PAPER NAME

Accelerating Sustainability Environment: Understanding Electric Vehicles (EVs) Ad option with Expande

AUTHOR

Agus Salim

WORD COUNT

10748 Words

CHARACTER COUNT

61699 Characters

PAGE COUNT

12 Pages

FILE SIZE

1.3MB

SUBMISSION DATE

Oct 4, 2024 5:46 PM GMT+8

REPORT DATE

Oct 4, 2024 5:47 PM GMT+8

10% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

- 6% Internet database
- 4% Publications database
- Crossref database
- Crossref Posted Content database
- 7% Submitted Works database

Excluded from Similarity Report

- Bibliographic material
- Quoted material
- Cited material
- Small Matches (Less then 8 words)
- Manually excluded sources
- Manually excluded text blocks

International Journal on Advanced Science Engineering Information Technology

Vol.14 (2024) No. 2
ISSN: 2088-5334

Accelerating Sustainability Environment: Understanding Electric Vehicles (EVs) Adoption with Expanded Technology Acceptance Model (TAM)

Agus Salim [a,*], Syafri [a], Nasrullah [b]

[a] Department of Urban and Regional Planning, Universitas Bosowa, Makassar, South Sulawesi, 90231, Indonesia
[b] Department of Architectural, Universitas Bosowa, Makassar, South Sulawesi, 90231, Indonesia
Corresponding author: *agus.salim@universitasbosowa.ac.id

***Abstract*— This research endeavors to implement and evaluate an expanded version of the TAM by incorporating perceived risk and utilizing the consolidative framework of beliefs-attitude-intention. This approach aims to gain insights into and forecast consumers' inclination towards adopting EVs. This study delves into the various factors that impact the uptake of electric vehicles, employing a purposive sampling strategy to target individuals aged 17 and above with a valid driving license and owning EVs. After a rigorous screening process, 247 out of 400 responses were analyzed. The survey comprised two sections: the first gathering demographic and vehicle ownership details, and the second assessing six cognitive dimensions related to EV adoption, including PEOU, PEU, PER, ATU, and AIU to adopt EV technology. Utilizing SPSS and AMOS software for data examination, the study applied SEM analysis to investigate the relationships between these dimensions with Maximum Likelihood Estimation. The research identifies the significant impact of perceived risks on adoption intentions, emphasizing the need for strategies to mitigate these apprehensions, especially in emerging markets like Indonesia. The findings underscore the importance of holistic approaches in promoting EV adoption, which involve highlighting the benefits and addressing potential barriers and concerns that consumers may have. By effectively managing perceptions of usefulness, ease of use, and risks, stakeholders can work towards fostering a more positive attitude towards EV technology and ultimately encouraging greater adoption of sustainable transportation options.**

***Keywords*—Attitudes; environmental awareness; ease of use; intention; perceived usefulness; perceived risk.**

Manuscript received 15 Jan. 2024; revised 7 Mar. 2024; accepted 2 Apr. 2024. Date of publication 30 Apr. 2024.

I. INTRODUCTION

Greenhouse gases, such as carbon dioxide (CO2), pose a threat to public health and human well-being [1]–[3]. Human activities, especially the large-scale emission of greenhouse gases, are a vital reason for temperature change and global warming [4]–[6]. The primary source of carbon emissions is burning fossil oils in the energy and transportation sectors [7], [8]. Transportation, in particular, is a significant energy consumer, accounting for 29% of worldwide energy consumption and 65% of oil use [8]–[10]. This segment accounts for around 24% of global CO2 production from fuel burning [9]–[12]. Addressing carbon emissions from transportation is essential for mitigating environmental issues and tackling climate change [13]–[17]. Therefore, the prevalent implementation of renewable energy in transportation is crucial [18], [19].

The public's comprehension of electric vehicles (EVs) currently needs to be improved [20], [21]. While some individuals express interest in EVs, skepticism prevails among specific population segments, hindering widespread adoption [22], [23]. As subsidy policies gradually diminish to accelerate EV market penetration, there is an urgent need to explore new avenues for enhancing public understanding of EVs and fostering adoption. Consumer adoption intentions regarding EVs are multi-faceted and influenced by internal and external factors [24]. Previous research has delved into various factors shaping users' intentions to embrace EVs. These aspects encompass not only product characteristics such as price, performance, range, charging time, and convenience, as well as external circumstances like subsidy policies, fuel costs, charging expenses, and infrastructure availability [25], [26] but also mental aspects such as perceived risks, emotions, attitudes, social norms, and environmental consciousness [27]–[29].

Several scholars have applied the TPB, Norm Activation Theory, or integrated frameworks to study how psychological factors affect user intentions to adopt EVs [25]. Given that EVs are an innovative and eco-friendly option with significant involvement, enhancing consumer acceptance involves opportunities for interaction, such as through widespread EV sharing, rental programs, and organized test drives by automobile dealers [27], [30]. These experiences offer direct access and driving experience, acting as marketing stimuli influencing consumer perceptions, attitudes, and adoption intentions. However, the impact of EV-driving experiences on user reasonings and insights and their implementation intentions has yet to be minimally explored and empirically assessed.

The utilization of electric vehicles (EVs) in Indonesia has garnered significance in light of the escalating environmental concerns stemming from the widespread use of motorized two-wheeled vehicles, contributing to detrimental pollution levels detrimental to health and exacerbating issues such as weather patterns, temperature rise, and the depletion of Indonesia's oil reserves. The government's concerted efforts to promote EV adoption aim to incentivize users to transition towards and embrace electric vehicles. However, understanding consumer preferences and expectations regarding EVs is imperative, given their novelty within the Indonesian market. Consumers typically evaluate EVs based on several factors, including price, maintenance, durability, and the availability of supporting infrastructure [31]. Despite governmental initiatives, skepticism persists regarding Indonesia's electric vehicle program due to concerns surrounding battery range limitations [32]. Nevertheless, the substantial demand for vehicles in Indonesia indicates a promising market outlook, fostering the government's optimism towards the gradual acceptance of EVs.

Contemporary sustainable transportation researchers use the cognitive theory-based TAM to understand user attitudes toward EVs and innovative technologies or eco-friendly products and services [33], [34]. The classic TAM framework, proposed by Davis (1989), has been criticized for focusing on positive cognitive views about technology qualities and disregarding users' negative impressions or resistance factors when forecasting usage behavior [35]. Incorporating perceived risk into attitude formation has received little attention in EV preferences research [36], which could inhibit EV adoption or vehicle technology dissemination [37]. While previous studies have examined the direct and optimistic effects of monetary incentives or subsidy policies on EV usage behavior, there has been little research into this critical external incentive as a potential mediator in EV implementation [38], leaving a gap in understanding this crucial mobility market stimulus.

The limited scholarly inquiry has been dedicated to exploring variations or adaptations of the TAM, encompassing favorable and unfavorable psychological elements such as PEU, PEOU, and PER, alongside external factors like fiscal assistance, to anticipate user inclinations towards embracing EVs [38]. Interestingly, no research has explicitly investigated the moderating consequence of monetary incentive policies on the connection between attitudes toward EVs and adoption behaviors. Given the nascent phase of EV adoption, studies examining TAM and its extensions must be reviewed, incorporating optimistic and pessimistic assessments to comprehend and forecast consumer intentions concerning EV adoption in the emerging EVs marketplace. With the pressing topic of air contamination and pollution originating from the transportation segment, the potential solution of user EV implementation emerges as crucial within the sustainability-focused transportation market.

This empirical study uses an integrated 'beliefs-attitude-intention' paradigm to add internal risk perceptions and external financial incentive schemes to the TAM. The goal is to understand user views about EV implementation and fill a research gap in the burgeoning sustainable transportation sector. The study uses route analysis in SEM to examine how PEU, simplicity of use, and risk affect EV attitudes and adoption intentions. It also explores how EV attitudes mediate adoption intentions and predictor variables. This study provides a theoretical basis supporting the research and formulating hypotheses to be tested.

A. Extension of Technology Acceptance Model (TAM)

TAM, first proposed by Davis (1989), is widely recognized as a leading paradigm for understanding consumer psychology regarding adopting new technology or goods within technology usage behavior [35]. TAM is built upon the 'belief-attitude-intention' paradigm, which has been elaborated and refined drawing from foundational cognitive theories such as Fishbein and Ajzen's [39] develop TRA, Ajzen and Fishbein's [40] developed TPB, Bhattacharjee [41] develop Expectation-Confirmation Theory and Rational Choice Theory [42], [43].

This model posits that individuals' beliefs about a technology influence their attitudes and intentions, ultimately shaping their behavior towards its usage. TAM's foundation lies in understanding how PEU and PEOU of a technology impact individuals' attitudes and intentions to use it [35], [44], [45]. However, while TAM has proven effective in explaining positive technology acceptance, scholars have critiqued its limited focus on positive attributes and neglected negative perceptions, such as PER or resistance to change [46], [47].

