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Synergizing Green Transitions: Exploring EV Usage Risks in South India through the UTAUT2 Model

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ABSTRACT Climate change can be combated, and sustainable transportation can be promoted by electric vehicles (EVs). Despite their versatility, they face multiple challenges when it comes to their uptake and habitual use. A comprehensive framework to clarify these factors, specifically in relation to EVs, is available through the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Due to perceived risks, many users are hesitant to use electric vehicles despite their potential benefits. to develop and empirically test a model that forecasts the elements that affect consumers' acceptance of electric vehicles, the research aims to construct and empirically validate a model. The risk factor plays a significant role in behavioral intentions and usage of EVs in the South Indian context, as assessed through the reworked United Theory of Acceptance and Use of Technology model (UTAUT). 430 electric vehicle (EV) owners living in South India were surveyed and survey data was analyzed using a variance-based structural equation model (SEM). The newly suggested model explained 67.52% of the variance in terms of behavioral intention, and 43.58% of the variance in terms of actual usage. EV behavior and actual use were primarily influenced by risk factors, with mixed relationships between them, according to the study's empirical findings.

Keywords: EV, UTAUT, UTAUT2, User Acceptance, Technology Adoption.

I. INTRODUCTION

Electric vehicles have emerged as a promising solution to air pollution, energy security, and climate change. The global market for EVs has grown rapidly, with a significant increase in the number of EV models available. In addition, the number of places where electric vehicles can be charged has grown. Despite this growth, the adoption and usage behavior of EVs remain a challenge, and several factors influence their usage, including attitudes, perceptions, and beliefs about EVs, the availability and accessibility of EV charging infrastructure, government policies and financial incentives. To encourage the switch to sustainable transportation, it is crucial to understand the elements that affect the adoption and usage behavior of electric cars (EVs).

To achieve our research objectives, we utilized the revised UTAUT model (UTAUT2), developed by [1][2] This model allows a comprehensive analysis of factors affecting technology usage decisions, especially in a consumer context. UTAUT2 is known to provide substantial explanations of behavioral intention and technology usage. Furthermore, it is a well-validated model extensively used in various fields including Computer Science, Psychology, and Information Systems [3][4][5].

We collected data from 430 EV users in South India to examine antecedents of EV adoption and usage using the UTAUT2 model. This research not only answers the call from [2] to test UTAUT2 in South India's electric vehicle usage is explored by including different countries and technologies in the model, as well as risk factors. Considering that influencing factors vary across countries, our study aligns with [2] suggestion to examine unique constructs relevant to different research contexts. Consequently, risk factors were considered to better comprehend individual and situational characteristics in EV acceptance and usage in India, offering novel insights into user behavior.

This study is structured as follows. The first section provides a detailed literature review and conceptual framework. The research methodologies are presented in the second section. The study's results are presented in the third section. The results and their consequences are discussed in the fourth part. Our hypothesis development is assisted by its contributions to the understanding of key theoretical bases of technology acceptance. Next, the research methodology and gaps in the research are discussed. Finally, the results of this research are discussed theoretically as well as practically. Our study also acknowledges the barriers in this field and suggests potential avenues to explore further.

II. LITERATURE REVIEW

1. UNFOLDING THE LANDSCAPE OF EV ADOPTION IN SOUTH INDIA:

The use and adoption of electric two-wheelers in India have been growing steadily in recent years due to increasing awareness about environmental sustainability, government incentives, and advancements in technology. However, there are still several factors and challenges that impact the adoption and use of electric two-wheelers in India, which have been explored in the literature.

Affordability: The upfront cost of electric two-wheelers, including the cost of the vehicle, battery, and charging infrastructure, can be higher compared to traditional gasoline-powered two-wheelers. Affordability is a major barrier for many potential buyers, especially in a price-sensitive market like India.

Range Anxiety: Range anxiety, which refers to the fear or uncertainty about the limited range or distance that electric two-wheelers can cover on a single charge, is a significant concern for potential buyers in India. The availability of charging infrastructure and the need for frequent recharging may impact the adoption of electric two-wheelers, particularly for long-distance travel.

Charging Infrastructure: Charging infrastructure availability and accessibility are critical for electric two-wheeler adoption in South India. The lack of sufficient and reliable electric two-wheeler stations, long recharging times, and inadequate recharging infrastructure in certain areas may hinder electric two-wheeler adoption.

Performance and Reliability: Performance and reliability are two main factors that influence the adoption of the two-wheeler EV. Potential buyers may have concerns about the performance, speed, and durability of electric two-wheelers, such as battery life, power output, and maintenance requirements.

