

Driving Change of Electric Vehicles (EVs) in India: How Technology Readiness (TR) and Social Influence (SI) Moderate Electric Vehicles (EVs) Purchase Intentions

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Abstract

The Indian automotive industry shifts towards the transition from gasoline- powered vehicles to Electric Vehicles (EVs) emphasizing the understanding of key drivers for the EVs adoption. The study investigated the factors affecting EVs adoption with moderating effects of Technology Readiness and Social Influence. The study investigated how TR and SI moderated the relationship between key variables like Perceived Benefits (PB), Environmental Attitude (EA), Government Incentives (GI) and Perceived Barriers (PBA). The quantitative research approach was used to collect data from existing and non-existing EV owners. Technology Readiness (TR) was found to moderate the relationship between Perceived Benefits (PB) and Intentions to Purchase (IP) indicating technology ready people can translate their perceived benefits into purchase decision. Social Influence (SI) positively moderated the relationship between Perceived Benefits (PB) and Intentions to Purchase (IP) as well as Perceived Barriers (PBA) and Intentions to Purchase (IP) indicating individuals are highly affected by social influence to overcome their perceived barriers to purchase EVs. Technology Readiness (TR) was not found to be moderated on Perceived Barriers (PBA) and Government Incentives (GI). Social Influence (SI) was also not found to moderate on Environmental Attitude (EA).

Keywords: Electric Vehicle (EV) Adoption, Structural Equation Model, PLS-SEM, Factors Affecting EV, Moderation Analysis.

Introduction

Electric vehicles (EVs) have started catching eyes on Indian roads now a day but they are not common as compared to gasoline-powered vehicles yet. India, the third-largest car market (www.ETAuto.com, n.d.) [1] has started witnessing increased pollution in the biggest cities as the transportation industry has witnessed tremendous growth. India's automative landscape has started witnessing a tremendous transformation now a days. The adoption of electric vehicles (EVs) seems to be promising solution to reducing carbon footprints, environment concerns and growing energy security issues (Chen & Fan, 2023; X. Zhang & Zhao, 2023; Tripathy et al., 2022; Song et al., 2022) [2][3][4] 5]. Climate change has now become more serious issue and most of the governments have started making policies about protecting an environment. Adoption of EVs might seem to be a feasible outcome to reducing carbon footprints and there is a growing need to find alternative means of transportation (Digalwar & Giridhar, 2015; Kumar et al., 2015; Sonar & Kulkarni, 2021) [6][7][8]. India has joined hands with global countries in reducing carbon footprints and support green initiative by setting a target of transforming 30

percent of traditional vehicles in to EVs by 2030 (Hema & Venkatarangan, 2022) [9]. However, adoption of EVs in India is not promising as electric vehicles constituting 6.38% of total car sales of 2023 (Singh, 2023) [10]. This slow adoption of EVs in India is a complex phenomenon influenced by various factors. On one hand, the Government of India (GoI) has initiated various promotional policies like Electric Mobility Promotion Scheme (EMPS) 2024, Phased Manufacturing Programme (PMP) to promote indigenous manufacturing of EVs, Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME), National Electric Mobility Mission Plan (NEMMP) and EV30@30 Campaign (KPMG India, 2024) [11]. On the other hand, challenges such as upfront cost (Fan et al., 2021) [12], consumer skepticism and limited charging infrastructure (Albert et al., 2022) [13], battery capacity (Tu et al., 2020) [14], continue to hinder the widespread adoption of EVs in India (Javadnejad et al., 2023) [15]. Understanding the factors that hinder EV adoption in India is crucial for manufacturers, policy makers and environmentalists etc. Previous studies have explored various aspects of EVs adoption

globally, but the unique socio-economic aspect in Indian context necessitates a focused analysis. This research aims to fill that gap by providing a comprehensive analysis of the factors shaping EV adoption intentions and behaviors in India. The study employs a multi-dimensional approach, considering a range of variables that potentially influence an individual's decision to adopt an EV. These include environmental attitudes, perceived benefits and barriers, social influence, government incentives, and technology readiness. By examining these factors, a holistic picture of the EV adoption process in India can be analyzed.

Review of Literature

Many researchers (R. R. Kumar & Alok, 2020; Tarei et al., 2021; Das & Bhat, 2022) [16][17][18] have devised researches for identifying barriers that hinder the adoption of EVs in many geographical locations. R. R. Kumar and Alok (2020) [16] identified various factors which were regarded as barriers to the adoption of EVs namely resilience of charging infrastructure, dealership experience, marketing strategies, total cost of ownership and alike. In order to give ranks and identify barriers to the EV adoption in India, Tarei et al., (2021) [17] used Best-Worst Method

(BWM). After identifying barriers like cost of ownership, lack of charging infrastructure, performance and range etc., Interpretative Structural Modeling (ISM) was used to establish mutual relationship among sub-barriers. Fu et al. (2021) [19] used block-chain technology to propose private charging pile sharing system. In order to recover from the trauma of pandemic, many companies started to devise policies for the EV adoption (Razmjoo et al., 2022) [20]. Many researchers (Bhat et al., 2021; Gunawan et al., 2022; Singh et al., 2023) [21][22][23] undertaken cross-cultural studies to understand the adoption patterns of EVs. In order to understand the individual's behavior, (Barbarossa et al., 2017) [24] studied value-belief-norms (VBN) model which provides detailed information about user's belief, values and norms for their particular behavior. Many researchers considered various factors responsible for the adoption of EVs like government subsidies and incentives (Brady & O'Mahony, 2011) [25], infrastructural requirements (Langbroek et al., 2016) [26], and climate change (Vidhi & Shrivastava, 2018) [27]. In India, many policies were framed to incentivize EVs. Researchers have also identified financial assistance/incentives to consumers as main

factor for the adoption of EVs like incentives (Potoglou & Kanaroglou, 2007) [28], user preferences for BEV (battery-electric) and PHEV (plug-in electric) (Helveston et al., 2015) [29] and promotional incentives for NEV (new electric vehicle) adoption (N. Wang et al., 2017) [30].

