Eduvest – Journal of Universal Studies
Volume 5 Number 11, November, 2025
p- ISSN 2775-3735- e-ISSN 2775-3727

What Fuels Electric Vehicle Adoption? Analyzing Determinants of Adoption Intention and Willingness to Pay

Nadiyatus Shofi, Imam Salehudin
Universitas Indonesia, Indonesia
Email: nadiyatusshofi@gmail.com, imams@ui.ac.id

ABSTRACT

Electric vehicles (EV) adoption in Indonesia is still lagging, with current sales volumes far below the government's target, particularly for battery electric vehicles (BEVs). This research aims to uncover the diffusion of BEVs by analyzing factors that influence their acceptance through adoption intention and willingness to pay, using an integrated model of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), which incorporates perceived risk, environmental concerns, and government support. Data from 329 respondents in major Indonesian cities were analyzed using partial least squares structural equation modeling (PLS-SEM). The results indicate that effort expectancy, habit, perceived risk, environmental concerns, and government support impact EV adoption intention. Additionally, performance expectancy, price value, and adoption intention were found to positively influence willingness to pay for EVs. These findings confirm the applicability of some factors of UTAUT2, perceived risk, environmental concern, and willingness to pay in examining EV adoption in Indonesia, contributing to the literature on technology adoption in the automotive sector. This study also discusses implications that offer valuable insights for stakeholders in the EV market, thereby helping to promote electric vehicle adoption in Indonesia.

KEYWORDS *Adoption intention, Battery electric vehicle, Electric vehicle, UTAUT2, Willingness to pay*

INTRODUCTION

Environmental issues have taken on greater global priority, particularly since the Paris Agreement was reached at the 2015 United Nations Framework Convention on Climate Change (UNFCCC) COP21 in Paris, which legally bound all countries to commit to the fight against climate change via their Nationally Determined Contributions (NDC) (UNFCCC, 2023). To achieve one of the long-term goals of COP21, which is net-zero emissions by 2050 (UN, 2022), the transportation sector becomes crucial as it contributes to 23% of global carbon emissions (World Bank Group, 2015), and its emissions are growing more rapidly compared to other end-use sectors, apart from the industrial sector (IEA, 2022a). Therefore, each country is required to implement regulations, incentives, and infrastructure investments that support low-emission vehicles in order to achieve carbon neutrality (IEA, 2022a).

The electrification of the transportation sector significantly reduces greenhouse gas emissions and decreases dependence on oil (Adnan et al., 2017). Electric vehicles (EVs), as a low-emission vehicle option, are recently receiving significant international attention. Evidently, the global EV fleet grew by 60% in 2022, increasing market share from 9% to 14%, over ten times its 2017 share (IEA, 2023). However, the sales of EVs are still concentrated in China, Europe, and the United States, which collectively contribute up to 95% of the total global EV market (IEA, 2023). Meanwhile, the adoption rate of EVs lags behind in the majority of developing countries, where there are only a few EV models available in the market and they are offered at prices that are unaffordable for the general population (IEA, 2022b).

Indonesia is among the developing countries experiencing sluggish EV adoption, significantly lagging the government's ambitious target of achieving just 0.38% against the NDC 2030 goal (IESR, 2022). Nevertheless, there's a glimmer of progress as EV adoption in 2022 surged nearly fourfold compared to the previous year (IESR, 2022). Furthermore, the market share of domestic EVs increased to approximately 1.5% in 2022 (IEA, 2023), compared to less than 0.5% in 2021 (Gaikindo, 2022). This indicates a positive signal for the EV market in Indonesia.

In addition to the emerging trend of increased sales and market share, Indonesia has a significant opportunity to become a large EV market due to the high number of car users in the country. Indonesia is the largest car user in Southeast Asia (AAF, 2022) and ranks among the top 15 countries with the largest car sales globally (OICA, 2022). The high number of users is an indicator that the demand for cars remains high, leading the government to be optimistic that the Indonesian market will gradually embrace EVs (Gunawan et al., 2022). Hence, examining efforts to expedite the penetration of the EV market is of significant relevance in this context.

EVs differ from conventional vehicles in terms of their technology, and they necessitate specific charging infrastructure to support their unique requirements. Unlike the increasingly common electric scooters, EVs are less numerous (Yuniza et al., 2021). They must undergo various stages of diffusion, including introduction and growth, before achieving widespread adoption (Rogers, 2003). Throughout these stages, technology innovation adopters exhibit diverse consumer behaviors. Indonesia's EV market is still in its early stages, with users primarily being early adopters (Candra, 2022). Early adopters, typically possessing a propensity for readily accepting novelty, tend to embrace new technology faster than the majority, signifying their initial approval within the broader population (Rogers, 2003). Thus, studying the EV adoption process within the early adopters' phase, especially in Indonesia as a developing nation, is crucial for understanding limitations and enhancing policy planning (Bhat et al., 2022).