Awareness and Information: Lack of awareness and information about electric two-wheelers, including their benefits, features, and charging infrastructure, may impact their adoption in India. Many potential buyers may have limited knowledge about electric two-wheelers and may require education and awareness campaigns to increase their understanding and confidence in adopting this technology.

Policy and Regulatory Framework: The policy and regulatory framework for electric two-wheelers, including incentives, subsidies, and charging infrastructure development, play a crucial role in their adoption. Changes in government regulations and policies may impact the demand for electric two-wheelers in India, and uncertainties in the policy landscape may create challenges for potential buyers.

Consumer Perceptions and Attitudes: Consumer perceptions and attitudes towards electric two-wheelers, including their perceptions about the environmental benefits, performance, and reliability, may impact their adoption. Negative perceptions or misconceptions about electric two-wheelers may create barriers to their adoption and use in India.

Social and Cultural Factors: Social and cultural factors, such as societal norms, preferences, and attitudes towards electric two-wheelers, may also influence their adoption in India. Factors such as social acceptance, peer influence, and cultural beliefs about electric vehicles may impact the adoption behavior of potential buyers.

Infrastructure and Traffic Conditions: The existing infrastructure and traffic conditions in India, such as road conditions, traffic congestion, and parking facilities, may impact the adoption and use of electric two-wheelers. Adequate infrastructure and traffic conditions that support electric two-wheeler usage, such as dedicated charging stations, parking facilities, and smooth traffic flow, are crucial for their widespread adoption.

Economic Factors: Economic factors, such as income levels, affordability, and financial incentives, may impact the adoption of electric two-wheelers in India. Higher income levels, favorable financing options, and financial incentives such as subsidies, tax benefits, and lower running costs may positively influence the adoption of electric two-wheelers.

2. EXPLORING THEORETICAL PERSPECTIVES ON TECHNOLOGY ADOPTION AND UTILIZATION:

Understanding the adoption and usage of technology like electric vehicles (EVs) often relies on theoretical frameworks. These frameworks predict and explain what factors might drive individuals or organizations to accept or use EVs. Notably, there are two primary theoretical approaches.

First, some studies approach adoption from an innovation standpoint, focusing on how organizational characteristics and innovative determinants lead to widespread technology acceptance. These studies typically rely on the Diffusion of Innovation (DOI) perspective, which posits that technology adoption depends on the innovation's attributes [6][7][8]. However, the DOI doesn't fully explain how individual attitudes towards an innovation are formed and why a technology might be ultimately used or rejected.

The second theoretical approach involves use-intention models, including TPB, TAM & TRA. These theories focus on linking individual beliefs, attitudes, norms, and intentions to their behavior towards technology. However, it's important to note that these models often assume that individuals have complete control over their behaviors, which might not always be the case.

The TAM integrates elements from the TRA and the TPB and proposes that A primary belief that influences technology use is perceived ease of use [9]. Technology acceptance is considered influenced by contextual variables, including process variables, but the model omits those.

Despite the widespread use of models like the DOI and TAM, they've faced criticism for not providing a extensive approach to explain adoption and usage behaviors in consumer contexts. To address this [2] integrated various technology acceptance models to develop the UTAUT model. This model offers a more extensive evaluation of individual adoption and usage behaviors in organizational contexts, gender, Moderation by age, and experience. However, the original UTAUT model didn't account for key factors like hedonic motivation and price value (PV), which are crucial in consumer settings. These additional constructs for the consumer environment were incorporated into the model.

To encapsulate, the prime of the UTAUT2 model for this examine was determined by multiple crucial aspects. Primarily, the study's milieu focuses on consumer acceptance and utilization, a context fittingly catered to by the UTAUT2 model. Additionally, in comparison to its predecessors, UTAUT2 demonstrates a superior explained variance in both behavioral intention and actual use. Although there's a proliferation of studies implementing in various technological and research contexts, none has probed the antecedents of behavioral intention and use within the Nigerian setting using the UTAUT2 model. Furthermore, our study is customized by scrutinizing the link between behavioral intention and use, a topic that we will delve deeper into in the following section.

3. THE RISK RELATION TO USE ON ELECTRIC VEHICLES:

The use of EVs comes with various perceived and actual risks that can influence consumer decisions. These risks can broadly be categorized as technological, financial, and infrastructure related.