Wang et al. (2017) [31] emphasized on three types of promotional measures to analyze the adoption of EVs namely financial incentives measures, convenience policy measures and information provision policy measures (Sun et al., 2023) [32] and also investigated user's environmental concern as moderator for the adoption of EVs. Various factors were regarded as the drivers for the huge adoption of BEVs (battery-electric vehicles) like energy efficiency, upfront cost and carbon footprints (Peters & Dütschke, 2014) [33].

Consumer intentions for the adoption of EVs are also affected/ moderated by various demographic factors like age, education and other moderators like charging infrastructure, fuel cost, environmental effect and alike (Hackbarth & Madlener, 2016) [34]. The study of Hidrue et al. (2011) [35] revealed fuel cost, charging time and driving range as the driving forces for the adoption of BEVs whereas Bühler et al. (2014) [36] 's study

revealed low noise, purchasing cost, driving range and family charging piles as the main influential factors in addition to home charging facility as main motivator for the adoption of EVs. Zhang et al. (2011) [37] argued family members, number of cars and governance policies as the main factors for the adoption of EVs (V. Singh et al., 2020) [38] whereas battery capacity (range) was to be regarded as main barrier (Adepetu & Keshav, 2017 ; Barth et al., 2016 ; Dumortier et al., 2015; Egbue & Long, 2012 ; Khazaei & Tareq, 2021) [39][40][41][42][43].

Free parking, financial incentives, preferential tax and government policies were also regarded as the positive factors for the EVs adoption (Hackbarth & Madlener, 2016; Helveston et al., 2015; Y. Zhang et al., 2011; Khazaei & Tareq, 2021) [34] [29] [37] [43]. The purchase of a product is generally affected by the individual's perception of the perceived economic benefits that the product has (Lai et al., 2015) [44]. The increasing cost of gasoline is also the main motivator for the huge adoption of EVs (Ing, 2011) [45].

Research Gap

In the context of Indian EV market, there has been a lack of comprehensive research on the

moderating effects of individual characteristics for adoption of EV although previous studies have been undertaken to examine the EV adoption in various contexts. There have been various studies on TR, its specific role for adoption of EVs in emerging markets like India is unexplored. TR's role as moderator for key variables included in the study in the context of Indian market is new. Social Influence (SI) has also been studied well in the literature, though its role in diverse culture like India is unexplored where people's norms and social effects play the most important role in the adoption intentions. Most of the studies are cross-sectional lacking proper exposure as the how these relationships among variables and moderators evolve over time. There has been a lack of comprehensive study which provides insights of how TR and SI's moderating effects on adoption intentions change as the market grow and matures as well as consumers' exposure to EV increases. India's socio-economic landscape has a vast disparity in income, technological adaptation and significant variations in adoption intentions of EVs. This necessitates more detailed study of how these factors moderate the relationships of various underlying constructs to the adoption of EVs.

Objectives

- 1) To analyze how individual and contextual variables like Perceived Benefits (PB), Environmental Attitude (EA), Government Incentives (GI) and Perceived Barriers (PBA) influence the strength and direction of relationships with Intentions to Purchase (IP) in Indian context.
- 2) To analyze how Technology Readiness (TR) moderates the relationship between key variables and EV purchase intentions.
- 3) To assess how Social Influence (SI) moderates the effects of various key constructs on the purchase intentions of EV in Indian context.
- 4) To contribute in developing effective and more targeted promotional and marketing strategies that consider moderating effects for certain individual and contextual factors for EV adoption in Indian market. Through emphasizing the above objectives, the study focuses on providing more effective and context-specific insights catered to Indian EV market. This research won't only support academic literature but also offer practical implementation for the manufacturers, policy-makers and other beneficiaries seeking to expand EV adoption across various segments in Indian market.

Hypotheses Technology Readiness (TR) as**Moderator:**

On the basis of Technology Readiness Index (TRI) by Parasuraman (2000) [46], Technology readiness increases individual's propensity to adopt new technology easily as it enhances his/her perceived benefits of technology (Son & Han, 2011) [47]. Parasuraman & Colby (2015) [48] came up with TRI 2.0 which indicates that TR significantly moderates the relationship between perceived usefulness and technology adoption intentions across various technologies. In the context of Enterprise Resource Planning (ERP) system, Godoe and Johansen (2012) [49] studied moderating effects of Technology Readiness (TR), concluding that TR strengthened the positive relationship between perceived usefulness and adoption intention. Technology Readiness (TR) also moderates the relationship between performance expectancy (e.g. perceived benefits) and intentions to use EVs for the individuals with higher TR, in the context of electric vehicles (EVs) (Higuera-Castillo et al., 2019) [50]. This indicates that TR positively moderates the relationship between Perceived Benefits (PB) and Intentions to Purchase (IP). From the work of Walczuch et

al. (2007) [51], it can be drawn that technology savvy individuals are less inclined to the perceptions of complexities of new technology. Tech savvy individuals might have more awareness and they are more responsive to the government's new policies and incentives for new technology (Claudy et al., 2015) [52]. Based on the above literature, Technology Readiness (TR) can be hypothesized as follows:

H1: Technology Readiness (TR) moderates the relationship between Perceived Benefits (PB) and Intentions to Purchase (IP) EVs indicating stronger relationship for individuals with higher Technology Readiness (TR).

H2: Technology Readiness (TR) moderates the relationship between Perceived Barriers (PBA) and Intentions to Purchase (IP) EVs, in such a manner that the relationship is weaker for individuals with higher Technology Readiness (TR).

H3: Technology Readiness (TR) moderates the relationship between Government Incentives (GI) and Intentions to Purchase (IP) EVs, in such a way that the relationship is stronger in individuals with higher Technology Readiness (TR).

