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Examining the Determinants of Electric Vehicle Acceptance in Jordan: A PLS-SEM Approach

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Abstract: Recently, technologies for electric mobility have developed rapidly. Since the introduction and spread of Electric Vehicles (EVs), several studies have attempted to investigate the benefits and risks that impact on the growth of the EV market by evaluating data gathered from various drivers. However, some variables were disregarded such as: Public Involvement, Knowledge of EVs, Perceived Risk, Behavioural Intention, and EV acceptance. These variables are considered vital when analysing the intention to use EVs. Therefore, this study compiles the above mentioned variables to evaluate their effect on the intention to use EVs in Jordan. 501 collected responses were examined using the Smart PLS-Structural Equation Model algorithm. In general, the analysis revealed high levels of EV acceptance. The study proposed twelve direct relationship hypotheses. Out of these hypotheses, ten hypotheses were supported and two were rejected. The final conclusions are that an increase in public involvement is associated with an increase in knowledge of EVs, and an increase in their perceived risk. Moreover, the knowledge of EVs has positively and significantly influenced the perceived usefulness and perceived ease of use, along with EV acceptance. However, no relationships were found between the following: 1. the knowledge of EVs and perceived risk; and 2. perceived risk and behavioural intention.

Keywords: electric mobility; electric vehicles; structural equation model; TAM model; smart PLS-SEM algorithm; Jordan; empirical study

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1. Introduction

The road transport sector is the one of the highest contributors to greenhouse gas emissions (GHG) after the energy sector, contributing to over 28%, as reported by [1]. Road transport generates several emissions: carbon dioxide (CO_2), nitrogen oxides, carbon monoxide, hydrocarbons, and lead compounds. Among all these emissions, CO_2 is considered to be the largest contributor (about 80%) to GHG [2]. To reduce CO_2, Electric Vehicles (EVs) have emerged in recent years as they run on electricity, and may result in very low carbon emissions [3]. This makes EVs a promising technology for achieving a sustainable transport sector in the long-term, compared to conventional vehicles (powered by burning petrol or diesel).

Substantial growth in EV sales has been observed lately as governments in most developed countries are encouraging their use in order to reduce CO_2 emissions, (see for example [4] among others). The situation in Jordan mirrors this trend, as the introduction of EVs into the Jordanian market has increased by up to 35% during the period from 2018 to 2022 [5]. The Jordan Free and Development Zones Group (JFDZG) statistics [5] have revealed that clearance rates for EVs have increased by about 105% this year (i.e., from about 5,265 vehicles in 2022 to about 10,803 vehicles in 2023).

The Jordanian government has put in place policies on electric transport that encourage the use of electric vehicles. They started by replacing hundreds of government gasoline vehicles with EVs [6,7]. Through this policy, the Jordanian Ministry of Environment [8] indicated that EVs have significantly increased in the last five years, with nearly 18,000 EVs on Jordan's roads in 2019.

The adoption of EVs for daily commuting depends on several factors such as EV efficiency, performance, and low maintenance costs [9–11]. However, there are some concerns about adopting EVs: such as equipment and system failures; handling varied weather and terrain; the limited availability of charging stations; performance of EV batteries; and potential EV maintenance and repair costs, as discussed by [12].

Since the development and first use of EVs in the early 2010s, several studies have sought to explore the benefits and risks that influence the acceptance of EVs, by evaluating data collected from various road users. Some studies investigated the effect of demographic factors on EV acceptance. For instance, ref. [13] conducted a questionnaire study in Greece. In their study, participants were asked to determine their acceptance level and intention to use EVs. They concluded that user diversity, including factors like age and gender, significantly influenced how respondents perceived the benefits and the barriers to EV adoption. Female and older respondents showed a higher level of acceptance, compared to male and younger participants. This is consistent with [14] who concluded that females in China were found to be more likely to adopt EVs.

Other studies focused on factors related to the environmental impacts, cost, or social influence on EV acceptance. For example, ref. [15] evaluated the impact of five factors, along with eight demographic characteristics on EV acceptance in China using the Structural Equation Model (SEM). Their results highlighted the significant role of peer impacts in influencing users' decisions to purchase EVs. Similarly, ref. [16] implemented the SEM to investigate the impact of various factors on users' intentions to adopt EVs in India. Their findings showed that factors such as social influence, marketing, perceived benefits, price acceptance, performance, technological awareness, distribution, along with after-sales services, positively influenced the intent to purchase EVs. Another study conducted by [17] identified other factors affecting individuals' intentions to purchase EVs in Pakistan. They found factors, such as environmental concerns, and ease of use, all positively influenced EV usage. This is in line with the findings of [10], in their investigation of EV acceptance in Shanghai. Ref. [18] highlighted that technical considerations, marketing strategies, risks, and environmental factors were revealed as the most vital factors influencing the acceptance of EVs.

Furthermore, ref. [19] found that about 67% of studies investigating the adoption of EVs were carried out in countries such as China, India, the USA, or Canada. However, it remains uncertain whether the findings drawn from previous studies can be applied to Middle Eastern countries like Jordan, with different cultural and economic contexts. Moreover, these prior investigations have overlooked certain pivotal variables that could significantly impact on the acceptance of EVs. These variables encompass facets, such as public involvement, knowledge pertaining to EVs, and perceived risk, each playing a vital role in shaping the disposition towards EV adoption. Consequently, tthe principal objective of this study is to empirically explore the fundamental determinants influencing the acceptance of EVs among Jordanian drivers. These determinants include public involvement, and factors such as media coverage and discussion, knowledge of EVs, as well as other aspects like EV performance, and perceived risk, which pertains to concerns regarding EV safety and system reliability. Furthermore, perceived usefulness, reflecting potential benefits like reduced fuel consumption, and perceived ease of use, considering beliefs that using EV will improve their performance, are also integral to this investigation. Finally, the study delves into behavioural intention, gauging the intention to purchase an EV among Jordanian drivers. To this end, the primary contribution of this study lies in its comprehensive examination of the factors shaping the intention to employ EVs within the context of Jordan. Thus, the investigation employs the Partial Least Squares (PLS), more specifically PLS Structural Equation Modelling (PLS-SEM), to rigorously assess the research hypotheses.

This work is arranged as follows. In Section 1, we summarise the findings of the relevant literature, then introduce the development of the theoretical framework in Section 3, and the Structural Equation Model (SEM), along with the related research hypotheses. Section 4 summarises the method used. Section 5 presents the data collection, and analysis, followed by the main findings. A discussion of the results, along with the implications of the main findings are presented in Section 6, followed by the conclusions and limitations in Section 7.

2. Overview of Previous Studies

The reviewed literature revealed that there is a variety of factors that could be considered in EV acceptance with various analysis tools. To this end, Table 1 summarises these factors, along with the analysis tool used. This summary revealed the following:

- approximately two-thirds of the research on EV adoption [19] was carried out in India, China, the USA, or Canada. However, it remains uncertain whether the findings from these regions can be reliably applied to Jordan, given its distinct cultural and economic circumstances.
- although several previous studies such as [11,20–23] had implemented the Technology Acceptance Model (TAM), the foundational TAM may not comprehensively and sufficiently explain the intention of EV acceptance;
- some independent variables were disregarded, such as Public Involvement (PI), Knowledge of EVs (KE), Perceived Risk (PR), or Behavioural Intention (BI), as summarised in Table 1. These variables are considered vital when analysing intention to use EVs. Therefore, this study compiles the above mentioned variables affecting the intention to use EVs among Jordanian drivers. To investigate the relationships among these factors, a detailed survey, along with robust analysis using Smart PLS-SEM, was implemented in order to evaluate the impact of each of these variables on the intention to use EVs, as detailed in the following sections.

All in all, a lot of work has been done to determine the constructs (variables) that affect EV adoption; however, there is always scope for improvement. This work aims at investigating the intention to use EVs in Jordan, and understanding the variables which impact on their acceptance using the PLS-SEM testing method. The results would help planners to develop short- and long-term strategies related to EV adoption and infrastructure planning. This is consistent with the new smart city vision of 2030 in Jordan [24].

Table 1. Summary of the related studies.