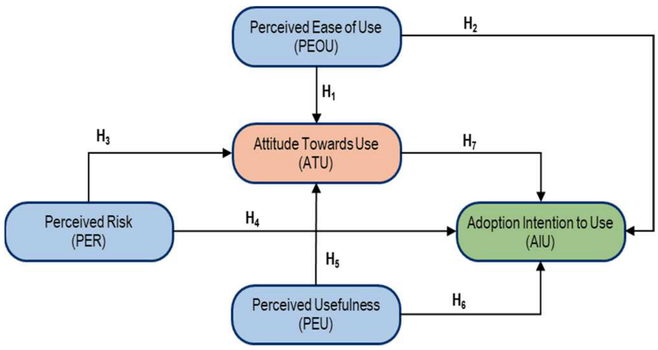

Fig. 1 Research Conceptual

An extended version of TAM has been proposed in response to these criticisms, incorporating additional factors such as PER alongside PEU and PEUO. This extended model offers a more inclusive thoughtful of technology adoption behavior, particularly in contexts such as the uptake of EVs in sustainable transportation [42], [48], [49]. Moreover, TAM's adaptability encompasses internal (e.g., individual perceptions) and external factors (financial incentives, government policies, trust) influencing technology acceptance. The Technology Acceptance Model strengthens its explanatory capacity by comprehensively considering these factors, facilitating a deeper understanding and predicting technology adoption [50].

Therefore, this study integrates the pessimistic factor of PER alongside its core optimistic factors of PEU and PEOU within the context of the implementation behavior of EVs. Consequently, this analysis aims to explore the expansion of TAM with perceived risk and validate the causal relationship of "beliefs-attitude-intention" by utilizing structural equation modeling to examine hypothesized direct, mediating, and moderating pathways [51]–[55]. This endeavor contributes to the existing information concerning user mindset surrounding EV preference.

Thus, the positive beliefs of PEU and PEOU and the negative beliefs of PER are assumed to influence attitudes towards EVs and adoption intention directly. Additionally, it is hypothesized that ATU EVs mediate between implementation intention and its predictor variables. This comprehensive investigation sheds light on the complex dynamics underlying consumers' decision-making processes regarding EV adoption, thus offering valuable insights for academia and industry.

B. Perceived Ease of Use (PEOU) for Adoption Intention to Use Technology Electric Vehicles

PEOU refers to users' subjective evaluation of the ease and comfort, both physically and mentally, associated with utilizing a specific technology. It represents a cognitive aspect that profoundly influences consumers' attitudes toward the technology and their inclination to adopt it [35], [42]. This perception holds immense significance as it not only shapes initial adoption decisions but also substantially impacts the continued usage and acceptance of the technology over time. When users perceive a technology as effortless, they are more inclined to integrate it into their daily routines and explore its full potential.

Moreover, current findings by Hong et al. [56] have consistently demonstrated a robust correlation between PEOU and PEU. Essentially, users are more inclined to perceive technological innovations as practical and beneficial only when they find them easy to adopt and seamlessly integrate into their routines. This underscores the status of user experience design and rigorous usability testing in ensuring that technological offerings align with users' needs and are intuitive and user-friendly. By prioritizing these aspects, companies can enhance user acceptance and drive the successful adoption of their innovations in the competitive market landscape. PEOU plays a fundamental role in technology adoption and recognition, influencing users' perceptions of usefulness and ultimately determining the success of technological innovations in the market. Consequently, the subsequent hypotheses are put forward:

- H1: Perceived ease of use is related to attitude towards using EVs.
- H2: Perceived ease of use is related to the intention to adopt EVs.

C. Perceived Risk (PER) for Adoption Intention to Use Technology Electric Vehicles

Users' subjective assessments of uncertainty or worry about embracing new technologies or creative items are known as perceived risks. This notion could negatively influence their decision-making process regarding EV implementation [37], [57]. More importantly, customers' subjective fear of loss or possible adverse outcomes is a common source of their unwillingness to embrace new goods or services [37], [57]. According to the reasoning, customers have a negative outlook on embracing innovative products and services when they perceive hazards connected with newer technology [37], [57].

PER and user attitudes toward breakthrough technology, such as eco-friendly automobiles and EVs, have been studied little in automobile user psychology. Wang et al. [58] found a direct and negative effect of PER on EV attitudes, while Zhang et al. [59] found an indirect negative result using the TAM. This psychological component some researchers have looked into this and found that users' intentions to use EVs, both directly and indirectly, as well as their confidence and positive attitudes toward them, are negatively impacted by perceived risk, which can act as a barrier or cause anxiety [24], [60]. Thus, attitudes, intentions, and perceived danger are causally related, and this impression of risk may prevent EV adoption.

Because EV implementation is still in its primary phases in emerging mobility markets, this remark may apply to customers' decision-making processes about implementing EVs as green, clean vehicles. Expanding on the previous topic, this study suggests that increased customer risk perceptions will reduce consumers' preferences and favorable attitudes toward EVs. Moreover, this unfavorable view could hinder their inclination to embrace EVs shortly. Consequently, the subsequent hypotheses are put forward:

- H3: Perceived risk relates to attitude towards the use of EVs.
- H4: Perceived risk has a relationship with the intention to adopt EVs.

D. Perceived Usefulness (PEU) for Adoption Intention to Use Technology Electric Vehicles

PEU, well-defined as the scale to which implementing a specific system is seen as beneficial in enhancing the performance of products or services, significantly impacts users' positive attitudes towards new technology or innovative products and their intentions to use them [35], [61], [62]. Within the context of adopting electric vehicles (EVs) as eco-friendly alternatives, PEU encapsulates several critical aspects: the capability of EVs to reduce CO2 emissions and gasoline consumption, their role in lowering household transportation expenses, and their contribution to enhancing health quality by protecting against air or smog pollution. Consequently, the subsequent hypotheses are put forward:

- H5: Perceived usefulness is related to attitude towards the use of EVs.
- H6: Perceived usefulness has a relationship with the intention to adopt EVs.

E. Attitude Towards Use (ATU) for Adoption Intention to Use Technology Electric Vehicles

Environmental consumer psychology research shows that a positive view of eco-friendly products indicates the desire to buy those products [63]–[65]. In the context of technology acceptance, Ajzen and Cote [66] say that how people feel about new goods or technologies is critical in determining how likely they are to adopt them. Users' positive or negative beliefs about new technology or products assess their attitudes, which are described as positive or negative evaluations of acceptance behavior [67]. Positive thoughts about technology can make people more likely to adopt it, leading to actual adoption behaviors [58]. This shows how important it is to change attitudes to get people to embrace technology how they want it to [68], [69]. TAM and its extensions say that how people feel about EVs as a new technology product is affected by their thoughts on "perceived usefulness," "ease of use," and "perceived risk" [36], [70]. Consequently, the subsequent hypotheses are put forward:

- H7: Attitude towards using EVs is related to the intention to adopt EVs.

III. MATERIALS AND METHOD

A. Sample and Data Collection

After screening the outliers and incompleteness, 400 answers were accepted, and only 247 were found valid for the study goal. The study determined the minimum sample by employing a rule of thumb, which multiplied the number of questionnaire items (247 > 18*10 = 180) required for this study and started to be appropriately constructed on the reference of researchers for a desired level of (5-10*indicator) per variable for applying SEM [71], [72]. The sample comprised 247 individuals, effectively representing the study population with a balanced distribution across genders, diverse educational backgrounds, and a wide range of age groups. Normality, multicollinearity, consistency, and validity assessments were meticulously conducted to mitigate sample error and biases. The researchers employed a purposive sampling strategy, targeting individuals aged 17 and older who possess a valid driving license and own a vehicle in Indonesia, thus ensuring the sample's adequacy in reflecting the target population of interest.

B. Research Measures

The study's questionnaire was carefully designed in two sections to collect detailed demographic data and assess green consumer behavior toward electric vehicle (EV) adoption. The first section gathered personal information such as gender, age, education level, household income, and vehicle ownership details, including the type and number of vehicles. The second section, based on established research, featured 18 items across six cognitive dimensions: PEU, PEOU, PER, ATU, and AIU to adopt technology electric vehicles, utilizing a 7-point Likert scale to measure responses from 'strongly disagree' (1) to 'strongly agree' (7). This comprehensive method aimed to understand the interplay between demographic factors and psychological constructs in shaping consumer attitudes and intentions toward EV adoption.

TABLE I
DEMOGRAPHIC OF RESPONDENTS (N = 247)

Construct	Item
Perceived Ease of Use (PEOU) [73]	1. Electric vehicles seem straightforward to use. 2. Driving electric vehicles appears to be uncomplicated for me. 3. Understanding and interacting with electric vehicles seems clear and manageable.
Perceived Usefulness (PEU) [28], [73]	1. Electric vehicles can cut carbon emissions and energy use. 2. Electric vehicles are believed to enhance my health. 3. Electric vehicles can lower my transportation costs. 4. Using electric vehicles is seen to enhance my travel efficiency.
Perceived Risk (PER) [28], [36], [38]	1. I fear financial losses with electric vehicles. 2. Safety worries arise when driving EVs. 3. Performance concerns exist with electric cars. 4. Inconveniences like range and charging trouble me.
Attitude Towards Use (ATU) [74], [75]	1. My interest lies in EVs. 2. I am fond of the concept of utilizing EVs. 3. Adopting electric vehicles as part of my travel choices brings me a positive outlook.
Adoption Intention to Use (AIU) [28], [36], [74]	1. I am dedicated to switching to electric vehicles for future purchases. 2. I am focusing on choosing EVs for my upcoming purchases. 3. I intend to make EVs my preferred choice for future purchases. 4. I encourage others to think about electric vehicles when selecting their vehicles.

C. Demographic of Respondents

Table 1 shows the demographic profile of 247 respondents involved in this survey. Of this total, 142 (40.92%) were male and 105 (30.26%) were female. Additionally, 12 respondents (3.46%) were under 20 years old, 31 respondents (8.93%) were between 20 and 30 years old, 86 respondents (24.78%) were between 31 and 40 years old, and 118 respondents (34.01%) were above 40 years old.