Social Influence as Moderator:

Based on the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 2000) [53] and studies of Jansson et al. (2017) [54], it can be drawn that social norms positively lead to personal norms and enhance eco-innovation adoptions. Drawing from Social Cognitive Theory (SCT) by Bandura (2002) [55], and work from Axsen et al. (2013) [56], highlighted how social influence affected perceived benefits of EVs. On the basis of Diffusion of Innovation Theory (DIT) by Rogers (2003) [57] and work from Arts et al. (2011) [58], it can be viewed how social influence could help remove perceived barriers to the technology adoption. Based on the above literature, Social Influence (SI) can be hypothesized as follows:

H4: Social Influence (SI) positively moderates the relationship between Environmental Attitudes (EA) and Intentions to Purchase (IP) EVs, in such a way that the relationship is stronger for individuals with higher SI.

H5: Social Influence (SI) positively moderates the relationship between Perceived Benefits (PB) and Intentions to Purchase (IP) EVs, in such a way that the relationship is stronger for individuals with higher SI.

H6: Social Influence (SI) negatively moderates the relationship between Perceived

Barriers (PBA) and Intentions to Purchase (IP) EVs, in such a way that the relationship is weaker for individuals with higher SI.

Research Methodology

With a view to examining the moderating effects for the adoption of EVs in Indian market, the quantitative approach was used. The survey method was employed to collect data from both EV owners and non-owners across different regions of India. Using structured questionnaire, a sample of 647 respondents was collected online to reach the diverse population. The collected samples included various respondents based on different age, income levels, geographical regions, i.e. urban and rural to ensure the diversity and heterogeneity of Indian population. The questionnaire includes various items representing key constructs namely Perceived Benefits (PB), Environmental Attitudes (EA), Social Influence (SI), Perceived Barriers (PBA), Technology Readiness (TR), Government Incentives (GI) and Intentions to Purchase (IP). These constructs were adopted from the previous literature and adapted to suit the Indian context. All these items in constructs were measured on 7-point Likert scale. The demographic information was also collected to

be used as moderators in the analysis. In order to analyze the questionnaire through SmartPLS 4.1 (Ringle et al., 2024) [59], Partial Least Squares Structural Equation Modeling (PLS-SEM) was used as it is well-suited for modeling complex relationships among underlying constructs and it doesn't require normality of data.

Data Analysis

Data Screening: the collected responses were analyzed for missing data treatment. No missing data were found in the preliminary screening. Further, all the responses were assessed for outliers using Mahalanobis ("Reprint Of," 2018) [60] distance in SPSS 26. In outlier detection, total 39 outliers were detected and removed in order to mitigate any incongruency of statistical tests. Thus, out of 647 data, only 608 were remained and tested for the further analysis.

Measurement Model Testing with the Inclusion of Moderator: After the inclusion of moderator variables in the PLS-SEM model, the reliability and validity of the measurement model of the moderator variables was carried out (Vinzi et al., 2010) [61].

First, the measurement model's reliability was assessed through Cronbach's alpha (α) and

rho_a (ρ_A). The Cronbach's alpha (α) of 0.814 (SI) and 0.887 (TR) were higher than threshold value of 0.7 (Sun et al., 2023) [32] indicating all the constructs are reliable. The composite reliability (ρ_A) values of 0.852 (SI) and 0.888 (TR) indicated internal consistency reliability among the underlying constructs. The convergent validity was also assessed through AVE and cross-loadings. All the indicators' loadings of two moderator variables were higher than 0.70 such that 0.761 (SI1), 0.835 (SI2), 0.718 (SI3), 0.852 (SI4), 0.867 (TR1), 0.839 (TR2), 0.871 (TR3) and 0.877 (TR4). AVE values of 0.629 (SI) and 0.746 (TR) indicated that the convergent validity was established providing support for the convergent validity of the two moderators SI and TR. In terms of discriminant validity of SI, the HTMT values of 0.193 (SI->PB), 0.144 (SI->PBA) and 0.268 (SI->EA) indicated that the discriminant validity of SI was established. Similarly, the HTMT values of TR with PB (0.823), PBA (0.759) and GI (0.758) indicated that the discriminant validity was firmly established. Thus, the measurement model was successfully assessed after the inclusion of moderator variables and their interaction effects.

Modelling the Moderating Effects:

With a view to modeling the moderating effects of the interaction term in the PLS path model (Vinzi et al., 2010) [61], several approaches are used namely product-indicator approach, two-stage approach and orthogonalizing approach (Henseler & Chin, 2010) [62]. In these approaches, the first two approaches namely product indicators approach and two-stage approach are often used in modelling the moderating effects in PLS-SEM (Fassott et al., 2016) [63]. Henseler The simple effect of PB on IP is 0.335 indicating respondents' perceived intentions to purchase EVs are greatly affected by their perceived benefits of EVs. Thus, for average level of TR, the relationship between PB & IP is 0.335 indicating higher effect of PB on IP. For higher levels of TR (e.g. TR is increased 1 SD unit), the relationship between PB and IP (PB & IP) increases by the value of interaction term (i.e., $0.335 + [1 \times 0.028] = 0.363$). This indicates that for individuals with higher level of TR, the relationship between Perceived Benefits and Intentions to Purchase (PB & IP) is stronger. Thus, the overall impact of PB on IP (PB & IP) becomes increasingly positive as TR increases. On the contrary, for lower levels of TR (e.g. TR is decreased 1 SD unit), the relationship between

