

**AN EMPIRICAL MODEL OF PRE-PURCHASE INTENTION
ANTECEDENTS OF ELECTRIC VEHICLES**

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In

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By

SUNIL D

Guide

DR. SANJEEV PADASHETTY



ALLIANCE
UNIVERSITY
Private University established in Karnataka State by Act No.34 of year 2010
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Alliance School of Business

Alliance University, Bengaluru

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DECLARATION

I declare that the thesis entitled “An Empirical Model of Pre-purchase Intention Antecedents of Electric Vehicles” has been prepared by me under the guidance of Dr. Sanjeev Padashetty, Professor of Marketing, Alliance School of Business, Alliance University. No part of this thesis has previously formed the basis for the award of any degree in any University or fellowship.

Sunil D

Alliance School of Business, Alliance University

Chikkahagade Cross, Chandapura-Anekal Main Road, Anekal, Bangalore,
Karnataka – 562106



Signature

Date: 11-July-2024

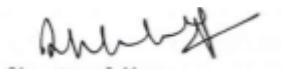
CERTIFICATE

I certify that Sunil D has prepared his thesis entitled “An Empirical Model of Pre-purchase Intention Antecedents of Electric Vehicles” for the Ph.D. degree of Alliance University award under my guidance. He has carried out the work at Alliance School of Business, Alliance University.

Dr. Sanjeev Padashetty

Alliance School of Business, Alliance University

Chikkahagade Cross, Chandapura-Anekal Main Road, Anekal, Bangalore,
Karnataka - 562106



Signature

DATE: 11-July-2024

DEDICATION

To my esteemed professors, I extend my sincere gratitude for your invaluable guidance and wisdom throughout this doctoral journey. To my supportive colleagues and friends, your encouragement has been instrumental in sustaining my perseverance. My heartfelt gratitude to my parents for their unwavering belief in my abilities. To my beloved wife, your endless patience and understanding have made this achievement possible.

I dedicate this thesis to my daughters, Spriha and Shanaya, whose joyful presence has been my greatest motivation.

Sincerely,

Sunil D

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To my family, your unwavering support has been my anchor. Even during the toughest times, your belief in me has been a constant source of strength. I am profoundly grateful for your love and encouragement.

To my friends and colleagues, thank you for your camaraderie and for being my sounding board. Your critiques, motivation, and occasional distractions have played crucial roles in this journey.

Lastly, to all the unnamed yet cherished individuals who have offered support, whether through kind words, helpful suggestions, or silent encouragement, I thank you. Your contributions, though not mentioned individually, have been invaluable.

This dissertation is a testament to the collective effort, support, and inspiration of so many. Thank you for being part of this journey.

ABSTRACT

The proposed model of pre-purchase intention draws on three primary literature domains: the cost-benefit framework (economics), psychology (risk), and utilitarian theory (technology). The cost-benefit framework serves as the foundation for any purchase decision, making it the starting point of this study. This framework is employed to validate hypotheses regarding electric vehicle purchases in India. The literature posits that purchase intention persists as long as the perceived marginal benefit exceeds the expected marginal cost, continuing until a threshold level of utility is reached. "Perceived risk" in product purchases is suggested to positively influence both technological and economic utility. Technological factors enhance purchase intention, while economic principles, such as costs, act as constraints. The perceived risk associated with electric vehicle purchases also plays a significant role in shaping purchase intention. Consumers evaluate information to compare products from established internal combustion engine technology with technologically advanced electric vehicles. Purchase intention is directly influenced by the technology involved. Urban consumers are expected to show a stronger preference for electric vehicles due to factors such as price diffusion and efficiency. It is proposed that incentives and driving range affect cost factors, aligning with the Economics of Information theory, which examines the relationship between cost and utility. This model analyzes the impact of these factors on overall purchase intention and its associated cost benefits.

We propose to investigate the significant differences between consumer search strategies for internal combustion engine (ICE) vehicles and electric vehicles within

the context of consumer durables. This research aims to address consumer purchase intentions and behaviors by applying relevant theories and techniques to identify, analyze, and resolve marketing challenges in emerging markets. A pilot study was conducted to develop reliable multiple-item scales based on the literature. The first pilot study included 113 samples, while the second had 54 samples, both aimed at identifying reliable and valid indicators. The main study utilized an e-survey method with 322 respondents. The reliabilities of the multiple-item scales closely matched those obtained in the pilot studies. The empirical model was tested using the Partial Least Squares (PLS) method, employing SmartPLS (4.0) as the statistical tool, designed to avoid manipulation and resolve any potential issues. Consistent with the study's objectives, the model was developed to assess the antecedents of purchase intention among buyers of durable, technology-driven products, specifically electric vehicles. The model fit results were highly encouraging.

Purchase intention is significantly influenced by the perceived risk associated with the product. Perceived risk impacts intention both directly and indirectly. Economic factors also play a major role in shaping purchase intention, affecting it through both direct and indirect pathways. Technological factors are the third key determinant. These three elements—perceived risk, economic factors, and technology—are the primary drivers of purchase intention explaining the 68 percent of total variance in purchase intention.

PREFACE

This thesis, titled "An Empirical Model of Pre-Purchase Intention Antecedents of Electric Vehicles," was undertaken between 2019 and 2024 as part of the requirements for completing my Ph.D. program at Alliance University in Bengaluru, Karnataka. The research and writing of this thesis represent the culmination of several years of dedicated academic pursuit and study. This work reflects my original contributions to the field, including formulating theoretical frameworks, collecting and analyzing empirical data, and interpreting findings.

In my earlier studies, I tended to stay within my comfort zone. This year, I deliberately chose a thesis topic that demanded new skills. I tackled unfamiliar theoretical frameworks, conducted comprehensive literature reviews, and applied statistical tools like SmartPLS and R. This process strengthened my existing skills and exposed me to new ones.

Through this journey, I've come to understand that facing challenges is an integral part of growth. This thesis has been a significant learning experience for me in terms of professional development and personal growth.

This thesis reflects the help and support of many individuals and professors. While the content here is my own work and findings to the existing body of knowledge, I acknowledge and am grateful for the contributions of those who made this journey possible.

TABLE OF CONTENTS

CHAPTER I: INTRODUCTION

1.1	Overview. 01
1.2	Technological Environment. 03
1.3	EV Global Market. 03
1.4	EV Market in India 05
1.5	Problem Statement. 07
1.6	Purpose of Research. 08
1.7	Research Questions 09
1.8	Objective of the Study. 11
1.9	Scope of the Study. 11
	1.9.1 Overview. 12
	1.9.2 Sample Frame. 12
	1.9.3 Key Mechanism of the EV. 13
1.10	Organization of Chapters. 14

CHAPTER II: LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1	Introduction. 16
2.2	Purchase Intention of EV: Perspective 17
2.3	Product Classification of EV. 18
	2.3.1 Battery Electric Vehicle (BAV) 19
	2.3.2 Hybrid Electric Vehicle. 20
	2.3.3 Plug-In Hybrid Electric Vehicle. 21
	2.3.4 Fuel Cell Electric Vehicle. 22
2.4	Further Classification of EVs.. 22
2.5	Technologies of Hybrid EV 25
	2.5.1 Conventional HEV. 25

2.5.2	Plug-In Hybrid EV (PHEV).	. . .	27
2.6	Theory of Consumer Perceived Risk..	. . .	29
2.7	Theory of Planned Behavior.	33
2.8	Technology Acceptance Model.	35
2.9	Behavior of Environmental Concern..	37
2.10	Lifestyle.	38

CHAPTER III: CONCEPTUALIZATION OF INTENTION MODEL

3.1	Introduction.	40
3.2	Perceived Risk	42
3.5.1	Performance Risk.	45
3.5.2	Financial Risk.	46
3.5.3	Psychological Risk.	46
3.3	Technology Factors.	48
3.3.1	Driving Range.	49
3.3.2	Recharging Time.	50
3.3.3	Safety and Reliability..	51
3.4	Economic Factors.	52
3.4.1	Price	54
3.4.2	Incentives	56
3.4.3	Charging Infrastructure	57
3.5	Purchase Intention.	59
3.5.1	Intention to Buy.	60
3.5.2	Willingness to Pay.	60
3.5.3	Performance Value.	61

CHAPTER IV: OPERATIONALIZATION OF INTENTION MODEL

4.1	Introduction.	64
4.2	Domains of the latent Constructs.	65
4.2.1	Perceived Risk	66

4.2.2	Technology Factors.	66
4.2.3	Economic Factors.	66
4.2.4	Purchase Intention.	67
4.3	Operational Measures of Latent Constructs.	67
4.4	Operational Measures: 2nd order Constructs.	70
4.5	Scale Development.	72
4.5.1	Stage 1.	72
4.5.2	Stage 2.	73

CHAPTER V: RESEARCH METHODOLOGY

5.1	Introduction.	75
5.2	Operational Measures of the Outer Model.	75
5.3	Questionnaire Development.	78
5.3.1	Scale Development	78
5.3.2	Likert Scale Standardization.	79
5.3.3	Pilot Study.	80
5.4	Final Operation Measures.	101
5.5	Research Design	104
5.5.1	Data Collection Method.	104
5.5.2	Sampling.	105
5.5.3	Sampling Frame.	106
5.5.4	The Representative Sampling.	106
5.5.5	Sampling Method.	107
5.5.6	The Sample Size.	109

CHAPTER VI: EMPIRICAL ANALYSIS AND RESULTS

6.1	Introduction	111
6.2	Examining the Data.	112
6.2.1	Missing Data Analysis	113
6.2.2	Outlier Analysis.	114
6.2.3	Testing Statistical Assumption.	114

6.3	Hierarchical Component Model.	116
6.4	Sampling Strategy.	117
6.5	Evaluation of Descriptive Statistics.	119
	6.5.1 Descriptive Statistics	119
6.6	Evaluation of PLS SEM Results.	127
	6.6.1 Evaluation of Measurement Model	132
	6.6.2 Evaluation of Structural Model.	154

CHAPTER VII: DISCUSSION OF THE RESULTS

7.1	Introduction	172
7.2	Discussion of the Model Results.	173
	7.2.1 Effect of Perceived Risk.	178
	7.2.2 Effect of Technology Factor	181
	7.2.3 Effect of Economic Factor	181

CHAPTER VIII: SUMMARY AND CONCLUSION

8.1	Introduction	185
8.2	Research Objectives	186
8.3	Research Design.	186
8.4	Method of Analysis.	187
8.5	Summary of Results.	188
8.6	Contribution of the Study.	191
8.7	Managerial Implication.	193
8.8	Limitation of the Study.	194
8.9	Directions for Future Work.	195

REFERENCES:	196
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LIST OF FIGURES

FIGURE 1.0 :	Global CO2 emissions from transport	: 03
FIGURE 2.0 :	Batter Electric Vehicle, Technology	: 20
FIGURE 2.1 :	Hybrid Electric Vehicle, Technology	: 20
FIGURE 2.2 :	Plug-in Electric Vehicle, Technology.	: 21
FIGURE 2.3 :	Fuel Cell Electric Vehicle, Technology	: 22
FIGURE 2.4 :	Classification of EVs	: 23
FIGURE 2.5 :	Energy diversification of EVs	: 24
FIGURE 2.6 :	Technology Acceptance Model	: 36
FIGURE 3.1 :	The prepositions of Perceived Risk equations can now be expanded	: 47
FIGURE 3.2 :	The prepositions of technological factors equations can now be expanded.	: 52
FIGURE 3.3 :	The prepositions of Economic Factors can now be expanded.	: 58
FIGURE 3.4 :	Conceptualized Model of Electric Vehicle's Purchase Intention.	: 62
FIGURE 4.1 :	Empirical Structural Model (First Order).	: 67
FIGURE 4.2 :	Operational MODEL OF electric vehicle purchase intention.	: 69
FIGURE 4.3 :	Measures Coded Operational MODEL OF electric vehicle purchase intention.	: 71
FIGURE 5.1 :	Operational MODEL OF electric vehicle purchase intention.	: 77
FIGURE 5.2 :	Measures Coded measurement model electric vehicle purchase intention.	: 103
FIGURE 6.1 :	The inner (structural) and outer (measurement) models of purchase intention.	: 129
FIGURE 6.2	Models Path Coefficients and (p-values).	: 158
FIGURE 6.3	Control Variables' effect on the model.	: 165
FIGURE 7.1	Hypothesized Path Relationship And Empirical Estimation	: 174
FIGURE 7.2	Specify Indirect Relationship	: 176
FIGURE 7.3	Total Effect of Relationship	: 177

