academic research purposes, and it would not be revealed to others or be used for any other purpose. The questionnaire consisted of two parts. The first part was about respondents’ sociodemographic details, including gender, age, education level, occupation, and car ownership. The sociodemographic details are important as they explain the respondent’s characteristics, which were further used to capture the group differences across the model. The second part contained the questions to measure the latent constructs, including environmental concerns, performance expectancy, effort expectancy, social influence, facilitating conditions, and public intentions to purchase EVs.

Environmental concerns refer to public awareness of environmental problems and support the effort to solve them or indicate the willingness to contribute personally to environmental issues [25–27]. Environmental concerns were measured with five items, EC1, EC2, EC3, EC4, and EC5 (see Table 1), on a five-point Likert scale ranging from (1) strongly disagree to (5) strongly disagree. Table 1 indicates that more than 50% of the respondents were concerned about the environment and willing to contribute to preserving the environment.

Table 1. Descriptive details of items used to measure latent constructs.

| Latent Constructs                                                                 | Factor Loading | Strongly Disagree (%) | Disagree (%) | Neutral (%) | Agree (%) | Strongly Agree (%) |
|----------------------------------------------------------------------------------|---------------|----------------------|--------------|-------------|-----------|-------------------|
| EC1—I am very concerned about current environmental pollution in Pakistan and its impact on health | 0.87          | 3.06                 | 1.11         | 10.86       | 14.48     | 70.47             |
| EC2—Automobile exhaust emission is one of the primary sources of air pollution  | 0.85          | 6.96                 | 1.67         | 4.74        | 16.71     | 69.92             |
| EC3—I have the responsibility to adopt a low-carbon travel mode                   | 0.84          | 4.46                 | 1.95         | 8.91        | 22.01     | 62.67             |
| EC4—I want to preserve the environment.                                          | 0.87          | 4.46                 | 6.13         | 5.01        | 12.53     | 71.87             |
| EC5—I want to buy an electric vehicle because of air pollution crisis.           | 0.75          | 2.79                 | 3.06         | +14.21      | 27.02     | 52.92             |
| PE1—I think that using EVs can improve my living and working efficiency.         | 0.89          | 6.69                 | 5.85         | 13.09       | 34.26     | 40.11             |
| PE2—If EVs are available, I would find the EV as a useful mode of transportation| 0.86          | 5.01                 | 3.34         | 13.37       | 32.03     | 46.24             |
| PE3—Using the EV will help me reach my destination more quickly                  | 0.66          | 6.69                 | 14.48        | 25.07       | 26.46     | 27.30             |
| EE1—I can imagine that my interaction with the EVs will be clear and understandable| 0.75          | 2.51                 | 3.90         | 26.18       | 33.15     | 34.26             |
| EE2—I can imagine that EVs is easy to use                                         | 0.85          | 4.74                 | 3.34         | 18.11       | 31.48     | 42.34             |
| EE3—I can imagine that Learning to use an EV is easy for me                       | 0.85          | 4.18                 | 3.62         | 15.04       | 31.48     | 45.68             |
| SI1—People who are important to me think that I should use EVs in future          | 0.92          | 8.64                 | 4.46         | 20.33       | 32.87     | 33.70             |
| SI2—People who influence my behavior think that I should use EVs in future       | 0.87          | 8.91                 | 6.96         | 28.13       | 25.91     | 30.08             |
| SI3—People whose opinions I value would like me to use EVs in future              | 0.92          | 7.52                 | 4.74         | 22.01       | 31.20     | 34.54             |
Table 1. Cont.

| Latent Constructs | Factor Loading | Strongly Disagree (%) | Disagree (%) | Neutral (%) | Agree (%) | Strongly Agree (%) |
|-------------------|----------------|------------------------|--------------|-------------|-----------|-------------------|
| FC1—I believe, the road infrastructure will be compatible to use EV in future. | 0.75 | 12.81 | 18.38 | 15.04 | 29.53 | 24.23 |
| FC2—I believe, the government and transportation authority will support the use of EV in future. | 0.84 | 7.52 | 11.70 | 26.74 | 25.35 | 28.69 |
| FC3—I believe, If I have difficulty in using EV, I can get help from others | 0.88 | 6.96 | 5.85 | 21.45 | 35.65 | 30.08 |
| BI1—I would consider buying EVs as long as it is available | 0.85 | 6.69 | 5.57 | 27.86 | 38.16 | 21.73 |
| BI2—I will be very likely to buy EVs if it is available | 0.85 | 1.95 | 3.62 | 15.60 | 35.38 | 43.45 |
| BI3—Assuming EVs available at an affordable price, I would like to buy it | 0.84 | 1.95 | 3.90 | 7.80 | 22.84 | 63.51 |
| BI4—Assuming EVs available at an affordable price, I will intend to recommend it to others | 0.79 | 2.79 | 1.67 | 13.93 | 23.12 | 58.50 |

Note: environmental concerns (EC), performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and behavioral intentions (BI).