Ref.	Year	Method [1]	Domain	Model	Country	Used Variables						
						PI	KE	PR	PU	EU	BI	EA
[25]	2018	SEM	EV adoption.	VAM	Korea			✓				
[26]	2019	PCA	Intention to buy a BEV.	TPB	Norway		✓	✓				
[21]	2019	SEM	Public acceptance of AEVs.	TAM	China	✓			✓	✓	✓	✓
[27]	2020	SEM	Intentions to adopt EVs.	SOR	Germany			✓		✓		
[28]	2021	SEM	Consumers next EVs decision.	TRA & RBM	USA			✓	✓			
[23]	2021	SEM	Intention to adopt EVs.	TAM	China		✓	✓	✓	✓		✓
[29]	2021	RT	Adoption intention of EVs.	TPB	Korea					✓		
[16]	2021	SEM	Purchase intention of EVs.	N/A	India					✓	✓	
[9]	2022	SEM	EVs adoption intentions.	DPM	China					✓	✓	

Table 1. *Cont.*

Ref.	Year	Method [1]	Domain	Model	Country	Used Variables PI	KE	PR	PU	EU	BI	EA
[30]	2022	SEM	EV purchase intention.	TPB	Hong Kong					✓	✓	
[14]	2022	SEM	Adoption intention for EVs.	TPB	China		✓				✓	
[31]	2022	PLS-SEM	Adoption intention of EVs.	TPB	China			✓			✓	
[32]	2022	SA	Public perception of EVs.	TPB	China		✓					
[33]	2022	SEM	EVs purchase intention.	TPB	Pakistan						✓	
[11]	2022	PLS-SEM	EVs purchase intention.	C-TAM-TPB	Malaysia			✓	✓	✓	✓	
[20]	2022	CB-SEM OLS	EVs adoption intention.	UTAUT	India			✓				
[22]	2022	PLS-SEM	Intentions of EV adoption.	TAM	Australia			✓	✓			
[28]	2022	PLS-SEM	Adoption intent of battery.	TPB	China		✓	✓	✓		✓	
[34]	2023	BA	Intention towards EVs.	TPB	Turkey		✓					
This study		PLS-SEM	Intention to use EVs.	TAM	Jordan	✓	✓	✓	✓	✓	✓	✓

[1] Note : SEM: Structural Equation Modelling; PLS-SEM: Partial Least Squares-SEM; CB-SEM: Covariance-Based Structural Equation Modelling; PCA: Principal Component Analysis; BA: Bibliometric Analysis; SA: Sentiment Analysis; RT: Regression Tree Technique; OLS: Ordinary Least Squares Regression; TPB: Theory of Planned Behaviour; DPM: Decision Process Model; VAM: Value-based Adoption Model; TAM: Technology Acceptance Model; UTAUT: Unified Theory of Acceptance and Use of Technology; C-TAM-TPB: Combined TAM-TPB; SOR: Stimulus Organism Response; TRA: Theory Reasoned Action; RBM: Risk-Benefit Models; PI: Public Involvement; KE: Knowledge of Electric Vehicles; PR: Perceived Risk; PU: Perceived Usefulness; EU: Perceived Ease of Use; BI: Behavioural Intention; EA: EVs Acceptance.

3. Theoretical Framework Development

The TAM was established to explore how the behavioural intention is affected by both perceived usefulness and perceived ease of use [35]. TAM is extensively utilised to evaluate the adoption and acceptance of emerging technologies [11,20–23]. Furthermore, researchers have also applied TAM to analyse consumers' intentions towards EVs [21–23]. However, it is worth noting that the foundational TAM may not illustrate the intention of EV acceptance comprehensively enough [36]. This emphasises the need for a more in-depth investigation into the factors influencing the acceptance of EVs. Therefore, the Partial Least Squares (PLS) path modelling method or PLS Structural Equation Modelling (PLS-SEM) is implemented in this work to investigate the factors influencing EV acceptance. The PLS-SEM method was developed by [37], and further improved by [38], as discussed later in Section 4.

Based on the reviewed literature, several hypotheses have been developed in this work, and tested using PLS-SEM, as described below.

3.1. Public Involvement (PI)

Public involvement EV context refers to active participation and interaction of the public with the concepts related to these types of vehicles. This means enabling individuals to express their thoughts, concerns, and preferences about EVs [39]. Public involvement influences decisions regarding policies, infrastructure development, and the overall progression of electric mobility; therefore, it should be established very well [40,41].

Public awareness of environmental protection improves public satisfaction and acceptance of new technologies [21]. However, few scientific studies investigate public involvement in EVs.

Therefore, this work sheds some light on PI, which should be highlighted as a potentially significant predictor of intention to use EVs. The primary aim of investigating PI is to integrate drivers' knowledge, perceptions, and values concerning EVs into the decision-making process, facilitating a deeper understanding of users' choices regarding the adoption of EVs.

Thus, two hypotheses related to PI are developed:

H1. *Active participation by the public positively contributes to the knowledge of EVs.*

H2. *Engagement of the public impacts positively on the perception of risk towards EVs.*

3.2. Knowledge of Electric Vehicles (KE)

Knowledge is an important variable in behavioural research and plays an important role in users' decisions [23,42]. Some studies [14,23,26,28,34] have revealed that users' knowledge has a substantial effect on their intentions in using innovative technologies.

According to [9], consumers with less knowledge about EVs tend to exhibit lower levels of acceptance on using these types of vehicles. Consequently, increasing consumer knowledge is expected to raise the likelihood of increased EV acceptance correspondingly. For instance, research conducted by [43] demonstrated that a higher level of knowledge about AVs corresponds to a more favourable acceptance of AV technology. In addition, ref. [18] showed that when users possess a comprehensive understanding of EVs, their perception of associated risks tends to decrease. This understanding often leads them to perceive EVs as vehicles that can yield benefits for both individuals and society at large. Moreover, a study conducted by [44] revealed a positive relationship between an individual's knowledge of contemporary technology and their perception of its ease of use.

Despite the fact that drivers are familiar with EV concepts, there is a need for more comprehensive understanding of them. In this study, knowledge of EVs refers to the level of awareness that consumers possess about EVs, encompassing their technologies, attributes, advantages, and limitations. Generally, users with high EV knowledge would be more likely to objectively evaluate their risks, usefulness, ease of use, and acceptance [23]. Therefore, considering the examinations presented above, we formulate the following hypotheses:

H3. *Familiarity with EVs impacts positively on the perception of risk towards them.*

H4. *Understanding of EVs contributes positively to their perceived usefulness.*

H5. *Familiarity with EVs impacts positively on the perceived ease of using them.*

H6. *Having knowledge about EVs positively affects their acceptance.*

3.3. Perceived Risk (PR)

In the EV context, the perceived risk refers to the subjective evaluation users make regarding potentially adverse consequences, uncertainties, or drawbacks associated with EV acceptance. It encompasses concerns related to aspects such as safety, reliability, or financial implications, which can influence consumers' attitudes and decisions regarding EV acceptance. Several studies [23,25–27,31,45] investigated the perceived risk factor. For instance, ref. [25] concluded that perceived risk was the most detrimental element affecting users' perceptions of how useful EVs were. As was also concluded by [20], in their empirical investigation, that the perceived risk positively affects the behavioural intentions to embrace EVs. According to [31], the perceived risk factor has an adverse impact on attitude towards EVs. Similarly, studies conducted by [11,20] found that the perceived risk has a negative effect on the intention to own an EV. Therefore, reducing users' perceived risk can positively influence their intention to EV acceptance. From these viewpoints, when users are fully aware of EV risk, their attitudes and decisions regarding EV acceptance will be enhanced [11,20,22,23]. Therefore, two hypotheses were developed:

H7. *The perception of risk has a positive impact on the perceived usefulness of EVs.*

H8. *The perceived risk positively influences behavioural intention towards EVs.*