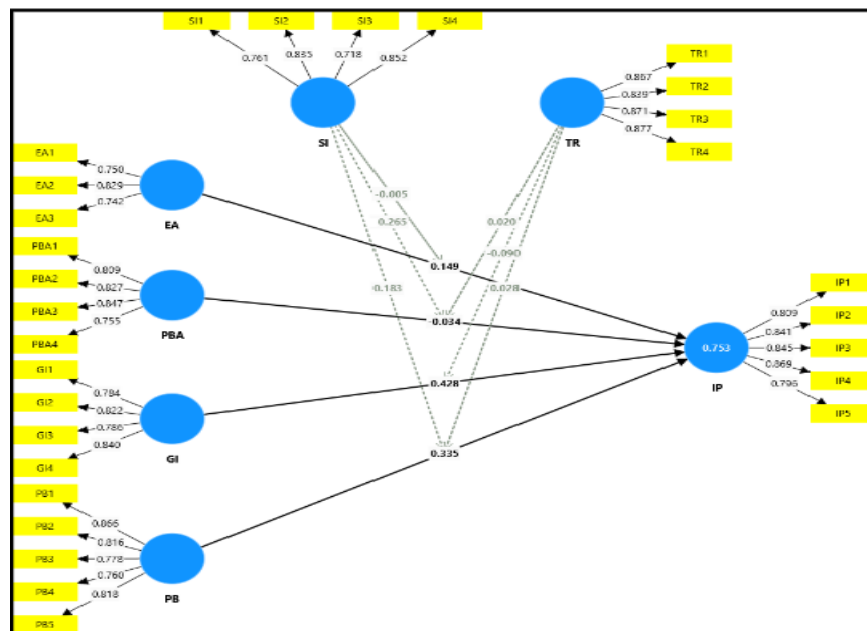
and Fassott (2010) [64] tested the superiority of two-stage approach over product-indicator approach while testing PLS-SEM model formatively. Thus, with a view to modeling the moderating effects of the interaction terms of both moderators, two-stage approach was used which is built-in approach in SmartPLS 4.1 and higher the interaction term (TR x PB) has a positive impact on IP (0.028) indicating that the effect of PB on IP becomes stronger as TR increases.

PB and IP (PB & IP) becomes less influential slightly (e.g., $0.335 + [-1 \times 0.028] = 0.307$). In terms of interaction term (TR x PBA), the effect is negative on IP (0.020) and the simple effect of PBA & IP is -0.034. The negative simple effect PBA & IP = 0.034 shows the negative impact of PBA on IP indicating decrease in IP with the increase in PBA. Thus, as people perceive more barriers, their intentions to purchase decreases. At higher-level of TR (e.g., TR is increased 1 SD unit), the negative effect of PBA & IP (-0.034) is weaker (e.g., $-0.034 + [1 \times 0.020] = -0.014$). This indicates that for people with higher level of TR, they perceive less barriers to the purchase/adoption of EVs. Similarly, at low level of TR (i.e., TR is decreased 1 SD unit), the negative effect of PBA & IP is

stronger (e.g., $-0.034 + [-1 \times 0.020] = -0.054$). Thus, as TR increases, the negative effect of PBA on IP becomes less intense and as TR decreases, the negative impact of PBA on IP

becomes more intense. Thus, for people having lower Technology Readiness (TR), Perceived Barriers (PBA) have a stronger negative impact on their Intentions to Purchase (IP).

Figure 1. EV Adoption Moderation Model



The simple effect of GI-> IP (0.428) indicates Government Incentives (GI) have more influence on Intentions to Purchase (IP) EVs. The interaction term (TR x GI) has a negative impact (-0.090) on IP. Jointly, simple effect and the interaction effects both indicate the relationship between GI and IP at 0.428 for an average level of TR. As TR increases (e.g., TR increases 1 SD unit), the positive impact of GI on PI (GI-> PI) becomes weaker ($0.428 [1 \times -0.090] = 0.338$). This indicates that people

with higher TR perceive Government Incentives (GI) less affected on their intentions to purchase. Similarly, at low level of TR (e.g., TR decreases 1 SD unit), the effect of GI-> GI becomes less intense ($0.428 + [-1 \times -0.090] = 0.518$). This indicates that for people with lower Technology readiness (TR), Government Incentives (GI) play crucial role in their Intentions to Purchase (IP). In terms of the simple effect of EA-> IP, it is 0.149 indicating moderate relationship of

Environmental Attitude (EA) and Intentions to Purchase (IP). This suggest that as individuals' environmental attitude increase, their intentions to purchase EVs also increase. The interaction term (EA x SI)-> IP has negative value of -0.005 which indicates very small negative moderating effect. At high level of SI (e.g., If SI increases 1 SD), the positive effect of EA-> IP becomes slightly lesser ($0.149 + [1 \times -0.005] = 0.144$). This indicates that individuals having higher Social Influence (SI), Environmental Attitude (EA) has marginally smaller impact on Intentions to Purchase (IP). Similarly, at low level of SI (e.g., SI decreases 1 SD unit), the positive effect of EA-> IP strengthens slightly ($0.149 + [-1 \times -0.005] = 0.154$). The interaction term (SI x PBA)-> IP is 0.265 which indicates stronger positive moderating effect of SI on the relationship between PBA-> IP. At high level of SI (e.g., If SI increases 1 SD unit), the effect of PBA-> IP changes to moderately positive ($-0.034 + [1 + 0.265] = 0.231$). It means that people having stronger social influence will have stronger intentions to purchase which are unaffected by their perceived barriers to EVs. At low level of SI (e.g., If SI decreases 1 SD unit), then negative effect of PBA-> IP becomes more negative

($-0.034 + [-1 + 0.265] = -0.299$). This indicates that people with lower social influence have stronger negative perceived barriers to the purchase intentions of EVs. In terms of the simple effect of PB-> IP, it is 0.335 indicating stronger relationship of Perceived Benefits (PB) and Intentions to Purchase (IP). This suggest that as individuals perceive more benefits, their intentions to purchase EVs also increase. The interaction term (SI x PB)-> IP has positive value of 0.183 which indicates moderate to stronger moderating effect of SI on Perceived Benefits and Intentions to Purchase. At high level of SI (e.g., If SI increases 1 SD unit), the positive effect of PB-> IP becomes stronger ($0.335 + [1 \times 0.183] = 0.518$). This indicates that individuals having higher Social Influence (SI), Perceived Benefits (PB) have stronger positive impact on Intentions to Purchase (IP). Similarly, at low level of SI (e.g., SI decreases 1SD unit), the positive effect of PB-> IP strengthens slightly ($0.335 + [-1 \times 0.183] = 0.152$). this indicates that for individuals with lower Social Influence (SI), their Perceived Benefits (PB) have a weaker influence on their Intentions to Purchase (IP), but this influence is still positive.