LIST OF TABLES

TABLE 5.1	: Case Processing Summary.	: 81
TABLE 5.2	: Descriptive Statistics	: 84
TABLE 5.3	: KMO and Bartlett's Test	: 87
TABLE 5.4	: Total Variance Explained	: 88
TABLE 5.5	: Case Processing Summary	: 91
TABLE 5.6	: Descriptive Statistics	: 93
TABLE 5.7	: KMO and Bartlett's Test	: 95
TABLE 5.8	: Communalities of the 52 measures	: 96
TABLE 5.9	: Total Variance Explained	: 98
TABLE 5.10	: The measures in the outer model	: 102
TABLE 6.1	: Pilot & Main Study Measures Reliability Comparison	: 112
TABLE 6.2	: Descriptives of Age	: 121
TABLE 6.3	: Description of Education	: 122
TABLE 6.4	: Descriptives of Employment	: 123
TABLE 6.5	: Descriptives of Monthly Income	: 124
TABLE 6.6	: Descriptives of Sample Participation	: 125
TABLE 6.7	: Evaluation of Reliability and Validity	: 134
TABLE 6.8	: Fornell-Larcker Analysis of the Model	: 147
TABLE 6.9	: HTMT Assessment of the Model	: 148
TABLE 6.10	: Variance Inflation Factor (VIF) of the model	: 155
TABLE 6.11	: Path Coefficients of Structural Model	: 159
TABLE 6.12	: Path Coefficients of Inner Model: T statistics	: 159
TABLE 6.13	: T-Statistics of Path Coefficients, Structural Model	: 160
TABLE 6.14	: f^2 effect sizes	: 166
TABLE 6.15	: Predictive relevance (Q^2) of variables	: 168
TABLE 6.16	: SRMR summary	: 169
TABLE 6.17	: d_{LS} summary of the model	: 170
TABLE 6.18	: d_G summary of the model	: 171
TABLE 7.1	: Hypothesized Relationships & Empirical Evidence.	: 173

LIST OF APPENDICES

Appendix 0 :	Missing Value Analysis	: 211
Appendix 2 :	Pilot Study Questionnaire	: 213
Appendix 3 :	Main Study Questionnaire	: 235

LIST OF ANNEXTURES

Annexure 1 :	Path Coefficients of Measurement Model	: 257
Annexure 2 :	Indirect Effects of Measurement Model	: 258
Annexure 3 :	Total Effect of Measurement Model	: 259
Annexure 4 :	Outer loadings of Measurement Model	: 260
Annexure 5 :	Latent Variables of Measurement Model	: 262
Annexure 6 :	Correlations of Measurement Model	: 270
Annexure 7 :	Covariance of Measurement Model	: 271
Annexure 8 :	Descriptives of Measurement Model	: 272
Annexure 9 :	Outer Model Correlation (Measurement Model)	: 273
Annexure 10 :	Outer Model Descriptives (Measurement Model)	: 274
Annexure 11 :	Quality Criteria of Measurement Model	: 276
Annexure 12 :	Construct Reliability and Validity (Measurement Model)	: 277
Annexure 13 :	Discriminant validity – HTMT (Measurement Model)	: 278
Annexure 14 :	Fornell-Larcker criterion (FL Criterion) of Measurement Model	: 279
Annexure 15 :	FL Collinearity VIF of Measurement Model	: 284
Annexure 16 :	Path Coefficients of Structural Model	: 287
Annexure 17 :	Indirect Effects of Structural Model	: 288
Annexure 18 :	Total Effect of Structural Model	: 289
Annexure 19 :	Outer loadings of Structural Model	: 290
Annexure 20 :	Latent Variables of Structural Model	: 291
Annexure 21 :	Correlations of Structural Model	: 302
Annexure 22 :	Covariance of Structural Model	: 303
Annexure 23 :	Descriptives of Structural Model	: 304
Annexure 24 :	Inner Model Correlation (Structural Model)	: 305
Annexure 25 :	Inner Model Descriptives (Structural Model)	: 306
Annexure 26 :	Quality Criteria of Structural Model	: 307
Annexure 27 :	Construct Reliability and Validity (Structural Model)	: 308
Annexure 28 :	Discriminant validity – HTMT (Structural Model)	: 309

	Model)	
Annexture 29 :	Fornell-Larcker criterion (FL Criterion) of Structural Model	: 310
Annexture 30 :	FL Collinearity VIF of Structural Model	: 311
Annexture 31 :	Path Coefficients of Bootstrapped Model	: 312
Annexture 32 :	Indirect Effects of Bootstrapped Model	: 314
Annexture 33 :	Specific Indirect Effect of Bootstrapped Model	: 315
Annexture 34 :	Total Effect of Bootstrapped Model	: 316
Annexture 35 :	Outer Loadings of Bootstrapped Model	: 317
Annexture 36 :	Quality Criteria of Bootstrapped Model	: 318
Annexture 37 :	Outer Loadings of Control Variable	: 320
Annexture 38 :	Quality Criteria of Control Variable	: 321
Annexture 39 :	PLS Predict LV Summary	: 322

CHAPTER 1

INTRODUCTION

1.1. Overview

In this section, the study delves into the contextual backdrop surrounding the primary focus of inquiry: the determinants influencing the inclination to purchase Electric Vehicles (EVs) within the Indian market. The research endeavour's to empirically explore the precursor variables impacting consumer decisions towards adopting electric vehicles, encompassing factors such as product aesthetics, quality, brand reputation, pricing dynamics (both fixed and variable costs), perceived value, convenience, utilitarian considerations, post-purchase service, research and development initiatives, battery quality, technological complexity, charging infrastructure availability, battery-related risks, consumer behavioural patterns, governmental policy support, financial incentives, and other internal determinants. Moreover, the investigation encompasses an examination of demographic and lifestyle factors, which exert both direct and indirect influences on the intent to purchase electric vehicles, while also considering their mediating effects within the Indian context and the broader perspective of emerging markets.

In today's interconnected world, the movement of people, goods, and services has accelerated to unprecedented levels. People, products, and commodities are moving faster and further than ever. This heightened mobility carries not only tangible expenses like the upfront cost of products and supply chain logistics but also intangible costs, notably environmental impacts stemming from transportation emissions. As of 2022, transport emissions alone constituted over 37% of global

carbon dioxide (CO₂) emissions originating from end-use sectors (Climate, 2020), Global carbon dioxide (CO₂). (IEA, 2023)

The primary data-driven analysis conducted by the International Energy Agency (IEA) in 2020 underscores that road transportation constitutes a significant portion of global transport emissions, amounting to three-quarters of the total. As depicted in Figure 1.1, nearly half of these emissions stem from passenger travel, encompassing vehicles such as two-wheelers, passenger cars, taxis, and buses, collectively contributing 45.1%. Meanwhile, freight-carrying trucks account for 29.4% of emissions. The remaining 25.5% is attributed to various sources, with human mobility (11.6%) and sea shipping (10.6%) representing notable contributors. Aviation and shipping combined contribute 22.2% to overall emissions, while rail and other modes of transport contribute 3.3%. Consequently, a substantial 62.2% of emissions can be attributed to human mobility and its associated industries, with the remaining 7.8% originating from the shipping of commodities (IEA I. , 2022).

Transportation-related emissions from human mobility constitute a significant majority, computing 62.2% of overall emissions. Effectively reducing this figure hinges on transitioning to alternative mobility solutions, exemplified by electric vehicles, capable of transporting individuals while emitting zero pollutants. Consequently, industry and academic research are increasingly directed towards understanding societal acceptance of these innovative technologies compared to traditional fuel-based modes of mobility.

Figure 1.0: Global CO₂ emissions from transport.



Source: WorldinData.org

1.2. Technological Environment

Technological advancements are trying to address and mitigate the upward trend in CO₂ emissions within the transportation sector. With the transition towards lower-carbon electricity sources, the proliferation of electric vehicles (EVs) emerges as a promising avenue for curtailing emissions associated with passenger vehicles. EVs are positioned as a viable alternative to address concerns regarding dependence on fossil fuels, the escalation of carbon dioxide (CO₂) emissions, and other environmental challenges.

1.3. EV Global Market

The landscape of clean energy exhibits greater dynamism than that of the electric vehicle market. Between 2020 and 2021, sales of electric cars surged twofold, reaching 6.6 million units. To put this growth into perspective, in 2012, global sales of electric cars amounted to just 0.12 million units. Remarkably, by 2021, the number of electric cars sold each week surpassed that figure. Presently, there are approximately 16.5 million electric vehicles in operation worldwide. The momentum continued into 2022, with global sales of electric vehicles experiencing a robust increase. Over 2

million electric vehicles were sold during the first quarter alone, marking a 75% surge compared to the corresponding period in 2021 (IEA, Global EV Outlook, 2022).

Several factors contribute to the success of electric vehicles (EVs), with sustained policy support emerging as a primary driver. Notably, public expenditure on EV incentives surged, nearly doubling to approximately USD 30 billion in 2021. Numerous nations have committed to phasing out internal combustion engines, including diesel and petrol variants. Furthermore, countries worldwide have set ambitious vehicle electrification targets over the following decades.

Meanwhile, numerous automakers are strategizing to electrify their fleets beyond what is mandated by policy targets. Additionally, the availability of electric vehicle (EV) models has significantly expanded, with five times more new EV models introduced in 2021 compared to 2015, enhancing consumer appeal. As of 2022, the number of EV models available stands at approximately 450 (IEA, Global EV Outlook, 2022).

In 2021, China emerged as the primary driver behind the electric vehicle (EV) sales surge, contributing to half of the global growth. Notably, in 2022, China's electric vehicle sales surpassed the global total, reaching 3.3 million units. Meanwhile, European sales sustained robust growth, experiencing a 65% increase to 2.3 million units following the 2020 boom. Additionally, sales in the United States rebounded to 630,000 units after two consecutive years of decline.

In China, electric vehicles are typically smaller than those found in other regions, resulting in lower development and manufacturing costs (IEA, Global EV Outlook, 2022). Consequently, this has contributed to a reduction in the unit price of electric vehicles as of 2022. Notably, in China, the sales-weighted median price of electric

vehicles is only 10% higher than that of internal combustion engine vehicles, whereas, in other automotive markets, this difference typically ranges from 45% to 50% on average (IEA, Global EV Outlook, 2022). A notable trend in China is the significant adoption of electric vehicles, with over 95% of new vehicle registrations being electric. Furthermore, electric two and three-wheeler vehicles now constitute half of China's total vehicle sales. Additionally, the deployment speed of charging infrastructure in China surpasses that of most other regions. (IEA, Global Electric Vehicle Outlook, 2023).

1.4. EV Market in India

The global spotlight is increasingly turning towards electric vehicle (EV) technology because it can mitigate emissions and alleviate the strain on natural resources. Forecasts indicate that by 2030, the Indian automobile industry is poised to ascend to the world's third largest (IBEF, 2024). Furthermore, the Indian EV sector is projected to experience significant growth, with a forecasted compound annual growth rate (CAGR) of 36%. (IEA, Global EV Outlook, 2022), (Niti Aayog, Electric Vehicles Road Map in India, 2022). With India's population on the ascent and the demand for vehicles rising, continued reliance on conventional energy sources may prove unsustainable, particularly considering India imports nearly 80% of its crude oil requirements. In response to this challenge, the NITI Aayog has set ambitious targets to bolster the adoption of electric vehicles (EVs). By 2030, the aim is to achieve a sales penetration rate of 70% for all commercial cars, 80% for two-wheelers, 30% for private vehicles, and 40% for buses. These targets align with the broader objective of attaining net-zero carbon emissions by 2070 (Niti Aayog, Electric Vehicles Road Map

in India, 2022). Electric Vehicles recorded robust growth in 2021, supported by the government's favourable policies and programs.

India has placed significant emphasis on the electrification of two-wheelers, which is evident through a substantial 50% increase in purchase incentives for this category under the modified FAME II scheme and through local policies, notably in Delhi. Projections indicate a noteworthy rise in the sales share of electric two/three-wheelers, escalating from 2% in 2021 to nearly 50% by 2030 under the Stated Policies Scenario and further to 60% under the Announced Pledges Scenario. However, the pace of electrification for buses and light-duty vehicles (LDVs) is comparatively slower, with anticipated sales shares of 6% and 12% for buses and LDVs, respectively, by 2030 in the Stated Policies Scenario. In the Announced Pledges Scenario, electric buses are projected to achieve a sales share of approximately 25%, while LDVs are expected to reach around 30% by 2030. These targets align with India's commitment, articulated during the Glasgow UN Climate Change Conference (COP26), to transition to 100% zero-emission LDV sales by 2040 (Nations, 2020).

Under the Stated Policies Scenario in India, the sales share of electric vehicles (EVs) across all modes, including two/three-wheelers, is projected to exceed 30% by 2030, with just over 10% excluding two/three-wheelers. Meanwhile, in the Announced Pledges Scenario, EV sales shares are expected to escalate to nearly 45% across all road vehicle modes by 2030, with around 30% excluding two/three-wheelers (IEA, Global Electric Vehicle Outlook, 2023).

