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Odisha's Path To Green Mobility: A Study On Consumer Adoption Of Electric Cars

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Abstract

Electric cars are driving a significant shift in consumer adoption as more people are transiting themselves from traditional internal combustion engine vehicles to embrace the promise of cleaner and sustainable transportation. This study investigates the key factors influencing the consumer adoption of electric cars in Odisha. Based on the theory of unified theory of acceptance and use of technology 2(UTAUT 2) , Theory of planned behavior, Value belief norm theory a conceptual framework is developed with 3 additional constructs namely :- Brand anthropomorphism, Brand love, , and status motivation . A cross sectional design is formulated in the study with the method of purposive sampling.Data is collected from 12 districts of Odisha with the sample of 400 respondents. Data were analysed using the method of Partial least square structural equation modelling using SMART PLS 3, to test the hypothesis and conceptual model.The findings revealed Performance expectancy, Effort expectancy, Hedonic motivation, Price value, Facilitating condition, Attitude, Brand love, Brand anthropomorphism, Biospheric values and Status motivation positively influence consumer adoption. Simultaneously , the Researcher analyzed the effect of control variables on consumer adoption and findings signifies that Gender specially Males, Age group of people within 28-40, married people, Govt / private job holders, Peoples having monthly household income between Rs. 50,000 – 1,00,000, Car users having previous driving experience, and the person's having more than one car in household have significant influence on consumer adoption of electric cars.

Keywords : Electric cars, Electric Vehicles, Consumer adoption, Battery electric vehicles, Hybrid electric vehicles

Introduction

Electric car registrations soared to nearly 14 million globally in 2023, with 95% of these sales occurring in China, Europe, and the United States. This increase pushed the total number of electric cars on the road to 40 million, closely following the 2023 projections from the Global EV Outlook .(International Energy Agency, 2023)The 2023 figures marked a substantial 35% rise from 2022, adding 3.5 million new electric cars and exceeding the number sold in 2018 by more than six times. Weekly new registrations surpassed 250,000, outpacing the entire annual total of new electric cars from 2013. In 2023, electric vehicles represented approximately 18% of all car sales, up from 14% in 2022 and just 2% in 2018. This significant growth highlights the ongoing expansion and maturation of the electric car market, with battery electric vehicles making up 70% of the electric car fleet in 2023. In India, electric car registrations surged by 70% year-on-year to 80,000 in 2023, a sharp contrast to the under 10% growth rate for total car sales. Electric vehicles comprised around 2% of all cars sold.(Energy Agency, 2024) This boost in demand has been driven by several factors, including purchase incentives from the Faster Adoption and Manufacturing of Electric Vehicles (FAME II) scheme, supply-side support through the Production Linked Incentive (PLI) scheme, tax benefits, and the Go Electric campaign. Additionally, the popularity of new models such as Mahindra's XUV400, MG's Comet, Citroën's e-C3, BYD's Yuan Plus, and Hyundai's Ioniq 5 has contributed to this growth compared to 2022. However, potential changes in the forthcoming FAME III scheme, including a possible reduction in subsidies as suggested by the 2024 budget, could impact future growth. Local manufacturers have retained a significant market share, buoyed by favorable import tariffs, accounting for 80% of cumulative electric car sales since 2010, with Tata leading at 70% and Mahindra at 10%. India is making bold strides in tackling oil dependency, greenhouse gas emissions, and urban air pollution by embracing alternative fuels and vehicles as pivotal solutions for decarbonizing its transport sector. Electric vehicles (EVs)—including hybrid EVs (HEVs), plug-in hybrid EVs (PHEVs), battery EVs (BEVs), and fuel cell vehicles (FCVs)—are gaining significant traction from government bodies, industry leaders, and researchers alike(Babaee .S et al., 2014,, Hossain MS et al., 2022). As the world's third-largest carbon emitter, India has committed to ambitious climate goals, pledging to meet the Nationally Determined Contributions (NDCs) for 2030 (Vikaspedia, 2014) and achieve carbon neutrality by 2070 (Viswanathan.R et al., 2021), as announced at the UN Climate Change Conference (COP26) in Glasgow. To support these targets, India's national and regional policies are strategically focused on advancing EV adoption. Initiatives like the National Electric Mobility Mission Plan (NEMMP) and the Faster Adoption and Manufacturing of Hybrid and Electric Vehicles in India (FAME I and II) aim to roll out 7,000 e-buses, 550,000 passenger EVs, and 1 million two-wheeler EVs, with an investment of US$1.4 billion in passenger vehicle electrification for 2022 .(Intelligence M. electric vehicle market report) Additionally, recent policy advancements are set to ensure that India sources 50% of its energy from renewable resources and cuts 1 billion tons of CO_2 emissions by 2030 (Energyworld Myth report), paving the way toward its net-zero emissions goal by 2070 (Sunitha N. 2021). To drive this transformation, India is also implementing sub-national policies designed to stimulate EV demand, bolster local manufacturing, enhance research and development (R&D), and improve infrastructure. States such as Odisha are actively developing their EV strategies, with additional incentives anticipated to follow suit.

Odisha Electric Vehicle Policy 2021

Odisha Electric Vehicle Policy, 2021, introduces a range of compelling incentives to boost the adoption of electric vehicles in the state. Among these, state government employees are eligible for 100% interest-free loans for purchasing electric vehicles, while individuals buying personal EVs can benefit from a 5% interest subvention over four years. The policy encourages government departments and public sector undertakings to prioritize electric vehicles for official use, extending the same purchase incentives to private buyers. To support personal EV owners, municipal authorities will provide subsidized parking, with individual towns and cities creating plans to accommodate on-street parking and charging stations for electric vehicles. OEMs are required to register their electric vehicle models, including those with swappable batteries, with the Transport Department . The policy sets specific performance criteria for electric two-wheelers to qualify for incentives, including a minimum top speed of 40 km/hour, an acceleration rate of 0.65 m/s^2, and a maximum energy consumption of 7 kWh/100 km, with a mandatory comprehensive warranty of at least three years from the manufacturer. These standards apply to both Fuel Cell Electric Vehicles (FCEVs) and Battery Electric Vehicles (BEVs) equipped with advanced battery technology comparable to or better than Lithium-Ion batteries.Incentives are particularly focused on two-wheelers, three-wheelers, and light motor vehicles (LMVs), offering a reduction on vehicle costs up to 1.50,000 for electric cars / four-wheelers. Additionally, the policy provides open permits for electric autos, giving drivers the flexibility to operate these vehicles. These measures are designed to promote a shift towards electric mobility, reduce vehicular pollution, and foster sustainable transportation across Odisha.