3.4. Perceived Usefulness (PU)

Perceived usefulness refers to the subjective assessment made by users regarding the degree to which they believe that using or owning an EV would enhance their effectiveness, convenience, or overall utility in fulfilling their transport needs and preferences [16]. The impact of perceived usefulness on behavioural intention has been widely investigated [11,16,21,23,28,29]. For instance, ref. [46] stated the that perceived usefulness factor had a significant effect on behavioural intention. n the same vein, ref. [29] emphasised that users' perceptions benefits have a significant impact on their intention to purchase EVs. Ref. [47] emphasised that the perceived usefulness of EVs positively affects their adoption. This way also pointed out by [21], that perceived usefulness is closely related to users' adoption of EVs. Moreover, ref. [28] asserted that perceived usefulness or 'benefit' plays a critical role in user behaviour. Ref. [23], in their empirical study asserted that consumers' choices regarding EV purchases are predominantly shaped by their perception of usefulness, rather than their pursuit of enjoyment or pleasure. Thus, comprehending consumers' perceived usefulness is importance for acceptance EVs. Hence, the hypothesis was formulated as follwos:

H9. *The perception of usefulness has a positive effect on behavioural intention toward using EVs.*

3.5. Perceived Ease of Use (EU)

Regarding the perceived ease of use, ref. [16] defined perceived ease of use as "the extent to which an individual believes that using an EV would enhance and improve their performance". This is in agreement with [48] as they defined the perceived EU as the degree to which an individual believes that they would not need to put in any additional effort to learn how to use and operate an EV to be. In our study, perceived ease of use refers to the users' subjective evaluation of how straightforward and user-friendly they perceive the operation, interaction, and overall experience of using an EV. Several studies in the literature [9,11,16,21,23,30,49] evaluated the influence of the perception of ease of use on usefulness and behavioural intention. For instance, refs. [11,50] maintained that users tend to believe that EVs are easy to use and effortless to learn, which positively affects their attitude towards these types of vehicles. Other studies have shown that the perception of ease of use substantially impacts on users' intentions to purchase and adopt EVs [50–52]. Also, the relationship between intention to purchase and perceived ease of use may change depending on other influencing factors, such as perceived usefulness [51]. In addition, ref. [11] emphasised, in their empirical study, that perceived ease of use has a direct positive effect on EV adoption. Therefore, the hypotheses below were drawn:

H10. *The perception of ease of use has a positive impact on the perception of usefulness toward using EVs.*

H11. *The perception of ease of use has a positive impact on behavioural intention toward using EVs.*

3.6. Behavioural Intention (BI)

Behavioural intention refers to the user's subjective willingness and inclination to engage in specific behaviours related to EV adoption, usage, or ownership. It expressed the user's readiness to take actions, such as purchasing an EV, using it regularly, recommending it to others, or supporting EV-related initiatives. Several studies in the literature, such as [9,11,14,21,28,30,31,33] displayed that behavioural intention is a significant variable for EV adoption. According to [14], the perceived behaviour factor has a positive influence on EV adoption, as users who perceive greater control over adopting EVs are more likely to have a higher intention to adopt them. This was also reported by [31], that perceived behavioural control had a significant positive impact on the adoption intention of EVs. This is consistent with [53], as they stated that behavioural intention to purchase EVs is influenced by the perceived behavioural control factor. According to [33], the perceptions of behaviour is positively related with an EV purchase intentions. Therefore, behavioural intention is a key precursor to actual behaviours and provides valuable insights into the likelihood of individuals adopting and integrating EVs into their lifestyles, as found by [54]. Thus, the hypothesis was formulated as follows:

H12. *Behavioural intention has a positive influence on the acceptance of EVs.*

These abovementioned hypotheses, along with the relationships, are summarised in Figure 1.

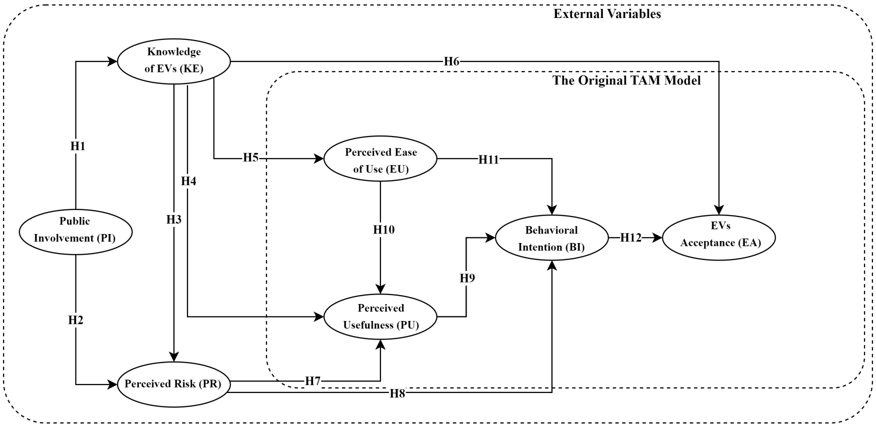

Figure 1. A path diagram for the development of the hypotheses.

4. Method

Based on the discussion in the above section, a questionnaire-based survey technique was developed to collect a wide variety of responses in Jordan. The questionnaire was designed based on [55,56], using fundamental design principles. The survey First Section consists of a short description of EV perception to guide the respondents in better understanding of the survey objectives. The Second Section includes demographic questions, which are used to investigate external variables, such as: age,gender, educational level, family income, driving license, driving frequency, place of residence, and the current fuel type preference of the respondents. The Third Section of the questionnaire is about variables to measure the acceptance of using EVs in Jordan, such as public involvement (PI), perceived risk (PR), knowledge of EVs (KE), perceived ease of use (EU), perceived usefulness (PU), and behavioural intention (BI). In this section of the survey, questionnaire items were designed and developed based on prior research, along with adjustments and recommendations from experts' feedback to ensure relevance to the research context. The five-point Likert scale is implemented in this study as found in the reviewed literature [42,57].

4.1. Population and Sample Size

Based on information from the Jordanian Department of Statistics (DOS), the Jordan population stood at approximately 11,057,000 as of 2021 [58]. For the purposes of our study, the targeted population is about 6,159,480 individuals, comprising all Jordanians above 18 years of age , i.e., those legally eligible to drive a vehicle. In order to determine the minimum acceptable sample size, we employed Equation (1), following the recommendation of [59].

$$\text{Sample size } = \left(\frac{z^2 \times std(1-std)}{e^2}\right) / \left(1 + \frac{z^2 \times std(1-std)}{e^2 \times n}\right) \tag{1}$$

where n refers to the population size which is about 6,159,480 inhabitants; std is the standard deviation, considered to be 0.5; e is the 0.05 margin of error; z is the z-score (i.e., 1.96). Implementing Equation (1), the acceptable sample size must exceed 384.13. Consequently, we collected a total sample size of 501, ensuring that the sample size of the survey would be a reliable representation of Jordan's population.

Also, the G* power software version 3.1.9.7 is used to calculate the minimal sample size, with the following setting: alpha (α) = 0.05, effect size F_2 = 0.02 "small conventions", power ($1-\beta$ err prob) = 0.80, and the number of predictors = 2 [60], as can be seen in

Figure 2. The recommended sample size required to test the model was 485. Consequently, we collected a total sample size of 501, ensuring that the survey's sample size would be a reliable representation of Jordan's population.

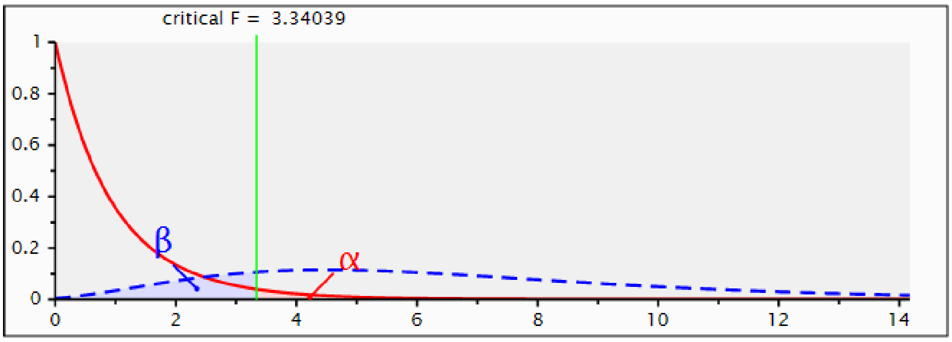

Figure 2. Sample size calculation with statistical power analysis.