In conditions of education, the majority of respondents held a bachelor's degree, with 137 (39.48%), followed by 95 (27.38%) holding a master's degree and 15 (4.32%) having a doctoral degree. Monthly household income varied among respondents, with 110 respondents (31.70%) earning less than 3,000,000 IDR, 85 respondents (24.50%) earning between 3,000,000 and 5,000,000 IDR, 43 respondents (12.39%) earning between 5,000,000 and 7,500,000 IDR, and nine respondents (2.59%) earning more than Rp. 7,500,000 IDR.

Concerning the categories of vehicles owned by respondents' families, 136 respondents (39.19%) owned motorcycles, 95 respondents (27.38%) owned economy cars, and 16 respondents (4.61%) owned premium vehicles. Furthermore, there were 35 respondents (10.09%) who only owned one vehicle, 141 respondents (40.63%) who owned two cars, and 71 respondents (20.46%) who owned more than two vehicles in their families.

TABLE II
DEMOGRAPHIC OF RESPONDENTS (N = 247)

Category	Frequency	Percent
Gender		
Man	142	40.92%
Female	105	30.26%
Age		
Less than 20 years	12	3.46%
20 – 30 years	31	8.93%
31 – 40 years	86	24.78%
More than 40 years	118	34.01%
Education Level		
Bachelor Degree	137	39.48%
Master Degree	95	27.38%
Doctoral Degree	15	4.32%
Income per month (IDR)*		
Less than 3.000.000	110	31.70%
3.000.000 – 5.000.000	85	24.50%
5.000.000 – 7.500.000	43	12.39%
More than 7.500.000	9	2.59%
Types of Vehicles in a Family		
Two-wheeler (Motorcycles)	136	39.19%
Economy Four-wheeler	95	27.38%
Premium Four-wheeler	16	4.61%
Number of Vehicles in a Family		
One	35	10.09%
Two	141	40.63%
More than two	71	20.46%

* 1 USD = 15.500 IDR

The demographic profile outlined in Table 1 has several implications for this study. Understanding the demographic descriptions of the respondents can help contextualize and interpret the study's findings effectively. The relatively balanced gender distribution among the respondents (40.92%) male and (30.26%) female suggests that the research sample is representative of both genders. This balance allows for gender-specific analyses if the research aims to explore gender-related factors or implications.

The distribution across different age groups, with a significant portion above 40 years old (34.01%), indicates that the research captures diverse perspectives. This diversity could influence responses and perceptions regarding technology adoption, lifestyle choices, or financial decision-making. The majority of respondents holding bachelor's degrees (39.48%), followed by master's degrees (27.38%) and doctoral degrees (4.32%), suggest a relatively well-educated sample. This implies that the research findings reflect perspectives from individuals with higher levels of education, potentially impacting the depth of analysis and the complexity of responses.

The variation in monthly household income among respondents indicates socio-economic diversity within the sample. This diversity could influence consumption patterns, preferences, and decision-making processes, particularly purchasing behavior, financial management, or resource access. The distribution of types and numbers of vehicles owned by respondents' families provides insights into their socio-economic status and lifestyle preferences. Understanding vehicle ownership patterns can be crucial for research focusing on transportation economic impact or urban planning.

D. Data Analysis

The study applied SPSS and AMOS software for data processing and analysis, employing SEM to investigate relationships and effects identified through questionnaire data. ML Estimation was used to evaluate the construct reliability and validity of the multi-item measurement scales. Within SEM, path analysis consists of two primary components: a structural model that establishes paths of effect between independent and dependent variables and a measurement model enabling the simultaneous measurement of independent, dependent, and variables [76]. SEM analysis is a robust statistical technique for concurrently examining multiple variables and constructs, providing an in-depth understanding of the research framework's complex interactions and causal relationships [77].

Structural Equation Modeling (SEM) analysis comprises two distinct models: the measurement model, which assesses the validity and reliability of observed variables, and the structural model, which examines hypothesized relationships among constructs. Following the methodology delineated by Anderson and Gerbing [78], the study commenced with CFA to justify the measurement model, ensuring an accurate representation of constructs by their indicators. Subsequently, path analysis was conducted on the structural model to explore and quantify direct and indirect relationships between constructs, thereby offering a comprehensive understanding of the underlying dynamics influencing the phenomena under investigation.

III. RESULTS AND DISCUSSION

A. Goodness of Fit (GOF)

GOF test evaluates the degree of agreement between the actual data distribution and a predetermined theoretic distribution. Several academics have offered suggestions on how to report model fit indices. Garson [79] suggests including the following indices in the report: CMIN, RMSEA, one index representative of the fit of the model to the baseline (such as CFI, TLI, NFI, RFI, or IFI), and one index representing the fit of the model to the parsimony (such as PNFI or PCFI).

The Goodness of Fit (GOF) criteria assess whether a simulation can be accepted or disallowed through a likelihood test employing various indices and cut-off evaluation standards [99]. Table III demonstrates that the GOF standards have been fulfilled, signifying the constancy of the model and its readiness for further analysis.

TABLE III

GOODNESS OF FIT (GOF) RESULT

Criteria	Value	Cut-Off	Sources
Chi-Square (X^2)	0.893	≥ 0.050	[80]–[82]
CMIN/DF	0.548	≤ 2.000	[83]–[85]
GFI	0.938	≥ 0.900	[80], [85], [86]
RMSEA	0.000	≤ 0.080	[85], [87]–[91]
TLI	1.163	≥ 0.900	[85], [92], [93]
CFI	1.000	≥ 0.900	[91], [94], [95]
IFI	1.102	≥ 0.900	[96]
PNFI	0.575	≥ 0.500	[97], [98]
PCFI	0.751	≥ 0.500	[97], [98]

B. Analysis of Loading Factor, Average Variance Extracted, and Composite Reliability

According to the criteria outlined, each variable should account for at least 50% of the variance in its constructs, necessitating an absolute relationship above 0.70 between variables and constructs [100]. Furthermore, the measurement model should remove construct with factor loadings < 0.40 [101]. While Table IV generally presents reasonable loading factor values for the measurement model, some specific values fall below the recommended threshold, suggesting that only a limited number of constructs adequately explain the relationship between variables. A loading factor value > 0.70 signifies a strong correlation.

TABLE IV

LOADING FACTOR, AVERAGE VARIANCE EXTRACTED (AVE), AND COMPOSITE RELIABILITY (CR)

Construct	Item	Loading Factor	AVE	CR
Perceived Ease of Use (PEOU)	PEOU1	0.785	0.778	0.891
	PEOU2	0.821		
	PEOU3	0.729		
Perceived Usefulness (PEU)	PEU1	0.887	0.835	0.944
	PEU2	0.755		
	PEU3	0.834		
	PEU4	0.863		
Perceived Risk (PER)	PER1	0.934	0.832	0.943
	PER2	0.764		
	PER3	0.806		
	PER4	0.823		
Attitude Towards Use (ATU)	ATU1	0.786	0.861	0.941
	ATU2	0.872		
	ATU3	0.926		
Adoption Intention to Use (AIU)	AIU1	0.763	0.821	0.938
	AIU2	0.791		
	AIU3	0.885		
	AIU4	0.845		

Notably, all reflective indicator values in the structural model surpass the required threshold, indicating no need for constructs from omitted latent variables. The measurement model undergoes evaluation based on validity and reliability, with Cronbach's Alpha often utilized to determine reliability, indicating consistency among all indicators in the model. Ideally, Cronbach's Alpha must be at least 0.70, with values of 0.80 or 0.90 considered even more desirable. The composite reliability value, interpreted similarly to Cronbach's Alpha, should also be considered [98]. In Table IV, the C.R values obtained from the outcomes of the SEM analysis on the dimension model were > 0.70, indicating satisfactory reliability levels for all models, rendering them applicable. Additionally, for good convergent validity, a latent variable should, on average, explain more than half of the construct's variance, as denoted by the AVE value [102]. The recommended AVE value begins at 0.50. Table IV shows positive outcomes, with an average AVE (0.931), representing excellent validity for the developed structural model.

C. Measurement model analysis

In the measurement model analysis utilized in our study, a total of 18 indicators represents the five key constructs: Perceived Ease of Use (PEOU), Perceived Usefulness (PEU), Perceived Risk (PER), Attitude Towards Use (ATU), and Adoption Intention to Use (AIU) Technology Electric Vehicles (EVs). Each indicator is deemed suitable for use and capable of serving as a parameter for the variables they represent. Thus, the model demonstrates robustness in approximating modifications in the dependent variable, namely the AIU EVs, as it meets the criteria for model fit assessment. Considering these constructs, our analysis deepens the awareness of the behavior regarding the intention to use EVs. It provides a solid foundation for designing effective strategies to enhance EV adoption in society. The consequences of the measurement model can be seen in Figure 2 as follows:

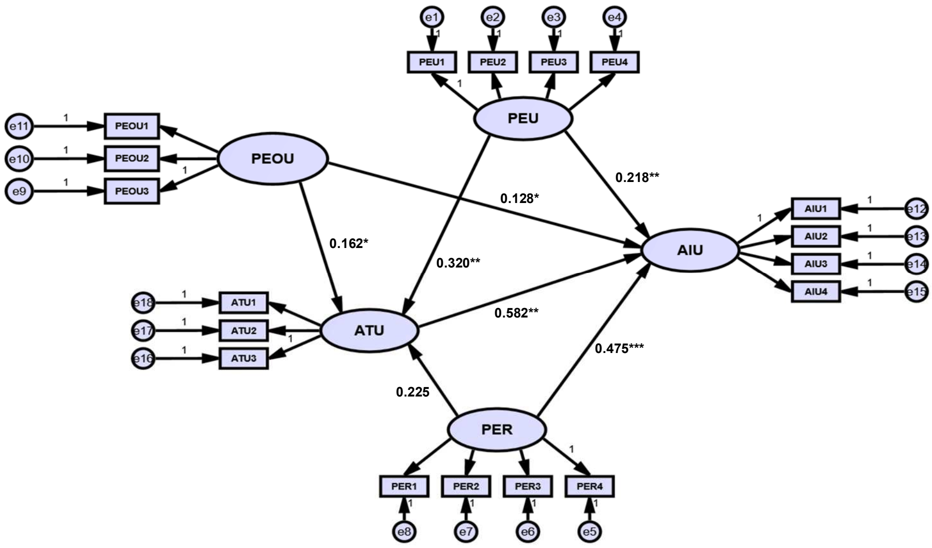

Fig. 2 Structural Model Result (* $p < 0.05$, or ** $p < 0.01$, or *** $p < 0.001$)

D. Hypothesis Testing Predictors of Perceived Ease of Use (PEOU)

The study's findings reveal significant positive associations between PEOU ATU and AIU regarding EVs. This implies that perceptions of the ease of using EVs positively influence individuals' attitudes and intentions to adopt this technology.