Technological Risks: This is a major concern for potential EV users. Consumers might worry about the longevity and reliability of the EV batteries. Replacement can be costly, which deters some users. Some people perceive the technology in EVs as being more complex than in conventional vehicles, which could discourage those who are less tech-savvy.

Financial Risks: Even though EVs can be cheaper to run over time, the initial purchase price is often higher than that of equivalent conventional vehicles. This can act as a barrier to many potential customers. As the EV market is relatively new, there's uncertainty about the resale value of these cars.

Infrastructure Risks: The lack of widespread, convenient charging infrastructure is a common concern. The worry of not being able to find a charging station when needed can deter potential users. While it's possible to charge an EV at home, a full charge can take a long time (several hours) compared to filling up a gasoline vehicle. Fast-charging options are available, but they're still not as quick as filling up a traditional car with fuel.

Behavioral Risk: People are generally habituated to using gasoline/diesel vehicles. The switch to electric vehicles involves a change in habits such as visiting gas stations, which some people might find inconvenient or unsettling. Addressing these risks is crucial for increasing the adoption of EVs. This can include technological improvements (like increasing the range of EVs and the life span of their batteries), infrastructure changes (such as installing more charging stations), and financial incentives (like subsidies or tax rebates for buying EVs). Education can also play a big role in informing potential users about the benefits of EVs and debunking common misconceptions.

The following sections are re-presenting hypotheses portraying how the UTAUT model incorporates the risk relationship.

4. RMD (RESEARCH MODEL DEVELOPMENT):

PE (Performance expectancy): PE is used to refer to "the degree to which using a technology will provide benefits to consumers in performing certain activities" [3] the belief that a technology will deliver benefits, impacts users' decision to adopt it. It's the perceived value assigned to a technology. In developing nations, studies indicate a strong association between performance expectancy and behavioral intention with various technologies, like mobile and internet banking or e-government services [10]. This factor has consistently been a key predictor of intent [11]. In the updated UTAUT2 model, it remains a significant predictor of behavioral intention [3]. We're applying this concept to EVs, hypothesizing that their performance expectancy significantly influences user adoption intention.

H1: Performance Expectancy Positively Influences Electric Vehicle Adoption Intentions.

Effort expectancy (EE): The second assessment evaluates the impact of effort expectancy on attitudes towards using electric vehicles. Effort expectancy theory addresses the amount of effort required to learn or become proficient in using a technology. This concept aligns closely with [3] Cognitive evaluations based on perceived ease of use measure how much effort individuals believe will be required to use a particular technology. The UTAUT2 theory, however, stems from the TAM. The perception of a technology being easy to use can foster positive attitudes, reduce perceived complexity, Engender feelings of comfort & enjoyment. Based on these premises, presented here is a hypothesis:

H2: Positive Correlation Between Effort Expectancy and Intent to Use Electric Vehicles.

Social influence (SI): Consumers' perception of SI is the extent to which they believe their significant others endorse their use of a product specific technology [3]. It highlights the sway of socially accepted norms and customs in guiding individual choices. Prior research indicates that social influence, particularly from friends and family, significantly impacts IT usage within the Indian context. Adoption and use of technology [14][15] increase when others use it. It has been confirmed that social influence impacts open access publishing intentions among Tanzanian academics. Consequently, within the Indian environmental Context for consumers are propose that an individual's decisions to adopt technology are likely swayed by the viewpoints of their social acquaintances [3]. Thus, our hypothesis is that:

H3: The Impact of Social Influence on Electric Vehicle Adoption Intentions.

Facilitating conditions: This research explores the influence of facilitating conditions, like the external environment and resource availability, on the use of EVs, as these can simplify the execution of an action [3]. Previous work suggests It is critical to consider facilitating conditions when adopting or utilizing technology, products, or services. The presence of supportive facilities and perceived control over the environment may cause individuals to adopt and use technology in a positive way. Facilities like these can increase readiness for adoption and use of technology by influencing preferences for capability and readiness. The following hypothesis is derived from these considerations:

H4(a): Positive behavioral intentions to utilize electric vehicles will be influenced by favorable situations.

H4(b): A favorable environment will influence how often electric vehicles are used (Hedonic motivation):

HM, the satisfaction gained from employing a technology [3], indicates the extent to which users find information system (IS) technologies entertaining. There's significant research demonstrating the positive relationship between HM and behavioral intention to adopt technology, with some studies even highlighting it as a dominant predictor. For instance, it is the second strongest predictor of behavioral intention in the UTAUT2 model [3] and has been confirmed as a vital factor in the decision to adopt mobile TV [16]. These findings emphasize the importance of designing consumer IS to meet hedonic needs, which can lead to increased adoption rates:

H5: A favorable effect of holistic motivation (HM) on behavioral intention to utilize electric automobiles.