Result Analysis

After modeling the moderating effects for both the moderators, SI and TR, their significance was also assessed through bootstrapping. The results are depicted in Table-1 as under:

Table 1. Significance of the Moderation Paths

PATH	HYPOTHESIS	BETA (B)	T STATISTIC	P VALUE	DECISION
TR x PB->IP	H1	0.028	2.545	.016	Accepted
TR x PBA->IP	H2	0.02	0.198	.840	Rejected
TR x GI->IP	H3	-.09	0.769	.443	Rejected
SI x EA->IP	H4	-0.005	0.061	.951	Rejected
SI x PB->IP	H5	0.183	2.056	.048	Accepted
SI x PBA->IP	H6	0.265	2.172	.030	Accepted

TR = Technology Readiness, SI= Social Influence, PB= Perceived Benefits, PBA= Perceived Barriers, GI= Government Incentives, EA=Environmental Attitude.

H1 evaluates that Technology Readiness (TR) moderates the relationship between Perceived Benefits (PB) and Intentions to Purchase (IP). The results revealed that the main effect (PB->IP) was significant ($\beta = 0.335$, $t = 3.094$, $p = .002$). The interaction effect (TR x PB)->IP was also significant ($\beta = 0.028$, $t = 2.545$, $p = .016$). This indicates that Technology Readiness (TR) positively moderates the relationship between Perceived Benefits (PB) and Intentions to Purchase (IP). Thus, H1 was supported. H2 evaluates that Technology Readiness (TR) moderates the relationship between Perceived Barriers (PBA) and Intentions to Purchase (IP) EVs, in such a

manner that the relationship is weaker for individuals with higher Technology Readiness (TR). The main effect was significant ($\beta = -0.034$, $t = 2.267$, $p = .012$) indicating negative relationship between PBA->IP. The interaction effect (TR x PBA) was not significant ($\beta = 0.02$, $t = 0.198$, $p = .840$) suggesting that Technology Readiness (TR) doesn't moderate the relationship between Perceived Barriers (PBA) and Intentions to Purchase (IP). Thus, H2 was not accepted. H3 evaluates that Technology Readiness (TR) moderates the relationship between Government Incentives (GI) and Intentions to Purchase (IP) EVs, in such a way that the

relationship is stronger in individuals with higher Technology Readiness (TR). The results revealed that the main effect (GI & IP) was significant ($\beta = 0.428$, $t = 5.284$, $p = .000$) indicating government incentives greatly leads to higher intentions to purchase decisions. The interaction effect (TR x GI & IP) was not significant ($\beta = -0.09$, $t = 0.769$, $p = .443$) indicating that Technology Readiness (TR) does not moderate the relationship between Government Incentives (GI) and Intention to Purchase (IP) in any meaningful way rejecting H3. H4 evaluates that Social Influence (SI) positively moderates the relationship between Environmental Attitudes (EA) and Intentions to Purchase (IP) EVs, in such a way that the relationship is stronger for individuals with higher SI. The main effect (EA & IP) was significant ($\beta = 0.149$, $t = 1.987$, $p = .048$) indicating environmental attitudes of individuals lead to higher intentions to purchase EVs. The results revealed that the moderating effect of SI (SI x EA & IP) was not significant ($\beta = -0.005$, $t = -0.061$, $p = .951$) indicating there is no significant moderation by SI on relationship between SI & IP. Thus, H4 was not accepted. H5 evaluates that Social Influence (SI) positively moderates the relationship

between Perceived Benefits (PB) and Intentions to Purchase (IP) EVs, in such a way that the relationship is stronger for individuals with higher SI. Without moderation, the main effect was significant ($\beta=0.335$, $t=3.094$, $p=.002$) indicating the higher the perceived benefits of EVs, the higher the intentions to purchase them. The interaction effect (SI x PB & IP) was also significant ($\beta=0.183$, $t=2.056$, $p=.048$) indicating Social Influence (SI) has a noticeable impact on how Perceived Benefits (PB) affect Intention to Purchase (IP) EVs. Thus, H5 was supported. H6 evaluates that Social Influence (SI) negatively moderates the relationship between Perceived Barriers (PBA) and Intentions to Purchase (IP) EVs, in such a way that the relationship is weaker for individuals with higher SI. The results revealed that the effect was significant ($\beta=0.265$, $t=2.172$, $p=.03$). Thus, individuals with high level of social influence have no barriers to their intentions to purchase EVs adoption.

Conclusion

This research study, through considering the moderating effects of both the variables, Social Influence (SI) and Technology Readiness (TR), has focused on the investigation of factors influencing the adoption intentions for EVs in India. It was observed that individuals

with higher technology readiness and social influence in themselves are more likely to transform the perceived benefits of EVs into purchase intentions. Perceived Barriers were found to be highly moderated by Social Influence (SI) as SI weakened the negative relationship between Perceived Barriers (PBA) and Intentions to Purchase (IP). Individuals who are prone to social changes are more likely to be unaffected by perceived barriers to adopt EVs. Significant moderation effects were not found for Technology Readiness (TR) on Government Incentives (GI) and Perceived Barriers (PBA). This research could be extended by including other moderators or exploring the mechanism inside these moderating effects in the study. More in-depth views could be gathered by including demographic moderators like age, gender, income to get the more insights about EVs adoption in India. In order to accelerate the transition of EVs adoption for policy-makers, corporates and researchers, this study provides valuable insights to develop effective strategies for the adoption of EVs. More emphasis should be given to social influence and community engagement to increase the perceived benefits on the part of individuals and overcome their perceived barriers.