In this study, the term EV refers to four-wheeled EVs, and the primary focus of this discussion will be on Battery Electric Vehicles (BEVs). In the Indonesian market, alongside BEVs, there are also hybrid EVs (HEV) and plug-in hybrid EVs (PHEV) available (Gaikindo, 2022). When compared to HEVs and PHEVs, which still rely on fossil fuels in their combustion processes, BEVs stand out as the cleanest and most environmentally friendly alternative, operating solely on electricity (Setiawan et al., 2022). However, based on Gaikindo (2022), HEVs sales are much more popular than BEVs because domestic EV consumers prefer the hybrid type due to its more affordable price and the presence of range anxiety associated with BEVs, especially considering inadequate infrastructure conditions (Yuniza et al., 2021). Additionally, the government has begun to prioritize the accelerated adoption of BEVs, signified by the gradual reduction of incentives for hybrid cars and the introduction of specific incentives tailored for BEVs, such as Ministry of Finance Regulation Number 38 of 2023.

Accordingly, this research primarily aims to uncover the diffusion of EVs, particularly BEVs, by analyzing the factors influencing EV acceptance. The significant future potential of the EV market and the gap between the government's ambitious targets and the current adoption rate underscore the importance of accelerating EV penetration in Indonesia. Therefore, this study investigates the adoption intention and willingness to pay for EVs to provide valuable insights for stakeholders seeking to expand their market reach and help facilitate a sustainable transition toward more environmentally friendly transportation.

RESEARCH METHOD

This research adopted a quantitative methodology, employing purposive sampling, to examine the factors influencing the adoption intention and willingness to pay for EVs in the Indonesian market. The diffusion of EVs, is currently in its early stages, with limited adoption among the general public (Setiawan et al., 2022). Emerging technologies, such as EVs, are typically adopted first in major cities (Jaiswal, 2022). In Indonesia, Java serves as the primary hub for economic and business activities and stands as the most densely populated island. Therefore, the study's sampling frame includes individuals who own at least one non-BEV vehicle and possess valid driver's licenses, residing in major cities in Java, Indonesia (i.e. Greater Jakarta, Bandung, Semarang, Solo, Yogyakarta, Surabaya, Gresik, and Malang).

The survey was conducted using a structured questionnaire designed on an online survey platform (Google Forms) and distributed through various social media channels. The survey comprised three sections, accompanied by a cover letter. The first section involved screening questions to ensure that respondents participating in the survey met the predetermined criteria. The second part evaluated the key constructs of the study. All the items used to measure the constructs (refer to Table 1) were adapted from prior research and translated into

Bahasa Indonesia to suit the specific context of electric vehicles in Indonesia before being disseminated. All the constructs, derived from existing literature, were gauged using a 7-point Likert scale, ranging from "strongly agree = 7" to "strongly disagree = 1. The third section gathered essential respondent's profile.

Seven participants were consulted to evaluate the wording test of the questionnaire. Following their suggestions, specific items were revised accordingly. Subsequently, a pre-test was carried out, garnering 30 valid responses, to assess the measurement's reliability and validity. In this process, four items (SI5, FC5, HB5, and PR4) were omitted due to their factor loading falling below 0.50, as recommended by Chin, 1998 and (Hair et al., 2019).

The survey was afterward distributed from late September to early October 2023. A total of 384 respondents took part in the survey. Incomplete responses and those from participants who did not meet the respondent criteria and failed to answer the attention check question were excluded, resulting in 329 valid responses with the effective response rate stood at 85.68%. The number of respondents in this study met the minimum sample requirement of at least five times the number of indicators on the variables under study, as per Hair et al.'s (2019).

This study utilizes the partial least squares structural equation modeling (PLS-SEM) approach with SmartPLS 3 software. PLS-SEM is chosen for its robust results and flexibility in handling various data assumptions, including the absence of a requirement for normal distribution (Hair et al., 2019). The analysis involves assessing the measurement model, indicating how measured variables represent constructs, and the structural model, showing the relationships between constructs, along with hypothesis testing (Hair et al., 2019).