Externally, India is obligated, pursuant to the Paris Agreement, to curb carbon emissions, yet its urban areas rank among the most polluted globally (UNFCCC, 2022). Internally, however, consumer preferences play a pivotal role in shaping the

market landscape. Within the manufacturing sector, there is a comprehensive integration of the entire production system, particularly concerning capital-intensive product development and production. Electric vehicles represent not merely an evolutionary progression but a revolutionary shift, encompassing both technology and operational aspects. This paradigm shift challenges consumers' traditional perceptions of vehicles, necessitating adaptability and acceptance of EVs as a viable alternative (Oliva, et al., 2024). This phenomenon offers a unique opportunity to explore and measure shifts in consumer behaviour, a subject of interest not only to academia but also to the corporate sector. Marketing professionals keenly observe consumer trends to comprehend choice-making behaviour and adapt their strategies accordingly (Oliva, et al., 2024).

1.5. Problems Statement

Global warming stands as the foremost contributor of pollution, with even a modest 1% increase in global temperatures potentially resulting in the loss of 56% of landmass. Pollution, a significant environmental concern, threatens the depletion of resources and biodiversity across continents, posing challenges for populations worldwide, including in India. Moreover, the fluctuating oil prices affecting personal and commercial mobility further compound the complexity of the Earth's ecosystem. Electric vehicles (EVs) emerge as a viable solution to mitigate these challenges, with markets worldwide already offering EV options to consumers in India.

In alignment with global carbon emission reduction agreements, both India's federal and select state governments have introduced incentive programs and policies aimed at reducing taxes on electric vehicle purchases. However, despite these efforts, the acquisition cost of EVs remains relatively high compared to developed nations and

China, making the introduction of EVs into the Indian market a multifaceted challenge. Nonetheless, compelling factors such as emission regulations, government incentives, pricing, convenience, charging infrastructure, and technological advancements underscore the importance of EV adoption in India.

Therefore, this study's objective is to explore the underlying factors influencing the acceptance of new mobility technologies among Indian consumers. One perspective posits that widespread acceptance of EVs hinges largely on consumers' perceptions of them (Schuitema, Anable, Skippon, & Kinnear, 2023). Consequently, understanding how consumers perceive EVs and identifying the potential drivers and barriers to their adoption intentions is crucial for promoting EV uptake.

In a diverse market like India, cost-effective alternatives to EVs are readily available to consumers. Thus, effecting a transition in the consumer decision-making process from conventional combustion engine vehicles to EVs will require substantial influence. Factors such as technology acceptance, attitudes toward EV adoption, and, notably, economic considerations will undoubtedly shape consumer purchase intentions.

1.6. Purpose of Research

Over the past few years, researchers have invested time and effort in studying the intention to adopt electric vehicles (Rezvani, Jansson, & Bodin, 2016).

The existing literature identifies key factors influencing the adoption of electric vehicles (EVs). This study aims to review this literature to identify gaps and focus on the factors influencing EV adoption in India. Notably, many existing studies are qualitative and lack data-driven validation. The contribution of this study lies in

empirically validating a purchase intention model for EVs from the Indian consumer perspective, providing a framework for companies to understand consumer behaviour in India.

This study operates on two fronts. Firstly, it evaluates and determines the significance of factors predicting variations in the formation of purchase intentions for EVs. Secondly, it empirically validates these factors using quantitative methods, specifically structural equation modelling.

The quantitative component involves surveying Indian consumers about their decision-making processes and intentions to purchase an electric vehicle. The sample includes consumers who are considering or planning to buy an automotive vehicle. A pilot study has been conducted using measures derived from the literature. The data collected from validated measures have been used to confirm the validation of the model.

The causal model specifically examines and contributes to understanding consumer behaviour in India by

- Identifying causative factors that influence consumer intention to purchase an electric vehicle.
- Determining the knowledge and skills that impact the decision to purchase an electric vehicle.
- Analysing the effect of these factors and the moderating effects between these factors and purchase intention.

1.7. Research Questions

In addition to attitude, social norms, and perceived behavioural control are critical elements that influence an individual's behavioural intention (Wan & Shen, 2024). Purchase intention may also be affected by psychological, economic, and product-related factors.

Key psychological characteristics influencing purchase intention include personal values, perceived risk, and perceived benefits (Parks-Leduc, Feldman, & Bardi, 2014). These factors have shown a strong correlation with purchase intention. Research on the decision to purchase an electric vehicle is essential for understanding consumers' propensity to buy, their values and attitudes, and for improving market targeting and product image.

This study aims to identify the —factors influencing consumer intention and addresses the following questions:

Sub-questions:

1. Which personality traits and attitudes influence the —purchase intention of electric vehicles (EVs) in India?
2. How do knowledge and perceived social influence impact the purchase intention of EVs in India?
3. To what extent do environmental concerns influence the purchase intention?
4. Is environmental sustainability more significant than price and EV range concerns?
5. Which financial incentives and factors affect the purchase intention?
6. How do the purchase price and operating costs influence the purchase intention?
7. How do technological factors impact the purchase intention?

8. What factors overall influence consumer intention to purchase EVs in India?
9. How do —socio-demographic characteristics affect consumer intention to purchase EVs?

1.8. Objectives of the Study

1.8.1. Developing indicators and measures influencing the purchase intention of electric vehicles from the perspective of emerging market consumers, specifically in India.

1.8.2. Conceptualizing a hypothetical pre-purchase intention model.

1.8.3. Operationalizing a hierarchical model of purchase intention.

1.8.4. Empirically validating the model with primary data from consumers intending to purchase a new vehicle.

1.8.5. Identifying and empirically validating antecedent variables of purchase intention and assessing their impact on the development of electric vehicle product strategies for India and other emerging markets.

1.9. Scope of Study

The findings of this study are valuable to corporate and business sectors within the automotive industry, as well as to businesses involved in technology development and value chains. Business owners can utilize these insights to refine and develop product specifications that better meet consumer needs. Understanding customer behaviour and the factors influencing the purchase intention of electric vehicles is crucial. The results will aid corporations in enhancing their strategies and business plans.

Scope: This research study identifies the antecedent variables affecting the purchase intention of electric vehicles in emerging markets in India. A primary data is collected using a survey method. Research Instrument is validated with scales borrowed from literature to gather data. The scope of the research study includes:

1.9.1 Overview

The research study focuses on factors such as perceived risk, technology factors, economics factors, and buying traits in relation to purchase intention. Additionally, knowledge, demographics, and lifestyle factors may influence the intention to purchase electric vehicles.

- *The study is centred on consumer insights and purchase intentions in emerging markets, specifically India.*
- *The research has been conducted through a survey utilizing a questionnaire. Indicators and measures are derived from existing literature.*
- *All the measures and indicators are borrowed from existing body of knowledge; hence no new scales are developed to validate and assess purchase intention.*
- *The research is conducted from Feb 2024 to March 2024.*
- *The sample frame consists of new car buyers in Karnataka (Bengaluru), based on the rationale provided in section 1.9.2 of the chapter.*

1.9.2 Sample Frame

People who intend to purchase an EV are the sample. The product frame is EV four-wheelers. Electric four-wheel vehicles can be pure electric or otherwise. —Electric Vehicles are classified into four types (Niti Aayog, Electric Vehicles Road Map in India, 2022).

- (1) Battery Electric Vehicles (BEVs),*
- (2) Plug-in Hybrid Electric Vehicles (PHEVs),*
- (3) Hybrid Electric Vehicles (HEV) and*
- (4) Fuel Cell Electric Vehicle (FCEV).||*

1.9.3 Key Mechanisms of These Electric Vehicles

- (1) Battery Electric Vehicles (BEVs): BEVs are powered solely by electric batteries, with no gasoline engine components. Also known as All-Electric Vehicles, BEVs operate entirely on a battery-powered electric motor. —Most BEVs are capable of fast charging and produce zero emissions||.*
- (2) Plug-in Hybrid Electric Vehicles (PHEVs): PHEVs are similar to traditional hybrids but feature a larger battery and electric motor. The battery can be charged externally by plugging into an electric source, using both standard and fast chargers.*
- (3) Hybrid Electric Vehicles (HEVs): HEVs are low-emission vehicles that combine an electric motor with a gasoline-powered engine. All energy comes from gasoline, as these vehicles cannot be charged from external sources like electric chargers. Instead, the battery is recharged through regenerative braking, which captures otherwise lost energy during braking to assist the gasoline engine during acceleration (IEA, Global EV Outlook, 2022).*

(4) *Fuel Cell Electric Vehicle (FCEV) employs —fuel cell technology to generate the electricity required to run the vehicle. The chemical energy of the fuel is converted directly into electric power. It generates zero emissions (IEA, Global EV Outlook, 2022), (Niti Aayog, Electric Vehicles Road Map in India, 2022).*

The scope of this study comprehensively includes all these four types.

1.10. Organization of the Chapters

Chapter 1: This chapter discusses the context of the internal and external market environment and technological evaluation. It provides a brief overview of the market, highlighting how environmental and technical factors shape the mobility market. Additionally, it outlines the problem setting and objectives of the dissertation, focusing on studying consumer behavior and the factors influencing the purchase decision of electric vehicles.

Chapter 2: This chapter offers a literature review, discussing the theoretical foundations of the four major approaches used by consumer researchers: the cost/benefit approach, the psychological approach, risk approach, and the theory of planned behavior. It also reviews the preliminary empirical results cited in the literature following the theoretical section.

Chapter 3: This chapter presents the conceptualization of the hypothetical model of information search. It identifies the various determinants influencing purchase activity, which serve as the building blocks for developing a causal purchase intention model.

Chapter 4: This chapter focuses on the operationalization of the proposed comprehensive model of purchase intention for electric vehicles. It outlines the

operational measures, noting that the topic of purchase intention has been extensively researched by economists and marketing professionals for decades. However, previous samples were traditional and non-technological. This chapter aims to draw measures from existing literature and, if necessary, develop and validate new measures through a pilot study, discussing reliability and validity.

Chapter 5: This chapter details the partial least square structural modeling analysis to be used in this study. It describes analytical tools such as —Smart-PLS or Rl and provides detailed descriptions and statistical assumptions. It also determines the proposed structural model's identification.

Chapter 6: This chapter explains the research methodology adopted for this study. It discusses the questionnaire, data collection procedure, research instrument, and indicators for various constructs in detail.

Chapter 2

Literature Review and Theoretical Framework

2.1 Introduction

This chapter will review consumer pre-purchase intentions and their multifaceted dimensions. To achieve this, the literature is categorized into four distinct classifications based on their theoretical frameworks and domains.

The first classification is the "theory of planned behaviour," which focuses on cost-benefit principles and related variables. The second classification is the "theory of the technology acceptance model," which considers prior experience, product class, product knowledge, and associated variables. The third classification is the "theory of consumer perceived risk," which addresses financial and technological variables. The fourth theory is —theory of price, which profound that —when a product is priced lower than similar offerings in the market, consumers tend to perceive it as an attractive opportunity. This perception can stimulate purchasing behaviour, as consumers perceive they are receiving favourable value for their investment. This study validated all the propositions of these studies to find antecedents of the purchase intention.

These three streams of literature are reviewed to form a comprehensive conceptualization of purchase intention. The review begins with the perspective of perceived risk, detailing its functional, financial, and other associated risks. Following this, the economic aspects of purchase intention are examined. The technological perspective will explore new and revolutionary specialized functionalities and utilitarian criteria.

Before delving into these literature streams and their theoretical frameworks, the chapter will discuss product differentiation. It will emphasize how the product stands out compared to traditional automobile products, particularly focusing on technological and utilitarian differentiators. The chapter will explain the rationale for studying the purchase intention of electric vehicles (EVs), their classifications, and the operating processes of various types of EVs.

Overall, this study comprehensively reviews the literature and the influence of technology, establishing propositions to examine the purchase intention behaviour of electric vehicles within the Indian consumer context.

2.2 Purchase Intention and Electric Vehicles: A Perspective.

The need for the product represents the initial stage of the consumer purchase decision-making process (Shim, Eastlick, Lotz, & Warrington, 2020) with purchase intention being the final stage. Purchase intention reflects an individual's readiness to perform a given behaviour (Ajzen, 2003). While purchase intention has been extensively studied and evolved over the years, examining the intention to buy electric vehicles (EVs) offers a novel perspective, particularly in emerging markets such as India.

Electric vehicles, prevalent in many developed countries for decades, entered the Indian market in 2010, presenting an opportunity to introduce new energy cars. Significantly, EV technology promotes green travel, which is crucial for cities grappling with population growth and increasing density. EVs are dedicated to mitigating pollution issues (Hiroyuki et al., 2013; (Cohen & Kietzmann, 2014).

Despite some barriers, such as driving range limitations, long charging times, technological errors, and specific vehicle features (Rachel et al., 2016), the market potential for EVs in a densely populated country like India is substantial. According to (McKinsey, 2020) report on Future Mobility, the market is increasingly focusing on EVs, which are anticipated to be well-received due to their technological advancements and eco-friendly features. Understanding the technology behind EVs requires a thorough grasp of their product classification.

2.3 Product Classification of Electric Vehicles

Electric vehicles (EVs) can be classified into four distinct types based on their power supplement and propulsion devices (Niti Aayog, 2022).