The regression analysis illustrates this relationship with notable coefficients and levels of significance. For ATU, the regression coefficient (β) is 0.162 with a significance level (p) of 0.027, indicating a meaningful positive relationship between PEOU and ATU. Similarly, the regression coefficient (β) for AIU is 0.128 with a significance level (p) of 0.032, reinforcing the significant positive association between PEOU and AIU.

These results align with previous studies in technology implementation and innovation diffusion theories. According to the TAM by Davis (1989), PEOU is a crucial determinant of individuals' attitudes and intentions toward adopting new technologies [35]. The positive relationship between PEOU and both ATU and AIU in the context of EVs supports the applicability of TAM in understanding consumer behavior towards this innovative technology.

The positive association suggests that efforts to enhance EVs' perceived ease of use could promote consumer adoption. Strategies such as user-friendly interfaces, clear instructions, and convenient charging infrastructure could help alleviate perceived barriers to adoption and encourage favorable attitudes and intentions toward EV use.

The assertion that users are more expected to embrace new products and perceive them as simple and convenient holds significant relevance in the context of EVs. This observation reflects a fundamental aspect of consumer behavior and decision-making processes, explored and supported by various studies [103], [104]. PEOU shapes user attitudes and intentions toward implementing innovative technologies like EVs. When individuals perceive EVs as straightforward and convenient, they are more inclined to develop positive attitudes toward them and are more willing to adopt them.

E. Hypothesis Testing Predictors of Perceived Risk (PER)

Based on the examination results, it was found that PER is not significantly associated with ATU in the context of EVs. The regression coefficient (β = 0.225) and significance (p = 0.270) suggest no significant relationship exists between PER and ATU for EVs. However, it is noteworthy that PER is significantly and positively associated with AIU in the use of EVs. The positive regression coefficient (β = 0.475) with a significant (p = 0.022) indicates a significant relationship between PER and AIU concerning EV technology adoption.

These findings align with the existing literature, which highlights users' uncertainties regarding innovative technology, particularly concerning doubts or anxieties related to utility risks associated with adopting new high-tech products like EVs [37], [105], [106]. Utility risks include implementation, suitability, long recharging time, charging infrastructure, and protection. The perception of these risks can influence users' attitudes and intentions towards adopting EV technology.

The survey by Alalwan et al. [107], Baabdullah et al. [108], and Roy et al. [109] highlights that when consumers perceive significant risks associated with using online banking services or shopping online, it can directly impact their attitudes and intentions to adopt such behaviors. These perceived risks can stem from various sources, including concerns about the security of personal data, uncertainties regarding transaction processes, or even worries about the quality of products or services obtained.

Perceived risk also emerges as a critical factor influencing consumer attitudes and intentions in the context of EV implementation. Users may need to be more concerned about EV performance, the availability of suitable charging infrastructure, or even issues related to battery durability and maintenance costs. Consumers tend to be less motivated to adopt EV products when these risks are perceived as high.

PER may not directly influence users' attitudes toward electric vehicles, but it plays a significant role in shaping their attitude toward innovation in EV technology. Additionally, perceived risk emerges as a vital consideration in understanding consumer attitudes and adoption intentions towards innovative technologies such as EVs, echoing findings from prior research in related domains like online banking and e-commerce.

F. Hypothesis Testing Predictors of Perceived Usefulness (PEU)

The positive regression coefficient ($\beta = 0.320$) and significance ($p = 0.006$) indicate that PEU is positively related to attitudes toward the use of EVs. This finding recommends that users who find EVs as easy to use will likely have positive attitudes toward them. This aligns with the TAM, which posits that perceived ease of use influences users' attitudes toward technology [35]. In the context of EV implementation, PEU may encompass factors such as the simplicity of charging, ease of navigation, and overall user experience with EVs.

Similarly, the positive regression coefficient ($\beta = 0.218$) and significance ($p = 0.000$) indicate that PEU positively relates to AIU. This suggests that users perceive EVs as easy to use and are likelier to use them in practice. This finding is consistent with previous research indicating that PEU significantly influences users' intentions to adopt technology [42], [110]. In EV implementation, PEU may affect users' confidence in their capacity to join EVs into their daily lives and routines.

PEU measures how much someone believes using a specific system would be easy. In EV implementation, users' perceptions of how easy it is to operate and integrate EVs into their lifestyles play a crucial role. Research by Venkatesh and Davis [42] found that PEU significantly influences users' attitudes and intentions towards technology implementation. Similarly, studies specific to EVs have shown that clients are more motivated to accept EVs when they perceive them as easy and convenient [111], [112].

The positive relationship between PEU and AIU identified in this study corroborates findings from prior research, contributing to the growing body of evidence supporting the importance of usability perceptions in shaping technology adoption. For instance, Hidrue et al. [113] studied user preferences for other fuel vehicles. They found that PEU significantly influenced users' willingness to adopt electric and hybrid cars. Zhang et al. [114] explored aspects influencing Chinese users' intention to adopt EVs and found that PEOU positively influenced adoption intentions.

Understanding the significance of PEU in influencing implementation intentions has practical implications for policymakers, manufacturers, and marketers in promoting EV adoption. Efforts to improve EVs' usability and user experience, such as enhancing charging infrastructure, simplifying vehicle operation, and providing user-friendly interfaces, can help alleviate consumer concerns and increase adoption rates [115], [116]. Moreover, educational initiatives highlighting the convenience and ease of integrating EVs into daily life can further enhance PEU and foster positive attitudes toward EV adoption.

G. Hypothesis Testing Predictors of Attitude Towards Using (ATU)

The significant and positive association between ATU EVs and AIU them, as indicated by a positive regression coefficient ($\beta = 0.582$) with a substantial ($p = 0.018$), underscores the critical role of consumer attitudes in the adoption process. This finding aligns with the TPB, which posits that a favorable attitude towards a behavior significantly predicts the intention to be involved in that behavior [43]. In EVs, this suggests that positive attitudes towards these vehicles will likely result in higher adoption intentions, reflecting a direct pathway through which user perceptions shape market trends.

Several studies highlight perceived risk as a significant barrier to EV adoption. Cheng & Huang [60], Luo et al. [117], and Tiwari et al. [118] all identify perceived risk—encompassing concerns about technology reliability, infrastructure availability, and cost implications—as a critical obstacle in forming favorable attitudes towards EV technology. This perspective is crucial in understanding consumer hesitation, as perceived risk can dampen enthusiasm towards new technologies despite their eco-friendly and financial benefits.

The influence of cognitive beliefs on adopting EVs is more pronounced than the technology's attributes [27], [119]. This observation suggests consumers weigh their beliefs about EVs' PEU and PEOU more heavily than the vehicles' actual features. Such cognitive beliefs are essential components of the TAM, which explains that PEU and PEOU affect users' attitudes towards and intentions to use new technology [35], [120]. Therefore, cognitive beliefs about EVs, shaped by information, experiences, and societal narratives, indirectly influence adoption intentions by mediating attitudes toward these vehicles.

Integrating these findings with the TPB and TAM offers a comprehensive framework for understanding EV adoption. It highlights the importance of addressing PER and enhancing the PEU and PEOU to foster positive attitudes towards EVs. Educational campaigns, improvements in EV infrastructure, and incentives can mitigate perceived risks and bolster positive perceptions, encouraging adoption.

H. Discussion

This study delves into the intricate dynamics influencing users' implementation of EVs in response to the pressing challenge of air contamination caused by the transportation segment. Recognizing EVs as a sought-after solution, policymakers and marketers are intensifying efforts to accelerate their uptake. This examination expands upon the traditional TAM to comprehensively understand the underlying factors driving users' intention to approve EVs. It incorporates additional dimensions such as perceived risk and the impact of commercial incentives policies within a rapidly evolving zero-emission mobility market, which aligns with global agendas for emission-free transportation.

The study used a comprehensive approach, examining direct, mediated, and moderated links to fill gaps in our understanding of the complex psychology behind electric vehicle adoption. Path analysis is employed to empirically examine hypothesized linkages based on the 'beliefs-attitude-intention' framework drawn from cognitive theories. The research intends to use mediation and moderation analyses to reveal the subtle impacts of mental elements, specifically perceived utility, PEU, PEOU, and PER, on the construction of attitudes towards EVs and the ultimate desire to use them.