References

1. Adepetu, A., & Keshav, S. (2017). The relative importance of price and driving range on electric vehicle adoption: Los Angeles case study. *Transportation*, 44(2), 353–373. <https://doi.org/10.1007/s11116-015-9641-y>
2. Ajzen, I., & Fishbein, M. (2000). Attitudes and the attitude-behavior relation: Reasoned and automatic processes. *European Review of Social Psychology*, 11(1), 1–33. <https://doi.org/10.1080/14792779943000116>
3. Albert, J. R., Selvan, P., Sivakumar, P., & Rajalakshmi, R. (2022). An advanced electrical vehicle charging station using adaptive hybrid particle swarm optimization intended for renewable energy system for simultaneous distributions. *Journal of Intelligent and Fuzzy Systems*, 43(4), 4395–4407. <https://doi.org/10.3233/JIFS-220089>
4. Arts, J. W. C., Frambach, R. T., & Bijmolt, T. H. A. (2011). Generalizations on consumer innovation adoption: A meta-analysis on drivers of intention and behavior. *International Journal of Research in Marketing*, 28(2), 134–144. <https://doi.org/10.1016/j.ijresmar.2010.11.002>
5. Axsen, J., Orlebar, C., & Skippon, S. (2013). Social influence and consumer preference formation for pro-environmental

technology: The case of a U.K. workplace electric-vehicle study. *Ecological Economics*, 95, 96–107.

<https://doi.org/10.1016/j.ecolecon.2013.08.009>

6. Bandura, A. (2002). Social cognitive theory in cultural context. *Applied Psychology*, 51(2), 269–290.

<https://doi.org/10.1111/1464-0597.00092>

7. Barbarossa, C., De Pelsmacker, P., & Moons, I. (2017). Personal values, green self-identity and electric car adoption. *Ecological Economics*, 140, 190–200.

<https://doi.org/10.1016/j.ecolecon.2017.05.015>

8. Barth, M., Jugert, P., & Fritsche, I. (2016). Still underdetected – Social norms and collective efficacy predict the acceptance of electric vehicles in Germany. *Transportation Research Part F*, 37, 64–77.

<https://doi.org/10.1016/j.trf.2015.11.011>

9. Bhat, F. A., Verma, M., & Verma, A. (2022). Measuring and modelling electric vehicle adoption of Indian consumers. *Transportation in Developing Economies*, 8(1), 6.

<https://doi.org/10.1007/s40890-021-00143-2>

10. Brady, J., & O’Mahony, M. (2011). Travel to work in Dublin. The potential impacts of

electric vehicles on climate change and urban air quality. *Transportation Research Part D*, 16(2), 188–193.

<https://doi.org/10.1016/j.trd.2010.09.006>

11. Bühler, F., Cocron, P., Neumann, I., Franke, T., & Krems, J. F. (2014). Is EV experience related to EV acceptance? Results from a German field study. *Transportation Research Part F*, 25, 34–49.

<https://doi.org/10.1016/j.trf.2014.05.002>

12. Chen, Z., & Fan, Z.-P. (2023). Improvement strategies of battery driving range in an electric vehicle supply chain considering subsidy threshold and cost misreporting. *Annals of Operations Research*, 326(1), 89–113.

<https://doi.org/10.1007/s10479-020-03792-5>

13. Claudy, M. C., Garcia, R., & O’Driscoll, A. (2015). Consumer resistance to innovation—A behavioral reasoning perspective. *Journal of the Academy of Marketing Science*, 43(4), 528–544.

<https://doi.org/10.1007/s11747-014-0399-0>

14. Das, P. K., & Bhat, M. Y. (2022). Global electric vehicle adoption: Implementation and policy implications for India. *Environmental Science and Pollution Research International*, 29(27), 40612–40622.

<https://doi.org/10.1007/s11356-021-18211-w>

15. Digalwar, A. K., & Giridhar, G. (2015). Interpretive structural modeling approach for development of electric vehicle market in India. *Procedia CIRP*, 26, 40–45. <https://doi.org/10.1016/j.procir.2014.07.125>
16. Dumortier, J., Siddiki, S., Carley, S., Cisney, J., Krause, R. M., Lane, B. W., Rupp, J. A., & Graham, J. D. (2015). Effects of providing total cost of ownership information on consumers' intent to purchase a hybrid or plug-in electric vehicle. *Transportation Research Part A*, 72, 71–86. <https://doi.org/10.1016/j.tra.2014.12.005>
17. Egbue, O., & Long, S. (2012). Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy Policy*, 48, 717–729. <https://doi.org/10.1016/j.enpol.2012.06.009>
18. <http://www.etauto.com>. (n.d.). India surpasses Japan to become 3rd largest auto market globally—ET Auto. ETAuto.com. Retrieved July 30, 2024. <https://auto.economictimes.indiatimes.com/news/industry/india-surpasses-japan-to-become-3rd-largest-auto-market-globally/96786895>
19. Fan, Z.-P., Huang, S., & Wang, X. (2021). The vertical cooperation and pricing strategies of electric vehicle supply chain under brand competition. *Computers and Industrial Engineering*, 152, 106968. <https://doi.org/10.1016/j.cie.2020.106968>
20. Fassott, G., Henseler, J., & Coelho, P. S. (2016). Testing moderating effects in PLS path models with composite variables. *Industrial Management and Data Systems*, 116(9), 1887–1900. <https://doi.org/10.1108/IMDS-06-2016-0248>
21. Fu, Z., Dong, P., Li, S., Ju, Y., & Liu, H. (2021). How blockchain renovate the electric vehicle charging services in the urban area? A case study of Shanghai, China. *Journal of Cleaner Production*, 315, 128172. <https://doi.org/10.1016/j.jclepro.2021.128172>
22. Godoe, P., & Johansen, T. S. (2012). Understanding adoption of new technologies: Technology readiness and technology acceptance as an integrated concept. *Journal of European Psychology Students*, 3(1). <https://doi.org/10.5334/jeps.aq>
23. Gunawan, I., Redi, A. A. N. P., Santosa, A. A., Maghfiroh, M. F. N., Pandyaswargo, A. H., & Kurniawan, A. C. (2022). Determinants of customer intentions to use electric vehicle in Indonesia: An integrated model analysis. *Sustainability*, 14(4), Article 4. <https://doi.org/10.3390/su14041972>
24. Hackbarth, A., & Madlener, R. (2016). Willingness-to-pay for alternative fuel vehicle