Price value: Defined as "consumers' cognitive trade-off between perceived benefits of the applications and monetary cost for using them" [3], PV is considered positive when the perceived benefits of using a technology outweigh the monetary costs of its usage. This concept is explored from the consumer's perspective in the context of electric vehicles. Costs incurred and perceived benefits are assessed when deciding to adopt technology. If the benefits derived from a technology are high and surpass an individual's expectations, Products with elevated perceived values lead to varying levels of satisfaction. Conversely, negative perceptions about a product's price can result in individual distrust and decreased interest in its usage. However, individuals who perceive a product as cost-effective tend to display a positive attitude towards it. With these considerations in mind, the following hypothesis has been proposed:

H6: The positive impact of price value on the intention to use electric vehicles.

Habit: An additional element incorporated into the revised UTAUT2 model is 'habit,' denoting automatic behaviors performed due to acquired learning [3]. Numerous studies align with the belief that habits significantly predict behavioral intentions across diverse technologies. Nonetheless, while past behaviors frequently repeated might shape future habits, they cannot dictate them directly, since these derive from evaluative processes and are seen as significant and beneficial for predicting future actions. The research illustrates those habits, established due to technological advancements, positively Mold attitudes. The 'habit' [3] concept targets respondents experienced in electric vehicle use, and it's explored in this study in terms of past habits influencing future directions. This technology, such as traditional petroleum-based vehicles, prompts a positive evaluation. This led to the formulation of the following hypothesis:

H7a: The behavioral intention to utilize electric automobiles will benefit from habit.

H7b: Habit will have a favorable effect on how electric vehicle users behave.

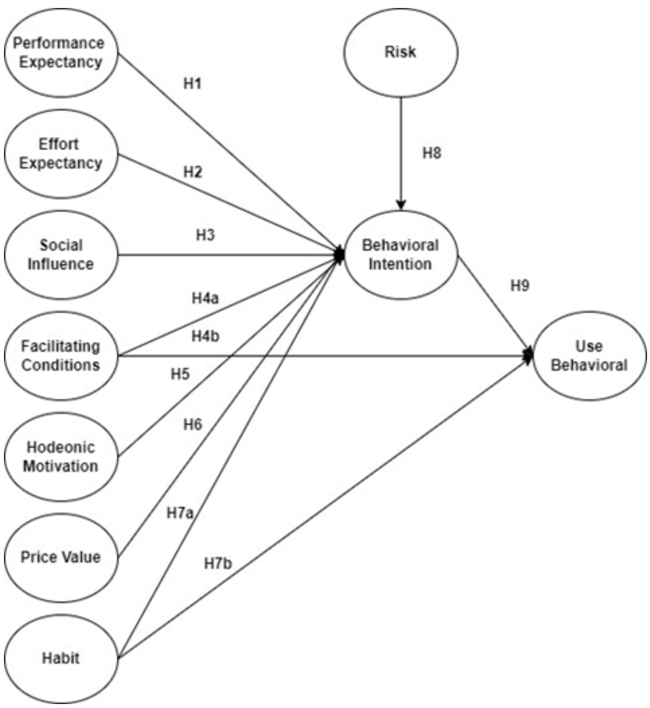

FIGURE 1. Theoretical Research Model

BI (Behavioral intention) and use behavior: The subjective probability of BI performing a behavior is referred to as technology use behavior. In line with [3], the following hypothesis is proposed: Behavioral intention will have a significant impact on usage behavior.

H8: The motive behind a behavior has a favorable effect on how an electric car is used.

Risk: Within this context, the environment plays a significant role in shaping individuals' behavior and decisions. Social values derived from others' views and opinions are deemed critical as they enhance individual confidence in decision-making, especially when these opinions come from leaders or experts. For high-value items like EV's, the perceived social risk pressure tends to be higher. However, the risk of social exclusion or negative feedback from one's social environment, such as family, friends, and co-workers, can lead individuals to resist and show negative attitudes towards innovative products. A negative response from the environment to an innovative product like an electric vehicle can trigger a similar negative reaction from potential consumers towards the product. Considering these considerations, the following hypothesis has been proposed:

H9: Risk has a negative impact on the behavioral intension to using electric vehicle.