Consistent with previous studies [7,27–30], performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), environmental concerns (EC), and behavioral intentions (BE) were measured with three items, respectively, as shown in Table 1. Regarding performance expectancy (PE), the majority of respondents (more than 50%) agreed that the usage of EVs would be useful for them to carry out their daily travel activities, as mentioned in Table 1. Likewise, the items used to measure effort expectancy and social influence also received agreement from the majority of respondents. This shows the agreement of the respondents in perceiving that EV usage will not be very difficult for them. Moreover, the people (friends and family) around them supported their EV usage. For the facilitating conditions, the majority of the respondents did not agree with the sufficient availability of EV infrastructure and government organizations’ support for EV usage. This is understandable as the EVs are in their early stage in Pakistan, and the EV infrastructure is not widely available [21,24]. Regarding behavioral intentions to purchase EVs, a huge number of respondents (more than 60%) showed their willingness to purchase EVs in the future. The detailed results to explore the relationship of the influencing factors with the behavioral intentions are presented in the Results section of this paper.

3.2. Data Collection

An online questionnaire survey was conducted to collect responses. The second-largest metropolitan area of Pakistan, named Lahore City, was selected for this study. It has recently hosted substantial infrastructural development in road transportation [54] and faces serious air pollution issues [55]. Under the supervision of experts in the transportation field, a pilot study was conducted to ensure that the terminology used in the questions was appropriate for the respondents to understand the questions clearly.

Following Alzahrani et al. [14], the questionnaires were randomly distributed by means of a combination of social media (Instagram, Facebook, and Twitter) and messaging (WhatsApp). The questionnaire remained available in various Lahore-based online social media groups from May 2019 to September 2019. To ensure a representative sample of respondents belonging to the selected area, we asked respondents to specify their area of residence when responding to the online questionnaire. Data collection resulted in the collection of 432 responses. Those responses where the respondent chose the same
choices for all questions and incomplete responses were removed during the data cleaning process. The exercise of data cleaning resulted in 359 valid responses to be considered for further analysis.

Generally, a sample size of 300 responses is recommended to conduct structural equation modeling [50,56]. According to the general consensus, the sample size for the partial least square path modeling approach of SEM should be larger than ten to fifteen times the number of variables in multi-factor analysis [50,57]. Considering the aforementioned studies and the number of variables involved in the analysis (21), the sample size of 359 was considered sufficient. Descriptive details of respondents are presented in Table 2.

Table 2. Respondents’ details.

| Sociodemographic Variables | Frequency | Percentage |
|----------------------------|-----------|------------|
| Gender                     |           |            |
| Male                       | 288       | 80.22%     |
| Female                     | 71        | 19.78%     |
| Age                        |           |            |
| 18–30 years                | 220       | 61.28%     |
| 30–40 years                | 77        | 21.45%     |
| Above 40                   | 62        | 17.27%     |
| Monthly household income (1PKR ≈ 0.0064 USD on March 2021) | | |
| Less than 50,000 PKR       | 164       | 45.68%     |
| More than 50,001 PKR       | 195       | 54.32%     |
| Education level            |           |            |
| Undergraduate or below     | 141       | 39.28%     |
| Master’s degree            | 154       | 42.90%     |
| Ph.D. degree               | 64        | 17.83%     |
| Occupation                 |           |            |
| Govt./Pvt. Employees       | 163       | 45.40%     |
| Self-employed              | 33        | 9.19%      |
| Students                   | 163       | 45.40%     |
| Car ownership              |           |            |
| No car                     | 125       | 34.82%     |
| One car                    | 138       | 38.44%     |
| Two cars or more           | 96        | 26.74%     |

There were 80.2% male respondents as compared to females (19.7%). The gender distribution is considered to reflect the driving-based gender differences in (Lahore) Punjab, Pakistan, where only 5.2% of total licenses were issued to women in 2017 [58]. Moreover, the working population of females is less in Lahore [59,60], and females have a low trip rate that is approximately one third of the males’ trips rate [61]. The young population of aged 18–30 years represented 61.28% of the total respondents, whereas respondents who were aged 30–40 years and above 40 years accounted for 21.45%, and 17.2%, respectively, as shown in Table 2. According to Pakistan’s National Human Development Report 2017, the youth population with an age of less than 30 years comprised 60% of the nation’s total population, which is approximately consistent with the present study’s sample [62].