4.2. Common Method Bias

Addressing method biases is of paramount importance as they constitute a primary source of measurement error within research endeavours [61]. To mitigate the potential impacts of common method biases (CMB), several procedural strategies were systematically implemented in alignment with established guidelines for enhancing the robustness of quantitative survey research [61–63]. In the initial phase, we thoughtfully appended a comprehensive cover letter, explicitly delineating the objectives of the study and with clear instructions. This also explained how the collected data would be utilised, reassuring respondents about data confidentiality and privacy. Notably, data were meticulously gathered from participants possessing substantive expertise in the field of EVs, ensuring the relevance and reliability of responses. To further enhance data quality, the survey questions were carefully structured to be unambiguous and direct, thereby minimising any potential misinterpretations. Additionally, care was taken to distinctly segregate the constructs under investigation, and double-barrelled questions were scrupulously avoided. After data collection, a variance inflation factor analysis was conducted, aiming to identify and assess any common method variance within the data set, as delineated in Table 2. The results unequivocally indicated that CMB did not pose a significant concern in this study.

4.3. Measurement Development

To construct these hypotheses, various measurement items were developed as presented in Table 3. In this table, the measurement items for public involvement were adopted from the instrument developed by [21,32]. The measurement items for knowledge of EVs were adopted from the instrument developed by [14,23,26,28,34]. The measurement items for perceived risk were adopted from [22,23,25–28,31,45]. The measurement items for perceived usefulness were adopted from the instrument originally used by [16,21–23,28,29,45]. Similarly, measurement items for perceived ease of use were adopted from [9,11,16,21,23,27,30]. Furthermore, the measurement items for behavioural intention toward acceptance of EVs were adopted from [9,14,30,31]. It is worth noting that all these constructs (variables) have a five-point Likert scale ranging from "strongly agree" to "strongly disagree".

It should be noted that, in Table 3, the item "Concerns about EV safety" was eliminated to improve the reliability of the instrument. In addition, the items "Using an EV would lead to reduced air pollution and improved air quality" , "Purchasing or leasing an EV as my next vehicle." and "Considering EV ownership to reduce my transport cost" were eliminated to improve the content validity as suggested by expert review.

Table 2. Multicollinearity results.

Variable	Item	VIF *	M	S.D	Skewness	Kurtoses
PI	PI01	1.428	1.605	0.728	1.233	1.904
	PI02	1.428	1.615	0.775	1.357	2.120
KE	KE01	1.540	2.040	0.818	0.585	0.311
	KE02	1.487	1.966	0.787	0.528	0.271
	KE03	1.280	1.633	0.761	1.274	2.012
PR	PR01	1.917	2.054	0.939	0.894	0.552
	PR02	1.845	2.110	0.961	0.834	0.460
	PR04	1.503	1.998	0.932	0.865	0.463
	PR05	2.092	2.082	0.956	0.813	0.351
	PR06	1.903	2.016	0.924	0.927	0.719
PU	PU01	1.465	1.784	0.892	1.215	1.366
	PU02	1.632	1.641	0.849	1.624	3.073
	PU03	1.507	1.601	0.748	1.261	1.753
EU	EU01	1.494	2.032	0.943	0.824	0.264
	EU02	1.940	2.044	0.919	0.702	0.305
	EU03	1.785	2.036	1.004	0.876	0.323
BI	BI01	1.803	1.912	0.995	0.967	1.164
	BI02	1.622	1.784	0.793	2.329	1.200
	BI03	1.618	2.198	1.075	0.171	0.836
EA	EA01	1.650	1.980	0.958	0.996	0.749
	EA02	1.650	1.986	1.067	1.015	0.380
	EA03	1.650	1.575	0.774	1.469	2.387

* VIF: variance inflation factor; Type of Measure: Reflective.

Table 3. Variables and measurement items (*N* = 501).

Construct (Variable)	Measurement Item	
Public Involvement (PI)	PI01	Public perception of EVs has become more positive in recent years
	PI02	Public interest in EVs is increasing, as evidenced by media coverage and discussions
Knowledge of EVs (KE)	KE01	Understanding the performance of EVs (such as electric range, refererring to the distance travelled by an EV on a single charge)
	KE02	Understanding the potential risks of EVs (such as Battery Degradation)
	KE03	Understanding the advantages of EVs (such as environmental benefits and fuel consumption reduction)
Perceived Risk (PR)	PR01	Concerns about system failures in EVs
	PR02	Concerns that EVs cannot handle varied weather conditions or terrain
	PR03	Concerns about EV safety *
	PR04	Concerns about the charging stations availability
	PR05	Worries about the long-term reliability and performance of EV batteries
	PR06	Concerns about the potential maintenance and repair costs of EVs
Perceived Usefulness (PU)	PU01	Owning an EV would lead to cost savings
	PU02	Using EVs reduces environmental impact and lower carbon emissions
	PU03	Charging infrastructure availability makes owning an EV more convenient
	PU04	Using an EV would lead to reduced air pollution and improved air quality **
Perceived Ease of Use (EU)	EU01	Understanding the EV charging process
	EU02	Driving an EV and understanding its features and functions
	EU03	Owning an EV fits seamlessly into my daily routines and lifestyle
Behavioural Intention (BI)	BI01	Intending to use an EV as my primary mode of transport soon
	BI02	Exploring the availability of charging infrastructure in my area
	BI03	Seeking information about EV models and their features
	BI04	Purchasing or leasing an EV as my next vehicle **
	BI05	Considering EV ownership to reduce my transport cost **

Table 3. *Cont.*

Construct (Variable)		Measurement Item
EV Acceptance (EA)	EA01	EVs are a reliable and practical mode of transport
	EA02	The next vehicle purchase is an EV
	EA03	The automotive industry will be dominated by EVs

* This item was eventually deleted to improve the reliability of the instrument. ** These items were eventually deleted to improve the content validity as suggested by experts' review.

4.4. Data Collection

To collect data about the intention to use EVs, an online survey was developed. The participants were contacted between July and August 2023. The estimated time to answer the questionnaire was about 10 min. Several methods were implemented to collect data via mobile phones, and personal interviews, along with distribution through social media and websites from different social groups. A total of 501 forms were collected.

It is worth noting that the questionnaire was translated into English using the standard method of translation-back-translation by four specialists with degrees in language translation, as suggested by [64]. The translation procedure was divided into four stages. First, a group of experts met to discuss cultural applicability, acceptability of the survey questions, format, and wording and phrasing. Second, each member of the experts was allocated a number of questions. Third, the proficient expert assessed the questionnaire's translation conducted by a separate expert specialist. Finally, a consensus session involving the entire panel of experts was convened following the completion of each questionnaire item, to address nuances related to the cultural and social significance of the wording and sentences.

Table 4 depicts the sample socio-demographic characteristics, compared to the 2021 Census data [58]. Among 501 participants, about 51% were male, and 49% were female, with minimal difference compared to the census data. Approximately 59% of participants were 18–28 years of age, 21% were 29–39, 12% were 40–50, and 8% were older than 50. About 77% of the participants had a driver's license. About 66% of the respondents had a bachelor's degree. About 87% of the responses involved are from the central governorates of Jordan. The final column of Table 4 depicts the 2021 Census data of Jordan (the most recent census data of Jordan). Therefore, the sample is a good representation of the population of Jordan. For instance, the difference between the females and males in the sample is about 0.02%.

Table 4. Respondents' demographic information (N = 501).