III. METHODOLOGY

Figure 1 shows the model construct were conducted using an integrated approach to UTAT2 factors. The next subchapters explain the sample, variable concept and measurement and prepare the study instruments and method.

Sample and sampling technique: Here we used the purposive sampling judgement technique was used, which requires the respond to be at least 18 years old and above before using a vehicle and obtaining a license in India. A total of 430 samples were collected out of 418 eligible samples are where suitable for this study. From 10 major cities in south India namely, Hyderabad, Visakhapatnam, Vijayawada, Guntur, Warangal, Tirupathi, Chennai, Bangalore, Trivandrum, Coimbatore. from October 2022 to Feb 2023, using hard copies and google forms in their local language.

measurement and variable concept: Using two or more study instruments, this study measures 10 latent variables directly. Endogenous or dependent variables use behavior and mediator as behavior intension meanwhile, exogenous, or dependent on variables consist of UTAUT2 model.

Questionnaire design: The survey structure consists of two sections. The initial part focuses on gathering demographic information about the respondents. The latter section deals with the variables associated with the intention to use, which is the main subject of the study. These variables include Performance Expectancy (PE) with four questions, Effort Expectancy (EF) with four questions, Social Influence (SI) with four questions, Facilitating Conditions (FC) with six questions, HM with five questions, PV with four questions, Habit (H) with four questions, Risk (RISK) with four questions, Behavioral Intention (BI) with five questions, and Use Behavior (UB) with three questions. This results in a total of 43 questions. For this study, a 5-point Likert scale was employed, with a score of 1 representing strong disagreement and a score of 5 indicating strong agreement.

IV. ANALYSIS AND RESULTS

Partial Least Square (PLS) analysis was carried out on the data using SmartPLS 3.2.7 [17]. Formative and reflective measurements may be modelled together using PLS. In comparison to more popular covariance-based SEM approaches, it also requires fewer assumptions regarding the distribution of the data [18]. Our research model was examined using PLS in two stages: (1) assessing the measurement model, which involved determining the validity and reliability of the model's many variables; and (2) the evaluation of the structural model. These two steps constitute the method by which judgements about the potential connections between the constructs can be reached [18].

Measurement Model: Our model's reflective constructs' measurement model was evaluated for Indicator reliability, construct validity, and discriminant validity. following the framework established by [19]. The construct validity gauges the degree to which the construct's measurement aligns with the theoretical propositions tied to the phenomenon being examined [20]. In this context, composite reliability was employed to assess construct validity. the estimated values for all constructs surpassed the advocated thresholds of 0.7 [21], which signifies robust construct validity. Moreover, each construct's internal consistency also markedly exceeded the recommended minimum of 0.7 [22], reflecting strong internal coherence. Indicator reliability is indicative of the dependability of a given indicator as a measure of the target latent construct [21]. As per [23], all indicators used should have loadings greater than 0.7, a criterion that has been met in this study. We conducted an analysis of the Average Variance Extracted (AVE). This metric quantifies the proportion of variance that a given construct retrieves from its indicators compared to the measurement error [24]. Scholars posit that to affirm AVE should exceed 0.5 when constructs explain more than half their variance, the AVE values attributed to the constructs satisfied this stipulation.

Last but not least, the discriminant validity of our measurement model was evaluated, indicating how dissimilar the model's constructs are from one another [25]. To ascertain the establishment of discriminant validity among our model's constructs, we utilized two methods: the Fornell-Larcker criterion [25] and the Heterotrait-Monotrait (HTMT) ratio of correlations [26]. We determined the square root of the Average Variance Extracted (AVE) for each construct to apply the Fornell-Larcker criterion. The diagonal elements in the relevant rows and columns should be significantly larger than the off-diagonal elements for good discriminant validity [24]. As shown in This study evaluated discriminant validity using the HTMT ratio and the Fornell-Larcker criterion. The average variance extracted (AVE) for each construct must be larger than the squared correlations between that construct and all other constructs to meet the Fornell-Larcker criterion. The mean correlations across constructs measuring different phenomena divided by the mean correlations of indicators gauging the same construct must be less than 0.9 to satisfy the HTMT ratio. All reflecting constructs were determined in this study to meet both requirements, demonstrating that discriminant validity was established [22] I suggest that a more cautious 0.85 value can be used for stringent models, whereas an HTMT threshold value of 0.9 is appropriate for the UTAUT model. According to both the Fornell-Larcker and HTMT criteria, our study successfully demonstrated discriminant validity, as seen in Table 3 where all values were below the suggested level.