There is an issue of limited access to the internet in Pakistani cities [63]. Only 15 percent of young people have access to the internet, whereas 52 percent of young people own a cell phone [62]. Furthermore, younger, more educated, and high-income people have
greater access to the internet around the world [62]. As we conducted an online survey to collect data, it is unsurprising that individuals with an income of more than 50,001 PKR constituted 54.32% of the total respondents compared to the respondents with an income level of less than 50,000 PKR. Most of the respondents in the current study had a Master’s degree (42.9%). This is because the respondents with a higher income had a higher share in the current data, and a higher income is correlated with a higher education level in Lahore, Pakistan [61]. The sample with a high household income for the present study is justifiable by considering the notion that middle-income and high-income groups in Lahore are more likely to own a car at present as well as in the future [60]. Most of the participants in the current survey were students, accounting for 45.4%. Government and private employees represented 45.4%; however, the self-employed participants represented only 9.19%. Among the participants, 26.7% had more than two cars. Only 38.4% of participants responded that they owned one car, and 34.8% responded that they had no car.

3.3. Analytical Instrument

The research aimed to test the influence of various factors, including environmental concerns, performance expectancy, effort expectancy, social influence, and facilitating conditions, on behavioral intentions to purchase EVs. Thus, the SEM approach was considered suitable for this research. Among the maximum likelihood method and partial least square (PLS) method of SEM, we chose PLS-SEM, consistent with [34], to test the hypothesis explained previously in Figure 1. Readers are referred to [31] to understand these two methods’ methodological differences. Simply, the partial least square path modeling (PLSPM) approach of SEM has no normality assumption for the data, and it is suitable for data that deviate from normality. This PLSPM approach includes measurement and a structural model. Equation (1) explains the linear relationship of the measurement model.

\[ X_x = \Lambda_x \xi + \epsilon_x \]  

where \( X \) denotes the observed variable (item) of latent variables, \( \Lambda \) represents the loading (pattern) coefficients, and \( \epsilon \) is the measurement error.

Mathematically, the structural model can be represented as Equation (2):

\[ \xi = B \xi + \zeta \]  

where \( B \) is the matrix of coefficients of their relationships, and \( \zeta \) represents the inner model residuals. The PLSPM-based analysis was carried out with the “plspm” package in an open-source software called R-project [32]. First, the measurement model was tested to ensure the validity and reliability of latent constructs. After this, the structural model was developed to test the relationships explained in the hypothesized model in Figure 1. A bootstrapping test was conducted to validate the results. We also tested our model for group differences based on gender, income, education level, and car ownership.

4. Results

4.1. Measurement Model

We checked the convergent validity, discriminant validity, and internal consistency to test the latent constructs’ reliability and validity, as suggested in previous studies [31]. The factor loadings of items on their respective latent constructs were observed to be greater than (0.5), as shown in Table 1, and considered acceptable to achieve convergent validity.

The discriminant validity of constructs was measured through the Fornell–Larcker criterion, as shown in Table 2 [64]. According to the Fornell–Larcker criterion, square root of average variance extracted (AVE) should be larger than the coefficients of correlation of constructs and 0.7 [30]. To evaluate internal consistency, the Cronbach alpha and AVE should be larger than 0.5. Meanwhile, composite reliability with a value of larger than 0.7 is also recommended to achieve internal consistency of the measurement model [31]. Thus,
Table 3 indicates that the measurement model has achieved the said criteria to achieve convergent validity, discriminant validity, and internal consistency.