Electric vehicles (EVs) have sparked considerable interest worldwide, yet in India, they remain an emerging concept with limited research on the factors influencing consumer adoption and acceptance (Bhat et al., 2022; Sahoo et al., 2022; Jaiswal et al., 2021; Shalender and Sharma, 2021; Khurana et al., 2020). While countries like China, the USA, and Europe have already made significant strides in integrating EVs into their automotive markets, the Indian industry is just beginning to explore this innovative technology (Singh et al., 2021). Recognizing the immense potential of EVs, the Government of India (GoI) has launched targeted strategies and policies to accelerate their adoption (Sahoo et al., 2022). Despite the clear global benefits of EVs in promoting environmental sustainability and advancing transportation systems, achieving widespread public and consumer acceptance in India is crucial to drive this transition (Rezvani et al., 2015). Ultimately, the decision to adopt EVs hinges on individual choices and consumer preferences, which will play a pivotal role in shaping the future of this technology in the country. Several researchers have explored electric car adoption intention from an individual perspective, focusing on the factors that influence adoption behavior (Singh et al., 2020; Kumar and Alok, 2020; Huang and Ge, 2019). These factors have been categorized into self-interest factors (Xia et al., 2022; Asadi et al., 2021; Singh et al., 2020) and socio-psychological factors (Jain et al., 2021; Shalender and Sharma, 2021; Adnan et al., 2018). The analysis of Electric car adoption is predominantly based on models that emphasize self-regarding aspects, such as social cognitive theory (Jaiswal et al., 2022; Wang et al., 2021), the theory of planned behavior (TPB) (Asadi et al., 2021; Sahoo et al., 2022; Jayasingh et al., 2021; Shalender and Sharma, 2021; Huang and Ge, 2019; Haustein and Jensen, 2018), the theory of reasoned action (Malik and Yadav, 2021; Alzahrani et al., 2019; Nosi et al., 2017), innovation diffusion theory (Verma et al., 2020; Tu and Yang, 2019), consumption value theory (Han et al., 2017), the technology acceptance model (Adu-Gyamfi et al., 2022; Jaiswal et al., 2021; Wu et al., 2019; Wang et al., 2018), and the unified theory of acceptance and use of technology (UTAUT) (Zhou et al., 2021; Gunawan et al., 2022; Abbasi et al., 2021; Khazaei and Tareq, 2021; Bhat et al., 2022; Jain et al., 2021). Several researches have done on the basis of value belief norm theory (Stern et al., 1999) to find the consumer's pro environmental behaviour and its consumer adoption on the basis of altruistic values, biospheric values, egoistic values. Biospheric values of consumers intends to influence consumer adoption of eco friendly products. Likewise several research have done on the basis of value belief norm theory to find out the impact of consumer adoption of electric vehicles (Lee et al., 2023). The study find outs biospheric values of consumers strongly influene consumer purchase of electric vehicle. Researches examining the relationship between brand love and consumers' emotions has yielded mixed findings. Some studies suggest that brand love indirectly influences consumers' well-being (Junaid et al., 2020) and other positive emotions(Bigne E. et al 2020). Conversely, other evidence highlights the significance of customer happiness with service facilities in fostering brand love (Kumar A et al 2021). When customers are happy, they tend to view everything around them more positively, and this upbeat mindset can favorably influence their future purchase decisions. Building on previous research, the current study proposes that customer happiness has a direct impact on brand love, particularly when it comes to high-involvement products. Anthropomorphism refers to the inclination to attribute human traits, motivations, intentions, and emotions to non-human entities (Epley, Waytz, & Cacioppo, 2007). While this concept is commonly encountered in literature and everyday life, it has gained significant attention from social psychologists in the twenty-first century, particularly in relation to brand anthropomorphism and its influence on consumer behavior. Aaker (1997) was the first to identify five dimensions of brand personality and explore the psychological process of assigning personalities to brands, a concept known as animism (Guthrie, 2000). Fournier (1998) described brand anthropomorphism as a form of animism that establishes a brand-as-partner relationship, whereas Freling and Forbes (2005b) viewed anthropomorphism as a natural human tendency to perceive brands as entities with distinct personalities. They further demonstrated that brand personality has a positive effect on product evaluations (Freling & Forbes, 2005a). Status concerns are frequently cited as a key driver behind car purchases and usage (see, for instance, Gatersleben, 2011; Griskevicius et al., 2010; Johansson-Stenman & Martinsson, 2006). These discussions often describe status in terms of various associations, such as "speed, home, safety, sexual desire, career success, freedom, family, masculinity, and genetic breeding" (Sheller & Urry, 2000, p. 738), or evoke feelings of being "special, influential, competent, powerful, proud, superior, successful, and sophisticated" (Gatersleben, 2011, p. 142). A notable gap exists in the existing literature, particularly regarding the integration of the UTAUT 2 theory, Value-Belief-Norm (VBN) theory, and the Theory of Planned Behavior (TPB) in the context of electric cars. Furthermore, research exploring the intersection of electric vehicle adoption with concepts like brand love, brand anthropomorphism, and status motivation remains limited. To address this gap, we developed a conceptual model (Figure 1) that incorporates key variables from these theories. Specifically, we draw on the attitude component from the Theory of Planned Behavior, as well as habit and social influence from UTAUT 2, recognizing that these variables are less relevant to our specific research focus. Additionally, we include biospheric values from the Value-Belief-Norm theory, given their significant impact on consumer behavior and preferences, particularly concerning environmental sustainability.