2.3.1 Pure Electric Vehicle (PEV) or Battery Electric Vehicle (BEV)

2.3.2 Hybrid Electric Vehicles (HEV), and

2.3.3 Plug-in Hybrid Electric Vehicles (PHEV)

2.3.4 Fuel Cell Electric Vehicle

Table 1 presents a concise classification of various types of electric vehicles (EVs).

Battery Electric Vehicle (BEV): This type relies entirely on electricity from a power storage unit, with propulsion provided solely by an electric motor.

Hybrid Electric Vehicle (HEV): —The driving system in an HEV combines an electric motor and an internal combustion engine, utilizing both electricity and gasoline or diesel as power sources.

Fuel Cell Electric Vehicle (FCEV): Propelled by an electric motor, an FCEV can be powered directly or indirectly by hydrogen, methanol, ethanol, or gasoline.

Table 1.0: Comparison of different electric vehicles.

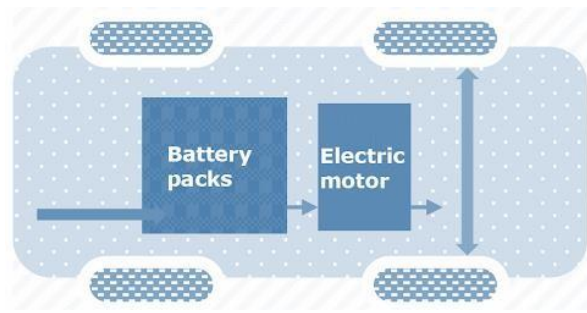
Types	BEV	PHEV	FCEV
Drive section	Electric Machine	Electrical machine, internal combustion engine (ICE)	Electrical machine
Energy sources	Battery, ultracapacitor	Battery, ultracapacitor, ICE unit	Fuel cell
Energy supplements	Electricity and power system	Electricity and power system, gasoline station	Hydrogen ide

2.3.1 Pure Electrical or Battery Electric Vehicle (BAV)

Battery Electric Vehicles (BEV), also called Pure Electric Vehicles (PAV), and All Electric Vehicles (AEV). However, the literature and synonymous name across literature and industry are Battery Electric Vehicles (BAV) (Ding & Prasad, The electric vehicle: A review, 2020).

The large, sleek battery pack stores the power needed to drive the vehicle. This battery pack can be charged or recharged by plugging it into external power grids. Once charged, the battery pack supplies energy to the electric motors, which propel the car. In a Pure Electric Vehicle, propulsion is provided exclusively by the electric motor.

Figure 2.0: Batter Electric Vehicle, Technology.

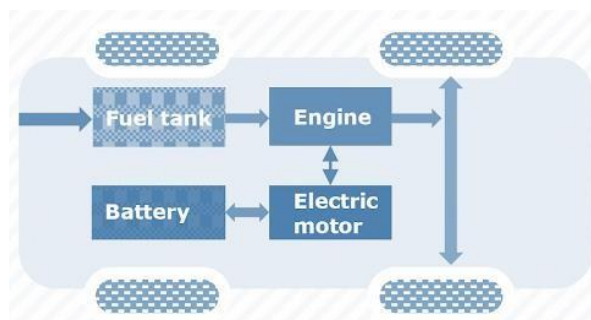


Source: Accelerated e-Mobility Revolution for India's Transportation

2.3.2 Hybrid Electrical Vehicle (HEV)

Hybrid Electric Vehicles (HEVs), also known as series or parallel hybrids, utilize both combustion engines and electric motors. —The engine derives energy from fuel, while the motor receives electricity from batteries. In HEVs, the transmission is simultaneously powered by both the engine and the electric motor. This combined driving system uses both electricity and gasoline or diesel to propel the wheels.

Figure 2.1: Hybrid Electric Vehicle, Technology.



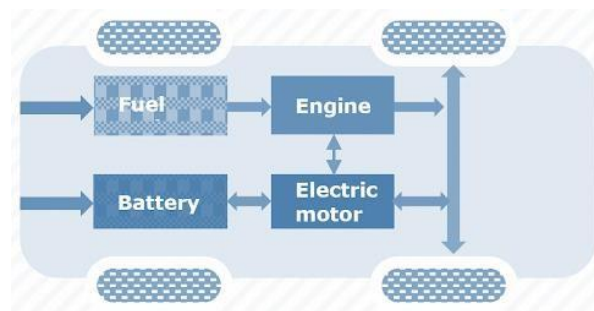
Source: Accelerated e-Mobility Revolution for India's Transportation

2.3.3 Plug-in Hybrid Electric Vehicle (PHEV)

Compared to the fixed amount of electricity from the battery pack in conventional HEVs, Plug-in Hybrid Electric Vehicles (PHEVs) can be directly connected to power grids (Chau & Li, 2024). The key advancement in PHEVs involves replacing the fixed battery pack used in conventional HEVs with rechargeable batteries (Akhavan-Rezai & El-Saadany, 2015). External recharging enhances the battery's capacity and extends the vehicle's range, allowing PHEVs to provide a longer pure electric driving range similar to that of Pure —Electric Vehicles (PEVs) and Internal Combustion Engine Vehicles (ICEVs).

Although PHEVs are developed from conventional HEVs, their operating mode differs significantly. Conventional HEVs depend primarily on gasoline, with electricity from the battery and generator supplementing the engine. In contrast, PHEVs prioritize electricity from the rechargeable battery, with the fuel engine serving as an auxiliary propulsion unit.

Figure 2.2: Plug-in Electric Vehicle, Technology.

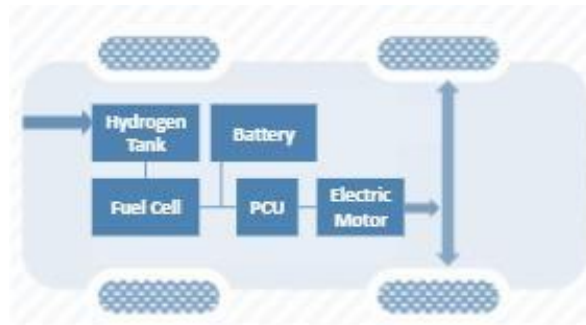


Source: Accelerated e-Mobility Revolution for India's Transportation

2.3.4 Fuel Cell Electrical Vehicle (FCEV)

—Fuel Cell Electric Vehicles (FCEVs) use fuel cell technology to generate the electricity needed to operate the vehicle. They are driven by an electric motor, which can be powered directly or indirectly by hydrogen, methanol, ethanol, or gasoline (Ding & Prasad, 2020). In FCEVs, the chemical energy of the fuel is converted into electrical power to drive the vehicle.

Figure 2.3: Fuel Cell Electric Vehicle, Technology.



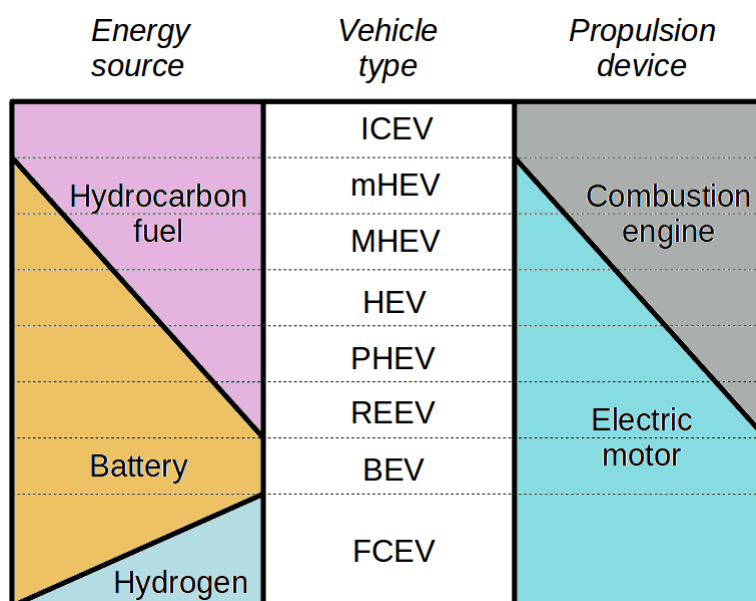
Source: Accelerated e-Mobility Revolution for India's Transportation

2.4 Further Classifications of Electric Vehicles

Hybrid Electric Vehicles (HEVs) combine the characteristics of Internal Combustion Engine Vehicles (ICEVs) and Battery Electric Vehicles (BEVs). The driving power sources for HEVs include both gasoline or diesel and electricity, with propulsion relying on both the engine and the electric motor (Ding, Prasad, & Lie, 2021). Based on different refuelling or recharging methods, HEVs can be classified as conventional HEVs. Additionally, HEVs can be further categorized into micro, mild, and full HEVs, depending on the level of electrification. HEVs can also be classified as Plug-in Hybrid Electric Vehicles (PHEVs) or Range-Extended Electric Vehicles (REVs) (Chau & Li, 2015).

Figure 1 illustrates the different categories of electric vehicles based on their energy source and propulsion device (Chau & Li, 2015); (Ding & Prasad, The electric vehicle: A review, 2020)

Figure 2.4: Classification of EVs



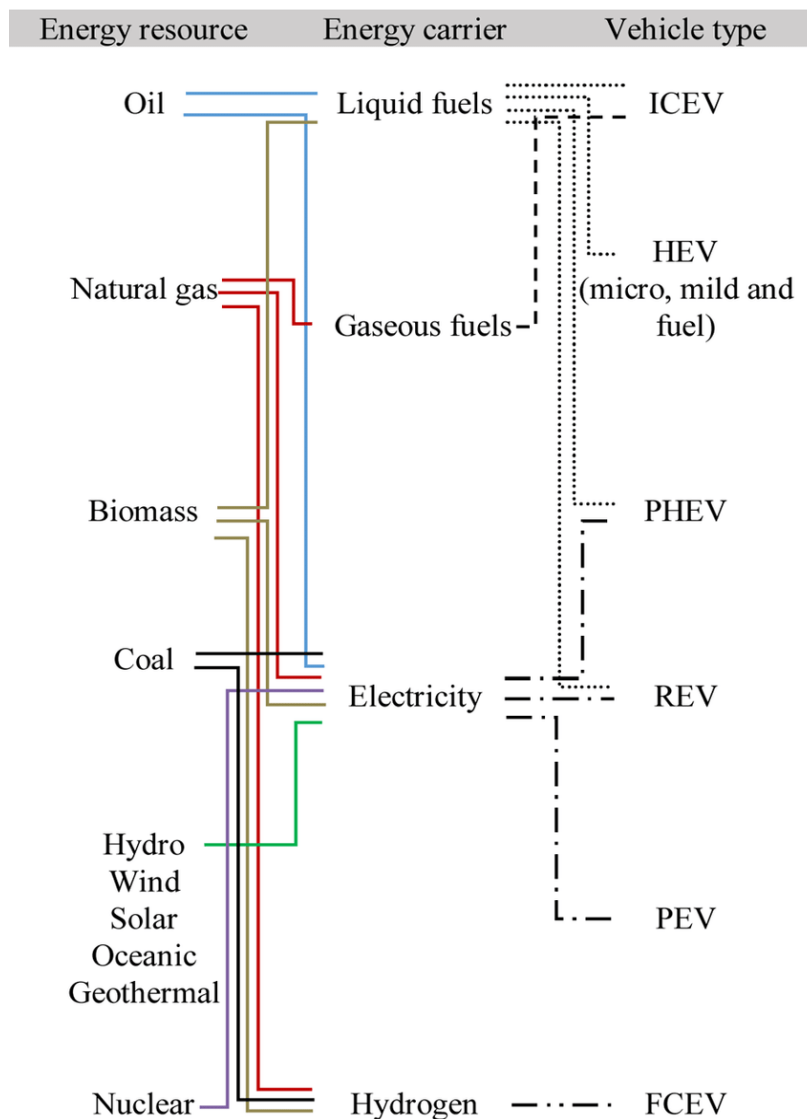
Source: Accelerated e-Mobility Revolution for India's Transportation

Since both electricity and petrol propel Hybrid Electric Vehicles (HEVs), their driving range is comparable to that of Internal Combustion Engine Vehicles (ICEVs). Economically, HEVs have certain advantages over Pure Electric Vehicles (PEVs) due to current battery technology limitations. However, HEVs still require an engine and gasoline, so they do not achieve zero emissions. The combination of electric generators and engines increases manufacturing complexity and initial costs (Ding, Prasad, & Lie, 2020). Consequently, the primary challenge for HEVs lies in effectively coordinating these two propulsion systems to maximize efficiency while minimizing design complexity (Wilamowski & Irwin, 2020). Given the overall development of electric vehicles (EVs), and considering both economic and

technological factors, HEVs are likely to have significant development potential and could dominate the market in the coming decades (Ding, Prasad, & Lie, 2021)

In terms of energy sources, EVs are powered either fully or partially by batteries, which can be charged directly from power stations or through electrochemical reactions. To improve the overall emissions profile of EVs, various renewable energy sources should be utilized. Figure 2 illustrates the energy diversification for EVs based on different charging methods (Chau K. , 2019)

Figure 2:5 Energy diversification of EVs



Source: Accelerated e-Mobility Revolution for India's Transportation

2.5 Technologies of Hybrid Electric Vehicles

2.5.1 Conventional HEV

2.5.1.1 Micro and mild HEV

The output power distribution of hybrid electric vehicles (HEVs), particularly those utilizing electric motors, can be categorized into micro, mild, and full HEV modes (Ding, N., Prasad, K. V., & Lie, T. T., 2017). In micro-HEVs, power is primarily managed through a belt-alternator start generator (BSG) assisting the engine start motor. This setup effectively minimizes motor idling and reduces gasoline consumption (Wen & Su, 2022). However, micro-HEVs cannot be strictly classified as hybrid electric vehicles due to the intermittent nature of the electric motor's power supply.