- characteristics: A stated choice study for Germany. *Transportation Research Part A*, 85, 89–111.
<https://doi.org/10.1016/j.tra.2015.12.005>
25. Helveston, J. P., Liu, Y., Feit, E. M., Fuchs, E., Klampfl, E., & Michalek, J. J. (2015). Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U.S. and China. *Transportation Research Part A*, 73, 96–112.
<https://doi.org/10.1016/j.tra.2015.01.002>
26. Hema, R., & Venkatarangan, M. J. (2022). Adoption of EV: Landscape of EV and opportunities for India. *Measurement: Sensors*, 24, 100596.
<https://doi.org/10.1016/j.measen.2022.100596>
27. Henseler, J., & Chin, W. W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 17(1), 82–109.
<https://doi.org/10.1080/10705510903439003>
28. Henseler, J., & Fassott, G. (2010). Testing moderating effects in PLS path models: An illustration of available procedures. In *Handbook of Partial Least Squares: Concepts, methods and applications* (pp. 713–735). Springer.
29. Hidrue, M. K., Parsons, G. R., Kempton, W., & Gardner, M. P. (2011). Willingness to pay for electric vehicles and their attributes. *Resource and Energy Economics*, 33(3), 686–705.
<https://doi.org/10.1016/j.reseneeco.2011.02.002>
30. Higuera-Castillo, E., Molinillo, S., Coca-Stefaniak, J. A., & Liébana-Cabanillas, F. (2019). Perceived value and customer adoption of electric and hybrid vehicles. *Sustainability*, 11(18), Article 18.
<https://doi.org/10.3390/su11184956>
31. India, K. P. M. G. (2024, August 2). KPMG. <https://kpmg.com/in/en/home.html>
32. Ing, A. (2011). Public acceptance of electric vehicles in Toronto. *Proceedings of the 55th Annual Meeting of the ISSS*. Hull, UK.
<https://journals.iss.org/index.php/proceedings55th/article/view/1708>
33. Jansson, J., Nordlund, A., & Westin, K. (2017). Examining drivers of sustainable consumption: The influence of norms and opinion leadership on electric vehicle adoption in Sweden. *Journal of Cleaner Production*, 154, 176–187.
<https://doi.org/10.1016/j.jclepro.2017.03.186>

34. Javadnejad, F., Jahanbakh, M., Pinto, C. A., & Saeidi, A. (2024). Analyzing incentives and barriers to electric vehicle adoption in the United States. *Environment Systems and Decisions*, 44(3), 575–606. <https://doi.org/10.1007/s10669-023-09958-3>
35. Khazaei, H., & Tareq, M. A. (2021). Moderating effects of personal innovativeness and driving experience on factors influencing adoption of BEVs in Malaysia: An integrated SEM–BSEM approach. *Heliyon*, 7(9), e08072. <https://doi.org/10.1016/j.heliyon.2021.e08072>
36. Kumar, A. G., Anmol, M., & Akhil, V. S. (2015). A strategy to enhance electric vehicle penetration level in India. *Procedia Technology*, 21, 552–559. <https://doi.org/10.1016/j.protcy.2015.10.052>
37. Kumar, R. R., & Alok, K. (2020). Adoption of electric vehicle: A literature review and prospects for sustainability. *Journal of Cleaner Production*, 253, 119911. <https://doi.org/10.1016/j.jclepro.2019.119911>
38. Lai, I. K. W., Liu, Y., Sun, X., Zhang, H., & Xu, W. (2015). Factors influencing the behavioural intention towards full electric vehicles: An empirical study in Macau. *Sustainability*, 7(9), Article 9. <https://doi.org/10.3390/su70912564>
39. Langbroek, J. H. M., Franklin, J. P., & Susilo, Y. O. (2016). The effect of policy incentives on electric vehicle adoption. *Energy Policy*, 94, 94–103. <https://doi.org/10.1016/j.enpol.2016.03.050>
40. Parasuraman, A. (2000). Technology Readiness Index (Tri): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, 2(4), 307–320. <https://doi.org/10.1177/109467050024001>
41. Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research*, 18(1), 59–74. <https://doi.org/10.1177/1094670514539730>
42. Peters, A., & Dütschke, E. (2014). How do consumers perceive electric vehicles? A comparison of German consumer groups. *Journal of Environmental Policy and Planning*, 16(3), 359–377. <https://doi.org/10.1080/1523908X.2013.879037>
43. Potoglou, D., & Kanaroglou, P. S. (2007). Household demand and willingness to pay for clean vehicles. *Transportation Research Part D*, 12(4), 264–274. <https://doi.org/10.1016/j.trd.2007.03.001>