Literature Review

Bhat et al. (2022) utilized the UTAUT model to investigate electric vehicle (EV) adoption among Indian consumers. Similarly, Jain et al. (2021) applied an integrated UTAUT model to predict Electric vehicle adoption intentions in India, incorporating factors like environmental concern, perceived risk, and government support. However, these studies did not address key factors such as price value (PV), habit (HB), and hedonic motivations (HM). Zhou et al. (2021) employed the UTAUT2 model to study Electric vehicle adoption among taxi drivers in China, while Khazaei and Tareq (2021) examined Electric vehicle adoption in Malaysia using the same model, though they did not include variables like effort expectancy (EE), HB, and PV. Gunawan et al. (2022) integrated the UTAUT2 and TPB models to analyze Electric vehicle adoption from an Indonesian perspective. Wahl et al. (2020a) developed an integrated UTAUT-NAM model, revealing that performance expectancy (PE), EE, facilitating conditions (FCs), social influence (SI), and personal norms (PNs) have a significant impact on Electric vehicle adoption. Extensive research utilizing Schwartz's norm-activation theory, Stern's value-belief-norm theory, or hybrid frameworks has consistently demonstrated that personal norms play a crucial role in explaining variations in pro-environmental behavior across diverse contexts . Both the norm-activation theory and the value-belief-norm theory underscore the significance of deep-seated values and environmental beliefs as foundational elements that shape personal norms, which subsequently guide pro-environmental actions. Nonetheless, empirical evidence indicates that individuals often exhibit inconsistent pro-environmental behavior across different domains . This inconsistency has prompted some scholars to challenge the normative behavioral theories' premise that a single, intrinsic motivational core underlies various pro-environmental behaviors . The Theory of Planned Behavior (TPB) posits that personal norms (BIN) are the most influential predictor of individual behaviors. Building on the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1977), which identified attitude toward the behavior (ATTB) and subjective norms (SBN) as key determinants of behavior, TPB refines and extends this model by introducing perceived behavioral control (PBCL) as an additional variable. As a result, TPB delineates ATTB, SBN, and PBCL as the three fundamental components shaping an individual's behavioral intentions. In this framework, ATTB represents the extent of positive or negative feelings an individual holds toward specific behaviors

Performance expectancy and Consumer adoption

Performance expectancy (PE) refers to the extent to which an individual believes that switching to an electric vehicle (EV) will enhance their performance compared to internal combustion engine vehicles (ICEVs) (Gunawan et al., 2022; Abbasi et al., 2021). This belief encompasses the idea that EVs can offer cost savings, time efficiency, a superior alternative to ICEVs, and environmental benefits. Research by Gunawan et al. (2022), Abbasi et al. (2021), Jain et al. (2021), Lee et al. (2021), and Wahl et al. (2020a) has shown that performance expectancy is a statistically significant factor influencing the intention to adopt EVs.

Effort expectancy and Consumer adoption

Effort expectancy (EE) measures how easy it is to use an electric vehicle (EV) (Abbasi et al., 2021; Jain et al., 2021). The likelihood of adopting EVs is influenced by how effortless consumers perceive the usage of these vehicles to be. Abbasi et al. (2021) found a strong link between ease of use and the intention to adopt EVs. Similarly, Lee et al. (2021) confirmed that a positive perception of ease of use significantly boosts the intention to adopt EVs.

Facilitating condition and Consumer adoption

Facilitating conditions (FC) refer to the extent to which a potential customer believes that the necessary infrastructure or technical support is available to use a technology (Khazaei and Tareq, 2021; Venkatesh et al., 2012). For electric vehicles (EVs), this includes having access to essential resources like charging stations, service centers, and guidance on using the technology, as well as ensuring compatibility with other equipment and having convenient parking with charging facilities. Gunawan et al. (2022) and Zhou et al. (2021) emphasize that having these support systems in place significantly impacts a consumer's intention to adopt EVs. Users who can access these facilities are more likely to have a positive intention toward using EVs.

Hedonic motivation and consumer adoption

Hedonic motivation (HM) refers to the pleasure, fun, and enjoyment that comes from using an electric vehicle (EV) (Gunawan et al., 2022). For EVs, this means experiencing the joy of driving a vehicle that stands out from traditional cars, finding excitement in the new technology, and having a preference for the enjoyable aspects of owning and using an EV

Price value and consumer adoption

Price value (PV) refers to how customers assess the price of a product or service in relation to its perceived worth (Kim et al., 2018). For electric vehicles (EVs), this includes comparing the purchase price of EVs to internal combustion engine vehicles (ICEVs), evaluating the value for money that an EV offers, and assessing whether the EV's current price reflects its value (Zhou et al., 2021). PV is crucial in shaping consumers' decisions about EVs, as a higher perceived value makes an EV more attractive for purchase (Kim et al., 2018). For instance, PV has been shown to positively influence attitudes toward EV adoption among taxi drivers (Zhou et al., 2021).

Attitude and Consumer adoption

Researchers such as Ajzen and Fishbein (2005) and Crites, Fabrigar, and Petty (1994) have refined the concept of attitudes towards behaviors into two key dimensions: instrumental and experiential. Instrumental attitudes focus on whether an action is viewed as desirable or undesirable, while experiential attitudes concern whether it is perceived as pleasant or unpleasant. In a related approach, Van der Laan, Heino, and De Waard (1997) described attitudes towards objects as predispositions that guide responses, framed as tendencies toward "approach or avoidance" and "favorable or unfavorable" (Van der Laan et al., 1997, p. 2). They identified two essential dimensions—satisfaction and usefulness—that capture the attitudinal acceptance of technological innovations. This sophisticated understanding of attitude has been successfully applied in studies on battery electric vehicles (BEVs), demonstrating its relevance in evaluating emerging technologies (e.g., Bühler, Cocron, Neumann, Franke, & Krems, 2014).

Biospheric Values and Consumer adoption

Boomsma and Steg (2014) describe biospheric values as embodying a fundamental belief in the importance of environmental protection as a life goal. These values have been shown to significantly influence preferences for eco-friendly products, intentions, and attitudes toward sustainable behaviors, as well as shape environmentally relevant norms. For example, individuals with strong biospheric values are more inclined to consume organic food (Soyez, 2012) and select environmentally friendly options (Haws et al., 2014). . Overall, biospheric values encapsulate a broad spectrum of motivations for green behavior, positioning them as a more comprehensive predictor of environmental norms and intentions than other influences like concerns or worldviews (Steg, de Groot, Dreijerink, Abrahamse, & Siero, 2011).