Table 1. Results of Confirmatory Factor Analysis for the Measurement Model

Construct	Indicator	Loading factor (λ)	CR	Cronbach's Alpha	AVE
PE	1	0.732			
	2	0.784			
	3	0.753	0.837	0.742	0.562
	4	0.730			
EE	1	0.788			
	2	0.726			
	3	0.752	0.855	0.777	0.597
	4	0.820			
SI	1	0.807			
	2	0.824			
	3	0.796			0.625
	4	0.796	0.893	0.850	
	5	0.727			
FC	1	0.846			
	2	0.848			
	3	0.861			
	4	0.872	0.932	0.909	0.732
	5	0.852			
HM	1	0.756			
	2	0.730			
	3	0.754	0.834	0.737	0.557
	4	0.745			
PV	1	0.727			
	2	0.843			
	3	0.727	0.830	0.738	0.552
	4	0.741			
H	1	0.865			
	2	0.734	0.845	0.727	0.646
	3	0.807			
BI	1	0.866			
	2	0.810	0.836	0.709	0.632
	3	0.807			

UB	1	0.845			
	2	0.857			
	3	0.811	0.889	0.834	0.668
	4	0.753			
R	1	0.774			
	2	0.841			
	3	0.810			
	4	0.817	0.902	0.864	0.648
	5	0.783			

Table 2. Evaluating Discriminant Validity Through the Fornell-Larcker Criterion.

	BI	**EE**	**FC**	**HA**	**HM**	**PE**	**PV**	**RISK**	**SI**	**UB**
BI	0.795									
EE	0.418	0.772								
FC	0.494	0.588	0.856							
HA	0.642	0.516	0.553	0.804						
HM	0.553	0.523	0.582	0.571	0.746					
PE	0.465	0.629	0.541	0.491	0.468	0.750				
PV	0.821	0.477	0.609	0.669	0.588	0.503	0.743			
RISK	0.691	0.481	0.543	0.656	0.558	0.489	0.677	0.805		
SI	0.560	0.636	0.792	0.556	0.576	0.593	0.597	0.588	0.791	
UB	0.643	0.552	0.686	0.641	0.590	0.535	0.700	0.661	0.658	0.817

Table 3. Evaluating Discriminant Validity: The Role of HTMT

	BI	**EE**	**FC**	**HA**	**HM**	**PE**	**PV**	**RISK**	**SI**	**UB**
BI										
EE	**0.544**									
FC	**0.597**	**0.703**								
HA	0.898	**0.664**	**0.659**							
HM	**0.757**	**0.698**	**0.698**	**0.775**						
PE	**0.617**	**0.827**	**0.658**	**0.665**	**0.629**					
PV	**0.733**	**0.627**	**0.743**	**0.714**	**0.795**	**0.660**				
RISK	0.891	**0.580**	**0.609**	**0.822**	**0.692**	**0.612**	**0.839**			
SI	**0.698**	**0.779**	**0.807**	**0.688**	**0.710**	**0.744**	**0.737**	**0.680**		
UB	**0.823**	**0.685**	**0.786**	**0.807**	**0.745**	**0.682**	0.883	**0.774**	**0.777**	

Structural model: The variance explained, the importance of the route coefficients (R2), and the predictive relevant Q2 value of the path model are the three key metrics we employ to evaluate the structural model [27]. We estimated T-values using 5000 resamples based on a bootstrapping approach using two-tailed distributions and two-tailed distributions (Ringle, 2016). The PLS-SEM's outcomes are detailed in table 4 and depicted in figure 2.

The research study presents a model containing eleven hypotheses, seven of which have been statistically validated through bootstrapping.

To simplify the results: 1. A positive connection exists between Behavioral Intention (BI) and Usage Behavior (UB). As a person's intent to behave in a certain way increase, their actual usage behavior follows suit. This is indicated by the Standard Beta value of 0.295 and statistically backed by a t-value of 6.148 and a P-value less than 0.05.

2. The idea that Effort Expectancy (EE) impacts Behavioral Intention (BI) is not statistically significant, proven by a P-value of 0.173, which is above the accepted threshold.

3. Facilitating Conditions (FC) negatively impact Behavioral Intention (BI). In simpler terms, as facilitating conditions increase, behavioral intentions decrease. This is supported by a t-value of 3.296 and a P-value less than 0.05.

4. Facilitating Conditions (FC), however, have a positive effect on Usage Behavior (UB), backed by a t-value of 8.520 and a P-value less than 0.05.