Demographic Variable	Item	Number	Percentage	Census (2021)
Gender	Male	255	50.9	52.9
	Female	246	49.1	47.1
Age	18–28 years	297	59.3	
	29–39 years	105	21.0	62.9
	40–50 years	62	12.4	10.9
	>50 years	37	07.4	11.7
Education level	Middle school	06	01.2	
	High school	48	09.6	
	Community college	44	08.8	
	Undergraduate	330	65.9	
	Postgraduate	73	14.6	

Table 4. *Cont.*

Demographic Variable	Item	Number	Percentage	Census (2021)
Family income (JOD) [1]	<500 Monthly	134	26.7	
	500–999 Monthly	204	40.7	
	1000–2000 Monthly	119	23.8	
	>2000 Monthly	44	8.8	
Driving licence	Yes	386	77.0	
	No	115	23.0	
Driving frequency	Drive every day	339	67.7	
	Drive 5–6 times a week	53	10.6	
	Drive 3–4 times a week	34	06.8	
	Drive less than twice a week	75	15.0	
Place of residence (Governorate)	Centre of Jordan (Amman, Balqa, Zarqa, Madaba)	434	86.6	63.5
	North of Jordan (Irbid, Ajloun, Jerash, Mafraq)	61	12.2	28.5
	South of Jordan (Ma'an, Tafilah, Karak, Aqaba)	06	01.2	08
Current fuel type	Natural Gas	19	03.8	
	Petroleum (Diesel or Gasoline)	268	53.5	
	Electric	80	16.0	
	Hybrid	134	26.7	

[1] One JOD = about USD 1.41.

4.5. Structural Equation Model (SEM)

In practice, the SEM is considered a comprehensive tool for analysing data and testing theoretical models in a variety of engineering research [29,33]. The SEM is a multivariate analytical approach that uses factor analysis and regression analysis to assess hypotheses systematically and to appraise theoretical models [65,66]. The SEM is divided into two sets of theoretical models: the measurement model (i.e., outer model), and the structural model (i.e., inner model), as found in [67,68]. Every variable in the model, whether observed (i.e., represents the data) or latent (i.e., represents the hypothetical constructs), is classified as either an independent or a dependent variable. A dependent variable is a variable in a path diagram that has a one-way arrow aiming at it (as illustrated in Figure 1). The set of these variables is collected into vector η. All the remaining variables are called independent variables, which are collected in vector ξ . According to [67–69], the structural model can be expressed as follows:

$$\eta = \gamma\xi + \beta\eta + \zeta, \tag{2}$$

Equation (3) connects the latent variable η to the endogenous variable Y (i.e., outcome of the dependent variable), demonstrating how the latent variable influences the observed outcome:

$$Y = \lambda\eta + \epsilon, \tag{3}$$

Equation (4) connects the latent variable ξ and the exogenous variable X (i.e., the independent variable), revealing how the latent variable influences the observed independent variable.

$$X = \lambda\xi + \delta. \tag{4}$$

where ξ is the dependent variable error; β is the correlation coefficient matrix of the dependent variable (auto-regressive effect: a variable's dependence on its own past values); δ measures the error of X ; ϵ measures the error of Y; X is the observed variables of ξ; Y observed variables of η; and γ is the correlation coefficient matrix between ξ and η.

In this study, Partial Least Squares SEM (PLS-SEM) is employed to calculate the relationship among variables by using SmartPLS software Version 04.

5. Data Analysis and Discussion

Two main techniques of data analysis were employed, namely descriptive statistics and the Structural Equation Model (SEM). Statistical analyses were deployed using the software package IBM SPSS Statistics Version 22 and its Complex Samples module. Descriptive Statistics was employed to summarise the demographic characteristics of study participants, presenting the distribution of scores on a measure of interest, to gain an understanding of the underlying patterns and relationships within the data. By contrast, for the SEM, SmartPLS software Version 4 was employed to study the relationships among the latent variables (also known as factors or constructs).

In the following data analysis:

- we first analysed descriptive statistics for key variables by identifying respondent range, mean, and standard deviation;
- we measured the outer model by conducting reliability and validity analysis, multi-collinearity check, and discriminant validity;
- we structured the inner model by using the SEM to investigate relationships among variables, we assessed the goodness of fit to gauge model alignment with data, and employed hypothesis testing to determine the significance of hypothesised relationships.

5.1. Descriptive Statistics for Key Variables

Table 5 presents a comprehensive overview of the descriptive statistics pertaining to variables in the study, encompassing the constructs of PI, KE, PR, PU, EU, BI, and EA. These statistical insights are based on data collected from a representative sample of 501 survey respondents. The data were systematically categorised into three distinct scales: a Positive Scale (including responses Strongly Agree and Agree), a Neutral Scale, and a Negative Scale (including responses Strongly Disagree and Disagree). The descriptive statistics are invaluable as they shed light on the central tendencies and variances present in the data observed from our study participants.

The participants' responses regarding public involvement were measured through two items (PI01, PI02) as described previously in Table 5. The data highlights that a significant proportion of the respondents were on the positive scale for PI01 = 90.22% and PI02 = 88.82%. In contrast, a smaller percentage expressed neutrality for PI01 = 7.98% and PI02 = 8.58%, and a negative scale for PI01 = 1.80%, PI02 = 2.59%. The mean score for PI was 1.6, with about 0.66 standard deviation. This means that participants' responses leaned toward agreement with items PI01 and PI02.

The KE was assessed through three items: KE01, KE02, and KE03. The data reveals that a substantial majority of respondents fell on the positive scale for KE01, KE02, and KE03: 74.65%, 76.45%, and 88.82% respectively. Conversely, a smaller proportion exhibited neutrality: 21.16%, 21.56%, 8.98%, for KE01, KE02, and KE03 respectively, and negative scales of 4.19%, 2.00%, 2.20%, for KE01, KE02, and KE03 respectively. The mean score for KE was 1.88, with a standard deviation of about 0.63, suggesting moderately positive perceptions of knowledge regarding EVs.

Similarly, the PR was explored through six items (PR01 to PR06). The data reveals varying degrees of agreement and disagreement across the scales. Notably, a significant number of respondents expressed strong agreement on the positive scale for items PR01, PR02, PR04, PR05, and PR06, while almost half of the respondents agreed with PR03 (58.48%), reflecting diverse perceptions of perceived risk. The mean score for PR is about 2.1, with a standard deviation of about 0.75. This indicates perceived risk in relation to EV acceptance.

Table 5. Descriptive statistics for key variables.

Variable	Item	Positive Scale N	%	Neutral N	%	Negative Scale N	%	Mean	Std. Dev
PI	PI01	452	90.22	40	7.98	9	1.80	1.6098	0.66176
	PI02	445	88.82	43	8.58	13	2.59		
KE	KE01	374	74.65	106	21.16	21	4.19		
	KE02	383	76.45	108	21.56	10	2.00	1.8796	0.63063
	KE03	445	88.82	45	8.98	11	2.20		
PR	PR01	380	75.85	76	15.17	45	8.98		
	PR02	362	72.26	94	18.76	45	8.98		
	PR03	293	58.48	120	23.95	88	17.56	2.1101	0.75352
	PR04	379	75.65	85	16.97	37	7.39		
	PR05	365	72.85	92	18.36	44	8.78		
	PR06	385	76.85	77	15.37	39	7.78		
PU	PU01	418	83.43	55	10.98	28	5.59		
	PU02	442	88.22	39	7.78	20	3.99	1.6753	0.68128
	PU03	447	89.22	44	8.78	10	2.00		
EU	EU01	376	75.05	81	16.17	44	8.78		
	EU02	356	71.06	118	23.55	27	5.39	2.0373	0.80357
	EU03	363	72.46	94	18.76	44	8.78		
BI	BI01	399	79.64	57	11.38	45	8.98		
	BI02	434	86.63	52	10.38	15	2.99	1.9647	0.80380
	BI03	342	68.26	97	19.36	62	12.38		
EA	EA01	386	77.05	75	14.97	40	7.98		
	EA02	371	74.05	78	15.57	52	10.38	1.8470	0.80807
	EA03	447	89.22	41	8.18	13	2.59		

The PU was assessed using three items, labelled as PU01, PU02, and PU03. The results demonstrated that the majority of respondents, accounting for 83.43%, 88.22%, and 89.22%, fell within the positive range. This indicated that respondents hold positive perceptions regarding PU. Conversely, within the neutral and negative ranges, a smaller percentage expressed neutrality (10.98%, 7.78%, 8.78%) or disagreement (5.59%, 3.99%, 2.00%), respectively. The calculated mean score for PU is about 1.67, with a standard deviation of about 0.68, suggesting that, on average, respondents view EVs as useful.