Brand love and consumer adoption

Carroll and Ahuvia (2006) characterize brand love as "the emotional and passionate connection an individual feels toward a brand." Roy et al. (2013) delved into the factors that shape consumer brand love and the subsequent outcomes. In a similar context, Albert et al. (2013) explored consumer brand love through the lens of brand passion. Thus, for the current study, brand love is defined as "a deep emotional and passionate attachment to a brand that can potentially result in long-term commitment or loyalty

Brand anthropomorphism and consumer adoption

Puzakova et al. (2009) define anthropomorphized brands as those for which consumers attribute human traits, including a range of emotional states, consciousness, and behaviors. In marketing, brands often employ various forms of anthropomorphism, such as using human endorsers or designing packaging with human-like features. For example, the brand Paper Boat uses packaging that evokes human characteristics, influencing consumers to perceive the brand as having human-like qualities, thereby enhancing brand anthropomorphism.

Status motivation and Consumer adoption

The perception of cars and driving as indicators of status has evolved significantly over time. Initially, the association between automobiles and social standing was closely tied to inherited class and elite social groups (Berger, 1986). However, this focus on inherited social distinctions diminished throughout the twentieth century and by the 1990s had largely shifted (Dittmar, 1992; Shaw & Docherty, 2014). The rise of global neoliberalism brought about a new emphasis on personal economic success, leading cars to become symbols of wealth accumulation and financial mobility (Dittmar, 1992; Shaw & Docherty, 2014; Turner, 1988; Watson, J., 1996). Today, contemporary discussions often view the status of cars through the lens of wealth (Gatersleben, 2011; Griskevicius et al., 2010; Johansson-Stenman & Martinsson, 2006; Mann & Abraham, 2006

Research question

1:- What are the factors influencing Consumer adoption of electric cars in Odisha ?

Research Objectives

1:- To analyze the factor influencing consumer adoption of electric car in Odisha

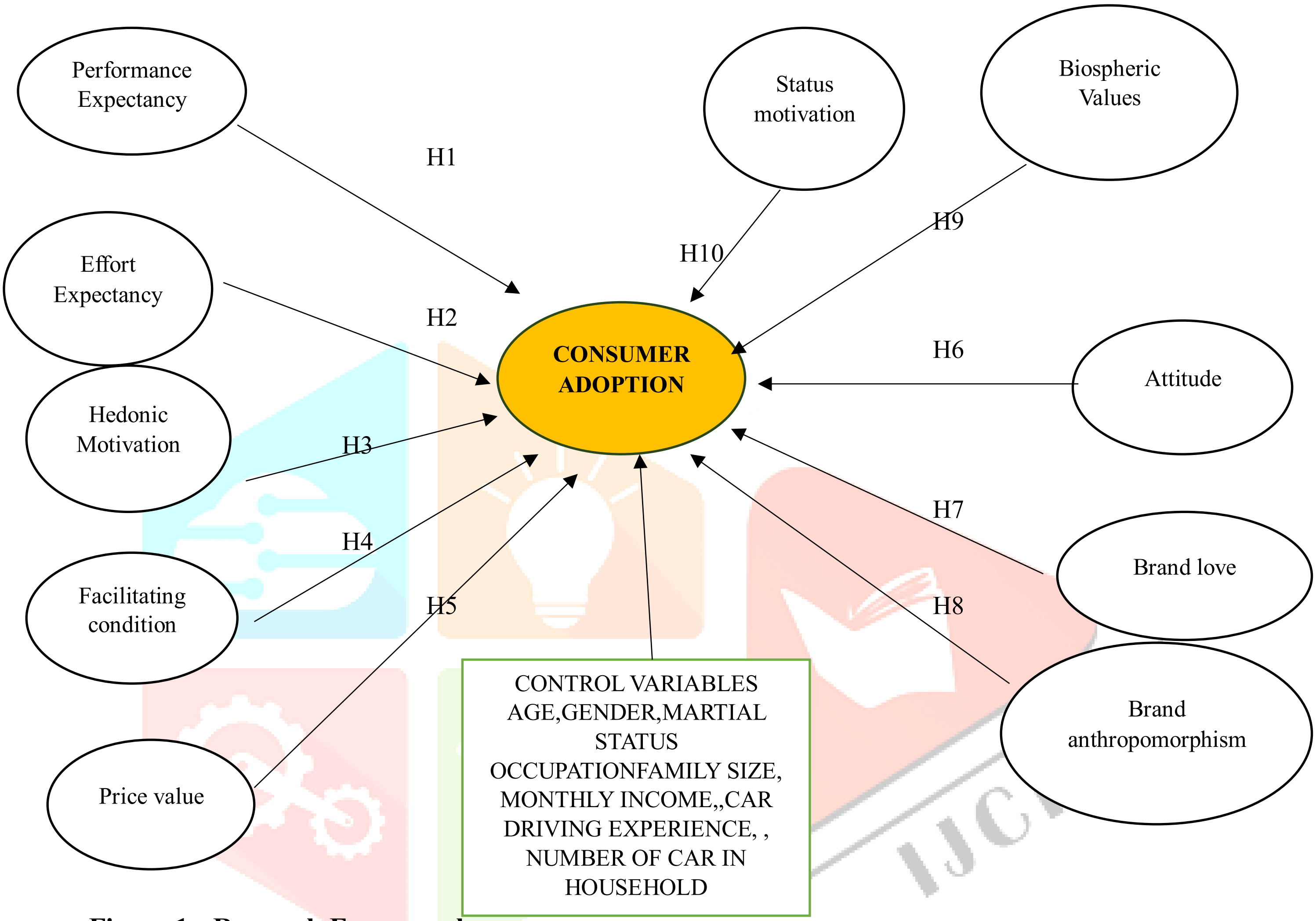


Figure 1 : Research Framework

Research Hypothesis

1:- Performance expectancy have a significant positive effect on Consumer adoption of electric car

2 :- Effort expectancy have a significant positive effect on Consumer adoption of electric car

3:- Hedonic motivation have a significant positive effect on Consumer adoption of electric car

4:- Facilitating condition have a significant positive effect on Consumer adoption of electric car

5:- Price value is positively linked to Consumer adoption of electric car

6 :- Attitude have a significant positive effect on Consumer adoption of electric car

7:- Brand love have a significant positive effect on Consumer adoption of electric car

8:- Brand anthropomorphism have a significant positive effect on Consumer adoption of electric car

9:- Biospheric value have a positive influence on consumer adoption of electric car

10:-Status motivation have appositive influence on consumer adoption of electric car

3.0 Research Methodology

3.1 Sampling Technique and Questionnaire

Quantitative research methodology is used to formulate the empirical analysis of consumer adoption of electric car with a cross-sectional research design is applied in the study to collect the data . The researcher used purposive sampling method to collect the data from Electric car owners of Odisha.The information is obtained from Regional transport Office of 12 districts of Odisha. A self administered questionnaire was employed to test the conceptual model, with the guidance of five experts. The questionnaire contains a good content validity index of 0.9**.** The questionnaire is divided into two parts :- First part contains the demographic characteristics of the respondents and the second part consists of items of independent, dependent variables to test the conceptual model.