Table 1. The Operationalizations of Variables

Construct	Code	Indicator
Performance Expectancy (adapted from Jain *et al.* (2022), Bhat *et al.* 2022), and Manutworakit & Choocharukul (2022))	PE1	I would find EV useful in my daily life
	PE2	Using EV would help me travel quickly
	PE3	I think using a EV would help make my travel more convenient
	PE4	Using EV would increase my productivity
	PE5	The EVs in the current market have an acceptable standard of performance in terms of speed, acceleration etc
Effort Expectancy (adapted from Jain *et al.* (2022))	EE1	My utility for EV would be understandable
	EE2	Learning how to drive EV would be easy for me
	EE3	I would find EV easy to use
	EE4	It would be easy for me to become skilful at using EV
Social Influence (adapted from Jain *et al.*, (2022) and Singh *et al.* (2023))	SI1	My family and friends would think that I should use EV
	SI2	People close to me would think I should use an EV
	SI3	People whose opinion I value would prefer that I use EV

Construct	Code	Indicator
	SI4	Driving EV would make a good impression about me on the other people
	SI5	I would use an EV if a number of other people use it
Facilitating Conditions (adapted from Jain *et al*. (2022) and Singh *et al*. (2023))	FC1	I have the resources necessary to use EV
	FC2	I have the knowledge necessary to use EV
	FC3	EV are compatible with other technologies I use (e.g., bluetooth connectivity on smartphones)
	FC4	I can get help from others when I have difficulties using EV
	FC5	I would be constrained by lack of infrastructure and other facilities to use an EV
Hedonic Motivation (adapted from Kapser and Abdelrahman (2020); Singh *et al*. (2023))	HM1	Driving an EV would be very enjoyable
	HM2	Driving an EV would be very fun
	HM3	Driving an EV would be very entertaining
	HM4	An EV would be a very exciting new technology
Price Value (adapted from Singh *et al*. (2023))	PV1	EVs are reasonably priced
	PV2	EV price paid may be in accordance with the features I will get
	PV3	At the current price, EV would give a good value
	PV4	With the current quality of EVs, it is quite natural that they are relatively expensive
Habit (adapted from Gunawan *et al*. (2022) and Singh *et al*. (2023))	HB1	I would be addicted to use an EV
	HB2	Using an EV would become natural to me
	HB3	I must use an EV as the habit
	HB4	My habit of using conventional oil-fueled vehicles makes it impossible for me to switch to using EV
	HB5	I would be addicted to use an EV
Perceived Risk (adapted from Jain *et al*. (2022) and He at al. (2018))	PR1	I would not feel totally safe when I drive an EV on the road
	PR2	Considering the disadvantages of EVs (e.g., limited driving range and long time recharging), I think using EVs could involve important time losses
	PR3	I am afraid of suffering financial losses when using EVs
	PR4	I worry about whether EVs will really perform as well as traditional gasoline vehicles
	PR5	I am afraid that EVs often break
Environmental Concerns (adapted from Jain *et al*. (2022) and Jaiswal *et al*. (2022))	EC1	I am deeply concerned about environmental pollution in Indonesia currently
	EC2	I want to preserve natural resources from being depleted
	EC3	I want to prevent air pollution
	EC4	I believe that every individual is responsible for choosing low carbon emission modes of transportation

Construct	Code	Indicator
	EC5	I believe that EVs are a good way to reduce my carbon footprint
Government Support (adapted from Jain *et al*. (2022), Jaiswal *et al*. (2022), and Wang *et al*. (2017))	GS1	Government direct subsidy policy is attractive to me to adopt an EV
	GS2	Tax incentive reductions is attractive to me to adopt an EV
	GS3	EVs are unrestricted by the rules of even-and odd-numbered license plates is attractive to me to adopt an EV
	GS4	Incentives related to home charging (such as discounts for new home charging installations and discounted electricity rates for home charging during specific hours) is attractive to me to adopt an EV
	GS5	Government incentives are important to me for purchasing an EV
	GS6	The government should provide other incentives for using an EV
Adoption Intention (adapted from Jain *et al*. (2022), Wang *et al*. (2021), He at al. (2018), and Khazaei & Tareq (2021))	AI1	I look forward to more EV brands and models being introduced on the market
	AI2	I am willing to adopt an EV when adopting a vehicle in the near future
	AI3	I plan to adopt an EV when adopting a vehicle in the near future
	AI4	I would like to recommend others to adopt EVs when they planned to adopt a vehicle
	AI5	There is a high probability that i will use an EV in the future
Willingness to Pay (adapted from Zhang *et al*. (2020), Wei *et al*. (2018), Ng *et al*. (2018), and Gregory-Smith *et al*. (2017))	WTP1	I am willing to pay a high price for an EV
	WTP2	I am willing to pay more for an EV compared to a conventional car
	WTP3	I am willing to pay extra to buy an environmentally friendly EV
	WTP4	I am willing to pay at least 30-40%* more for an EV than a conventional car
	WTP5	I am willing to pay at least 600-700 million** rupiahs for an EV

Note: *the average price comparison of EVs compared to conventional cars (CNN, 2022); ** the average price of EVs in Indonesia (CNN, 2022) and the highest-selling EV in Indonesia during the first semester of 2023 (GAIKINDO, 2023).