Regarding ease of use measurement, three items were used: EU01, EU02, and EU03. The results showed that the vast majority of respondents, encompassing 75.05%, 71.06%, and 72.46%, agreed with the statements on the positive scale, indicating positive perceptions of ease of use toward EVs. In contrast, a smaller proportion expressed (16.17%, 23.55%, 18.76%) on the neutral scale and disagreement (8.78%, 5.39%, 8.78%) on the negative scale, respectively. The mean score for the EU is about 2.03, with a standard deviation of about 0.80, suggesting moderately positive perceptions of the ease of using EVs.

In the same way, the BI was captured through three items: BI01 to BI03. The data illustrates that a significant proportion of respondents agreed (79.64%, 86.63%, 68.26%) with the statements on the positive scale, indicating positive behavioural intentions. Conversely, a smaller percentage expressed neutrality (11.38%, 10.38%, 19.36%) and disagreement (8.98%, 2.99%, 12.38%) in the neutral and negative scales, respectively. The mean score for BI is about 1.9, with a standard deviation of about 0.80, indicating moderately high behavioural intentions related to EVs.

Finally, EV acceptance was assessed through three items: EA01, EA02, and EA03. The data reveals a significant proportion of respondents on the positive scale (77.05%, 74.05%, 89.22%, respectively), indicating positive acceptance of EVs. The mean score for EA is about 1.8, with a standard deviation of about 0.81, suggesting high levels of acceptance of EVs.

5.2. The Measurement Model Assessment

The measurement model should be tested, before examining the structural inner model [70]. Therefore, in this section, we used the heterotrait-monotrait (HTMT) ratio criterion to test the measurement model reliability. The reliability of the measurement model signifies the internal consistency among the items within each construct. Also, a rigorous multicollinearity check was employed among variables to impede the clarity of relationships within an outer model. Therefore, Variance Inflation Factor (VIF), the mean, standard deviation, skewness, and kurtosis of variables were examined. Furthermore, a discriminant validity test was conducted to ensure the measurements effectively differentiate between the variables they intend to represent. For this purpose, the HTMT criterion was deployed, and the correlations between constructs, to ensure the robustness and accuracy of the model.

Reliability and Validity Analysis

Convergent validity evaluates the factor loadings via confirmatory factor analysis, internal consistency reliability via Cronbach's coefficient alpha, composite reliability, and Average Variance Extracted (AVE). These factors are presented in Table 6, and they demonstrate strong reliability and convergent validity for the reflective measures within the research model. The factor loadings for the items within each construct are well above the recommended threshold of 0.7 [71,72], indicating strong relationships between the items and their respective constructs. Cronbach's Alpha values were used to assess the internal consistency of items within each construct [73], given the number of statistical analyses reported in this study. The minimum value of Cronbach's alpha is 0.707, and all results obtainedare above the recommended minimum value of 0.700 [70,73], which indicates excellent reliability as internal consistency. The composite reliability values, another measure of reliability for reflective constructs, vary from 0.835 to 0.896, meeting the recommended minimum value of 0.70, and further indicating high reliability [65,74]. The AVE values measure convergent validity, and they were all above the acceptable threshold of 0.5, indicating that each construct (variable) captures a significant proportion of variance among its items [72,74]. These findings provide confidence in the robustness of the measurement model, ensuring that the items effectively measure their respective constructs.

Multicollinearity Check

According to [66], the multicollinearity check needs to be handled well for some of the PLS-SEM. Thus, a collinearity test was employed to be aware of problems related to multicollinearity. The latter occurs when predictor constructs in a regression analysis are correlated highly with each other, potentially leading to unstable coefficient estimates and challenges in interpreting the results [66]. To check for multicollinearity in PLS-SEM, a Variance Inflation Factor (VIF) is a recommended metric for assessing the inflation of standard errors in regression coefficients. A higher VIF value suggests a greater degree of collinearity among the variables. Generally, a VIF value greater than, or equal to, five is considered to indicate serious severe collinearity issues among the predictor constructs [65,75], whereas, a VIF value below three implies no collinearity. Based on the results shown in Table 2, the VIF values range from 1.487 to 2.092, which is below three. This suggests that multicollinearity is not a significant issue among the reflective measures in our model among the predictor constructs. Therefore, it can be concluded that the reflective measures used in analysis do not correlate highly with each other, and there is no severe collinearity present.

Table 6. Reliability and convergent validity.

Variable	Item	F.L *	CA	CR	AVE
PI	PI01	0.898	0.707	0.872	0.773
	PI02	0.960			
KE	KE01	0.823			
	KE02	0.731	0.714	0.835	0.628
	KE03	0.820			
PR	PR01	0.714			
	PR02	0.706			
	PR04 **	0.805	0.841	0.880	0.596
	PR05	0.847			
	PR06	0.780			
PU	PU01	0.827			
	PU02	0.825	0.756	0.860	0.671
	PU03	0.805			
EU	EU01	0.779			
	EU02	0.880	0.792	0.878	0.706
	EU03	0.859			
BI	BI01	0.875			
	BI02	0.821	0.791	0.877	0.705
	BI03	0.821			
EA	EA01	0.873			
	EA02	0.894	0.825	0.896	0.741
	EA03	0.814			

* F.L: Factor Loading; CA: Cronbach's Alpha; CR: Composite Reliability; AVE: Average Variance Extracted; Type of Measure: Reflective; Note: PR03 is removed due to low loadings. ** PR03 is removed due for low loadings.

Discriminant Validity

Discriminant validity refers to the degree to which the indicators differentiate across constructs by examining the correlation between potentially overlapping measures [76]. Therefore, to assess the discriminant validity, the heterotrait-monotrait (HTMT) ratio criterion was employed. The HTMT criterion [77] is a widely recognised method for assessing discriminant validity in SEM research. It is utilised to evaluate whether the constructs (variables) in a model are distinct from each other [31,76,78].This criterion examines the HTMT ratio, where values less than 0.85 are indicative of good discriminant validity [77]. In Table 7, the findings highlight that most of the HTMT values are well below the recommended threshold of 0.85, indicating that there is good discriminant validity among these constructs. This suggests that the variables (constructs) in the study were well-distinguished from one another. This is a crucial aspect in ensuring the robustness of the SEM in the study [78].

Table 7. Discriminant validity result.

	BI [1]	EA	EU	KE	PI	PR	PU
BI							
EA	0.749						
EU	0.612	0.747					
KE	0.619	0.637	0.658				
PI	0.576	0.732	0.547	0.682			
PR	0.186	0.130	0.075	0.160	0.184		
PU	0.617	0.687	0.765	0.720	0.720	0.280	

[1] Source: heterotrait-monotrait (HTMT) ratio criterion, Outputs of statistical analysis using Smart PLS software.

5.3. Structure Model Assessment

Model Goodness of Fit

After analysing and fitting the measurement of the outer model, the validity of the structural inner model must be assessed to ensure model goodness of fit as recommended by [66,79]. Thus, the structural inner model was assessed by employing the coefficient of determination R^2 and adjusting R^2 for each latent factor, as well as the Q^2 values that signify the predictive relevance of the model [79]. Additionally, model fit indices, including the Normalised Fit Index (NFI) and the Standardised Root Mean Square Residual (SRMR), are provided to assess the overall model fit . It should be noted that R^2 values below 0.1 may be considered weak, values between 0.1 and 0.25 may be considered moderate, and values greater than 0.25 may be considered strong [80].

As presented in Table 8, the R^2 value for KE indicates that the model accounts for approximately 0.262 of the variances in this latent factor. The Adj. R^2, considering the complexity of the model, remains consistent at 0.261. The corresponding Q^2 value of 0.254 suggests that the predictive capability of the model is evident for KE. The model shows a substantial degree of variance in PU, as reflected by an R^2 of 0.476 and an Adj. R^2 of 0.473. However, the Q^2 value of 0.227, while positive, suggests that the model's predictive relevance is moderate for perceived usefulness. Similarly, for KE, EU it exhibits an R^2 of 0.262 and an Adj. R^2 of 0.261. The Q^2 value of 0.144 indicates that the model holds predictive relevance for this latent factor, although to a lesser extent. Also, the model accounts for a substantial portion of the variance in BI, with an R^2 of 0.609 and an Adj. R^2 of 0.607, while the Q^2 value of 0.150 suggests that the predictive relevance of the model is moderate for behavioural intention. The highest R^2 value among the latent factors is observed for EA, at 0.626, with an Adj. R^2 of 0.624 and the Q^2 value of 0.224 indicates the predictive relevance of the model for EV acceptance. However, for PR, the R^2 value is 0.025 which is notably the lowest among all factors, with the Adj. R^2 at 0.021, while the Q^2 value of 0.016 indicates limited predictive relevance for this latent factor within the model. The outcome provides clear evidence that the study model accurately represents the empirical data and possesses a satisfactory level of predictive capability [81].