| Latent Factors | Cronbach Alpha | Composite Reliability | AVE   | Fornell–Larcker Criterion |
|----------------|----------------|-----------------------|-------|--------------------------|
|                |                |                       |       | (Off-Diagonals = Correlations, Diagonal = SQRT of AVE) |
| EC             | 0.893          | 0.92                  | 0.70  | 0.83                      | PE          | EE          | SI          | FC          | BI          |
| PE             | 0.748          | 0.86                  | 0.66  | 0.57                      | 0.81        | –           | –           | –           | –           |
| EE             | 0.753          | 0.86                  | 0.67  | 0.52                      | 0.65        | 0.82        | –           | –           | –           |
| SI             | 0.884          | 0.93                  | 0.81  | 0.50                      | 0.69        | 0.63        | 0.90        | –           | –           |
| FC             | 0.764          | 0.86                  | 0.68  | 0.44                      | 0.51        | 0.64        | 0.60        | 0.82        | –           |
| BI             | 0.853          | 0.90                  | 0.70  | 0.71                      | 0.63        | 0.58        | 0.53        | 0.45        | 0.83        |

Note: environmental concerns (EC), performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and behavioral intentions (BI). Square root (SQRT); Average variance extracted (AVE).

4.2. Structural Model

A structural model was developed to test the hypothesized relationships among latent constructs, as shown in Figure 2. The structural relationships among latent constructs were evaluated based on a significance level of 5% and the bootstrapping test.

Figure 2 illustrates the path coefficients, with p-values displayed in small brackets for each hypothesized path among latent constructs. R-square values are also presented for the endogenous variable (intentions to purchase EVs). R-square values of the endogenous variable (intentions to purchase EVs) represent the total variance explained by the endogenous variable and are considered a typical criterion to evaluate the PLSPM model’s quality. The values of (0.2 < R-square < 0.50) were considered moderate, and the values above 0.5 can be considered substantial to measure the PLSPM model’s quality. Given this, the structural model in Figure 2 substantially explains the total variance of its predictors as the value of R-square is 0.60. The final model was also evaluated from the value of goodness of fit 0.649, depicting a good fit for the model, as explained in [31].

Consistent with hypothesis H1, the environmental concerns significantly affected EV purchase intentions as the path coefficient (β = 0.48, p < 0.001) is significant, as shown in Figure 2. The relationship indicates that individuals with high environmental concerns are more likely to purchase EVs. Regarding hypothesis H2, the path from performance
expectancy to behavioral intentions has a significant coefficient ($\beta = 0.23$, $p < 0.001$), indicating the positive and direct relationship between effort expectancy and behavioral intentions to purchase EVs. This means that the participants who perceived higher effort expectancy had higher intentions to purchase EVs in the future. Consistent with hypothesis H3, effort expectancy significantly influences behavioral intentions to purchase EVs, given that ($\beta = 0.16$, $p < 0.001$). The path relationship between effort expectancy and behavioral intentions indicates that individuals with higher perceived effort expectancy showed higher intentions to purchase EVs in the future. For hypotheses H3 and H4, associated with the facilitating conditions ($p = 0.83$) and social influence ($p = 0.46$), their relation with behavioral intentions was not significant for the present study. The possible reason for the insignificant relationship is that the EV is in its infancy in Pakistan. Thus, the facilitating conditions and social influence might not have been very appealing for all the respondents, which led to non-significant relationships for these paths in our study. Bootstrapping test results are presented in Table 4, which further validates the structural model presented in Figure 2.

Table 4. Bootstrapping test for validation.

| Path Relationship | Path Coefficients | Validation through Bootstrapping (1000 Samples) | Results |
|-------------------|-------------------|-----------------------------------------------|---------|
|                   |                   | Mean.Boot | Std.Error | 95% CI            |
| EC → BI           | 0.48              | 0.48      | 0.06      | (0.36, 0.59)      | Supported |
| PE → BI           | 0.23              | 0.23      | 0.05      | (0.13, 0.35)      | Supported |
| EE → BI           | 0.16              | 0.16      | 0.05      | (0.07, 0.26)      | Supported |
| SI → BI           | 0.04              | 0.04      | 0.05      | (−0.06, 0.14)     | Not supported |
| FC → BI           | −0.01             | −0.01     | 0.05      | (−0.10, 0.09)     | Not supported |

Note: environmental concerns (EC), performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and behavioral intentions (BI).