RESULTS AND DISCUSSION

Respondent Profile

The demographic profile reveals a predominance of male respondents, constituting 65.65% of the cohort, and mostly millennials. Moreover, the educational distribution indicates that the majority monthly personal expenditures ranging from IDR 3,000,000 to IDR 6,000,000 and above IDR 9.000.000. The respondents in this study indicate that 80.24% own a singular car. A notable majority of respondents (56.23%) express a willingness to allocate a budget ranging from 250 million to 500 million Indonesian Rupiah for the acquisition of any car, but mostly are amenable to the notion that the cost of EVs should be comparable to or less than that of conventional cars. Table 2 presents in-depth information regarding the characteristics of the participants.

Table 2. Respondents' Profile

Profile	Category	Frequency	Percentage
Gender	Male	216	65.65%
	Female	113	34.35%
Age	< 27 years	27	8.21%
	27-36 years	184	55.93%
	37-46 years	48	14.59%
	47-56 years	53	16.11%
	> 56 years	17	5.17%
Residence	Greater Jakarta/Bandung	133	40.34%
	Surabaya/Gresik/Malang	104	31.61%
	Yogyakarta/Solo/Semarang	92	27.96%
Education level	High school or below	28	8.51%
	Associate's degree	25	7.60%
	Bachelor's degree	217	65.96%
	Master's degree	54	16.41%
	Doctoral degree	5	1.52%
Personal monthly expenditure	< IDR 3,000,000	30	9.12%
	IDR 3,000,000 - IDR 6,000,000	107	32.52%
	IDR 6,000,000 - IDR 9,000,000	88	26.75%
	> IDR 9,000,000	104	31.61%
Intention to Buy a Car 1-2 Years Ahead	Yes	179	54.41%
	No	150	45.59%
Number of owned cars	1	264	80.24%
	2	56	17.02%
	≥3	9	2.74%
General car budget	< IDR 250 million	128	38.91%
	IDR 250-500 million	185	56.23%
	IDR 500-750 million	12	3.65%
	> IDR 750 million	4	1.22%
EV budget	Not willing to spend	35	10.64%
	< IDR 250 million	133	40.43%
	IDR 250-500 million	143	43.47%
	IDR 500-750 million	16	4.86%
	> IDR 750 million	2	0.61%
Percentage of willingness to pay for EVs compared to conventional cars	Not willing to spend	21	6.38%
	Same or cheaper	186	56.53%
	1-20% more expensive	98	29.79%
	20-40% more expensive	23	6.99%
	40% more expensive	1	0.30%

Measurement Model Evaluation

The measurement model elucidates how the measured variables represent a construct through indicator loadings, construct reliability, convergent validity, and discriminant validity (Hair et al., 2019). Ideally, acceptable indicator values should have outer loadings above 0.707 or 0.708, although a value of 0.5 is still deemed acceptable, while in general, the acceptable threshold for the Average Variance Extracted (AVE) is 0.5 (Chin, 1998; Hair et al., 2019). As depicted in Table 3, all indicator variables and latent variables meet the criteria for acceptable outer loadings and AVE. Based on Table 4, it can also be inferred that all variables pass the reliability test, obtaining Composite Reliability and Cronbach's Alpha above 0.70 (Hair et al., 2019).

Table 3. Measurement Model Evaluation

Variable	Indicator	Mean	SD	Loading	AVE	CR	CA
Performance Expectancy	PE1	5.213	1.392	0.836	0.703	0.922	0.893
	PE2	4.532	1.444	0.856			
	PE3	4.970	1.334	0.868			
	PE4	4.614	1.321	0.880			
	PE5	4.933	1.402	0.745			
Effort Expectancy	EE1	5.274	1.354	0.794	0.739	0.919	0.881
	EE2	5.884	1.174	0.857			
	EE3	5.681	1.271	0.912			
	EE4	5.641	1.281	0.872			
Social Influence	SI1	4.219	1.514	0.905	0.768	0.930	0.899
	SI2	4.267	1.534	0.902			
	SI3	4.198	1.542	0.893			
	SI4	4.532	1.611	0.801			
Facilitating Conditions	FC1	4.526	1.703	0.750	0.588	0.850	0.769
	FC2	5.161	1.421	0.827			
	FC3	5.568	1.282	0.805			
	FC4	4.739	1.584	0.675			
Hedonic Motivation	HM1	5.404	1.297	0.938	0.786	0.936	0.906
	HM2	5.267	1.317	0.936			
	HM3	5.173	1.327	0.904			
	HM4	5.790	1.147	0.757			
Price Value	PV1	3.623	1.699	0.862	0.698	0.902	0.856
	PV2	4.398	1.537	0.852			
	PV3	3.878	1.608	0.859			
	PV4	4.526	1.619	0.766			
Habit	HB1	4.283	1.459	0.917	0.824	0.949	0.929
	HB2	4.143	1.516	0.897			
	HB3	4.295	1.451	0.930			
	HB4	4.243	1.665	0.887			
Perceived Risk	PR1	4.103	1.623	0.639	0.574	0.840	0.772
	PR2	5.088	1.602	0.601			
	PR3	4.240	1.598	0.880			
	PR5	4.149	1.516	0.867			
Environmental Concerns	EC1	6.024	1.223	0.685	0.581	0.873	0.826
	EC2	5.854	1.166	0.727			
	EC3	5.967	1.117	0.807			