The NFI attains a value of 0.722, indicating a satisfactory fit of the model to the data. A higher NFI indicates a better fit, and our obtained value suggests a satisfactory level of fit. Additionally, the SRMR value is 0.700, providing an assessment of the average absolute discrepancy between the predicted and observed correlations of our model. In this case, the SRMR value indicates a reasonably good fit [82]. These findings collectively indicate that the model offers reasonable explanatory power for several latent factors, particularly EV acceptance, perceived usefulness, and behavioural intention. However, some latent factors, such as perceived risk, exhibit limited variance explained and predictive relevance. The model fit indices for NFI and SRMR provide additional support for the overall fit of the proposed model.

Hypothesis Testing Analysis

The study proposed twelve direct relationships hypotheses as depicted in Figure 3. Thus, the structural model analysis was conducted by using Smart PLS4 package software to examine the relationships between the hypothesised constructs (variables). A bootstrapping approach was employed by re-sampling 5,000 samples to determine the inner path outcomes and calculate the standardised beta coefficients (β), means (M), standard errors, *t*-values, *p*-values, and decisions for each hypothesis as presented in Table 9. The results show that out of twelve direct hypotheses, ten hypotheses (H01, H02, H04–H07, H09–H12) were supported, and two were rejected (H03, H08). The supported hypotheses are statistically significant at 0.05: they have the predicted sign directions, and have standardised beta coefficient values (β) ranging from 0.024 to 0.681.

Table 8. Coefficient of determination (R^2) and model fit (SRMR-NFI).

Latent Factors	R^2	Adj. R^2	Q^2
KE	0.262	0.261	0.254
PR	0.025	0.021	0.016
PU	0.476	0.473	0.227
EU	0.262	0.261	0.144
BI	0.609	0.607	0.150
EA	0.626	0.624	0.224
Model Fit	NFI	SRMR	
	0.722	0.079	

As shown in Table 9, the first hypothesis (H01), the relationship between PI and KE was found to be significant (β = 0.512, t-value = 11.189, p-value < 0.001), indicating that an increase in public involvement is associated with an increase in KE. Hence, Hypothesis H01 was accepted. Furthermore, the relationship is affirmative, given that the value of β is 0.512, indicating a positive outcome. For the second hypothesis (H02), it was also found that public involvement has a positive and significant effect relationship on PR, as the (β = 0.145, t-value = 02.661, p-value = 0.008). This suggests that higher levels of public involvement are related to an increase in perceived risk. Thus, hypothesis H02 was accepted. However, for the third hypothesis H03, the relationship between KE and perceived risk was not found to be significant (β = 0.024, t = 00.422, p-value = 0.673), as the p-value was greater than 0.05 and the t-value (0.422) was less than 1.96. Therefore, H03 was rejected, suggesting that the KE factor does not have significant influence on the perceived risk factor. The result of the fourth hypothesis (H04) revealed that the KE was positively and significantly influenced by the PU factor (β = 0.328, t-value = 07.330, p-value < 0.001), as the p-value was less than 0.05. This implies that individuals who gain knowledge related to EVs are more likely to perceive that knowledge for EVs usefulness, thus, hypothesis H04 was accepted.

Similarly, for the fifth hypothesis, the relationship between KE and EU was found to be statistically significant (β = 0.512, t-value = 12.255, p-value < 0.001). This indicates that an increase in knowledge is associated with an increase in ease of use, thus supporting Hypothesis H05. Furthermore, the sixth hypothesis, indicated that KE was positively related to EA (β = 0.190, t-value = 05.348, p-value < 0.001). This suggests that individuals who gain KE are more likely to increase acceptance to use them, so hypothesis H06 was accepted. In the same way, the seventh hypothesis H07, was found to have a positive and significant effect (β = 0.174, t-value = 05.277, p-value < 0.001) as the p-value is less than 0.05, and the t-value (05.277) was greater than 1.96, suggesting that higher levels of perceived risk are associated with increased perceived usefulness. Therefore, Hypothesis H07 was accepted. However, for the eighth hypothesis H08, the relationship between the perceived risk factor and the BI factor was not found to be significant (β = 0.058, t-value = 0.116, p-value = 0.116), as the p-value was greater than 0.05 and the t-value was less than 1.96. As a result, H08 was rejected, suggesting that the KE factor does not have significant influence on the perceived risk factor, and indicating that the perceived risk factor did not have an effect on the behavioural intention factor.

The ninth hypothesis (H09) also revealed that the PU factor had a positive and significant effect on the BI factor (β = 0.310, t-value = 07.227, p < 0.001), implying that individuals who recognised the usefulness of EVs are more likely to have a higher BI. Thus, Hypothesis H09 was accepted. Similarly, for H10 it was found that the perception of ease of use has a positive impact on EVs (β = 0.420, t-value = 09.786, p < 0.001) as the p-value was less than 0.05 and the t-value was greater than 1.96. This finding suggests that individuals who perceive information as easy to use are more likely to view EVs as useful for their purposes. In other words, the perception that using external information is convenient encourages individuals to believe that such use will result in beneficial outcomes. Therefore, hypothesis H10 was accepted. Also, the analysis of the eleventh Hypothesis (H11), indicates a significant and positive relationship between the constructs (β = 0.543, t-value = 13.808, p < 0.001).

The results indicate that individuals who actively recognised ease of use are more likely to have a higher behavioural intention toward EVs. This emphasises the pivotal role that perceived ease of use plays in shaping individuals' intentions to adopt behaviours related to EVs. Hence, Hypothesis H11 was accepted. Finally, for H12, behavioural intention was found to strongly predict EV acceptance (β = 0.681, t-value = 19.980, $p < 0.001$). This highlights the significant role of behavioural intention in getting EVs accepted, and, as a result Hypothesis H12 was accepted. The final SEM is presented in Figure 3, along with the obtained results.

Table 9. Structural model analysis.

Hypo.	Relationship	β	M	Std. Error	*t*-Value *	*p*-Value *	Decision
H01	PI→ KE	0.512	0.512	0.046	11.189	0.000	Accepted
H02	PI→ PR	0.145	0.148	0.054	02.661	0.008	Accepted
H03	KE→ PR	0.024	0.027	0.057	00.422	0.673	Rejected
H04	KE→ Pu	0.328	0.327	0.045	07.330	0.000	Accepted
H05	KE→ Eu	0.512	0.512	0.042	12.255	0.000	Accepted
H06	KE→ EA	0.190	0.190	0.035	05.348	0.000	Accepted
H07	PR→ PU	0.174	0.175	0.033	05.277	0.000	Accepted
H08	PR→ BI	0.058	0.059	0.037	01.573	0.116	Rejected
H09	PU→ BI	0.310	0.311	0.043	07.227	0.000	Accepted
H10	EU→ rPu	0.420	0.419	0.043	09.786	0.000	Accepted
H11	EU→ BI	0.543	0.542	0.039	13.808	0.000	Accepted
H12	BI→ EA	0.681	0.681	0.034	19.980	0.000	Accepted

* Note: p-value $<$ 0.05; t-value $>$ 1.96.