4.3. Multi-Group Comparisons

The heterogeneity in the collected responses based on the respondent’s sociodemographic characteristics was observed through multi-group comparisons. For each categorical group, including gender, age, income, education level, occupation, and car ownership, a multi-group analysis was conducted at the structural level, as suggested in previous studies [31,34]. Each categorical variable was divided into two subgroups, and the significant difference among the path coefficients for the subgroups was considered to compare two groups. The path links inconsistent with the whole model cannot be considered significant for the subgroups, as guided by Wang et al. [34]. Thus, we only discussed the significant paths consistent with the whole model, as illustrated in Tables 5–8.

Table 5. Comparisons based on gender differences.

| Paths   | Global | Female | Male | diff.abs | t.Stat | deg.fr | p-Value |
|---------|--------|--------|------|----------|--------|--------|---------|
| EC → INT| 0.48   | 0.76   | 0.37 | 0.39     | 2.37   | 357.00 | 0.01    |
| PE → INT| 0.23   | −0.19  | 0.33 | 0.53     | 3.98   | 357.00 | 0.00    |
| EE → BI | 0.16   | 0.26   | 0.18 | 0.08     | 0.45   | 357.00 | 0.33    |
| SI → BI | 0.04   | −0.11  | 0.02 | 0.13     | 0.99   | 357.00 | 0.16    |
| #FC → BI| −0.01  | 0.33   | −0.02| 0.35     | 2.60   | 357.00 | 0.00    |

Note: environmental concerns (EC), performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and behavioral intentions (BI). Bold text illustrates a significant relationship; # illustrates that the relationship was not significant in the whole model and cannot be considered significant for two subgroups.
Table 6. Comparisons based on income levels.

| Paths   | Global | Income ≤ 50,000 PKR | Income > 50,000 PKR | diff.abs | t.Stat | deg.fr | p-Value |
|---------|--------|---------------------|---------------------|----------|--------|--------|---------|
| EC → BI | 0.48   | 0.52                | 0.46                | 0.06     | 0.57   | 357.00 | 0.28    |
| PE → BI | 0.23   | 0.23                | 0.21                | 0.02     | 0.18   | 357.00 | 0.43    |
| EE → BI | 0.16   | 0.29                | 0.08                | 0.22     | 2.08   | 357.00 | 0.02    |
| SI → BI | 0.04   | 0.03                | 0.06                | 0.04     | 0.48   | 357.00 | 0.32    |
| #FC → BI| −0.01  | 0.16                | 0.11                | 0.27     | 2.39   | 357.00 | 0.01    |

Note: environmental concerns (EC), performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and behavioral intentions (BI). Bold text illustrates a significant relationship; # illustrates that the relationship was not significant in the whole model and cannot be considered significant for two subgroups.

Table 7. Comparisons based on car ownership.

| Paths   | Global | Respondents with No Car | Respondents with Car | diff.abs | t.Stat | deg.fr | p-Value |
|---------|--------|-------------------------|---------------------|----------|--------|--------|---------|
| EC → BI | 0.48   | 0.71                    | 0.26                | 0.45     | 3.76   | 357.00 | 0.00    |
| PE → BI | 0.23   | 0.10                    | 0.38                | 0.28     | 2.09   | 357.00 | 0.02    |
| EE → BI | 0.16   | 0.00                    | 0.21                | 0.21     | 1.93   | 357.00 | 0.03    |
| #SI → BI| 0.04   | 0.19                    | −0.07               | 0.26     | 2.29   | 357.00 | 0.01    |
| #FC → BI| −0.01  | −0.05                   | 0.11                | 0.16     | 1.42   | 357.00 | 0.08    |

Note: environmental concerns (EC), performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and behavioral intentions (BI). Bold text illustrates a significant relationship; # illustrates that the relationship was not significant in the whole model and cannot be considered significant for two subgroups.

Table 8. Comparisons based on education level.

| Paths   | Global | Postgraduates | Undergraduates or below | diff.abs | t.Stat | deg.fr | p-Value |
|---------|--------|---------------|-------------------------|----------|--------|--------|---------|
| EC → BI | 0.48   | 0.33          | 0.64                    | 0.31     | 2.72   | 357.00 | 0.00    |
| PE → BI | 0.23   | 0.34          | 0.07                    | 0.26     | 2.08   | 357.00 | 0.02    |
| EE → BI | 0.16   | 0.24          | 0.11                    | 0.14     | 1.14   | 357.00 | 0.13    |
| #SI → BI| 0.04   | −0.02         | 0.16                    | 0.18     | 1.62   | 357.00 | 0.05    |
| #FC → BI| −0.01  | 0.07          | −0.07                   | 0.15     | 1.58   | 357.00 | 0.06    |

Note: environmental concerns (EC), performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and behavioral intentions (BI). Bold text illustrates a significant relationship; # illustrates that the relationship was not significant in the whole model and cannot be considered significant for two subgroups.