Variable	Indicator	Mean	SD	Loading	AVE	CR	CA
	EC4	6.465	0.951	0.765			
	EC5	5.924	1.189	0.818			
Government Support	GS1	5.131	1.644	0.913	0.721	0.939	0.921
	GS2	5.210	1.640	0.920			
	GS3	5.188	1.573	0.839			
	GS4	5.392	1.425	0.862			
	GS5	5.456	1.525	0.856			
	GS6	5.672	1.526	0.682			
Adoption Intention	AI1	5.763	1.354	0.676	0.721	0.927	0.901
	AI2	5.410	1.452	0.872			
	AI3	4.757	1.595	0.884			
	AI4	4.872	1.445	0.879			
	AI5	5.100	1.456	0.912			
Willingness to Pay	WTP1	3.085	1.631	0.840	0.682	0.915	0.884
	WTP2	3.723	1.855	0.816			
	WTP3	3.945	1.670	0.837			
	WTP4	3.675	1.715	0.855			
	WTP5	2.982	1.755	0.780			

Note: SD—Standard Deviation; AVE—Average Variance Extracted; CR—Composite Reliability; CA—Cronbach's Alpha.

Subsequently, discriminant validity, measuring to what extent a construct truly differs from another, is assessed using the HTMT test, as recommended by Hair et al. (2019) in the context of PLS-SEM. The minimum HTMT value is less than 0.9 or preferably less than 0.85 (Hair et al., 2019). Based on the HTMT test results, as shown in Table 5, it can be concluded that all variables in this study meet the HTMT test. Additionally, the Fornell-Larcker test, also depicted in Table 4, was conducted, and all variables in this study meet the criteria for accepting the test.

Table 4. Measurement Model Evaluation 2: Discriminant Validity

	AI	EC	EE	FC	GS	HB	HM	PE	PR	PV	SI	WTP
AI	**0.849**	*0.400*	*0.620*	*0.563*	*0.738*	*0.707*	*0.634*	*0.667*	*0.344*	*0.348*	*0.627*	*0.430*
EC	0.365	**0.762**	*0.393*	*0.321*	*0.327*	*0.128*	*0.368*	*0.221*	*0.207*	*0.125*	*0.153*	*0.144*
EE	0.547	0.351	**0.860**	*0.792*	*0.547*	*0.504*	*0.634*	*0.555*	*0.238*	*0.237*	*0.527*	*0.209*
FC	0.485	0.301	0.680	**0.767**	*0.526*	*0.579*	*0.650*	*0.637*	*0.240*	*0.469*	*0.703*	*0.373*
GS	0.675	0.305	0.495	0.447	**0.849**	*0.604*	*0.651*	*0.644*	*0.203*	*0.347*	*0.607*	*0.336*
HB	0.663	0.117	0.459	0.484	0.566	**0.908**	*0.638*	*0.733*	*0.352*	*0.536*	*0.814*	*0.532*
HM	0.575	0.331	0.570	0.559	0.593	0.583	**0.887**	*0.753*	*0.218*	*0.410*	*0.703*	*0.339*
PE	0.612	0.214	0.497	0.533	0.594	0.670	0.678	**0.838**	*0.304*	*0.580*	*0.799*	*0.548*
PR	-0.342	0.064	-0.242	-0.225	-0.213	-0.316	-0.192	-0.297	**0.757**	*0.235*	*0.330*	*0.227*
PV	0.334	0.087	0.206	0.366	0.326	0.485	0.361	0.514	-0.222	**0.836**	*0.549*	*0.694*
SI	0.583	0.152	0.472	0.574	0.558	0.745	0.633	0.716	-0.306	0.490	**0.876**	*0.480*
WTP	0.399	0.127	0.183	0.297	0.314	0.487	0.306	0.490	-0.202	0.611	0.430	**0.826**

Note: The square root of the AVE for each variable is depicted in bold on the diagonal; The off-diagonal elements exhibit inter-correlation values between variables; The HTMT ratios are presented in italics above the square root of the AVE.