In addition, the study investigates how external factors, specifically financial incentive programs, influence the connection between users' attitudes and their intentions to approve.

Through an in-depth examination of intricate connections, this study aims to offer valuable perspectives on the factors motivating users' choices when implementing EVs. Ultimately, the goal is to provide policymakers and marketers with valuable insights into successful strategies for encouraging the widespread use of EVs. This will help shift towards a more sustainable and eco-friendly transportation system. The research findings offer valuable insights into consumer attitudes toward EVs and their intention to adopt them. The study also examines the influence of predictor variables, including PEU, PEOU, and PER. The findings suggest that individuals' perspectives on EVs influence their likelihood of adopting them and their PEU and PEOU. These findings align with psychological theories highlighting attitudes as a connection between beliefs and behavior [40].

Previous studies, such as those conducted by Degirmenci and Breitner [121] on driver preferences for EVs in Germany, Wang et al. [58] on aspects influencing the intention to buy EVs through a perception-based path mapping approach, and Policarpo and Aguiar [122] on the influence of attitudes, risk, and trust on EV implementation, support these findings by highlighting the importance of attitudes as a primary driver of acceptance intention.

However, this research also indicates that attitudes do not mediate the connection between PER and AIU. This recommends the complexity of factors involved in consumers' decision-making regarding EV implementation, where perceived risk may directly influence adoption intention without going through attitudes. This study contributes valuable insights into the factors influencing EV implementation and their implications for policy and marketing strategies. The findings strengthen the 'belief-attitude-intention' in the context of EV acceptance and underscore the importance of considering user PEU, PEOU, and PER in designing promotional programs and incentives.

Furthermore, this research reveals a significant moderating consequence of fiscal incentive policies on the connection between attitudes toward EVs and adoption intention. This indicates that external aspects, such as financial incentives, influence users' decisions regarding EV adoption. These findings are consistent with previous investigations [70], [123], highlighting the importance of considering external stimuli in understanding user behavior in the background of EV implementation.

Overall, the findings of this study, which adopts an extended TAM approach, indicate that consumers' intentions to adopt EVs are influenced directly or indirectly by factors such as ATU, PEU, PEOU, and PER, along with the moderating factor of monetary incentive policies. These outcomes support the descriptive potential of the model used in this study and align with previous research in vehicle acceptance [59], [124].

IV. Conclusion

The study significantly impacts the ongoing discussion on knowledge receipt by extending the TAM to incorporate the effect of incentive policies on user attitudes and intentions toward adopting electric vehicles (EVs). This extension acknowledges the evolving landscape of technology adoption, particularly within emerging markets where policy incentives are essential in influencing user behavior. The study addresses the attitude-intention gap toward EV adoption, emphasizing the intricate interplay of factors influencing consumers' decision-making. By delving into the 'beliefs-attitude-intention' framework, the research enriches existing theoretical models, offering a deeper understanding of the adoption process and highlighting the role of beliefs in determining attitudes and intentions.

The exploration elucidates the facilitating role of attitude, revealing that PEU and PEOU drive user attitudes toward EVs, subsequently impacting adoption intentions. This finding underscores the importance of these factors in shaping consumer behavior and informs strategies aimed at promoting EV adoption. The study uncovers the direct results of perceived risks on adoption intentions, such as monetary losses, safety concerns, and performance issues, particularly relevant within emerging markets like Indonesia, where EV adoption is still in its infancy. This highlights the need to address consumer apprehensions and build trust in the technology to facilitate widespread adoption.

The investigation reaffirms PEU and PEOU's enduring significance in influencing attitudes and intentions to implement EVs. These factors remain vital determinants of technology acceptance and provide valuable insights for representatives, industry investors, and academics seeking to accelerate the transition toward sustainable mobility solutions. The research offers valuable contributions to theoretical advancements and practical implications for promoting EV adoption, providing insights that can inform policy interventions, marketing strategies, and product development efforts to drive the uptake of electric vehicles in emerging markets.

References

[1] M. I. H. Soiket, A. O. Oni, and A. Kumar, "The development of a process simulation model for energy consumption and greenhouse gas emissions of a vapor solvent-based oil sands extraction and recovery process," *Energy*, vol. 173, pp. 799–808, 2019, doi: 10.1016/j.energy.2019.02.109.

[2] A. O. Oni, I. C. Toro Monsalve, and A. Kumar, "The development of life cycle greenhouse gas emission footprints of novel pathways for the solvent-assisted and solvent-electromagnetic heating oil sands extraction processes," *Fuel*, vol. 346, p. 128399, 2023, doi:10.1016/j.fuel.2023.128399.

[3] S. M. Hafram, S. Valery, and A. H. Hasim, "Calibrating and validation microscopic traffic simulation models VISSIM for enhanced highway capacity planning," *Int. J. Eng. Trans. B Appl.*, vol. 36, no. 8, pp. 1509–1519, 2023, doi: 10.5829/ije.2023.36.08b.11.

[4] V. Ramanathan and Y. Feng, "Air pollution, greenhouse gases and climate change: Global and regional perspectives," *Atmos. Environ.*, vol. 43, no. 1, pp. 37–50, 2009, doi: 10.1016/j.atmosenv.2008.09.063.

[5] K. O. Yoro and M. O. Daramola, "CO2 emission sources, greenhouse gases, and the global warming effect," in *Advances in Carbon Capture: Methods, Technologies and Applications*, Elsevier, 2020, pp. 3–28.

[6] A. J. Patandean and A. H. Hasim, "Geophysical Exploration in Hot Springs Region Soppeng Regency, Indonesia," *Journal of Physics: Conference Series*, vol. 1028, no. 1. p. 12197, 2018, doi:10.1088/1742-6596/1028/1/012197.

[7] L. Liu, K. Wang, S. Wang, R. Zhang, and X. Tang, "Assessing energy consumption, CO2 and pollutant emissions and health benefits from China's transport sector through 2050," *Energy Policy*, vol. 116, pp. 382–396, 2018, doi: 10.1016/j.enpol.2018.02.019.

[8] R. Quadrelli and S. Peterson, "The energy-climate challenge: Recent trends in CO2 emissions from fuel combustion," *Energy Policy*, vol.

35, no. 11, pp. 5938–5952, 2007, doi: 10.1016/j.enpol.2007.07.001.

[9] S. Solaymani, "CO2 emissions patterns in 7 top carbon emitter economies: The case of transport sector," *Energy*, vol. 168, pp. 989–1001, 2019, doi: 10.1016/j.energy.2018.11.145.

[10] N. Rajabi Kouyakhi, "CO2 emissions in the Middle East: Decoupling and decomposition analysis of carbon emissions, and projection of its future trajectory," *Sci. Total Environ.*, vol. 845, p. 157182, 2022, doi:10.1016/j.scitotenv.2022.157182.

[11] L. A. R. Umali, I. C. Recto, R. S. Lansangan, L. D. G. Torres, and E. R. Basilio, "Modified Tricycles as Public Transport during Tidal Flooding Events: The Case of Tikling in Hagonoy, Bulacan, Philippines," *Int. J. Environ. Eng. Educ.*, vol. 5, no. 2, pp. 45–55, 2023, doi: 10.55151/ijeedu.v5i2.102.

[12] M. Ichsan Ali, A. Hafid Hasim, and M. Raiz Abidin, "Monitoring the built-up area transformation using urban index and normalized difference built-up index analysis," *Int. J. Eng. Trans. B Appl.*, vol. 32, no. 5, pp. 647–653, 2019, doi: 10.5829/ije.2019.32.05b.04.

[13] Ronny, M. I. Arif, and H. B. Notobroto, "Water Pollution Index: Measurement of Shallow Well Water Quality in Urban Areas," *Int. J. Environ. Eng. Educ.*, vol. 1, no. 3, pp. 75–81, 2019.

[14] A. Al-Sarraj, H. T. Salloom, and S. Z. Oleiwi, "Reviewing Energy Efficiency with the Development of Luminescent Solar Panels," *Int. J. Environ. Eng. Educ.*, vol. 2, no. 2, pp. 1–6, 2020, doi:10.55151/ijeedu.v2i2.28.

[15] N. Bhalerao and S. Metkar, "The Renewable Energy: Environmentally Friendly Algae Biofuel," *Int. J. Environ. Eng. Educ.*, vol. 2, no. 3, pp. 13–21, Dec. 2020, doi: 10.5281/zenodo.4309022.

[16] G. Schuitema, J. Anable, S. Skippon, and N. Kinnear, "The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles," *Transp. Res. Part A Policy Pract.*, vol. 48, pp. 39–49, 2013, doi: 10.1016/j.tra.2012.10.004.

[17] M. Coffman, P. Bernstein, and S. Wee, "Electric vehicles revisited: a review of factors that affect adoption," *Transp. Rev.*, vol. 37, no. 1, pp. 79–93, 2017, doi: 10.1080/01441647.2016.1217282.

[18] M. R. Hasrul, M. J. Rahman, A. R. A. P. Helmy, A. Y. Cheng, and M. Ahsan, "Exploring Research Trends and Themes in Intelligent Transportation Systems in the Last 10 Years (2014–2023)," *Int. J. Environ. Eng. Educ.*, vol. 5, no. 3, pp. 141–153, 2023.

[19] R. Buehler, J. Pucher, and A. Altshuler, "Vienna's path to sustainable transport," *Int. J. Sustain. Transp.*, vol. 11, no. 4, pp. 257–271, 2017, doi: 10.1080/15568318.2016.1251997.