Mild HEVs, on the other hand, replace the traditional engine start motor with an integrated starter-generator (ISG) positioned between the engine and the transmission (Ding & Prasad, 2020). Notable examples include vehicles like the Buick Lacrosse, which debuted in 2006. The operational principle of mild HEVs involves the electric generator initiating when the vehicle starts, with the petrol engine remaining inactive. Subsequently, the vehicle's operations rely solely on the electric motor. As acceleration occurs upon releasing the brake pedal, the petrol engine ignites to provide propulsion at higher speeds. This sequence integrates an idle stop-start feature, shutting down the engine when the vehicle is stationary. Battery recharging primarily occurs during deceleration or braking, with the ISG design requiring collaborative efforts between the engine and electric motor during heavy acceleration (Chau & Li, 2015). A prime example of a mild HEV is the Honda CR-Z.

2.5.1.2 Full and dual-mode HEV

In full hybrid electric vehicles (HEVs), the pivotal technology lies in the electric variable transmission (EVT), which serves as both a power splitter and controller. The EVT's power-splitting capability facilitates electric launch, enabling initial acceleration solely through electric power. This approach retains nearly all the benefits associated with conventional HEVs, including idle stop-start, regenerative braking, downsized engines, and electric launch (Ding, N., Prasad, K. V., & Lie, T. T., 2017). Toyota Prius spearheaded the adoption of full HEV mode in mass production as early as 1997 and subsequently enhanced it by incorporating a planetary gear for optimized power distribution (Debnath, 2020). Following the successful integration of hybrid power systems into the automotive market, numerous manufacturers have committed to refining these technologies for improved fuel efficiency and environmental sustainability (Jorgensen, 2018). Lexus LS600HL stands as a testament to the advancements in full hybrid mode, achieving genuine zero- emission starts (Sabri, Danapalasingam, & Rahmat, 2021).

Addressing fuel consumption challenges during urban driving scenarios, a dual-mode system based on a comprehensive hybrid electric vehicle configuration emerges as a solution to enhance overall efficiency. In this context, "dual mode" signifies a synergistic collaboration between the hybrid system and electric motor to deliver superior performance during rapid acceleration and at full speed (Chau K., 2019). Prominent examples such as the next-generation motors found in Lexus ct200h and BMW x6 demonstrate the effectiveness of this approach, garnering widespread recognition and acceptance (Hutchinson, Burgess, & Herrmann, 2022). Notably,

dual-mode technology has not only advanced conventional HEV platforms but has also influenced certain plug-in HEV configurations.

Extensive research efforts have significantly refined conventional HEV technologies (Sabri, Danapalasingam, & Rahmat, 2019). As traditional HEV systems progressed from micro and mild modes to full modes, the operational dynamics of these vehicles underwent a transformation. Micro and mild conventional HEVs primarily rely on gasoline or diesel engines, with electric generators or batteries serving as auxiliary components. In contrast, full or dual-mode HEVs prioritize electric propulsion, marking a shift in the powertrain paradigm (Guille & Gross, 2009). While conventional HEVs can be optimized through dual-mode or full configurations to extend driving range and enhance fuel economy, challenges such as reliance on fossil fuels, bulky battery packs, and high initial costs persist. Additionally, manufacturing complexities pose another hurdle. Consequently, conventional HEVs may still fall short in terms of transmission loss, gear noise, and lubrication concerns (Hermance & Sasaki, 1998). Nonetheless, it's crucial to acknowledge that perceptions of HEVs as "high initial cost" systems often overlook key factors such as production line establishment costs, maintenance expenses, and infrastructure development for refuelling or recharging facilities.

2.5.2 Grid-able HEV (PHEV)

In contrast to conventional hybrid electric vehicles (HEVs), grid-able HEVs offer a notable advantage by enabling direct connectivity to power grids (Chau & Li, 2015). Extensive research spanning decades has focused on plug-in hybrid electric vehicles (PHEVs) (Riba, López-Torres, Romeral, & Garcia, 2016). A fundamental alteration in PHEVs involves replacing the fixed battery pack found in conventional HEVs with

rechargeable batteries. This modification facilitates battery recharging from external power sources, concurrently boosting electricity storage capacity (Ding & Prasad, 2020). As a result, PHEVs can deliver extended pure electric driving ranges comparable to both pure electric vehicles (PEVs) and internal combustion engine vehicles (ICEVs).

Despite evolving from conventional HEV platforms, the operational mode of PHEVs diverges significantly. Conventional HEVs primarily rely on gasoline, with battery and generator electricity serving as supplementary power sources for the engine. In contrast, PHEVs prioritize electricity from rechargeable batteries, relegating the fuel engine to a supporting role as an auxiliary propulsion unit.

Summary of Electric Vehicle Technology

An electric vehicle (EV) is a type of alternative fuel vehicle that employs electric motors and engine controllers for propulsion, replacing more traditional propulsion methods such as internal combustion engines (ICE). Electricity serves as the primary fuel to power battery electric vehicles (BEVs), which store energy in a storage device like a battery. This stored energy then drives the vehicle's wheels through an electric motor. EVs typically have limited energy storage capacity, necessitating recharging by connecting to an electrical power source.

What sets electric vehicles apart from fossil fuel-powered cars is their ability to draw power from various sources, including fossil fuels, nuclear power, and renewable sources like tidal, solar, and wind energy, or a combination thereof (Das & Sharma, 2017). Regardless of the source, the energy is transmitted to the vehicle through means such as overhead lines, wireless energy transfer like inductive charging, or direct connection via an electrical cable. Subsequently, the electricity may be stored

onboard the vehicle using a battery, flywheel, supercapacitor, or fuel cell. In contrast, vehicles relying on combustion engines typically derive their energy from a limited set of sources, primarily non-renewable fossil fuels.

An important advantage of electric or hybrid electric vehicles lies in their ability to recapture braking energy through regenerative braking, converting it back into electrical energy to recharge the onboard battery or feed back into the grid. With growing concerns over the environmental impact of petroleum-based transportation systems and the looming threat of peak oil, interest in electric transportation systems has seen a resurgence. Consequently, vehicles powered by renewable energy sources, such as hybrid or pure electric vehicles, are gaining popularity.

In an electric vehicle, the power generated by the motor is stored in a battery or other energy storage device. Recharging EV batteries requires access to a power source, typically achieved by parking the vehicle at a charging station. Some electric vehicles feature onboard chargers, while others connect to an external charger. Regardless of the method, both types draw power from the electrical grid. Despite potential environmental impacts associated with electricity generation, EVs are often considered zero-emission vehicles since their motors produce no exhaust emissions.

2.6 The Theory of Consumer Perceived Risk

Decision theorists characterize "risk" as a scenario in which a decision-maker possesses prior knowledge of the consequences of various alternatives and their probabilities of occurrence (Wayne & Mitchell, 1999). However, the concept of Perceived Risk (PR) utilized by consumer researchers aligns more closely with partial ignorance, wherein neither the consequences of alternatives nor their probabilities of occurrence are accurately known (Bakewell & Mitchell, 2003). Since the meanings of

concepts serve as the foundation of theories, it is crucial to assess the level of clarity attained by the PR concept.

Initially, Bauer (1960) defined perceived risk with a two-dimensional structure comprising uncertainty and adverse consequences. Subsequent research has predominantly focused on the uncertainty dimension (e.g., Amdt, 1968a,b; Schiffman, 1972; Gronhaug, 1975; Herman & Locander, 1977; Shimp and Bearden, 1979, 1982; Toh & Heeren, 1982), with uncertainty often operationalized as an individual's probabilistic beliefs (Peter and Tarpey, 1975). Notably, Bauer's original paper did not explicitly define the adverse consequences dimension of perceived risk.

Taylor (1974) later conceptualized adverse consequences as the "importance of loss," while Bloch and Richins (1983) introduced the notion of "instrumental importance" to replace the negative consequences component.

In addition to these principal dimensions, researchers have proposed that perceived risk encompasses various types of loss, such as performance, social, physical, psychological, psychosocial, time, and frustration (Wen, 2016). Most studies have incorporated one or more of these loss types into their analysis. For instance, Peter and Tarpey (1975a, b), Peter and Ryan (1976), Vincent and Zikmund (1976), Bearden and Mason (1978), and Dowling (1985) constitute a group that defines perceived risk as a multi-faceted construct with two dimensions: importance and probability of loss, encompassing performance, social, physical, financial, and psychological loss, among others. However, achieving consensus regarding the precise nature of the construct has proven challenging, as evidenced by the divergent viewpoints of scholars such as Bettman (1973), Hampton (1977), and Horton (1979). Perceived risk remains a somewhat "fuzzy" concept.

Measures of Perceived Risk

Perceived Risk = Uncertainty

Overall Perceived Risk = Uncertainty X Adverse Consequences

Overall Perceived Risk = $\sum_{i=1}^n U_{uncertainty-i}$ X Adverse

Consequences i

Overall Perceived Risk = $\sum_{i=1}^n P_{probability-i}$ X Probability of loss i

Overall Perceived Risk = $\sum_{i=1}^n P_{probability-i}$ X Probability of loss i X

Importance of Loss

Equations (1)-(5) can also be considered mathematical models of Perceived risk. They posit a linear relationship between the products and perceived risk. These models have formal parallels with subjective expected utility models in psychology and the attitude models used extensively in marketing and psychology. They are characteristic of an information-processing view of decision-making.

Risk represents an abstract concept aiming to foresee potential future outcomes and their adverse effects on a subject's state. However, due to its abstract nature, risk lacks widespread acceptance as a measurement unit. The scientific literature offers various approaches to measuring risk.

Before delving into these approaches, it's crucial to distinguish between objective risk assessment, often termed canonical rationality (Horlick-Jones, 2005), such as evaluating the decline in brand equity during an economic downturn (Munteanu, 2011), and consumers' perceived risk. These two types of risk differ not only in terms of the risk holder, whether institutional or individual, but also in evaluation and intentionality.

Consumer perceived risk was initially conceptualized by Bauer (1960) as the potential undesirable outcome anticipated by a consumer following their current actions. Mitchell (1999) subdivides perceived risk into two components: uncertainty about the consequences of a wrong choice and uncertainty about the outcome, with the latter deemed insignificant for goods or services (Hem et al., 2003). Cunningham (1967) suggests utilizing two additional dimensions – the magnitude of risk and the probability of risk occurrence – to evaluate perceived risk. By multiplying these dimensions, the overall perceived risk, also known as mathematical hope, can be derived. Recent research (Florea & Munteanu, 2012) introduces a third component – the risk horizon – inversely proportional to the resulting risk.

Perceived risk theory posits that risk is a multidimensional concept with components that vary across individuals, each exerting varying influence on a consumer's overall perceived risk (Mitchell, 1999). This formation implies a weighted average formula for calculating overall perceived risk, akin to Fishbein's (1963) observations, which closely resemble the multi-attribute attitude model. Additionally, Mulino et al. (2009) find that risk aversion is not constant for an individual but varies across decision contexts, resulting in different reactions to the same perceived risk.

Previous research primarily focuses on identifying sources of perceived risk without offering a comprehensive view. Broadly, sources of perceived risk can be categorized into brand-related, product and product category-related, and individual and cultural factors.

At the brand level, factors such as brand extension fit and brand quality consistency are believed to enhance brand reliability, thereby reducing perceived risk (Aaker & Keller, 1990; Munteanu & Pagalea, 2014; DelVecchio, 2000). However, opinions

vary regarding the impact of the number of products associated with a brand on its reliability, with some suggesting brand dilution and others noting increased reliability with more associated products (Keller, 2008; Ries & Trout, 1986; DelVecchio, 2000). Brand familiarity also plays a role, influencing consumer willingness to try unfamiliar brands and their inclusion in the evoked set (Ghosh et al., 1995).

Product and product category-related sources of perceived risk are crucial in consumer decision-making. These sources pertain to specific options and the overall perception of risk associated with buying products within a particular category (Dowling & Staelin, 1994; Florea & Munteanu, 2012).

Perceived risk and risk aversion are often viewed as cultural factors influencing consumer decision-making styles (Hofstede, 1991; Mitchell et al., 1996; Ueltschy et al., 2004). However, this approach finds more support in organizational contexts than in individual perceived risk research.