3.2 Sample Size and Data Collection

The sample size was determined using Morgan's formula, indicating that 302 samples were necessary for the analysis. Data collection occurred across 12 districts in Odisha, including Khordha, Cuttack, Balasore, Mayurbhanj, Angul, Keonjhar, Puri, Berhampur, Sambalpur, Jharsuguda, Sundargarh, and Kalahandi, between July and August 2024. Initially, 425 responses were gathered through an offline survey questionnaire. After data cleaning and eliminating invalid entries, 400 responses were considered suitable for the final analysis.

3.3 Measurement scale and Construct Operationalization

A Likert 5 point scale was used for all the variables in our study . The scale ranged from 5 i.e., Strongly agree to 1 i.e., Strongly disagree. Performance expectancy variables was to be measured using 5 items . Effort expectancy was measured using 4 items, Hedonic motivation measured using 4 items ,Facilitating condition was measured with 4 items,Price value was measured using 5 items, Similarly attitude was measured with 4 items, likewise brand love, brand anthropomorphism, biospheric values, status motivation all are measured with 4 items . All the scale items for the questionnaire are taken from previous studies.

3.4 Characteristics of Demographic Respondents

The Characteristics of demographic respondents are elaborated in Table 1. The respondents consist of 240 males (60%) and 160 females (40%) . The age of the respondents are classified in 3 groups which are 18-27, 28-40, 41-60. The age group of the people between 28-40 are maximum in number (N = 180, 45%). Researcher has classified the occupation into three categories :- Government/ private job, Businessman, and Housewife. In which the categories of people having government/private job are maximum (N=270, 67.5%), likewise the married people have maximum ownership of electric car (N = 300, 75%).. Monthly household income of the respondents are classified in 3 groups i.e. Rs. 50,000- 1,00,000 , 1,00,001-1,50,000, more than 1,50,000, in which the people earning between Rs.50,000- 1,00,000 are highest (N=220, 55.5%). The electric car users who possess previous car driving experience(N=260, 65%) are significantly higher than non previous car driving experience. The owners having more than one car in household(N= 215, 53.75%) are more in number than users having a single car.

Profile of the Respondents	Frequency (N=400)	Percentage
Gender		
Male	240	60
Female	160	40
Age		
18-27	130	32.5
28-40	180	45
41-60	90	22.5
Occupation		
Government / Private job	270	67.5
Businessman	80	20
Housewife	50	12.5
Martial Status		
Married	300	75
Unmarried	100	25
Monthly household income		
Rs. 50,000 – 1,00,000	220	55
Rs, 1,00,001- 1,50,000	120	30
More than Rs.1,50,000	60	15
Previous Car driving experience		
Yes	260	65
No	140	35

Number of Cars in Household		
Only one	185	46.2
More than one	215	53.7

Table 1

3.5 Control Variables

Control variables play a crucial role in enhancing the predictive accuracy of a research model (Becker, 2005; Li et al., 2008). Several studies in the field of technology adoption have found that demographic factors such as gender, age, and educational qualifications significantly influence internet usage (Chong et al., 2012; Li et al., 2017; Teo, 2001). Hence we have taken the following demographic as control variable as Gender, Age, Occupation, Martial status,monthly household income, previous car driving experience, no. of cars in household

4.0 Data Analysis

Data analysis in this study was conducted using SmartPLS 3, developed by Ringle et al. (2015), to perform partial least squares structural equation modeling (PLS-SEM) instead of co-variance-based structural equation modeling (CB-SEM). PLS-SEM was chosen due to its advantages, such as its appropriateness for exploratory research, predictive accuracy, and flexibility in handling non-normal data and smaller sample sizes. Consequently, SmartPLS 3 was employed to test the proposed hypotheses. The analysis adhered to a two-step procedure, assessing both the measurement and structural models, as outlined by Anderson and Gerbing (1988).

4.1 Power Analysis

Hair et al. (2014) suggested conducting a priori power analysis to determine the minimum sample size needed for the study, using G*Power software (Faul et al., 2009). The analysis revealed that for a linear multiple regression model, a minimum sample size of 243 is required to detect a small effect size. Therefore, the current dataset of 400 respondents was considered suitable for validating the hypothesized model.

4.2 Multivariate normality test

Before choosing the appropriate statistical tool for data analysis, a normality test should be performed (Hair et al., 2013). Mardia's multivariate skewness and kurtosis (Mardia, 1974) were evaluated using the "web power" software (Cain et al., 2017). The p-values for both kurtosis and skewness were found to be less than 0.05, indicating non-normality in the data, likely due to the heterogeneity of responses (Singh and Srivastava, 2021).

4.3 Common Method Bias

Common method bias was identified as a potential concern (Podsakoff et al., 2003). To mitigate this bias, several measures were implemented, following the guidance of previous research (Podsakoff et al., 2003; Reio, 2010). Firstly, during data collection, the cover letter accompanying the research instrument made it clear that participation was entirely voluntary and that all responses would remain confidential. Additionally, the researchers ensured that all survey statements were clear and easy to understand. Beyond these qualitative safeguards, a quantitative check was also performed using Harman's single-factor test, where an exploratory factor analysis was conducted in SPSS 25 (Harman, 1967). The analysis revealed that the single factor accounted for 40.743% of the variance, indicating that common method bias was not a significant issue, as the total variance explained was below the 50% threshold (Chen and Hung 2016; Memon et al., 2019).

4.4 Assessment of Measurement Model

The reliability, convergent validity, and discriminant validity of the reflective measurement model were assessed using PLS-SEM, following the guidelines by Choi and Chung (2013). SmartPLS offers two key indicators to establish the internal consistency (reliability) of the constructs:

1. Cronbach's alpha (α)
2. rho_A (r A) (Hair et al., 2019)

For reliability, the values of these indicators should fall between 0.7 and 0.95 (Chin, 2010; Hair et al., 2017). As shown in Table 2, all constructs met these threshold values, confirming their reliability.