[20] M. Burgess, N. King, M. Harris, and E. Lewis, "Electric vehicle drivers' reported interactions with the public: Driving stereotype change?," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 17, pp. 33–44, 2013, doi: 10.1016/j.trf.2012.09.003.

[21] Z. Y. She, Qing Sun, J. J. Ma, and B. C. Xie, "What are the barriers to widespread adoption of battery electric vehicles? A survey of public perception in Tianjin, China," *Transp. Policy*, vol. 56, pp. 29–40, 2017, doi: 10.1016/j.tranpol.2017.03.001.

[22] C. A. Klöckner, "The dynamics of purchasing an electric vehicle - A prospective longitudinal study of the decision-making process," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 24, pp. 103–116, 2014, doi: 10.1016/j.trf.2014.04.015.

[23] C. A. Klöckner, A. Nayum, and M. Mehmetoglu, "Positive and negative spillover effects from electric car purchase to car use," *Transp. Res. Part D Transp. Environ.*, vol. 21, pp. 32–38, 2013, doi: 10.1016/j.trd.2013.02.007.

[24] T. Fontes, V. Costa, M. C. Ferreira, L. Shengxiao, P. Zhao, and T. G. Dias, "Mobile payments adoption in public transport," *Transp. Res. Procedia*, vol. 24, pp. 410–417, 2017, doi:10.1016/j.trpro.2017.05.093.

[25] R. Ozaki and K. Sevastyanova, "Going hybrid: An analysis of consumer purchase motivations," *Energy Policy*, vol. 39, no. 5, pp. 2217–2227, 2011, doi: 10.1016/j.enpol.2010.04.024.

[26] K. Y. Bjerkan, T. E. Nørbech, and M. E. Nordtømme, "Incentives for promoting Battery Electric Vehicle (BEV) adoption in Norway," *Transp. Res. Part D Transp. Environ.*, vol. 43, pp. 169–180, 2016, doi:10.1016/j.trd.2015.12.002.

[27] Z. Rezvani, J. Jansson, and J. Bodin, "Advances in consumer electric vehicle adoption research: A review and research agenda," *Transp. Res. Part D Transp. Environ.*, vol. 34, pp. 122–136, 2015, doi:10.1016/j.trd.2014.10.010.

[28] N. Wang, L. Tang, and H. Pan, "Analysis of public acceptance of electric vehicles: An empirical study in Shanghai," *Technol. Forecast. Soc. Change*, vol. 126, pp. 284–291, 2018, doi:10.1016/j.techfore.2017.09.011.

[29] A. H. Hasim, L. B. Said, and M. Hafram, "Have a Personal Vehicle: Really Need or Simply Want?," *International Journal of Environment, Engineering and Education*, vol. 1, no. 1. pp. 7–16, 2019, doi:10.55151/ijeedu.v1i1.8.

[30] L. V. White and N. D. Sintov, "You are what you drive: Environmentalist and social innovator symbolism drives electric vehicle adoption intentions," *Transp. Res. Part A Policy Pract.*, vol. 99, pp. 94–113, 2017, doi: 10.1016/j.tra.2017.03.008.

[31] N. Berkeley, D. Jarvis, and A. Jones, "Analysing the take up of battery electric vehicles: An investigation of barriers amongst drivers in the UK," *Transp. Res. Part D Transp. Environ.*, vol. 63, pp. 466–481, 2018, doi: 10.1016/j.trd.2018.06.016.

[32] A. Ajanovic and R. Haas, "Electric vehicles: solution or new problem?," *Environ. Dev. Sustain.*, vol. 20, pp. 7–22, 2018, doi:10.1007/s10668-018-0190-3.

[33] N. Shanmugavel, C. Alagappan, and J. Balakrishnan, "Acceptance of electric vehicles: A dual-factor approach using social comparison theory and technology acceptance model," *Res. Transp. Bus. Manag.*, vol. 45, p. 100842, 2022, doi: 10.1016/j.rtbm.2022.100842.

[34] N. Wang, H. Tian, S. Zhu, and Y. Li, "Analysis of public acceptance of electric vehicle charging scheduling based on the technology acceptance model," *Energy*, vol. 258, p. 124804, 2022, doi:10.1016/j.energy.2022.124804.

[35] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Q.*, pp. 319–340, 1989.

[36] X. He, W. Zhan, and Y. Hu, "Consumer purchase intention of electric vehicles in China: The roles of perception and personality," *J. Clean. Prod.*, vol. 204, pp. 1060–1069, 2018, doi:10.1016/j.jclepro.2018.08.260.

[37] M. Featherman, S. (Jasper) Jia, C. B. Califf, and N. Hajli, "The impact of new technologies on consumers beliefs: Reducing the perceived risks of electric vehicle adoption," *Technol. Forecast. Soc. Change*, vol. 169, p. 120847, 2021, doi: 10.1016/j.techfore.2021.120847.

[38] M. K. Kim, J. Oh, J. H. Park, and C. Joo, "Perceived value and adoption intention for electric vehicles in Korea: Moderating effects of environmental traits and government supports," *Energy*, vol. 159, pp. 799–809, 2018, doi: 10.1016/j.energy.2018.06.064.

[39] M. Fishbein and I. Ajzen, *Belief, attitude, intention and behavior: An introduction to theory and research*. 1975.

[40] I. Ajzen and M. Fishbein, "Understanding attitudes and predicting social behavior," *Englewood Cliffs, NJ Prentice-Hall*, 1980.

[41] A. Bhattacherjee, "Understanding information systems continuance: An expectation-confirmation model," *MIS Q.*, pp. 351–370, 2001.

[42] V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," *Manage. Sci.*, vol. 46, no. 2, pp. 186–204, 2000.

[43] I. Ajzen, "The theory of planned behavior," *Organ. Behav. Hum. Decis. Process.*, vol. 50, no. 2, pp. 179–211, 1991.

[44] I. Benbasat and H. Barki, "Quo vadis TAM?," *J. Assoc. Inf. Syst.*, vol. 8, no. 4, p. 7, 2007.

[45] M. I. Ali, "The Consequences of Illegal Mining in the Environment: Perspectives Behavioral, Knowledge and Attitude," *Int. J. Environ. Eng. Educ.*, vol. 1, no. 1, pp. 25–33, 2019, doi:10.55151/ijeedu.v1i1.10.

[46] P. Legris, J. Ingham, and P. Collerette, "Why do people use information technology? A critical review of the technology acceptance model," *Inf. Manag.*, vol. 40, no. 3, pp. 191–204, 2003, doi:10.1016/S0378-7206(01)00143-4.

[47] K. Mathieson, E. Peacock, and W. W. Chin, "Extending the Technology Acceptance Model: The Influence of Perceived User Resources," *Data Base Adv. Inf. Syst.*, vol. 32, no. 3, pp. 86–112, 2001, doi: 10.1145/506724.506730.

[48] O. Egbue, S. Long, and V. A. Samaranayake, "Mass deployment of sustainable transportation: evaluation of factors that influence electric vehicle adoption," *Clean Technol. Environ. Policy*, vol. 19, no. 7, pp. 1927–1939, 2017, doi: 10.1007/s10098-017-1375-4.

[49] G. Xu, S. Wang, and D. Zhao, "Transition to sustainable transport: understanding the antecedents of consumer's intention to adopt electric vehicles from the emotional research perspective," *Environ. Sci. Pollut. Res.*, vol. 28, no. 16, pp. 20362–20374, 2021, doi:10.1007/s11356-020-12006-1.

[50] V. Teeroovengadum, N. Heeraman, and B. Jugurnath, "Examining the antecedents of ICT adoption in education using an Extended Technology Acceptance Model (TAM)," *Int. J. Educ. Dev. Using Inf. Commun. Technol.*, vol. 13, no. 3, pp. 4–23, 2017.

[51] A. M. Idkhan and M. M. Idris, "The Impact of User Satisfaction in the Use of E-Learning Systems in Higher Education: A CB-SEM Approach," *Int. J. Environ. Eng. Educ.*, vol. 5, no. 3, pp. 100–110, 2023.

[52] A. Padalia and T. Natsir, "End-User Computing Satisfaction (EUCS) Model: Implementation of Learning Management System (LMS) on