We observed significant differences for a few path links only in the subgroups of gender, income, education level, occupation, and car ownership. However, there was no significant difference in the two age groups (≤30 years old) and (>30 years old).

For the group gender (Table 5), the two subgroups were male and females. We observed significant differences in two path links EC→BI and PE→BI. For the females, environmental concerns were more associated with EV purchase intentions, and a smaller change in environmental concerns was found to bring a higher change in behavioral intentions to purchase EV. Thus, females who have higher perceived environmental concerns will have higher intentions to purchase EVs in the future as compared to males. For the PE→BI, males were found to have a higher influence ($\beta = 0.33$) from performance expectancy to behavioral intentions to purchase EVs as compared to females, as illustrated in Table 5. The females perceived negative effects of performance expectancy on behavioral intentions to purchase EVs compared to males. This may be because the females drive less than males in Pakistan [58]. Thus, females’ perceived performance expectancy effects might not be evident in predicting behavioral intentions to buy EVs.
For the group income (Table 6), the two subgroups of respondents were people having (≤50,000 PKR) and (>50,000 PKR) monthly incomes. Only one path link, EE→BI, was found to have a significant difference between the two income groups. The participants with (≤50,000 PKR) experienced a higher positive influence (β = 0.29) towards behavioral intentions to purchase EVs as compared to participants with a monthly income of (>50,000 PKR), as shown in Table 6. A smaller positive change in effort expectancy perception for (≤50,000 PKR) will bring a higher positive change in EV purchase intentions for this group, compared to those who have a (>50,000 PKR) monthly income.

The categorical group of car ownership was divided into two subgroups, namely one with no cars and the other with cars, as shown in Table 7. Performance expectancy association with behavioral intentions was higher in the participants who had cars. However, effort expectancy association with behavioral intentions to purchase EVs was lower in the people who had cars. This might be because of their perception that fuel cars are easier to operate than EVs. People who did not have cars perceived a higher association of environmental concerns to INT. This means that if people with no cars and with higher environmental concerns were given opportunities to buy EVs, they would be more likely to buy EVs than those who already have fuel cars. On the other hand, people who have cars should be targeted to increase their awareness of environmental pollution to shift their fuel car usage to EVs.

The participants were divided into two subgroups for the education level of undergraduates or less and postgraduates. For EC→BI, people with the education level of undergraduate or below experienced a strong influence of environmental concerns to the behavioral intentions to purchase EVs compared to those with postgraduate education, as illustrated in Table 8. For PE→BI, there was a significant difference between the two groups. The postgraduates experienced a greater influence from performance expectancy to behavioral intentions as compared to those who had an education level of undergraduate or below.

5. Discussion

This study aimed to examine the factors influencing the behavioral intentions to purchase EVs among individuals from low-income countries. Generally, the findings illustrate that the respondents from Lahore, Pakistan were highly concerned about the environment and were willing to adopt mitigation measures to preserve the environment, consistent with the findings of Alvi et al. [45]. The results also revealed that the respondents perceived a high performance expectancy, effort expectancy, and social influence regarding the EVs in Lahore, Pakistan. Comparatively, the respondents were reluctant to show their agreement to perceive sufficient facilitating conditions for EV usage as the EV infrastructure is not widely available. Overall, more than 60% of the respondents showed their willingness to purchase EVs in the future. Such findings indicate a strong possibility of EV usage at a large scale in Lahore, Pakistan in the future with the support of EV policy.

As expected, environmental concerns, performance expectancy, and effort expectancy were related to behavioral intentions to purchase EVs. However, social influence and facilitating conditions were found to be insignificant to explain behavioral intentions to purchase EVs. The comparison of results based on subgroups, including gender, age, education level, occupation, and car ownership, led to interesting findings relevant to the research’s scope. Thus, a clear understanding of psychological factors and sociodemographic differences is important to enhance public behavioral intentions to purchase EVs.