Lastly, individual uniqueness can influence perceived risk through emotions like regret and disappointment, with conflicting evidence regarding their effects on the conative component of attitude (Sevdalis et al., 2008).

2.7 Theory of Planned Behavior

The Theory of Planned Behaviour (TPB) serves as an extension of the Theory of Reasoned Action (TRA) and is rooted in Fishbein's seminal work on attitude-behaviour (Ajzen & Fishbein, 1969). TPB focuses primarily on the motivational influences that shape individuals' behaviour, assuming rationality among people, their acquisition of knowledge and beliefs from various sources including personal experiences, and systematic processing of information (Venkatesh, MG Morris,

Davis, & Davis, 2003)). The model consists of several key elements, with behavioural intentions playing a pivotal role reflecting the actual behaviour influenced by two other components: the individual's attitude and subjective norms during the behaviour enactment (Ellen & Ajzen, 1992). TPB posits that an individual's attitude, social norms, and perceived control are reliable predictors of behavioural intentions (Shaw, 2016). Attitude is shaped by behavioural beliefs derived from personal experiences and influences an individual's intention to engage in a specific behaviour (Fishbein & Ajzen, 1975; Ajzen, 1991; Fishbein & Ajzen, 2011). Subjective norms represent an individual's normative beliefs about others' perspectives or judgments regarding engaging or refraining from a behaviour (Yuzhanin & Fisher, 2016). Although the assumptions of TPB have proven adequate over time, its popularity among researchers remains high, as it has emerged as a widely used social-psychological model across various fields for behaviour prediction (Madden et al., 1992; Sheppard et al., 1998; Bagozzi et al., 1992). The theory has been further extended by incorporating an additional component to explain actual behaviour: Perceived Behaviour Control (PBC), which refers to the perception of the ease or difficulty of executing the behaviour (Ajzen, 2002).

TPB has undergone various extensions incorporating different cognitive components to enhance its adequacy (Armitage & Conner, 2001; Liang et al., 2019). It has often been integrated with other theories to enhance its effectiveness by considering additional social and psychological variables for streamlining individuals' decision-making processes. It has been paired with Configuration Theory, Technology Adoption Model, Discrete Choice Model, Functional Theory, Constructive Theory, Diffusion Theory, Norm Activation Theory, Normative Theory, Rational Choice Theory, Theory of Innovation Adoption, among others.

In one such extension, TPB has been augmented by personal norms, perceived mobility necessities, and Battery Electric Vehicle (BEV) experience. Attitudes related to EVs emerge as the most critical factor influencing intention, while perceived functional barriers regarding driving range are particularly relevant for EV users' intentions. EV users demonstrate an ability to manage longer distance trips effectively, a fitting adaptation. Additionally, in households with multiple cars, actual BEV usage percentages correlate with the types of other cars in the household, perceived functional barriers of BEVs, and successful behavioural adjustments for longer trips using BEVs.

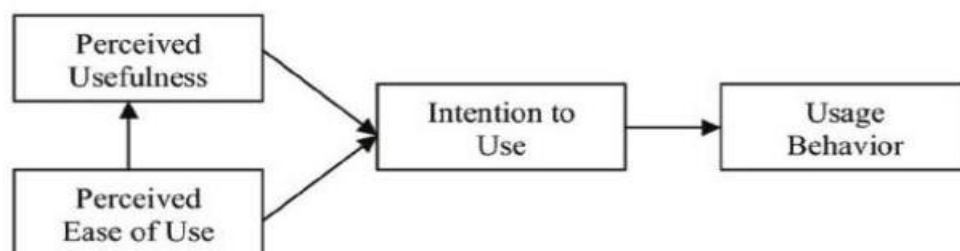
2.8 Technology Acceptance Model

The Technology Acceptance Model (TAM), as elucidated by (Marangunić, & Granić, 2015), derives from the theories of reasoned action (TRA) and planned behaviour (TPB). First conceptualized by Fred D. Davis (1989) in the late 1980s, TAM aims to forecast user acceptance of computer usage and new IT products, focusing on two key variables: perceived usefulness (PU) and perceived ease of use (PEOU). PU is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance," while PEOU refers to "the degree to which a person believes that using a particular system would be free of effort." TAM has long served as a fundamental theory in examining consumer acceptance of innovation. TAM2, proposed by Viswanath Venkatesh and Fred D. Davis (2000), builds upon TAM, incorporating social and cognitive influence processes that significantly impact user acceptance behaviour. Subsequently, TAM 3 was developed by Venkatesh and Bala (2008) from TAM2, aimed at enhancing managerial decision-making on IT implementation by incorporating more comprehensive determinants at the individual level.

Various studies have explored the acceptance of technological propositions, often considered antecedents of acceptance. (Hawlitschek, Teubner, & Gimpel, 2016) devised an enhanced model combining TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine user behavior in the sharing service market. (Claudy, Garcia., & O'Driscoll, 2015) and colleagues applied TAM to develop a behavioural reasoning theory, investigating attitudes, intentions, and usage behaviour towards Electric Vehicles (EVs).

Despite TAM's widespread use in elucidating consumer behaviour towards new information systems, relatively few studies have applied TAM to car purchases or innovative business models. Saleh Alharbi and Steve Drew (2014) utilized TAM to gauge purchase intention for a newly emerging tool, Learning Management Systems (LMS), in the Middle East. Their findings confirmed a positive effect of PEOU on attitude and purchase intention to use LMS. A.B. Ozturk (2016) and collaborators also identified PEOU as a critical component in technology adoption and usage behaviour, with PEOU positively influencing purchase intention, loyalty-building, and recommendations to others.

Fig: 2.6: Technology Acceptance Model



Source: Perceived Usefulness, Ease of Use, and User Acceptance of Information Technology (Davis, 1990).

2.9 The behavior of Environmental Concern

An environmentally sustainable lifestyle is increasingly becoming the norm among consumers, with individuals adhering to green values demonstrating distinct behaviours compared to those less attentive to pro-environmental objectives. Pro- environmental behaviour (PEB), a concept enriched over decades in literature, was initially explained solely by individuals' environmental knowledge in the 1990s, a view later expanded by Price and Pitt (2011) to include ecological values, situational factors, and psychological variables.

Jan Krajhanzl (2010) defines environmental behaviour as all human actions continuously interacting with the environment, with PEB serving as a measure to assess whether an impact on the environment aligns with environmentally friendly practices. Dian R. Sawitri, H. Hadiyanto, and Sudharto P. Hadi (2014) refined the concept of PEB as conscious actions aimed at mitigating the negative impact of human activities on the environment. Various definitions of PEB have been proposed, ranging from purpose-driven to fact-oriented dimensions (Kiyo K., 2016), with literature categorizing behaviours into 12 distinct categories under different targets and elucidating their relationship with users.

Extensive studies in psychology and sociology have aimed to identify influential elements consistent with PEB performance. Christopher F. Clark (2002) and colleagues investigated internal and external influences on PEB, identifying biocentric, altruistic, and egoistic motives as significant factors. Environmental concern and a positive attitude towards frugality have also been found to effectively promote PEB (S. Fujii, 2007), with research indicating varying degrees of influence on specific PEB.

Self-identity, or the sense of self, is commonly believed to strongly influence consumer behaviours. Birgitta Gatersleben (2014) and colleagues found that identity significantly predicted the intention to purchase PEBs, while green values directly influenced identity. L. Whitmarsh and S. O'Neil (2010) reinforced the importance of self-identity and past behaviour in predicting environmentally significant conduct, noting differences in the influence of self-identity on purchase intention for various pro-environmental behaviours.

Recent studies, such as that by J. Dermody et al. (2017), have examined the role of self-identity and consumer behaviour in the era of innovation, highlighting the dynamic expression of pro-environmental self-identity (PESI) on sustainable consumption behaviour. Environmental concern, often used as a moderator, alongside environmental attitude, environmental friendliness, environmental consequences, and ecological consciousness, are significant variables influencing consumer behaviour and increasing environmental responsibility. Additionally, informing consumers about environmental protection aspects, often overlooked for superior performance metrics, is crucial (Rezvani et al., 2015). Ferri and Pedrini (2018) even differentiate the effects of conventional consumerism and steer consumers towards green consumerism.

2.10 Lifestyle

Despite its widespread colloquial usage, the concept of lifestyle has not received significant scholarly attention since its inception in the early twentieth century. Independently developed by psychologist Adler (1933) and sociologist Weber (1943, as cited in Gerth & Mills, 1958), lifestyle was introduced to describe aspects of human beings that were not adequately captured by existing social science

terminology. Both scholars and their followers sought a concept that could encapsulate the entirety of an individual's being and behaviour (Reed, 1976).

The elucidation of human behaviour has often relied on "low-level" descriptors such as income, expenditures, personality traits, attitudes towards specific issues, age, and family structure, without attempting to depict the individual within a comprehensive context. Unfortunately, when attempts are made to employ multivariate approaches, the temporal dimension is often overlooked. The cross-sectional nature of many "low-level" social descriptors has failed to capture the consistency of behaviour over the long term. This research aims to explore the primary motivations behind purchasing an electric vehicle, delving into the lifestyle preferences of customers who opt for electric vehicles exclusively.

Chapter 3

Conceptualization of Purchase Intention Model

3.1 Introduction

This chapter outlines the framework for understanding electric vehicle (EV) purchase intentions. It critically reviews existing literature on the factors influencing EV purchase decisions and their impact on purchase intention. Building on theoretical foundations, the chapter conceptualizes a purchase intention model, elucidating hypothetical correlations and their effects on the endogenous variable—intention to purchase. The chapter concludes with a discussion of relevant theories and their propositions to better understand consumers' intentions to buy EVs.

Purchasing any product can be viewed as a problem-solving task involving a sequential decision-making process: problem recognition, information search, alternative evaluation, and choice (Engel, Blackwell, & Miniard, 1993). However, consumers do not necessarily follow this process in its entirety for all purchases, as each purchase is unique. —Purchases may be categorized into routinized response behaviour, limited problem-solving, or extensive problem-solving (Howard, 1977), with distinctions based on the amount of information required. Routinized response behaviours require minimal information, whereas extensive problem-solving situations demand substantial information.

This study focuses on durables due to the higher likelihood of consumers engaging in extensive problem-solving, which typically involves a thorough information search. Durable goods purchase often entail a considerable decision-making period and the use of various information sources, providing a good opportunity to investigate the information-gathering process crucial in decision-making. The final choice outcome

depends on the preceding choices made during information acquisition. Both external and internal information searches contribute to building the necessary database for processing information and evaluating alternatives. While traditional assumptions hold that consumers gather comprehensive information about all available options, research has documented variability in the extent of these searches (see Chapter 2 for more details). Understanding the information based on which decisions are made is critical for comprehending final choices. This chapter aims to develop a model of antecedents affecting the extent of information searched, including both internal and external searches, resulting in a comprehensive model of consumer pre-purchase information search behaviour.

Theoretical Antecedents of Purchase Intention

The antecedents of purchase intention are multifaceted, encompassing perceived risk and technological and economic factors. This distinction is essential due to the intricate relationships between these sources and purchase intention (Engel, Blackwell, & Miniard, 1993; Bettman, 1979).

Factors Influencing EV Purchase Intention

This study examines consumers' intentions to adopt EVs by analysing various factors that influence and impact purchase intention. Empirical research (Ajzen, 2003; Rezvani, Jansson, & Bodin, 2020; Hjorthol, 2022) has validated the drivers and barriers to purchase intention, focusing on technological factors and consumer characteristics (Carley, Krause, Lane, & Graham, 2013). Psychological perceptions also play a significant role in adoption intention (She, Sun, Ma, & Xie, 2019). Integrative factors influencing purchase intention are categorized into three broad groups: technological, contextual, and economic.

Perceived Risk and EV Purchase Intention

Perceived risk is a critical factor in the decision to purchase a consumer durable product, especially with EVs being a new mobility platform. The economic cost of owning an EV is significantly higher than that of an internal combustion engine (ICE) vehicle. Technologically, EVs pose new risks regarding reliability and validity, with performance concerns such as range and dependability also contributing to perceived risk.

Comprehensive Model

Based on the theories discussed, and reviewed literature, the study consolidates propositions into three independent factors:

- Perceived risk factors
- Technological factors
- Economic factors

The fourth factor, purchase intention, is treated as the endogenous variable. The study adopts a hierarchical model method to evaluate purchase intention, providing a structured approach to understanding the factors influencing consumers' decisions to purchase electric vehicles.

3.2 Construct – Perceived Risk

Consumer Perceived Risk and Its Impact on Purchase Decisions Consumer perceived risk is defined as "the consumer's perceptions of the uncertainty and adverse consequences of buying a product or service" (Dowling & Staelin, 1994). This concept forms the basis of the descriptive model proposed by Dowling & Staelin

(1994), which suggests that when consumers perceive a purchase as risky, they prefer to consider it within their known evoked set. When contemplating the purchase of a durable product, consumers may experience feelings of uncertainty, concern, discomfort, and anxiety about post-purchase outcomes, leading to intense post-purchase remorse. Dowling & Staelin (1994) posit that these feelings stem from the consumer's perceived risk.