5. The theory that Habits (HA) influences Behavioral Intention (BI) doesn't stand up to statistical scrutiny (P-value is 0.085). However, a positive connection exists between Habit (HA) and Usage Behavior (UB), supported by a t-value of 4.268 and a P-value less than 0.05.

6. The influence of HM and Performance Expectancy (PE) on Behavioral Intention (BI) does not meet the statistical significance threshold with P-values of 0.166 and 0.493 respectively.

7. Strong positive correlations exist between PV, Risk, and Social Influence (SI) with Behavioral Intention (BI). As these factors increase, so does BI, each substantiated with t-values and P-values less than 0.05.

Table 4 containing 'f2' values signifies the effect sizes for each relationship, showcasing the strength of these relationships within

the model. To give a sense of scale, 0.03, 0.16 and 0.34 are considered as small, medium, and large effects. To evaluate the model's quality, the coefficient of determination (R2) is considered, which reflects the amount of explained variance for each variable (Hair, 2014). R2 values of 0.68, 0.32, and 0.18 represent large, moderate, and weak explanations of variance [27].

Table 4. Outcome Analysis of the Structural Model Assessments

Direct relationships	Standard Beta	t-value (bootstrap)	*f2*	P Values	Hypothesis validation
BI -> UB	0.295	6.148	0.127	0.000	Supported
FC -> BI	-0.171	3.296	0.035	0.001	Supported
FC -> UB	0.418	8.520	0.303	0.000	Supported
HA -> UB	0.220	4.268	0.065	0.000	Supported
PV -> BI	0.623	13.050	0.559	0.000	Supported
RISK -> BI	0.200	4.233	0.063	0.000	Supported
SI -> BI	0.142	2.553	0.022	0.011	Supported
HM -> BI	0.058	1.387	0.006	0.166	Not supported
PE -> BI	0.027	0.686	0.001	0.493	Not supported
HA -> BI	0.095	1.720	0.014	0.085	Not supported
EE -> BI	-0.062	1.362	0.007	0.173	Not supported

Note: Bootstrap is based on 5000 resamples; f2 = effect size, with cut-off values of 0.02, 0.15 and 0.35 indicating weak, moderate, and strong effects respectively.

Table 5, In terms of indirect effects on Usage Behaviour (UB) via Behavioural Intention (BI), here are the highlights: Effort Expectancy (EE), Habit (HA), HM, and Performance Expectancy (PE) do not have statistically significant indirect effects on UB through BI (P-value > 0.05). However, Facilitating Conditions (FC), Risk, and Social Influence (SI) do display significant indirect effects on UB through BI (P-value < 0.05). This implies that these factors, when acted through BI, have an impact on UB.

Table 5. Indirect effects of the predictors of use behaviour

Indirect effects	Standard Beta	t-value	p-value
EE -> UB	-0.018	1.356	0.175
FC -> UB	-0.050	2.802	0.005
HA -> UB	0.028	1.696	0.090
HM -> UB	0.017	1.303	0.193
PE -> UB	0.008	0.678	0.498
PV -> UB	0.184	5.453	0.000
RISK -> UB	0.059	3.461	0.001
SI -> UB	0.042	2.350	0.019