Convergent validity was evaluated based on three criteria:

1. **Outer/factor loadings for all items** should exceed 0.5 (Bagozzi and Yi, 1988) or 0.7 (Hair et al., 2013), our values ranging between 0.725 to 0.886.
2. **Average Variance Extracted (AVE)** for each construct must be greater than 0.5 (Hair et al., 2019), values ranging between 0.602 to 0.718.
3. **Composite reliability** of all constructs should be above 0.7 (Fornell and Larcker, 1981; Hair et al., 2019), values ranging between 0.857 to 0.936 (see Table 2).

Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio of correlations. According to the Fornell-Larcker criterion, the square root of each construct's AVE must exceed the correlations between constructs (Fornell & Larcker, 1981). Additionally, the HTMT value between any two constructs should be under 0.85 (Henseler et al., 2015). As demonstrated in Table 3 and Table 4, this study does not address discriminant validity.

Latent Constructs	Items	Average Variance Extracted	Cronbach alpha	Composite Reliability	rho_A	Factor/outer loadings
Performance expectancy(PE)	PE 1	0.634	0.874	0.888	0.876	0.818
	PE 2					0.802
	PE 3					0.756
	PE 4					0.834
	PE 5					0.828
Effort expectancy (EE)	EE 1	0.602	0.912	0.924	0.913	0.778
	EE 2					0.848
	EE 3					0.852
	EE 4					0.832
Facilitating condition (FC)	FC 1	0.656	0.913	0.936	0.914	0.886
	FC 2					0.734
	FC 3					0.786
	FC 4					0.775
Hedonic Motivation (HM)	HM 1	0.676	0.892	0.902	0.894	0.856
	HM 2					0.725
	HM 3					0.748
	HM 4					0.792
	HM 5					0.742
Price Value (PV)	PV 1	0.702	0.842	0.876	0.845	0.818
	PV 2					0.834
	PV 3					0.808
	PV 4					0.776
Attitude(ATT)	ATT 1	0.684	0.846	0.894	0.848	0.879
	ATT 2					0.748
	ATT 3					0.777
	ATT 4					0.886
Brand anthropomorphism (BA)	BA 1	0.646	0.894	0.902	0.896	0.862
	BA 2					0.856
	BA 3					0.777

	BA 4					0.858
Brand love(BL)	BL 1	0.718	0.874	0.892	0.876	0.872
	BL 2					0.814
	BL 3					0.892
	BL 4					0.808
Biospheric values(BV)	BV 1	0.686	0.844	0.857	0.846	0.862
	BV 2					0.846
	BV 3					0.824
	BV 4					0.808
Status Motivation(SM)	SM 1	0.702	0.866	0.912	0.868	0.848
	SM 2					0.816
	SM 3					0.774
	SM 4					0.786
CONSUMER ADOPTION(CA)	CA 1	0.672	0.892	0.902	0.894	0.822
	CA 2					0.784
	CA 3					0.846
	CA 4					0.826

Table 2

Constructs	PE	EE	FC	HM	PV	ATT	BA	BL	BV	SM	CA
PE	**0.796**										
EE	0.602	**0.775**									
FC	0.594	0.677	**0.80**								
HM	0.616	0.613	0.722	**0.822**							
PV	0.523	0.594	0.686	0.567	**0.837**						
ATT	0.602	0.606	0.609	0.595	0.624	**0.827**					
BA	0.678	0.622	0.624	0.636	0.655	0.578	**0.803**				
BL	0.588	0.613	0.714	0.555	0.456	0.567	0.624	**0.847**			
BV	0.614	0.598	0.636	0.578	0.586	0.622	0.655	0.714	**0.828**		
SM	0.637	0.633	0.682	0.602	0.454	0.677	0.688	0.702	0.599	**0.837**	
CA	0.629	0.644	0.672	0.532	0.630	0.652	0.567	0.689	0.602	0.732	**0.819**

Table 3 : Fornell Lacker criterion

Note :- Bold values represent square root of Average variance extracted , while off diagonal values represent correlation

Constructs	PE	EE	FC	HM	PV	ATT	BA	BL	BV	SM	CA
PE											

EE	0.612										
FC	0.604	0.634									
HM	0.622	0.606	0.736								
PV	0.576	0.618	0.702	0.589							
ATT	0.614	0.634	0.614	0.602	0.646						
BA	0.684	0.676	0.636	0.656	0.564	0.608					
BL	0.602	0.688	0.722	0.589	0.604	0.614	0.634				
BV	0.618	0.602	0.644	0.586	0.602	0.656	0.676	0.728			
SM	0.644	0.652	0.692	0.612	0.577	0.687	0.696	0.714	0.616		
CA	0.634	0.666	0.684	0.585	0.687	0.662	0.602	0.696	0.634	0.72	

Table 4 : HTMT criterion

4.5 Assessment of Structural Model

4.5.1 Multicollinearity

Before analyzing structural relationships, it is crucial to check for collinearity to ensure it doesn't compromise the regression results (Hair et al., 2019). Multicollinearity occurs when two or more independent variables are highly correlated, potentially leading to redundant findings. Collinearity was assessed for the inner model, with variance inflation factor (VIF) values expected to be below 3 (Hair et al., 2019) or 3.33 (Kock & Lynn, 2012). In this study, the VIF values for the inner model range from 1.00 to 3.227, indicating no collinearity issues. The model fit was then evaluated using the standardized root mean square residual (SRMR) (Henseler et al., 2016). With an SRMR value of 0.062, which is below the 0.08 threshold, it can be concluded that the model fits .

4.5.2 Coefficient of determination (R^2)

Since collinearity is not an issue in this study, the next step in structural model testing involves evaluating the explanatory power of the PLS model and the significance of the path coefficients. R^2 values are calculated to determine the model's explanatory power (Hair et al., 2019). R^2, which ranges from 0 to 1, indicates explanatory power, with higher values reflecting stronger explanatory capability—0.75 is considered large, 0.50 moderate, and 0.25 weak (Hair et al., 2019; Vinzi et al., 2010). As shown in Table 5, the R^2 value for CA is 0.696, indicating that 69.6% of the variation in CA of electric cars can be explained by the proposed model.