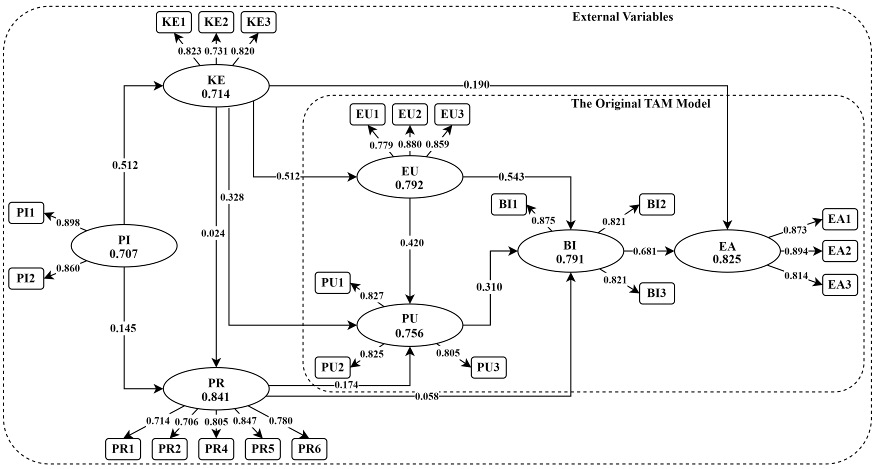

Figure 3. Structural and measurement model results.

6. Discussion and Implications

This study had the primary objective of conducting an empirical investigation into the underlying factors influencing the acceptance of EVs within the Jordanian driver population. The outcomes of this investigation reveal ten significant positive associations: firstly, between public involvement and both knowledge of EVs and perceived risk; secondly, between knowledge of EVs and perceived usefulness, perceived ease of use, and EV acceptance; thirdly, between perceived risk and perceived usefulness; fourthly, between perceived usefulness and behavioural intention; fifthly, between perceived ease of use and both perceived usefulness and behavioural intention; and lastly, between behavioural intention and EV acceptance. Data was meticulously gathered from a sample of 501 Jordanian participants, and the analysis was carried out employing the PLS-Structural Equation Model with the aid of SmartPLS software. The key findings are elaborated upon in the subsequent sections.

Regarding the role of public involvement, this study found a positive association between public involvement and factors such as knowledge of EVs and perceived risk. This result implies that individuals who exhibit heightened awareness regarding potential risks and who stay informed about environmental infrastructure developments are more likely to engage with the evolving landscape of electric mobility. This observation aligns with findings in existing literature [18,26,32,40,41,83], suggesting that many consumers exhibit hesitancy toward electric mobility due to their reservations about EV technology, concerns about associated risks, perceptions of poor EV performance, and perceived high purchase and operating costs. Furthermore, the study reveals the pivotal role of knowledge about EVs in shaping individuals' perceptions and attitudes toward these vehicles. Prior research has consistently demonstrated that a well-informed population tends to view EVs as valuable, user-friendly, and acceptable, ultimately fostering their integration into the broader transportation ecosystem [14,23,26,34,84]. Therefore, efforts geared toward enhancing public knowledge about EVs can be a strategic avenue to supporting their acceptance and adoption.

Furthermore, a higher perceived risk of electric vehicles tends to be associated with perceived usefulness. As perceived risk increases, individuals are more likely to view EVs as more practical, efficient, and beneficial for their transportation needs. Ref. [20] pointed out that the perceived risk has a positive effect on behavioural intention to adoption of EVs. Increasing perceived risk, therefore, becomes essential in promoting the perceived usefulness of EVs [20,22,23,27].

Regarding the construct of perceived usefulness, a positive association was observed with behavioural intention. This outcome highlights that individuals who perceive EVs as valuable for their requirements and anticipate favourable outcomes from their usage are more inclined to express an intention to incorporate these vehicles into their transportation choices. These findings resonate with multiple prior investigations [21–23,28,84], underscoring the substantial impact of perceived usefulness in shaping attitudes and behavioural intentions. Hence, perceived usefulness emerges as a pivotal factor in fostering individuals' willingness to integrate EVs into their daily transportation routines, in alignment with existing research.

In addition, we found that behavioural intention has a strong positive influence on the acceptance of EVs. Our findings are in line with the established literature [9,14,21,30,31,33,45,84], which collectively emphasizes that behavioural intention significantly impacts on EV acceptance. Therefore, our findings contribute to the growing body of evidence in support of the idea that enhancing the behavioural intention to use EVs in Jordan can effectively promote their acceptance in society. This highlights the importance of understanding and positively influencing the intentions of potential EV users to drive widespread adoption and contribute to a more sustainable future. Thus, the current research findings are mostly in line with the viewpoints of prior research.

This study provides implications of factors that influence the acceptance of EVs among Jordanian drivers, considering the impact of public involvement on knowledge of EVs and the perceived risk towards acceptance of electric vehicles. More efforts should be made towards a deeper understanding of the dynamics between public involvement, knowledge, and perceived risk toward towards acceptance of electric vehicles [18,21,26]. These findings have practical applications for the public to promote the wider acceptance and adoption of electric vehicles in Jordanian society, thus fostering a more sustainable and environmentally friendly transportation ecosystem. Besides, manufacturers could organise EV test rides to invite consumers to be more aware of the overall progression of electric mobility.

Also, the examination of the impact of knowledge of EVs on perceived usefulness, perceived ease of use, and EV acceptance carries significant practical and theoretical implications. On a practical level, understanding the positive relationship between knowledge of EVs and perceived usefulness underscores the importance of educating potential consumers about the advantages and benefits of EVs [43]. Organisations and policymakers can develop informative campaigns and materials to enhance public knowledge, thus boosting the perceived usefulness of EVs and potentially increasing their adoption [18]. Moreover, a positive correlation between knowledge of EVs and their perceived ease of use highlights the importance of reducing the learning curve associated with EV operations [44]: providing comprehensive information on how to use EVs, including everyday practicalities to enhance user confidence and comfort, ultimately promoting their adoption [23,42]. Thus, practical interventions like user manuals, training programs, and user-friendly interfaces can significantly contribute to improving ease of use.

Similarly, considering the impact of perceived ease of use on both perceived usefulness and behavioural intention in the context of electric vehicles, substantially impacts on real-world implications for the design, marketing, and promotion of EVs. The study underscores the importance of designing EVs with user-centric features, promoting technological literacy among users, and employing effective marketing strategies emphasizing user-friendliness. These strategies can enhance user experiences, positively impacting on perceived usefulness and the intentions to embrace EVs. On a theoretical level, the study contributes to the validation of the TAM by reaffirming the central role of perceived ease of use in determining technology acceptance in Jordan, thereby strengthening the model's relevance in the domain of EVs.

7. Conclusions and Limitations

To sum up, this work compiles variables to evaluate their effect on the intention to use EVs in Jordan: namely, Public Involvement, Knowledge of EVs, Perceived Risk, Behavioural Intention, and EV acceptance. These variables are considered vital when analysing the intention to use EVs. The 501 collected responses were analysed using the Smart PLS-Structural Equation Model algorithm. In general, the analysis revealed high levels of EV acceptance. The study proposed twelve direct relationship hypotheses. Out of the twelve direct hypotheses, ten hypotheses were accepted and two were rejected. The final conclusions that are an increase in public involvement is associated with an increase in knowledge of EVs, and an increase in their perceived risk of EVs. Moreover, the knowledge of EVs was positively and significantly influenced the perceived usefulness and perceived ease of use, along with the acceptance of EVs. However, no relation was found between the knowledge of EVs and their perceived risk, nor the relationship between perceived risk and behavioural intention. Despite the importance of the obtained results, this study is limited in several points. Firstly, only three external variables of EVs (i.e., public involvement, related knowledge, and perceived risk) were considered in this work. Future research exploration could be conducted to consider variables such as perceived trust, perceived value, user satisfaction, perceived behavioural control, policy intervention, and perceived convenience. Secondly, this study only examines the relationships among variables by using a structure equation model, and it does not further detect the causes and effects among variables. Further analysis could be conducted (e.g., multiple regression, logistic regression, and path analysis) to evaluate cause and effect among the variables. Finally, this work considers all types of EVs, and does not distinguish between the different types of EVs (e.g., battery EVs, hybrid EVs, and plug-in hybrid EVs). Users' perceptions and understanding of EVs may vary for various EV types. Therefore, further research can investigate specific EV type.

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Abbreviations

The following abbreviations are used in this manuscript:

EVs	Electric Vehicles
SEM	Structural Equation Model
PLS	Partial Least Squares
DoS	Jordanian Department of Statistics
VIF	Variance Inflation Factor

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