44. Razmjoo, A., Ghazanfari, A., Jahangiri, M., Franklin, E., Denai, M., Marzband, M., Astiaso Garcia, D., & Maheri, A. (2022). A comprehensive study on the expansion of electric vehicles in Europe. *Applied Sciences*, 12(22), Article 22. <https://doi.org/10.3390/app122211656>
45. Ringle, C. M., Wende, S., & Becker, J.-M. (2024). SmartPLS 4. SmartPLS. <https://www.smartpls.com/>
46. Rogers, E. M. (1983). *Diffusion of innovations* (3rd ed.). Free Press; Collier-Macmillan.
47. Reprint of: Mahalanobis, P.C. (1936) "On the Generalised Distance in Statistics." (2018). *Sankhya A*, 80(S1), 1–7. <https://doi.org/10.1007/s13171-019-00164-5>
48. Singh, H., Singh, V., Singh, T., & Higuera-Castillo, E. (2023). Electric vehicle adoption intention in the Himalayan region using UTAUT2 – NAM model. *Case Studies on Transport Policy*, 11, 100946. <https://doi.org/10.1016/j.cstp.2022.100946>
49. Singh, J. (2023, December 30). How India will navigate EVs in 2024. *Tech. Crunch*. <https://techcrunch.com/2023/12/29/india-ev-market-2024/>
50. Singh, V., Singh, V., & Vaibhav, S. (2020). A review and simple meta-analysis of factors influencing adoption of electric vehicles. *Transportation Research Part D*, 86, 102436. <https://doi.org/10.1016/j.trd.2020.102436>
51. Son, M., & Han, K. (2011). Beyond the technology adoption: Technology readiness effects on post-adoption behavior. *Journal of Business Research*, 64(11), 1178–1182. <https://doi.org/10.1016/j.jbusres.2011.06.019>
52. Sonar, H. C., & Kulkarni, S. D. (2021). An integrated AHP-MABAC approach for electric vehicle selection. *Research in Transportation Business and Management*, 41, 100665. <https://doi.org/10.1016/j.rtbm.2021.100665>
53. Song, M., Tao, W., & Shen, Z. (2022). Improving high-quality development with environmental regulation and industrial structure in China. *Journal of Cleaner Production*, 366, 132997. <https://doi.org/10.1016/j.jclepro.2022.132997>
54. Sun, M., Gao, X., Jing, X., & Cheng, F. (2023). The influence of internal and external factors on the purchase intention of carbon-labeled products. *Journal of Cleaner Production*, 419, 138272. <https://doi.org/10.1016/j.jclepro.2023.138272>
55. Tarei, P. K., Chand, P., & Gupta, H. (2021). Barriers to the adoption of electric vehicles: Evidence from India. *Journal of*

- Cleaner Production, 291, 125847. <https://doi.org/10.1016/j.jclepro.2021.125847>
56. Tripathy, A., Bhuyan, A., Padhy, R., & Corazza, L. (2022). Technological, organizational, and environmental factors affecting the adoption of electric vehicle battery recycling. *IEEE Transactions on Engineering Management*, 71, 12992–13005. <https://doi.org/10.1109/TEM.2022.3164288>
57. Tu, Q., Cheng, L., Yuan, T., Cheng, Y., & Li, M. (2020). The constrained reliable shortest path problem for electric vehicles in the urban transportation network. *Journal of Cleaner Production*, 261, 121130. <https://doi.org/10.1016/j.jclepro.2020.121130>
58. Vidhi, R., & Shrivastava, P. (2018). A review of electric vehicle lifecycle emissions and policy recommendations to increase EV penetration in India. *Energies*, 11(3), Article 3. <https://doi.org/10.3390/en11030483>
59. Vinzi, V. E., Chin, W. W., Henseler, J., & Wang, H. (2010). *Handbook of Partial Least Squares: Concepts, Methods and Applications*. SpringerLink. Springer. <https://link.springer.com/book/10.1007/978-3-540-32827-8>
60. Walczuch, R., Lemmink, J., & Streukens, S. (2007). The effect of service employees' technology readiness on technology acceptance. *Information and Management*, 44(2), 206–215. <https://doi.org/10.1016/j.im.2006.12.005>
61. Wang, N., Pan, H., & Zheng, W. (2017). Assessment of the incentives on electric vehicle promotion in China. *Transportation Research Part A*, 101, 177–189. <https://doi.org/10.1016/j.tra.2017.04.037>
62. Wang, S., Li, J., & Zhao, D. (2017). The impact of policy measures on consumer intention to adopt electric vehicles: Evidence from China. *Transportation Research Part A*, 105, 14–26. <https://doi.org/10.1016/j.tra.2017.08.013>
63. Zhang, X., & Zhao, C. (2023). Resale value guaranteed strategy, information sharing and electric vehicles adoption. *Annals of Operations Research*, 329(1–2), 603–617. <https://doi.org/10.1007/s10479-020-03901-4>
64. Zhang, Y., Yu, Y., & Zou, B. (2011). Analyzing public awareness and acceptance of alternative fuel vehicles in China: The case of EV. *Energy Policy*, 39(11), 7015–7024. <https://doi.org/10.1016/j.enpol.2011.07.055>
65. Orji, E. I., Idika, D. O., Okeke, S. U., Anakwue, A. L., & Ntamu, B. A. (2023). Global Warming and Impacts: Green entrepreneurship to the rescue. *Shodh Sari-An International Multidisciplinary Journal*,

02(04), 222–237.

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66. Mishra, S., & Gupta, S. (2023). Atal tinkering labs and the global notion of STEM education. *Shodh Sari-An International Multidisciplinary Journal*, 02(04), 131–137.

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<https://doi.org/10.59231/sari7629>

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67. Kumar, S., & Simran. (2024). Equity in K-12 STEAM education. *Eduphoria*, 02(03), 49–55. <https://doi.org/10.59231/eduphoria/230412>

68. Kumar, S. (2023). Artificial Intelligence Learning and Creativity. *Eduphoria*, 01(01), 13–14.

<https://doi.org/10.59231/eduphoria/230402>

69. Kumar, A. (2023). Promoting youth involvement in environmental sustainability for a sustainable Future. *Edumania-An International Multidisciplinary Journal*, 01(03), 261–278.

<https://doi.org/10.59231/edumania/9012>