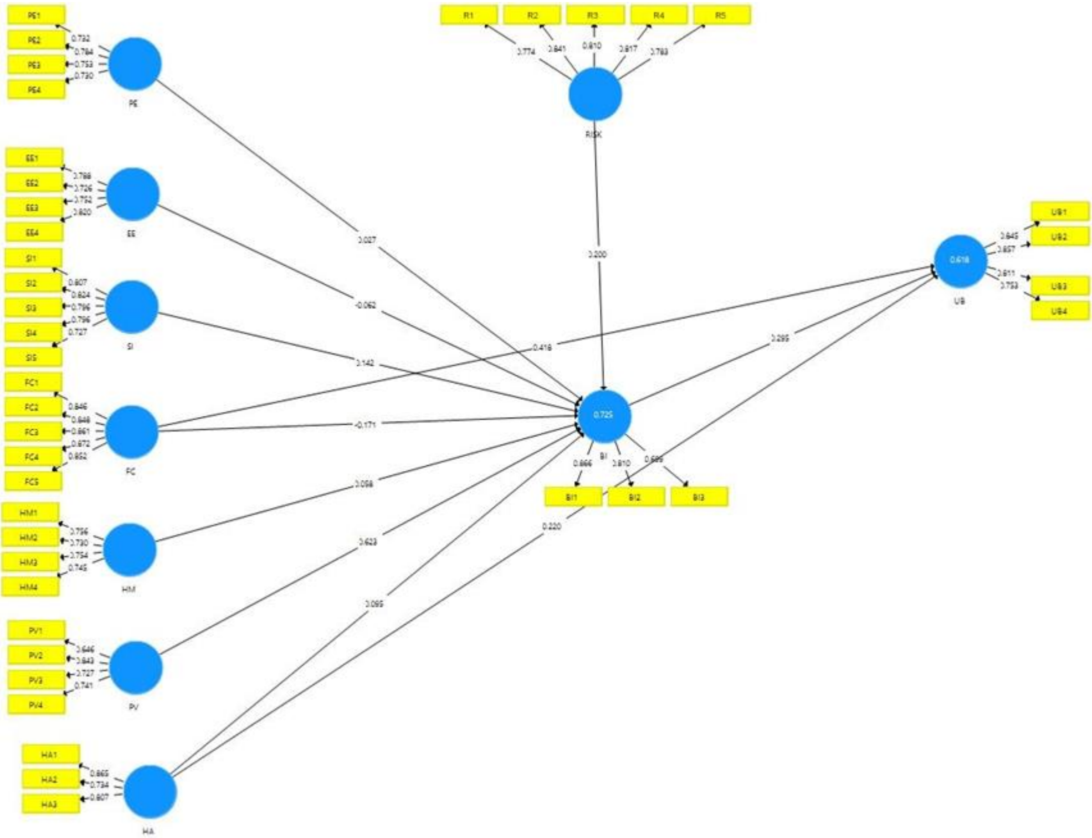

FIGURE 2. PLS-SEM structural model Results

V. DISCUSSIONS

The present study conducts a comprehensive analysis an UTAUT2 model, exploring behavioral intentions and usage behaviors within the context of vehicle usage in South India. The research encompasses several key factors.

The results disclose support for seven hypotheses out of the total eleven. Notably, a positive correlation emerges between behavioral intention and actual usage, indicating that as behavioral intention increases, the likelihood of practical usage also rises. Facilitating conditions exhibit a negative influence on behavioral intention, suggesting that an increase in facilitating conditions corresponds to a decrease in behavioral intention. However, facilitating conditions positively impact usage behavior. Habit demonstrates a positive association with usage behavior. Furthermore, PV (Perceived Value) significantly influences behavioral intention, and a positive relationship is observed between risk and behavioral intention. Finally, social impact operates a beneficial impact on behavioral intention.

Surprisingly, contrary to initial expectations, both effort expectancy and HM do not significantly affect behavioral intention. Additionally, performance expectancy is found to have no substantial impact on behavioral intention. This indicates that the vehicle usage, the performance expectancy, ease of use and the pleasure derived from system usage HM may not act as strong determinants of behavioral intention.

Overall, this study provides valuable insights into the factors influencing vehicle utilization behavior in the Indian context. Such findings hold significance for policymakers, urban planners, and transportation companies aiming to comprehend user behavior and devise effective strategies. The limitations of the study include its geographical focus on South India and the reliance on self-reported data. Future research could incorporate a more diverse demographic and potentially include other modes of transportation.

VI. CONCLUSIONS

In conclusion, this analysis provides significant highlights into the acceptance of own electric vehicles among users in South Indian cities. By utilizing the UTAUT2 model, we were able to identify key determinants that influence users' behavioral intentions towards electric vehicle usage. Our findings UTAUT2 factors significantly shape users' intent to use their own electric vehicles. Interestingly, in contrast to prior literature, we found that the risk construct positively correlates with behavioral intention, suggesting that perceived risk might act as a stimulus rather than a barrier in the context of electric vehicle usage in South India. However, certain elements from the UTAUT2 model, such as habit, did not affect behavioral intentions in this setting, hinting that cultural, demographic, or regional factors may play a part when implementing this model.

This study offers significant implications for policymakers, car manufacturers, and energy suppliers. Policies should aim to lower the cost of electric vehicles, enhance infrastructure, and inform the public about the advantages of electric vehicles. Despite the valuable insights gained, the study is not without its limitations, thus paving the way for future research. More studies are needed to corroborate these findings in different geographical areas, with larger sample sizes, considering more demographic variables and other potentially influential factors. In summary, this study mainly concerns the user perceptions in adopting advanced technology, particularly in the circumstance of sustainable development, and advocates for additional research in this intriguing and pressing area.

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