When evaluating the magnitude and probability of potential adverse consequences associated with acquiring a product, consumers consider the perceived risk involved (Dowling & Staelin, 1994). The actual outcomes of any purchase decision can only be known post-purchase, and during the decision-making process, consumers deal with uncertain information.

To mitigate perceived risk, consumers engage in extensive external information searches. Perceived risk can be seen as a potential loss due to inadequate external information. For instance, in the scenario of a car purchase, an impulse purchase could result in several types of loss: psychological, financial, performance, physical, social, or convenience (Peter & Tarpey, 1975; Peter & Ryan, 1976; Dholakia, 2001). Each type of loss represents a dimension of perceived risk (Dholakia, 2001). The likelihood and significance of these losses must be considered from each consumer's perspective to form a meaningful representation of perceived risk.

Every product purchase carries inherent risk, which may or may not be unique to the consumer's situation (Bettman, 1979). For durables, particularly automobiles, perceived risk is significant because higher-priced items involve longer consumer commitment, thus increasing perceived risk (Beatty & Smith, 1987). Consumers typically adopt strategies to moderate perceived risk, such as (1) extensive external

information searches to build confidence in processing information and making better choices (Beatty & Smith, 1987; Dowling & Staelin, 1994) and (2) brand loyalty (Howard & Sheth, 1969). Empirical studies support the second strategy, with findings indicating that consumers often resort to brand loyalty to mitigate risk when choosing durables like automobiles (Punj & Staelin, 1983).

However, empirical research has shown varying relationships between perceived risk and information search. Gemunden (1985) found that perceived risk does not always significantly affect internal or external information searches. Conversely, Dowling & Staelin (1994) concluded that perceived risk does influence consumers' search behaviour. Extending the findings of Beatty & Smith (1987), search activity increases with the perceived risk associated with a product category. For example, high-risk products like automobiles prompt more extensive information searches to mitigate risk.

Rather than a direct link between perceived risk and external search, this model proposes —a relationship between risk and perceived benefit (Srinivasan & Ratchford, 1991)¶. Greater perceived risk leads to increased perceived benefits from searching, as risk reduction is a key benefit of information search. Thus, perceived risk acts as an antecedent to perceived benefit (Dommermuth, 1965).

Conceptual confusion may arise when distinguishing between perceived risk and perceived benefit, especially if similar scales are used (Peter & Tarpey, 1975). —The perceived risk model addresses negative utility or potential loss, while the perceived benefit model focuses on positive utility or potential gain from external search¶. Peter & Tarpey (1975) clarify this distinction, emphasizing that perceived risk underlies the

construct of perceived risk, whereas attitude research on product attributes forms the basis of the perceived benefit model.

High perceived risk strongly correlates with increased information search (Bettman, 1973), as reducing risk is a perceived benefit. Handled risk is minimized by balancing the benefits and costs of search. If initial perceived risk is high, search activity reduces it to an acceptable level, leading to higher perceived benefits of the search.

Srinivasan & Ratchford (1991) found that "perceived risk will increase the size of the evoked set of brands," suggesting that higher perceived risk enhances the need for brand searches to obtain clear product class information. Thus, we propose that perceived risk positively influences the size of the evoked set.

(Mauricio, Jia, Califf, & Hajli, 2024) profound three types of perceived risks from the electric vehicle purchase point of view. The three types of risk are. financial, performance, and psychological risk.

3.2.1 Performance Risk

The authors define the perceived risk as —The combined evaluation of the likelihood and severity of negative consequences and personal losses resulting from EV purchase.

The following dimensions are measured (Mauricio, Jia, Califf, & Hajli, 2024).

The first dimension of perceived risk, known as performance risk, pertains to concerns regarding the reliability of electric vehicles (EVs). Although EVs have been commercially available for over a decade, there remains a significant portion of the population who may not have had the opportunity to see or experience an EV in their own community. This limited exposure can foster skepticism and apprehension about

the dependability and efficiency of EVs. Furthermore, these doubts extend beyond the vehicles themselves to include worries about the robustness and availability of the necessary maintenance services and charging infrastructure within their area. Consequently, even with the advancements and growing presence of EVs globally, the unfamiliarity among some consumers contributes to ongoing uncertainties about their overall performance and support systems.

3.2.2 Financial Risk

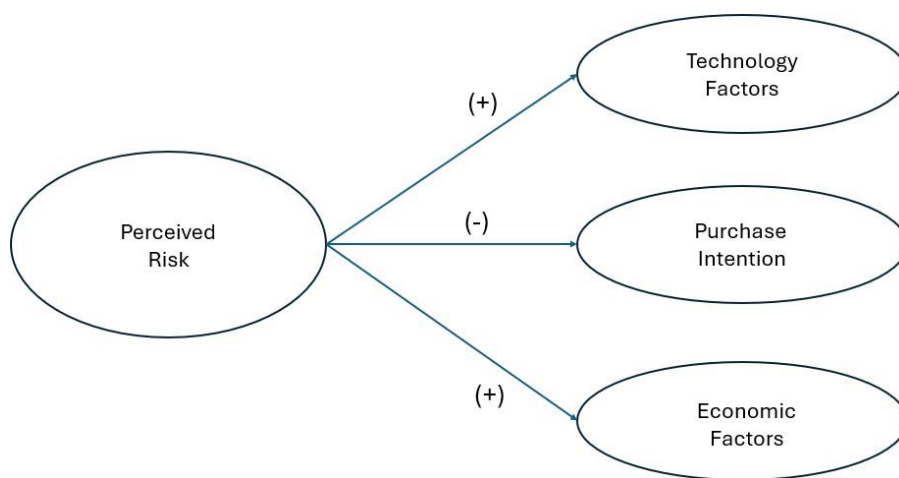
The second type of loss we investigate is financial risk. Electric vehicles (EVs), while offering the promise of long-term utility and environmental benefits, come with a significant initial price tag. This high upfront cost represents a considerable financial burden for many consumers, necessitating careful consideration of financing options and insurance coverage. Additionally, the adoption of EVs often requires investments in supporting infrastructure, such as home charging stations, which further adds to the overall expense. Beyond these immediate costs, there is also the potential for substantial future financial commitments, particularly concerning the replacement of essential components like batteries or motors. These anticipated expenses contribute to the broader financial risk associated with EV ownership, causing potential buyers to weigh the long-term economic implications carefully.

3.2.3 Psychological Risk

Psychological risk involves the emotional challenges and stress that can arise from the adoption of electric vehicles (EVs), impacting a person's ego and sense of peace. The decision to purchase an EV can trigger a range of emotional reactions in consumers, from minor discomfort to significant anxiety, thereby unsettling their mental equilibrium. As highlighted by Slovic (2010), consumers often express their

concerns about various threats and dangers in terms of risk. Consequently, some individuals may avoid new technologies that necessitate learning new skills, altering their lifestyle, or confronting perceived dangers, resulting in avoidance behaviour. For instance, some consumers might experience ongoing emotional frustration because the sound of an EV's engine does not replicate the distinctive roar of their beloved 'muscle car,' underscoring a significant psychological obstacle to the adoption of EVs.

Figure 3.1: The prepositions of Perceived Risk equations can now be expanded.



Knowledge Search and Technology Optimism in EV Purchases

When purchasing a product, buyers engage in both internal and external knowledge searches (Biehal & Chakravarti, 1986). Accumulating knowledge from similar past experiences can mitigate the perceived risk associated with purchasing similar products. This differentiation in perceived risk is particularly evident between first-time and experienced buyers.

Optimism about technology generally correlates with a favourable attitude towards electric vehicles (EVs). Public attitudes and interests can further explain the Technology Readiness Index (TRI) concerning EVs. Previous studies strongly support the notion that individuals with a positive attitude towards EVs—either through actual purchase or general interest—are more likely to purchase an EV or recommend it to others (Lane, S Carley, & JD Graham, 2016) Salari, 2022).

Based on this understanding, we propose the following hypotheses:

H1: Perceived risk positively affects technology factors.

H2: Perceived risk positively affects economic factors.

H3: Perceived risk negatively affects purchase intention.

3.3 Construct – Technology Factors

While electricity as a vehicle fuel offers numerous benefits, it also presents certain challenges. Disadvantages include the bulkiness of storage, higher costs, and slower refueling times. These factors result in current electric vehicles (EVs) having a smaller range compared to conventional diesel and petrol vehicles and difficulties in recharging quickly and easily while on the road (Pearre, Kempton, Guensler, & Elango, 2021).

This context highlights the significant technological factors affecting EV adoption, which include:

- 3.3.1 Driving range anxiety,
- 3.3.2 Recharging time,
- 3.3.3 Reliability and EV Model Variety.

3.3.1. *Driving range anxiety*

Driving range anxiety is a significant barrier to consumers' decisions to purchase electric vehicles (EVs) (Jensen et al., 2013; (S Haustein, 2021)). Research indicates that consumers prefer an ideal driving range between 300 km (Daziano & Chiew, 2012) and 450 km (Zhu, 2022). However, achieving this range is often impractical, leading to range anxiety. This anxiety is particularly evident during long drives when the battery charge depletes, and drivers are unable to predict the remaining distance they can cover accurately. The limited and uncertain vehicle range raises concerns about the reliability of EVs for long journeys (Noel et al., 2020).

Consumers are particularly sensitive to the limited driving range of EVs (Ona Egbue, Long, & Samaranayake, 2017). Although some EV models offer ranges of up to approximately 400 km, these models are typically among the most expensive. In contrast, internal combustion vehicles (ICVs) can average around 800 km on a full tank of petrol. This disparity is identified as a primary barrier to EV adoption (Kumar & Thakur, 2021), (Lim & Yue, 2015). Enhancing range through improved charging infrastructure can facilitate greater EV adoption (Lim et al., 2015).

(T Franke & JF Krems, 2013) acknowledge that while range is a barrier to adoption, the driving experience of an EV can adapt over time, mitigating the practical

limitations of a shorter driving range. Nevertheless, range anxiety remains a significant concern for users and negatively impacts the adoption of EVs (Jensen et al., 2014; She et al., 2017).

3.3.2. Recharging Time

Influence of Charging Time on Electric Vehicle Purchase Intention. Charging time is a critical factor influencing the intention to purchase electric vehicles (EVs) (Chiew & Daziano, 2016), (Abotalebi, Ferguson, Mohamed, & Scott, 2015). The time required to recharge the battery is directly related to the driver's desired range; the more the battery is charged, the greater the range provided (Daziano & Chiew, 2012). However, this extended charging time is due to the slow refuelling capacity of EVs (Egbue & Long, 2012). Although considered less problematic than other factors, charging time still contributes to the reluctance to purchase EVs (Carley, Krause, Lane, & Graham, 2013). —Many drivers perceive charging an EV as more inconvenient compared to refuelling an Internal Combustion Engine (ICE) vehicle (Brückmann, Willibald, & Blanco, 2021). They believe that the longer charging time could disrupt their daily routines, particularly for on-road drivers who cannot quickly refuel and continue their journey (Graham-Rowe et al., 2022)¶. Additionally, if a charging station is available only at home, it limits the ability to make sudden, unplanned trips, thereby reducing flexibility.

The adoption of EVs is heavily influenced by the speed of charging infrastructure (Castillo et al., 2020). —Users generally prefer faster electric vehicle supply equipment (Moon et al., 2018). While refuelling an ICE vehicle takes approximately four minutes, charging an EV can take at least 30 minutes at a fast-charging station and up to 8 hours at lower power (Glerum et al., 2014; Kumar & Thakur, 2020).

Reducing charging time is essential to increase EV adoption (Sellmair & Schelo, 2019). However, recent studies suggest that users are willing to adapt to the EV charging process (Schmalfuß et al., 2017). Therefore, reducing charging time and increasing the range of EVs should significantly enhance the intention to purchase them (Junquera et al., 2016)¶.

Overall, consumers are generally dissatisfied with the performance of EVs in terms of range and charging time (Chen et al., 2020; Kester et al., 2018). However, EVs have the potential to outperform ICE vehicles, which could offset less favourable factors such as limited range, long charging times, and high prices (Skippon, 2014). Performance attributes significantly affect consumer acceptance, often more so than financial or environmental awareness factors (Zhang et al., 2013). —Conversely, other studies highlight that environmental benefits and incentives are more influential than performance characteristics (Peters & Dutschke, 2014)¶.