Environmental concerns refer to public awareness of environmental problems and support the effort to solve them or indicate the willingness to contribute personally towards environmental issues. EVs are an environmentally friendly alternative to traditional vehicles. The positive and direct relation of environmental concerns with behavioral intentions to purchase EVs is understandable. This finding is also understandable in the Pakistani context as the country faces serious air pollution issues that adversely affect the residents’ health [55]. It is reasonable for the respondents to be concerned about the environment and
show their willingness to reduce environmental pollution. Such findings are also consistent with previous studies. For example, a survey from China has confirmed the direct influence of environmental concerns on behavioral intentions to purchase automated EVs [25]. Another anecdotal study from Germany also had consistent findings, where environmental performance significantly influenced the attitudes towards EVs and purchase intentions of EVs [46]. Moreover, a study which was conducted in Malaysia found positive effects of environmental concerns on behavioral intentions to adopt EVs [26]. From Pakistan, Alvi et al. [45] confirmed the public willingness to adopt mitigating strategies to preserve the environment. From China, Wang et al. [65] highlighted the importance of environmental concerns affecting the financial policy measures and convenience policy measures for EV adoption. However, Pakistan’s policies fail to include a mechanism to spread environmental awareness [24]. Therefore, to enhance the public behavioral intentions to purchase EVs, policymakers need to pay attention to the perceived knowledge about environmental concerns through effective marketing campaigns, i.e., training courses and poster displays. This study also suggests consideration of environmental concerns while preparing marketing strategies, including social and traditional media advertisements for EVs. By doing so, consumers’ intentions to purchase EVs will increase in relevance with the increase in their environmental concerns. The effect of environmental concerns on behavioral intentions to purchase EVs was higher for females as compared to males. Considering the research findings, this study suggests a parameter of gender differences, while preparing policy campaigns to enhance knowledge of environmental concerns. Females will be more easily motivated to purchase EVs by increasing the environmental concerns as compared to males. People who do not have cars perceived a higher association of environmental concerns to behavioral intentions to purchase EVs.

The findings regarding performance expectancy influence on behavioral intentions to purchase EVs are in line with previous studies from Germany [53], China [30], and Pakistan. The German study found a significant relationship between performance expectancy and battery electric vehicles’ adoption [53]. Likewise, the Chinese study confirmed the similar findings for public acceptance of electric car-sharing systems. Performance expectancy was found to have a positive influence on the acceptance of public cloud technology [51]. Thus, EV manufacturers need to enhance the consumer’s perceived performance expectancy by intensifying the EVs’ benefits, such as reducing air pollution, working efficiency, and usability. Performance expectancy association with behavioral intentions to purchase EVs was higher in the participants who had cars. The postgraduates experienced a greater influence of performance expectancy to behavioral intentions as compared to those who had an education level of undergraduate or below. Thus, initial campaigns should be targeted towards people who have fuel cars and have a higher education level.

Consistent with recent studies from Germany [53] and China [30], effort expectancy significantly influenced behavioral intentions to purchase EVs. The finding is also in line with a study conducted in Pakistan on the adoption of public cloud technology [51]. From this finding, EV manufacturers’ possible implication is to spread awareness about EVs’ usage to make the public aware of EVs’ easy usage. Furthermore, the marketing strategies should be developed to disclose EVs’ consumer-friendly features, which could help to enhance the perceived effort expectancy and purchase intentions towards EVs. Policymakers and the government should also play their role in reducing the uncertainty and complexity regarding EV usage, which hinders the public from adopting this environmentally friendly mode of transportation. The possible implication for increasing purchase intentions by effort expectancy is to spread public awareness that EV usage is simple and easy. The participants with (≤50,000 PKR) monthly household income experienced a higher positive influence (β = 0.29, p < 0.01) of effort expectancy towards behavioral intentions as compared to participants with a monthly household income of (>50,000 PKR). A smaller positive change in effort expectancy perception for those with a (≤50,000 PKR) monthly income will bring a higher positive change in EV purchase intentions for this group, compared to those who have a (>50,000 PKR) monthly household income. Moreover, effort expectancy associ-
ation with behavioral intentions to purchase was lower in the people who had cars. Thus, car ownership and income differences should be considered while preparing strategies to spread awareness about the effort expectancy of EVs.