4.5.3 Hypothesis Testing

The path coefficients indicate the magnitude and significance of the relationships among constructs (refer to Table 6 and Figure 2). To evaluate the significance of the coefficients for each path in the research model, a bootstrapping technique was applied using 10000 re-samples (Hair et al., 2017). The structural model results reveal a positive relationship between PE and CA (H1) (β = 0.324, t = 7.105, p = 0.001). Additionally, EE is a strong predictor of Consumer adoption of electric car (H2) (β = 0.522, t = 7.209, p = 0.001). As hypothesized in H3, FC is a significant antecedent of CA (β = 0.616, t =7.039, p = 0.001). Similarly HM has a positive influence on consumer adoption (H4) (β= 0.232, t = 4.345 , p = 0.001) , likewise PV exerts a positive influence on consumer adoption (β = 0.608 , t = 2.657, p = 0.001) (H5), Attitude positively influence on consumer adoption (β = 0.567, t = 4.462, p= 0.001) (H6), BA proves to be a strong predictor of consumer adoption (H7) (β = 0.392 , t = 3.765, p = 0.001) , BL has a positive influence on consumer adoption (β = 0.385 , t = 3.782, p =0.01) (H8). BV has also significant influence on CA (β = 0.312, t = 2.867, p = 0.001) (H9) , Similarly SM has positive relationship on CA (β = 0.353, t = 3.653, p = 0.001) Hence H1, H2, H3, H4, H5 ,H6,H7,H8 are supported. Finally the proposed model also find outs the relationship of control variables in which it is identified that gender i.e., male customers (β = 0.145 , t = 3.043, p = 0.001) , martial status specially married people (β = 0.158, t = 2.045, p = 0.001), age particularly 28-40 (β = 0.127, t = 1.267, p = 3.456, p = 0.001), occupation of govt job holders (β = 0.113, t = 3.678, p = 0.001) , people having monthly household income of 50,000 – 1,00,000 (β = 0.178, t = 2.679, p = 0.001) , possess previous driving experience (β = 0.164, t = 3.564, p = 0.001), people having more than one car in household (β = 0.189, t= 2.786, p = 0.001)

Construct	R^2	Consideration of R^2	Q^2	Predictive relevance of Q2
CA	0.696	Moderate	0.482	Large predictive relevance

Table 5

Hypothesis	**Path relationship**	**Path coefficient (β)**	**t-statistics**	**p-values**	**Results**	**F^2**
H1	PE → CA	0.324	7.105	0.001	Supported	0.234
H2	EE → CA	0.522	7.209	0.001	Supported	0.365
H3	FC → CA	0.616	7.309	0.001	Supported	0.532
H4	HM → CA	0.232	4.345	0.001	Supported	0.169
H5	PV → CA	0.608	2.657	0.001	Supported	0.505
H6	ATT → CA	0.567	4.462	0.001	Supported	0.462
H7	BA → CA	0.392	3.765	0.001	Supported	0.283
H8	BL → CA	0.385	3.782	0.001	Supported	0.214
H9	BV → CA	0.312	2.867	0.001	Supported	0.202
H10	SM → CA	0.353	3.653	0.001	Supported	0.256