Students Satisfaction at Universities," *Int. J. Environ. Eng. Educ.*, vol. 4, no. 3, pp. 100–107, 2022, doi: 10.55151/ijeedu.v4i3.72.
[53] H. Zhang, "Structural Equation Modeling," in *Management for Professionals*, vol. Part F525, Routledge, 2022, pp. 363–381.
[54] J. E. Collier, *Applied Structural Equation Modeling using AMOS: Basic to Advanced Techniques*. Routledge, 2020.
[55] E. Schumacker and G. Lomax, "A Beginner's Guide to Structural Equation Modelling. 4th edtn." London: Routledge, 2016.
[56] J. Hong, Y. She, S. Wang, and M. Dora, "Impact of psychological factors on energy-saving behavior: Moderating role of government subsidy policy," *J. Clean. Prod.*, vol. 232, pp. 154–162, 2019, doi:10.1016/j.jclepro.2019.05.321.
[57] J. Dunn, M. Slattery, A. Kendall, H. Ambrose, and S. Shen, "Circularity of Lithium-Ion Battery Materials in Electric Vehicles," *Environ. Sci. Technol.*, vol. 55, no. 8, pp. 5189–5198, 2021, doi:10.1021/acs.est.0c07030.
[58] S. Wang, J. Wang, J. Li, J. Wang, and L. Liang, "Policy implications for promoting the adoption of electric vehicles: Do consumer's knowledge, perceived risk and financial incentive policy matter?," *Transp. Res. Part A Policy Pract.*, vol. 117, pp. 58–69, 2018, doi:10.1016/j.tra.2018.08.014.
[59] T. Zhang, D. Tao, X. Qu, X. Zhang, R. Lin, and W. Zhang, "The roles of initial trust and perceived risk in public's acceptance of automated vehicles," *Transp. Res. Part C Emerg. Technol.*, vol. 98, pp. 207–220, 2019, doi: 10.1016/j.trc.2018.11.018.
[60] Y. H. Cheng and T. Y. Huang, "High speed rail passengers' mobile ticketing adoption," *Transp. Res. Part C Emerg. Technol.*, vol. 30, pp. 143–160, 2013, doi: 10.1016/j.trc.2013.02.001.
[61] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Q.*, pp. 425–478, 2003.
[62] T. T. Haile and M. Kang, "Mobile augmented reality in electronic commerce: investigating user perception and purchase intent amongst educated young adults," *Sustain.*, vol. 12, no. 21, pp. 1–28, 2020, doi:10.3390/su12219185.
[63] I. Vermeir and W. Verbeke, "Sustainable food consumption: Exploring the consumer 'attitude - Behavioral intention' gap," *J. Agric. Environ. Ethics*, vol. 19, no. 2, pp. 169–194, 2006, doi:10.1007/s10806-005-5485-3.
[64] D. Jaiswal and R. Kant, "Green purchasing behaviour: A conceptual framework and empirical investigation of Indian consumers," *J. Retail. Consum. Serv.*, vol. 41, pp. 60–69, 2018, doi:10.1016/j.jretconser.2017.11.008.
[65] R. Lavuri, E. Jusuf, and A. Gunardi, "Green Sustainability: Factors Fostering and Behavioural Difference Between Millennial and Gen Z: Mediating Role of Green Purchase Intention," *Ekon. i Sr.*, vol. 76, no. 1, pp. 8–38, 2021, doi: 10.34659/2021/1/1.
[66] I. Ajzen and N. G. Cote, "Attitudes and the prediction of behavior," *Attitudes Attitude Chang.*, vol. 13, pp. 289–312, 2011, doi:10.4324/9780203838068.
[67] M. Fishbein and I. Ajzen, "The influence of attitudes on behavior," *Handb. attitudes*, pp. 173–222, 2005.
[68] D. Liu, Y. Song, L. Li, H. Liao, and Y. Peng, "On-line life cycle health assessment for lithium-ion battery in electric vehicles," *J. Clean. Prod.*, vol. 199, pp. 1050–1065, 2018, doi: 10.1016/j.jclepro.2018.06.182.
[69] S. Khaleghi, Y. Firouz, J. Van Mierlo, and P. Van den Bossche, "Developing a real-time data-driven battery health diagnosis method, using time and frequency domain condition indicators," *Appl. Energy*, vol. 255, p. 113813, 2019, doi: 10.1016/j.apenergy.2019.113813.
[70] Z. A. Lashari, J. Ko, and J. Jang, "Consumers' intention to purchase electric vehicles: Influences of user attitude and perception," *Sustain.*, vol. 13, no. 12, p. 6778, 2021, doi: 10.3390/su13126778.
[71] J. F. Hair Jr, G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, and S. Ray, "Partial least squares structural equation modeling (PLS-SEM) using R: A workbook." Springer Nature, 2021.
[72] J. F. Hair, W. C. Black, B. J. Babin, R. E. Anderson, and R. Tatham, *Multivariate Data Analysis*. Hampshire, United Kingdom: Cengage Learning EMEA, 2019.
[73] J. Wu, H. Liao, J. W. Wang, and T. Chen, "The role of environmental concern in the public acceptance of autonomous electric vehicles: A survey from China," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 60, pp. 37–46, 2019, doi: 10.1016/j.trf.2018.09.029.
[74] L. Han, S. Wang, D. Zhao, and J. Li, "The intention to adopt electric vehicles: Driven by functional and non-functional values," *Transp. Res. Part A Policy Pract.*, vol. 103, pp. 185–197, 2017, doi:10.1016/j.tra.2017.05.033.
[75] C. Peng, Z. OuYang, and Y. Liu, "Understanding bike sharing use over time by employing extended technology continuance theory," *Transp. Res. Part A Policy Pract.*, vol. 124, pp. 433–443, 2019, doi:10.1016/j.tra.2019.04.013.
[76] T. A. Whittaker and R. E. Schumacker, *A Beginner's Guide to Structural Equation Modeling*. Routledge, 2022.
[77] R. B. Kline, *Principles and practice of structural equation modeling*. Guilford publications, 2023.
[78] J. C. Anderson and D. W. Gerbing, "Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach," *Psychol. Bull.*, vol. 103, no. 3, pp. 411–423, 1988, doi: 10.1037/0033-2909.103.3.411.
[79] G. D. Garson, *Structural Equation Modeling*, Blue Book. Asheboro, North Corolina: Statistical Associates Publishing, 2012.
[80] K. G. Jöreskog and D. Sörbom, *LISREL 8: Structural equation modeling with the SIMPLIS command language*. Scientific Software International, 1993.
[81] G. D. Garson, *Partial Least Squares: Regression & structural equation modeling*. Asheboro, USA: Statistical Publishing Associates, 2016.
[82] J. J. Hox and T. M. Bechger, "An introduction to structural equation modeling," 2007.
[83] B. Wheaton, B. Muthen, D. F. Alwin, and G. F. Summers, "Assessing Reliability and Stability in Panel Models," *Sociol. Methodol.*, vol. 8, p. 84, 1977, doi: 10.2307/270754.
[84] E. G. Carmines, "Analyzing models with unobserved variables," *Soc. Meas. Curr. issues*, vol. 80, 1981.
[85] R. E. Schumacker and R. G. Lomax, *A Beginner's Guide to Structural Equation Modeling*, 3rd ed. Mahwah, NJ: Lawrence Erlbaum Associates, 2015.
[86] J. S. Tanaka and G. J. Huba, "A general coefficient of determination for covariance structure models under arbitrary GLS estimation," *Br. J. Math. Stat. Psychol.*, vol. 42, no. 2, pp. 233–239, 1989.
[87] J. H. Steiger and J. C. Lind, "Statistically based tests for the number of common factors," 1980.
[88] M. W. Browne and R. Cudeck, "Alternative ways of assessing model fit," *Sage Focus Ed.*, vol. 154, p. 136, 1993.
[89] L. J. Williams and E. O'Boyle Jr, "The myth of global fit indices and alternatives for assessing latent variable relations," *Organ. Res. Methods*, vol. 14, no. 2, pp. 350–369, 2011.
[90] F. Chen, P. J. Curran, K. A. Bollen, J. Kirby, and P. Paxton, "An empirical evaluation of the use of fixed cutoff points in RMSEA test statistic in structural equation models," *Sociol. Methods Res.*, vol. 36, no. 4, pp. 462–494, 2008.
[91] L. T. Hu and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," *Struct. Equ. Model.*, vol. 6, no. 1, pp. 1–55, 1999, doi:10.1080/10705519909540118.
[92] L. R. Tucker and C. Lewis, "A reliability coefficient for maximum likelihood factor analysis," *Psychometrika*, vol. 38, no. 1, pp. 1–10, 1973.
[93] P. M. Bentler and L. T. Hu, "Evaluating model fit," in *Structural equation modeling: Concepts, issues, and applications*, Thousand Oaks, CA: SAGE Publications, 1995, pp. 76–99.
[94] P. M. Bentler, "SEM with simplicity and accuracy," *J. Consum. Psychol.*, vol. 20, no. 2, pp. 215–220, 2010, doi:10.1016/j.jcps.2010.03.002.
[95] P. Wood, *Confirmatory Factor Analysis for Applied Research*, 2nd ed., vol. 62, no. 1. New York: The Guilford Press, 2008.
[96] K. A. Bollen, "A new incremental fit index for general structural equation models," *Sociol. Methods Res.*, vol. 17, no. 3, pp. 303–316, 1989.
[97] S. A. Mulaik, L. R. James, J. Van Alstine, N. Bennett, S. Lind, and C. D. Stilwell, "Evaluation of goodness-of-fit indices for structural equation models.," *Psychol. Bull.*, vol. 105, no. 4, pp. 430–445, 1989.
[98] L. James, S. Mulaik, and J. M. Brett, *Causal analysis: Assumptions, models, and data*. Beverly Hills: Sage publications, 1982.
[99] W. R. Dillon, K. A. Bollen, and J. S. Long, *Testing Structural Equation Models*, vol. 33, no. 3. Sage, 1996.
[100] M. S. Khine, *Application of structural equation modeling in educational research and practice*, 7th ed. Rotterdam, Netherlands: Sense Publishers, 2013.
[101] R. H. Hoyle, *Structural Equation Modeling : Concepts, Issues, and Applications*. Thousand Oaks, California: SAGE Publications, Inc., 1995.
[102] R. P. Bagozzi and Y. Yi, "On the evaluation of structural equation models," *J. Acad. Mark. Sci.*, vol. 16, no. 1, pp. 74–94, 1988.

[103] T. Lieven and B. Hügler, "Did electric vehicle sales skyrocket due to increased environmental awareness while total vehicle sales declined during COVID-19?," *Sustain.*, vol. 13, no. 24, p. 13839, 2021, doi:10.3390/su132413839.