Structural Model Evaluation

Having established the reliability and validity of the measurement model, the assessment of the structural model was carried out (Hair et al., 2019). The examination of inner VIF values was undertaken to assess collinearity, revealing that all values were below 3.3, signifying the absence of common method bias (Kock, 2015). The subsequent step involves assessing the significance and magnitude of structural path coefficients through bootstrapping with 5,000 sub-samples Hair et al., 2019).

Table 5. Structural Model Evaluation

Hypothesis	Path	VIF	β	T Statistics	P Values	Supported
H1	PE→ AI	2.887	0,099	1,493	0,068	No
H2	PE→ WTP	1.932	0,153	2,695	0,004	Yes
H3	EE→ AI	2.286	0,110	1,902	0,029	Yes
H4	SI→ AI	3.124	-0,006	0,086	0,466	No
H5	FC→ AI	2.305	-0,014	0,262	0,397	No
H6	HM→ AI	2.470	0,006	0,104	0,458	No
H7	PV→ AI	1.512	-0,044	1,129	0,130	No
H8	PV→ WTP	1.362	0,485	10,420	0,000	Yes
H9	HB→ AI	2.692	0,337	5,559	0,000	Yes
H10	PR→ AI	1.181	-0,141	3,938	0,000	Yes
H11	EC→ AI	1.272	0,189	3,866	0,000	Yes
H12	EC→ WTP	1.156	-0,001	0,016	0,494	No
H13	GS→ AI	1.924	0,303	5,487	0,000	Yes
H14	AI→ WTP	1.762	0,144	2,851	0,002	Yes

Note: PE—performance expectancy; EE—effort expectancy; SI—social influence; FC—facilitation conditions; HM—hedonic motivation; PV—price value; HB—habit; PR - perceived risk; EC—environmental concerns; GS—government support; AI—adoption intention; WTP—willingness to pay; VIF—variance inflation factor; β—path coefficient.
SRMR: 0.068; R^2 AI: 0.645; R^2 WTP: 0.429.

The results presented in Table 6 confirm the acceptance of 8 hypotheses. Specifically, effort expectancy (H3, β = 0.110), habit (H9, β = 0.337), perceived risk (H10, β = -0.141), environmental concerns (H11, β = 0.189), and government support (H13, β = 0.303), were found to exert a significantly positive influence on EV adoption intention. Additionally, performance expectancy (H2, β = 0.153), price value (H8, β = 0.485), and adoption intention (H14,β = 0.144) were also found to have positive influences on EV willingness to pay. However, there were 6 hypotheses rejected. These include the impact of performance expectancy (H1), social influence (H4), facilitating conditions (H5), hedonic motivation (H6), price value (H7) on EV adoption intention and the influence of environmental concern on willingness to pay (H11). The predictive power of the adoption intention model (AI) falls into the moderate category, and the willingness to pay falls into the weak category. Table 5 and Figure 2 elucidate the comprehensive results and statistical scores of the PLS–SEM.

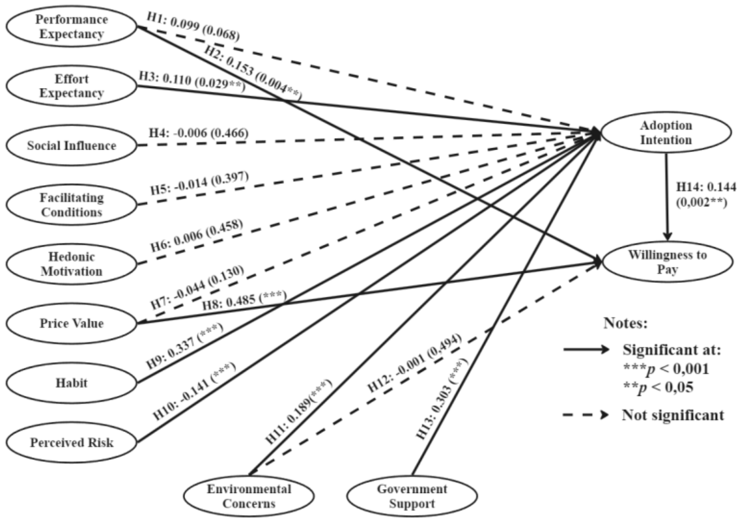

Figure 2. Results (n = 329)

The results confirm the applicability of using UTAUT2 integrated with perceived risk, environmental concerns, and government support to examining EVs adoption in Indonesia. This research does not support the positive influence of performance expectancy on adoption intention for EVs, however, performance expectancy does have a positive impact on willingness to pay for EVs. This finding contradicts some earlier studies that even identified performance expectancy as a key factor in the adoption of EVs (Jain et al., 2022; Zhou et al., 2021) and are consistent with the findings of (Abbasi et al., 2021) and Sweet et al. (2023) and Gu and Liu (2019).