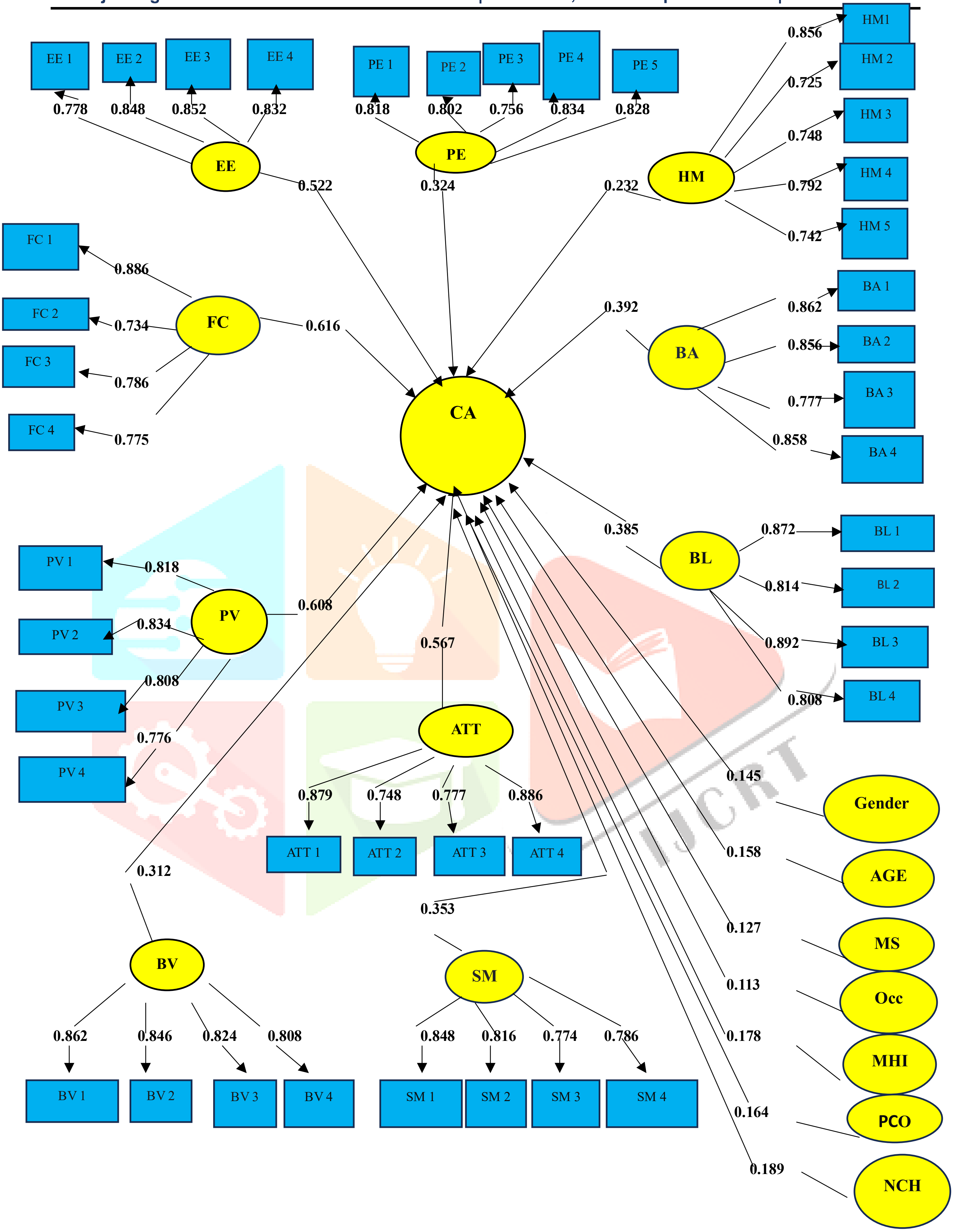
Table 6

4.5.4 Effect size (f^2)

The f^2 value evaluates the effect size of each exogenous construct in predicting the endogenous construct, as measured by R^2. According to Cohen (1988), f^2 values greater than 0.02 indicate a small effect size, values above 0.15 denote a medium effect size, and values exceeding 0.35 represent a large effect size. As from table 6 , FC and PV, ATT has strong effect size (0.532, 0.505, 0.462) while other have moderate effect

4.5.5 Prediction accuracy (Q^2)

The Q^2 value is employed to assess the predictive accuracy of the PLS path model (Geisser, 1974). Through the blindfolding procdur , Q^2 values for the endogenous variable are calculated, where values above 0, 0.25, and 0.50 indicate small, medium, and large predictive power, respectively (Hair et al.,2019 **.**Hence in table 5 value for Q^2 , estimating large predicting power


EE 1
EE 2
EE 3
EE 4
0.778
0.848
0.852
0.832
EE
0.522
PE 1
PE 2
PE 3
PE 4
PE 5
0.818
0.802
0.756
0.834
0.828
PE
0.324
HM1
HM 2
HM 3
HM 4
HM 5
0.856
0.725
0.748
0.792
0.742
HM
0.232
FC 1
FC 2
FC 3
FC 4
0.886
0.734
0.786
0.775
FC
0.616
BA 1
BA 2
BA 3
BA 4
0.862
0.856
0.777
0.858
BA
0.392
CA
BL 1
BL 2
BL 3
BL 4
0.872
0.814
0.892
0.808
BL
0.385
PV 1
PV 2
PV 3
PV 4
0.818
0.834
0.808
0.776
PV
0.608
ATT
0.567
0.879
0.748
0.777
0.886
ATT 1
ATT 2
ATT 3
ATT 4
0.312
0.353
BV
0.862
0.846
0.824
0.808
BV 1
BV 2
BV 3
BV 4
SM
0.848
0.816
0.774
0.786
SM 1
SM 2
SM 3
SM 4
0.145
Gender
0.158
AGE
0.127
MS
0.113
Occ
0.178
MHI
0.164
PCO
0.189
NCH

Discussion and conclusion

This study sheds light on the factors driving consumer adoption of electric vehicles (EVs) in Odisha, revealing a nuanced landscape shaped by both technological and psychological influences. Among the critical determinants**,** performance expectancy stands out as a key motivator. Consumers are particularly impressed by the advanced performance features of EVs, such as quick acceleration, precise steering, regenerative braking, and adaptive driving modes like sports, eco, and normal. These features not only enhance the driving experience but also align with the performance benchmarks set by traditional vehicles, thereby encouraging adoption. Effort expectancy also plays a significant role in influencing consumer behavior. The ease of driving electric cars, enhanced by cutting-edge artificial intelligence (AI) systems and intuitive software upgrades, simplifies the driving experience compared to traditional petrol and diesel vehicles. The reduced physical and cognitive demands of operating an EV make the transition more appealing to potential adopters. The impact of hedonic motivation is evident, as the enjoyment and pleasure derived from driving an electric car are powerful incentives. Features such as state-of-the-art infotainment systems, whisper-quiet cabins, and futuristic interior designs amplify the joy of driving, making electric cars not just a practical choice but an exciting one.Facilitating conditions are another crucial factor, particularly the availability of charging infrastructure. While there has been progress in Odisha, the study highlights the need for further development, especially in expanding the charging network and reducing battery refueling times. Addressing these infrastructure challenges could significantly bolster consumer confidence and accelerate adoption.The price value of electric cars, despite the high upfront cost and uncertain resale value, is positively linked to adoption. Consumers are increasingly recognizing the long-term savings associated with the low cost of electricity, as well as the environmental and economic benefits of strong hybrid electric cars. These vehicles offer features like extended battery life, regenerative braking, and seamless transitions between electric and fuel modes, making them an attractive option in the Indian market.Attitude towards electric vehicles is another powerful influence, with a growing number of consumers viewing EVs as a forward-thinking, desirable choice. This positive attitude is closely tied to brand anthropomorphism, where brands are personified and perceived as trustworthy and relatable. Companies like Tata, Mahindra, and Maruti Suzuki have successfully cultivated these brand perceptions, strengthening consumer loyalty and driving adoption.The concept of brand love also plays a significant role in adoption. Consumers’ emotional attachment to certain brands, often fueled by national pride and a sense of identity, drives their preference for domestic brands, which are seen as symbols of Indian innovation and quality.Status motivation further contributes to the appeal of electric vehicles. Owning an EV increasingly viewed as a status symbol, reflecting a commitment to modernity, technological advancement, and environmental responsibility. This desire to be perceived as progressive and eco-conscious motivates many consumers to choose electric vehicles.Lastly, biospheric values positively influence adoption, particularly among consumers who prioritize environmental sustainability. These individuals view electric vehicles as a responsible choice that aligns with their commitment to reducing their carbon footprint. Features like zero emissions, high energy efficiency, and a reduced environmental impact resonate strongly with this demographic, encouraging adoption. In conclusion, the adoption of electric vehicles in Odisha is driven by a combination of technological advancements, ease of use, emotional connections to brands, and a growing commitment to environmental sustainability. While challenges remain—particularly in expanding charging infrastructure and addressing price concerns—the overall trajectory points toward increasing acceptance and enthusiasm for electric vehicles. By addressing these challenges and capitalizing on the factors that drive adoption, stakeholders can help ensure that electric vehicles become a central component of Odisha's transportation ecosystem

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