[104] K. Shalender and N. Sharma, "Using extended theory of planned behaviour (TPB) to predict adoption intention of electric vehicles in India," *Environ. Dev. Sustain.*, vol. 23, no. 1, pp. 665–681, 2021, doi:10.1007/s10668-020-00602-7.

[105] M. S. Featherman and P. A. Pavlou, "Predicting e-services adoption: A perceived risk facets perspective," *Int. J. Hum. Comput. Stud.*, vol. 59, no. 4, pp. 451–474, 2003, doi: 10.1016/S1071-5819(03)00111-3.

[106] T. Roselius, "Consumer Rankings of Risk Reduction Methods," *J. Mark.*, vol. 35, no. 1, p. 56, 1971, doi: 10.2307/1250565.

[107] A. A. Alalwan, Y. K. Dwivedi, N. P. P. Rana, and M. D. Williams, "Consumer adoption of mobile banking in Jordan: Examining the role of usefulness, ease of use, perceived risk and self-efficacy," *J. Enterp. Inf. Manag.*, vol. 29, no. 1, pp. 118–139, 2016, doi: 10.1108/JEIM-04-2015-0035.

[108] A. M. Baabdullah, A. A. Alalwan, N. P. Rana, H. Kizgin, and P. Patil, "Consumer use of mobile banking (M-Banking) in Saudi Arabia: Towards an integrated model," *Int. J. Inf. Manage.*, vol. 44, pp. 38–52, 2019.

[109] S. K. Roy, M. S. Balaji, A. Kesharwani, and H. Sekhon, "Predicting Internet banking adoption in India: a perceived risk perspective," *J. Strateg. Mark.*, vol. 25, no. 5–6, pp. 418–438, 2017, doi:10.1080/0965254X.2016.1148771.

[110] V. Venkatesh and S. Goyal, "Expectation disconfirmation and technology adoption: polynomial modeling and response surface analysis," *MIS Q.*, pp. 281–303, 2010.

[111] S. Wang, J. Fan, D. Zhao, S. Yang, and Y. Fu, "Predicting consumers' intention to adopt hybrid electric vehicles: using an extended version of the theory of planned behavior model," *Transportation (Amst).*, vol. 43, no. 1, pp. 123–143, 2016, doi: 10.1007/s11116-014-9567-9.

[112] S. Wang, J. Li, and D. Zhao, "The impact of policy measures on consumer intention to adopt electric vehicles: Evidence from China," *Transp. Res. Part A Policy Pract.*, vol. 105, pp. 14–26, 2017, doi:10.1016/j.tra.2017.08.013.

[113] M. K. Hidrue, G. R. Parsons, W. Kempton, and M. P. Gardner, "Willingness to pay for electric vehicles and their attributes," *Resour. Energy Econ.*, vol. 33, no. 3, pp. 686–705, 2011, doi:10.1016/j.reseneeco.2011.02.002.

[114] J. Zhang, S. Xu, Z. He, C. Li, and X. Meng, "Factors Influencing Adoption Intention for Electric Vehicles under a Subsidy Deduction: From Different City-Level Perspectives," *Sustain.*, vol. 14, no. 10, p. 5777, 2022, doi: 10.3390/su14105777.

[115] S. Carley, R. M. Krause, B. W. Lane, and J. D. Graham, "Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites," *Transp. Res. Part D Transp. Environ.*, vol. 18, no. 1, pp. 39–45, 2013, doi: 10.1016/j.trd.2012.09.007.

[116] F. Siraj and P. Mehra, "The influence of financial incentives and other socio-economic factors on two-wheeler EV adoption in the NCR region," *Sustain. Growth Glob. Soc. Dev. Compet. Econ.*, vol. 68, pp. 248–279, 2023, doi: 10.4018/978-1-6684-8810-2.ch013.

[117] X. Luo, H. Li, J. Zhang, and J. P. Shim, "Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services," *Decis. Support Syst.*, vol. 49, no. 2, pp. 222–234, 2010, doi:10.1016/j.dss.2010.02.008.

[118] P. Tiwari, S. K. Tiwari, and A. Gupta, "Examining the Impact of Customers' Awareness, Risk and Trust in M-Banking Adoption," *FIIB Bus. Rev.*, vol. 10, no. 4, pp. 413–423, 2021, doi:10.1177/23197145211019924.

[119] O. Egbue and S. Long, "Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions," *Energy Policy*, vol. 48, pp. 717–729, 2012, doi: 10.1016/j.enpol.2012.06.009.

[120] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User acceptance of computer technology: a comparison of two theoretical models," *Manage. Sci.*, vol. 35, no. 8, pp. 982–1003, 1989.

[121] K. Degirmenci and M. H. Breitner, "Consumer purchase intentions for electric vehicles: Is green more important than price and range? – Authors' reply," *Transp. Res. Part D Transp. Environ.*, vol. 65, pp. 846–848, 2018, doi: 10.1016/j.trd.2017.07.024.

[122] M. C. Policarpo and E. C. Aguiar, "How self-expressive benefits relate to buying a hybrid car as a green product," *J. Clean. Prod.*, vol. 252, p. 119859, 2020, doi: 10.1016/j.jclepro.2019.119859.

[123] G. Xu, S. Wang, J. Li, and D. Zhao, "Moving towards sustainable purchase behavior: examining the determinants of consumers' intentions to adopt electric vehicles," *Environ. Sci. Pollut. Res.*, vol. 27, no. 18, pp. 22535–22546, 2020, doi: 10.1007/s11356-020-08835-9.

[124] T. Zhang *et al.*, "Automated vehicle acceptance in China: Social influence and initial trust are key determinants," *Transp. Res. Part C Emerg. Technol.*, vol. 112, pp. 220–233, 2020, doi:10.1016/j.trc.2020.01.027.

10% Overall Similarity

Top sources found in the following databases:

- 6% Internet database
- 4% Publications database
- Crossref database
- Crossref Posted Content database
- 7% Submitted Works database

TOP SOURCES

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	eprints.unm.ac.id Internet	<1%
2	Deepak Jaiswal, Vikrant Kaushal, Rishi Kant, Pankaj Kumar Singh. "Con... Crossref	<1%
3	University of Warwick on 2024-09-02 Submitted works	<1%
4	University of Northampton on 2024-09-28 Submitted works	<1%
5	stmlportal.net Internet	<1%
6	discovery.researcher.life Internet	<1%
7	pure.rug.nl Internet	<1%
8	Asia Pacific University College of Technology and Innovation (UCTI) on... Submitted works	<1%

9	University of Sheffield on 2021-09-07 Submitted works	<1%
10	repository.ju.edu.et Internet	<1%
11	ebin.pub Internet	<1%
12	Ghana Technology University College on 2024-08-06 Submitted works	<1%
13	Segi University College on 2024-08-07 Submitted works	<1%
14	The University of the South Pacific on 2024-08-15 Submitted works	<1%
15	archive.conscientiabeam.com Internet	<1%
16	koreascience.or.kr Internet	<1%
17	frontiersin.org Internet	<1%
18	Asia Pacific University College of Technology and Innovation (UCTI) on... Submitted works	<1%
19	pubmed.ncbi.nlm.nih.gov Internet	<1%
20	VinUniversity on 2024-02-02 Submitted works	<1%

21	University of Bradford on 2023-09-06 Submitted works	<1%
22	University of Hull on 2022-08-12 Submitted works	<1%
23	University of Oxford on 2024-09-29 Submitted works	<1%
24	ijasce.org Internet	<1%
25	Heriot-Watt University on 2023-04-05 Submitted works	<1%
26	Meenakshi Handa, Swati Jain, Parul Ahuja. "Is it cost saving or environ... Crossref	<1%
27	Seen Yee Choo, Ali Vafaei-Zadeh, Haniruzila Hanifah, Ramayah Thuras... Crossref	<1%
28	Segi University College on 2024-08-13 Submitted works	<1%
29	media.neliti.com Internet	<1%
30	mpra.ub.uni-muenchen.de Internet	<1%
31	repository.kulib.kyoto-u.ac.jp Internet	<1%
32	cell.com Internet	<1%

33	mdpi.com Internet	<1%
34	Brickfields Asia College on 2024-08-17 Submitted works	<1%
35	Chao Wang, Xiaoxia Yao, Paresha N. Sinha, Hong Su, Yong-Ki Lee. "Wh... Crossref	<1%
36	Colorado Technical University Online on 2024-09-08 Submitted works	<1%
37	Curtin University of Technology on 2022-09-23 Submitted works	<1%
38	Foreign Trade University on 2023-11-30 Submitted works	<1%
39	Galileo Global Education on 2024-09-06 Submitted works	<1%
40	INTI Universal Holdings SDM BHD on 2023-12-02 Submitted works	<1%
41	Liu Han, Shanyong Wang, Dingtao Zhao, Jun Li. "The intention to adopt... Crossref	<1%
42	National Economics University on 2024-04-01 Submitted works	<1%
43	Nisar Ahmed Dahri, Noraffandy Yahaya, Waleed Mugahed Al-Rahmi, H... Crossref	<1%
44	Sinung Adi Nugroho, Sunu Widianto. "Exploring Electric Vehicle Adopti... Crossref	<1%

45	University of Bristol on 2015-09-14 Submitted works	<1%
46	University of Southampton on 2023-09-14 Submitted works	<1%
47	University of Warwick on 2022-09-04 Submitted works	<1%
48	Yong-Jin Alex Lee, Isabelle Nilsson. "An examination of the effect of ex... Crossref	<1%
49	journals.rta.lv Internet	<1%