Effort expectancy significantly and positively influences the adoption intention for EVs. The finding is also consistent with Manutworakit & Choocharukul (2022), Zhou et al. (2019), and Zhou et al. (2021). This study imposed criteria on respondents, requiring them to own at least one car and possess a valid driving license, ensuring that respondents are already familiar with car usage. Thus, there is a possibility that respondents believe operating EVs is not significantly different from operating conventional cars, and therefore, the use of EVs does not require substantial adjustments.

This study does not provide evidence for a positive influence of social influence on the adoption intention for EVs. The non-significant finding may be attributed to a low level of awareness among the Indonesian population, resembling the situation in India, where Jain et al. (2022) observed no positive relationship between social influence and adoption intention for EVs. Another potential factor is a lack of environmental concern among the general public, where people may not perceive the purchase of EVs as conferring valuable status or even as a necessity, while EVs are marketed with a strong emphasis on their environmental factors. Therefore, social pressure may not significantly impact EV adoption intention.

This research does not affirm the positive influence of facilitating conditions on the intention to adopt EVs. Initially, the study aimed to use one indicator to represent the supporting infrastructure for the use of EVs, but it was excluded in the subsequent research phase due to low validity during the pre-test, with a component matrix value of 0.254. Consequently, facilitating conditions in this study encompass resources, knowledge, compatibility with existing technology, and support in the form of assistance to facilitate the use of EVs, where the indicators align with those used by Jain et al. (2022) and Kapser and Abdelrahman (2020); however, contradict the results of this study. The lack of significance in the influence of facilitating conditions on adoption intention in this study may be attributed to the invalidity of indicators related to infrastructure. In contrast, Singh et al. (2023) incorporated infrastructure in explaining this variable, and their results indicated a significant influence of facilitating conditions on adoption intention. This finding aligns with the results of Manutworakit & Choocharukul (2022) and Korkmaz et al. (2022)

This study does not provide support for the positive influence of hedonic motivation on adoption intention for EVs. Respondents tend to have positive responses regarding the pleasure and attractive technology of EVs, but apparently, this is not sufficient to encourage individuals to adopt EVs. The findings of this research align with the study by Korkmaz et al. (2022), which found no evidence indicating a positive influence of hedonic motivation on behavioral intention.

The affirmative impact of price value on the intention to adopt EVs is not endorsed by this study. According to Brown and Venkatesh (2005), price value is the balance between the perceived benefits of new technology and the cost paid to acquire that technology, and Vafaei-Zadeh et al. (2022) consider it as a cost-benefit relationship. Thus, the absence of an impact from price value may be attributed to limitations in knowledge about the available benefits and costs of EVs, or it could be due to the limited options available in the market. Additionally, this may also occur because consumers are still considering other factors in adopting EVs. This non-significant finding aligns with the results of the research by Manutworakit & Choocharukul (2022) in the context of Thailand, Gulzari et al. (2022) regarding rental intentions for EVs in the United States, and Korkmaz et al. (2022) concerning autonomous public transportation in Turkey. However, price value is a key factor in willingness to pay in this study. This research aligns with the findings of Gulzari et al. (2022), which indicate the lack of support for the relationship between price value and adoption intention but significantly support the positive influence of price value on willingness to pay. Thus, it can be concluded that consumers who perceive the price of EVs as reasonable do not necessarily mean they will adopt EVs in the future. This may be due to other factors that more significantly influence consumer decisions. Nevertheless, an increasing perception of the fairness of EV prices can enhance consumers' willingness to pay a higher price for these vehicles.

Habit is a primary factor in adoption intention for EVs in this study. The research initially sought to explore whether the habit of using conventional cars impedes respondents from transitioning to EVs. However, the indicator did not meet validity criteria and was ultimately removed from the model due to a lack of significant correlation with the habit variable overall. Thus, habit in this study reflects the use of cars that will become a routine, addictive, natural, and a necessity for using EVs in the future, similar to the indicators used by Singh et al. (2023), whose respondents were also largely inexperienced in driving EVs. This research is consistent with the findings of Zhou et al. (2021) and Korkmaz et al. (2021), which identified habit as one of the technology acceptance factors. Therefore, it can be concluded that the higher an individual's habit related to EVs in the future, the higher the likelihood of their adoption intention to use EVs in the future.