Contrary to previous studies from Malaysia [26], Austria [7], and Pakistan [51], the present study could not find a significant relationship between social influence and behavioral intentions to purchase EVs. The rationale for this finding is that EVs are in their infancy in Pakistan; therefore, more time is required for people to purchase EVs at a large scale, positively influencing others. However, the insignificant relationship of social influence and behavioral intentions to purchase EVs is consistent with a German [53] and a Chinese study [30].

The findings indicate the insignificant relationship between facilitating conditions and behavioral intentions to purchase EVs. This finding is unexpected and contradicts the findings from Germany [53] and China [50]. The possible reason for this lies in the understanding of public perceptions regarding new facilities in low-income countries. Chen et al. [52] discussed the weak relation between facilitating conditions and individuals’ behavioral intentions to use driverless buses in China. They argued that the driverless bus is an emerging technology for Chinese respondents, and a vague understanding of policy support and government initiatives to the new technologies resulted in an unexpected finding. Likewise, EVs are an emerging technology for Pakistan. The general public is unaware of government policies to ease the taxes and plans for infrastructural development [24]. Thus, there is a need to disclose the e-mobility plans to the general public to understand the available facilitating conditions in Pakistan.

Furthermore, no significant difference was found in the two age groups, (≤30 years old) and (>30 years old), regarding the effects of environmental concerns, performance expectancy, effort expectancy, social influence, and facilitating conditions on behavioral intentions to purchase EVs. This finding was unexpected and contrary to a previous study from China [30]. The possible reason is the early stage of EVs in Pakistan, leading to similar perceptions regarding EVs for different age groups.

In summary, environmental concerns, performance expectancy, and effort expectancy significantly affected behavioral intentions to purchase EVs in the Pakistani context. Such findings are similar to those in other parts of the world, including Germany [53], Austria [7], and China [25,30,50]. However, the social influence and facilitating conditions did not significantly affect the public intentions to purchase EVs, inconsistent with previous studies from China [50], Germany [53], and Malaysia [26]. Such complex and unpredictable findings helped to elucidate the regional differences in public perceptions across the globe.

Finally, all measures and implications discussed above need to be taken collectively to promote EV purchase intentions in the general public effectively. For example, manufacturers need to consider the consumer’s perceived importance of environmental concerns, performance expectancy, and effort expectancy. Marketing strategies in line with psychological factors can enhance the public intentions to purchase EVs significantly. Thus, advertisement for EVs should highlight the environmentally friendly aspects and reduce the uncertainty about EVs regarding performance and effort expectancy. Such implications will ease the psychological barriers to adopting EVs. In the long run, this will develop a social environment in which individuals are willing to purchase EVs and contribute to the reduction of environmental pollution.

6. Conclusions

This study categorically investigated the relationship among environmental concerns, performance expectancy, effort expectancy, social influence, and facilitating conditions with people’s behavioral intentions to purchase EVs in Pakistan. In Pakistan, the use of EVs is in its infancy, and this is the first study that explored the public intentions to purchase EVs. The results were obtained by analyzing a valid sample of data of 359 respondents through the partial least square structural equation modeling approach. Environmental concerns, performance expectancy, and effort expectancy significantly affect public intentions to
purchase EVs. By shedding light on the factors influencing EV purchase intentions in Pakistan, this study advises EV manufacturers to articulate effective marketing strategies to encourage people towards EVs. Moreover, it advises policymakers to promote e-mobility for sustainable transportation through a better understanding of public intentions to purchase EVs. The empirical evidence in the present study highlights the need for educational interventions, advertisements, and poster displays to enhance environmental knowledge and clarity about EVs’ performance and usage. The lack of information about EVs hindered the local population from choosing EVs. Thus, government organizations and EV manufacturers should arrange awareness programs to underline EVs’ advantages compared to traditional gasoline vehicles. Undoubtedly, it can be inferred that EV usage will gradually increase in the future.

Despite discussing EVs’ purchase intentions for the first time in the Pakistani context, this study has a few limitations. The readers should be wary of generalizing these study findings to a broader population because all the participants were literate and had access to the internet as the survey was conducted online. We suggest that future studies should include participants from more diverse backgrounds, which will help to elucidate the issue from a wider perspective. Other socio-psychological factors, including price, incentives, policy support, perception, and attitudes, may further expand the understanding of the behavioral intentions to purchase EVs in developing countries. Finally, the findings of the study provide valuable information for policymakers, stakeholders, and EV manufacturers interested in EV technology and its spread in Pakistan.

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