Perceived risk significantly negatively influences adoption intention for EVs in this study. This finding aligns with prior research by He et al. (2018), Wang et al. (2018), Featherman et al. (2021), Jain et al. (2022), Vafaei-Zadeh et al. (2022), and Zheng et al. (2022), which identified the influence of perceived risk on the acceptance of EVs, measured through purchase intention, adoption intention, and behavioral intention. Financial risk is the most strongly correlated with the latent variable of perceived risk. This can be interpreted as follows: the higher an individual perceives the risk associated with EVs, the lower their intention to adopt such vehicles. In other words, a high perception of risk acts as a barrier in the EV adoption process. This result is linked to the financial risk indicator showing the strongest correlation, possibly because the majority of respondents in this study were unwilling to pay more for EVs compared to conventional vehicles. Consumer unfamiliarity with EVs can also be considered a risk, especially given the current higher prices of EVs compared to more familiar conventional vehicles, which are perceived as having lower risks. Perceiving a high potential for financial loss influences their decision to adopt EVs. This is in line with Kapser & Abdelrahman (2020), stating that consumers not only consider positive incentives or utilities but also threats or negative utilities in their adoption decisions, such as perceived risk.

This research reveals that environmental concerns significantly positively influence adoption intention for EVs. The findings of this study support earlier research (Wang et al., 2017; He et al., 2018; Wang et al., 2021; Jain et al., 2022; Jaiswal et al., 2022). EVs are designed to reduce negative environmental impacts by minimizing carbon emissions and air pollution. Therefore, when respondents feel a responsibility to choose environmentally friendly transportation modes, it reflects their awareness of their role in environmental preservation and is directly related to the positive perception of EVs as a sustainable solution. However, environmental concerns do not positively impact willingness to pay for EVs. Most likely, consumers still perceive EV prices as too high, potentially influencing their decision not to adopt EVs, despite their relatively high levels of environmental concerns.

This suggests that environmental awareness alone may not be sufficient to influence consumer decisions in adopting this technology. Supporting this, respondent profiles indicate that less than 6% of them are willing to pay more than IDR 500 million for an EV. In comparison, the prices of the two most popular EVs in the market in the first half of 2023 are around IDR 200 million and IDR 600 million. This indicates that pricing may be a constraint that needs to be addressed to increase EV adoption among consumers. In addition to examining direct path coefficients, this study also analyzes mediation relationships to determine whether adoption intention can mediate the influence of environmental concerns on willingness to pay. The results of the mediation test yielded t-values and p-values of 2.261 and 0.012, respectively, both meeting significance criteria. Therefore, it can be concluded that environmental concerns significantly positively influence willingness to pay for EVs, with adoption intention playing a mediating role. In other words, consumers with environmental concerns are willing to pay a higher price for EVs when they have the intention to adopt them.

Government support significantly positively influences adoption intention for EVs. This research finding aligns with previous studies, where government support significantly positively influenced the adoption intention of EVs in India (Jain et al., 2022; Jaiswal et al., 2022), South Korea (Kim et al., 2018), and China (Wang et al., 2017; Wang et al., 2021). As repeatedly mentioned before, high purchase prices and maintenance costs are major barriers to buyer acceptance of BEV (Wang et al., 2018; Jaiswal et al., 2022), including in Indonesia (Veza et al., 2022). Government support provides a significant boost to individuals' willingness to adopt EVs. In this study, ranked by the highest loading values, tax incentives, general direct subsidies, home charging incentives, non-financial incentives, and other incentives that may be further added by the government.

Adoption intention significantly positively influences the willingness to pay for EVs in this study. This finding is consistent with research by Zheng et al. (2022) and Shi et al. (2022), highlighting the pivotal role of behavioral intention and willingness to adopt as primary factors influencing willingness to pay for EVs and IoT technology in the agricultural sector, respectively. However, in contrast to these studies, adoption intention in this research is not the primary factor in willingness to pay. Individuals typically determine their purchase intention before establishing their willingness to pay (Zheng et al., 2022). If someone has a high intention to adopt EVs, they are more likely to pay a higher price for the vehicle. This is because they are more willing to incur higher costs due to the perceived additional values or benefits provided by EVs, such as energy efficiency, environmental contributions, or other innovative features. Therefore, the higher the adoption intention for EVs, the higher the willingness to pay for them.

CONCLUSION

This study highlights the critical role of government support in accelerating EV adoption to meet 2030 NDC targets, recommending enhanced financial and non-financial incentives alongside stronger home-charging support by PLN to address concerns over long battery charging times. Expanding charging infrastructure through collaboration with public venues can reduce range anxiety, while automotive companies should focus on improving the driving experience, technological benefits, and developing affordable models to boost willingness to pay. Clear, coordinated communication emphasizing environmental benefits, progress toward net-zero emissions, and transparent information on risks and total ownership costs is essential to build consumer confidence. Additionally, promoting habitual use through test drives, loyalty programs, electrified public transport, and mandates for government and state-owned enterprises can further increase adoption. Future research should investigate the long-term effectiveness of these combined strategies and explore behavioral interventions that foster sustained EV usage within diverse population segments.

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