3.3.3. Safety and Reliability

Essential Factors for Electric Vehicle Adoption

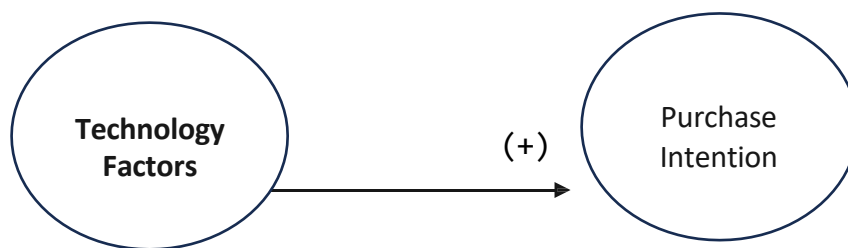
Safety and reliability are among the primary concerns for consumers considering electric vehicles (EVs) (Thananusak et al., 2017; Zhang et al., 2013). In the study by She et al. (2017), these factors scored the highest, indicating a significant level of distrust and concern regarding the safety of EV technology. These concerns are partly due to incidents where EV batteries have caught fire in accidents, highlighting the hazardous nature of battery components like lithium, which are highly flammable.

Despite these concerns, reliability is identified as a key motivator for purchasing an EV (Higuera-Castillo et al., 2019). In support of this, Ingeborgrud and Ryghaug (2019) found that EV owners generally perceive their vehicles as safe, silent, and exciting technological advancements.

Therefore, we propose the following hypothesis:

H4: Technological factors have a positive influence on Purchase Intention.

Figure 3.2: *The prepositions of technological factors equations can now be expanded.*



3.4 Construct – The Economic Factors

Economic Factors Influencing Electric Vehicle Adoption Economic factors encompass the various monetary costs associated with the purchase and use of a vehicle. These factors, also referred to as financial attributes in marketing literature and economic determinants in economic literature, can be either direct or indirect.

For durable products, such as vehicles, price is a critical determinant of purchase decisions. Numerous studies have included purchase price as a key variable, often using a pivoted design where price levels are customized based on a reference vehicle provided by each respondent. Across all studies, purchase price consistently showed a negative and highly significant impact on EV utility. Most research treats this

relationship as linear, with a few exceptions like (Ziegler, 2012), who explored a non-linear effect using logarithms of the price.

Price sensitivity varies among different populations. Rasouli and Timmermans (2013) found high heterogeneity in price sensitivity, especially when EV prices significantly exceed those of conventional vehicles (CVs). Several studies identified an income effect, where higher-income individuals are less sensitive to price (Achtnicht et al., 2012; Hackbarth & Madlener, 2013; Hess et al., 2012; Mabit & Fosgerau, 2011; Molin et al., 2012; Potoglou & Kanaroglou, 2007; Valeri & Danielis, 2015). However, Jensen et al. (2013) found this effect to be insignificant. Car size preferences also influence price sensitivity; for instance, buyers of smaller cars have higher marginal utility (Jensen et al., 2013). Additionally, price is more critical for used car buyers (Hoen & Koetse, 2014; Jensen et al., 2013), and those focused on practical aspects rather than design are less affected by price (Glerum et al., 2014).

High purchase prices are a significant barrier to EV adoption, as noted in many consumer surveys (Carley et al., 2013; She et al., 2017). The advanced technology used in EV manufacturing, particularly Lithium-ion batteries, increases vehicle costs (Noel et al., 2020). As efforts continue to enhance EV range, the complexity and cost of batteries rise (Biresselioglu, Kaplan, & Yilmaz, 2018). Consequently, future battery replacements will also be expensive. Additionally, a lack of understanding of fuel and maintenance costs exacerbates this barrier. The poor economy of scale for new technologies often results in less favorable price comparisons with established designs.

Consumer perception of the monetary value of EVs is another factor. Although EVs have lower service and maintenance costs compared to ICE vehicles, the high initial

purchase price deters many consumers. This indicates a lack of awareness that lower operating costs can lead to significant long-term savings (Krause et al., 2013).

The significant economic factors influencing the purchase of electric vehicles includes:

Purchase Price: A major determinant consistently shown to impact EV utility negatively.

Income Sensitivity: Higher-income individuals are generally less price-sensitive.

Car Size and Type: Smaller car buyers and used car buyers are more price sensitive.

Technology Costs: Advanced battery technology increases vehicle and replacement costs.

Operational Savings: Lower maintenance and fuel costs can offset the high purchase price, though this is not widely recognized by consumers.

3.4.1. Price

3.4.2. Incentives

3.4.3. Infrastructure

3.4.1 Price

The expensive buying price is one of the most substantial obstacles to the adoption of electric vehicles (EVs). Consumers are generally unwilling to pay a significant premium for an EV (Larson et al., 2014). Research by Sierzchula et al. (2014), covering —approximately 30 countries, demonstrates that the price of EVs negatively correlates with market share. Various authors have suggested that reducing the cost

could —increase the willingness to buy an EV (Junquera et al., 2016) and enhance its competitiveness (Feng & Figliozzi, 2013)¶.

Consequently, the high cost remains a primary concern for consumers (Rezvani et al., 2015), making it a significant disadvantage (Heyvaert et al., 2015).

Conversely, EVs offer benefits in terms of recharge and maintenance costs, which are key motivations for their purchase (Ozaki & Sevastyanova, 2011). Zhang et al. (2013) identify financial benefits as a major driver of EV acceptance. Given current fuel and energy prices, the cost of charging EV batteries is lower than refueling internal combustion vehicles (ICVs) (Carley et al., 2013). Chu et al. (2019) highlight that the lower recharging cost is a significant motivation for buying an EV. Consequently, the low price of electricity contributes to increased EV adoption (Soltani-Sobh et al., 2017). —Furthermore, there are considerable savings in societal costs and the total cost of ownership compared to diesel vehicles (Boren, 2019). Electric motors, being less complex than ICV propulsion systems, are also less costly to maintain (Taefi et al., 2016). Thus, the perceived financial benefits positively influence purchase intentions (He et al., 2018; Kim et al., 2018)¶.

However, despite these savings, consumers might still hesitate to buy an EV due to the energy-efficiency paradox or energy-efficiency gap (Gillingham & Palmer, 2014). Some studies indicate that respondents either undervalue or are unaware of the potential cost savings associated with EVs (Carley et al., 2013). As a result, consumers tend to focus more on the high purchase price rather than considering the total cost of ownership (Sierzchula et al., 2014).

3.4.2 Incentives

Both monetary and non-monetary incentives significantly influence consumers' intentions to purchase electric vehicles (EVs). Economic incentive measures, such as direct subsidies for purchasing EVs, tax breaks, and exemptions from road and registration taxes, positively impact both the purchase and use of EVs (IEA, Global Electric Vehicle Outlook, 2023).

In India, the sales of electric vehicles have tripled, increasing EVs' share of total vehicle sales to 1.5 percent. Literature suggests that incentives and effective economic policies are likely to further boost the market share of EVs in India (IEA I. , 2022).

Globally, governments, including India, have implemented policies to enhance environmental sustainability by encouraging EV adoption. These policies aim to attract consumer attention and increase purchase intention for EVs (Lieven, 2015; Sierzchula et al., 2014).

Countries like the USA (Jin et al., 2014), European nations (Gass et al., 2014; Kley et al., 2012), and China (Leurent & Windisch, 2011) have established EV policies and incentive programs that have successfully influenced consumer behavior. A significant portion of global EV sales originates from these markets, highlighting the correlation between incentives and EV purchase intention (IEA, Global Electric Vehicle Outlook, 2023; Sierzchula et al., 2014).

Consumers often evaluate a product's Total Cost of Ownership (TCO) when making purchase decisions. Research by Levay et al. (2017) and Bjerkan et al. (2016) shows that incentives effectively reduce the TCO of EVs compared to internal combustion engine vehicles (ICEVs). These incentives not only decrease the overall cost but also

positively influence consumer purchase intentions (Zheng et al., 2022). The literature consistently demonstrates that incentives play a crucial role in increasing EV acceptance (Kim et al., 2018; Langbroek et al., 2016), making the cost of purchasing an EV more comparable to that of an ICEV.

3.4.3 Charging Infrastructure

One significant risk is the lack of charging stations when traveling (Krupa et al., 2022). Consequently, consumers often demand that public charging stations be made available at more locations to accommodate long-distance drives (Habla, Huwe, & Kesternich, 2022). The cost of establishing these networks is notably high (Brückmann, Willibald, & Blanco, 2021), leading to uncertainty regarding the future expansion of charging infrastructure. Investments in EV infrastructure by the government and manufacturers could facilitate higher EV adoption rates among consumers (Bhalla, Ali, & Nazneen, 2020).

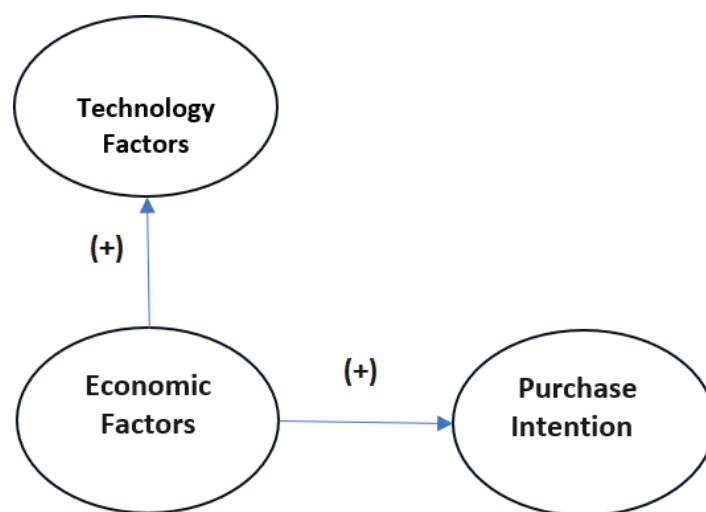
The inconsistency of charging systems often discourages some drivers from relying on them. There remains debate about the extent to which public charging facilities are needed to increase consumer willingness to adopt EVs. It is likely that expanding the number of charging points and making them more accessible would reassure consumers that EVs are a viable transportation alternative (Noel, de Rubens, Kester, & Sovacool, 2020).

Monitoring how public perceptions of EVs evolve in cities where charging points are introduced will be essential to understanding the increasing prominence of EVs (Bunce, Harris, & Burgess, 2021).

The availability of charging infrastructure is crucial, and its absence poses a significant barrier to EV adoption (Tran et al., 2012). She et al. (2017) identified the lack of charging infrastructure as the most significant impediment to adoption. Jensen et al. (2013) demonstrated that public charging stations are essential for purchasing EVs. While Krupa et al. (2014) emphasized the importance of home charging facilities for overnight battery charging and vehicle safety, Caperello and Kurani (2012) noted the critical nature of the charging cable's role. —Consequently, the number of charging stations is a predictor of EV adoption (Sierzchula et al., 2014), and access to these stations is a crucial determinant of adoption (Mersky et al., 2016)¶.

The charging infrastructure is the critical differentiator between electric and conventional vehicles (Gnann et al., 2018). According to Wang et al. (2019), charger density positively correlates with EV purchase intention and market share. Egner and Trosvik (2018) also found that infrastructure investment significantly impacts the adoption rate. Hence, we propose the following hypothesis

Figure 3.3: *The prepositions of Economic Factors can now be expanded.*



Hence, we propose that.

H5: Economic factors positive impact the technology factors.

H6: Economic factors positively impact the purchase intention.

3.5 Construct – Purchase Intention

Though still representing a small percentage of total new vehicle sales globally, the demand for electric cars has surged in recent years. Electric vehicles (EVs) are revolutionizing mobility platforms in mature consumer markets. However, in India, the EV market share remains in its emerging phase. Global electric car sales reached 10 million in 2022 (IEA, Global Electric Vehicle Outlook, 2023) and are expected to hit 14 million in 2023 (IEA, Global Electric Vehicle Outlook, 2023). This exponential growth has increased the EV market share of overall passenger vehicles from 4 percent to 14 percent in 2022. Recent forecasts by the IEA project that the EV market share may grow to 18 percent in 2023.

India is experiencing similar exponential growth. The electric vehicle passenger segment saw a 154 percent increase in 2022 compared to 2021 and is forecasted to grow more than 2.5 times in 2023 (IEA, Global Electric Vehicle Outlook, 2023). This indicates a substantial shift in the global and Indian automobile industries toward accepting new, eco-friendly technologies. According to the IEA, "Electric vehicles are one of the driving forces in the new global energy economy that is rapidly emerging – and they are bringing about a historic transformation of the car manufacturing industry worldwide."

As technology evolves, so does consumer behavior. Therefore, understanding consumer purchase intentions is a critical area of research. This study aims to measure purchase intention by evaluating factors such as the intention to use EVs, willingness to pay, and performance value.

3.5.1. Intention to Buy EVs or Willingness to Purchase

Purchase intention or intention to buy is a key focus in consumer behavior studies, particularly within behavioral models such as the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Theory of Reasoned Action (TRA) (Yang et al., 2020; Wang et al., 2018). Literature reviews indicate that consumer attitudes, including willingness to purchase or pay, are positively related to the purchase intention of electric vehicles (Khurana et al., 2019).

The intention to buy significantly influences the adoption of electric cars. Therefore, this study proposes that the intention to buy electric vehicles directly impacts purchase intention.

3.5.2. Willingness to Pay

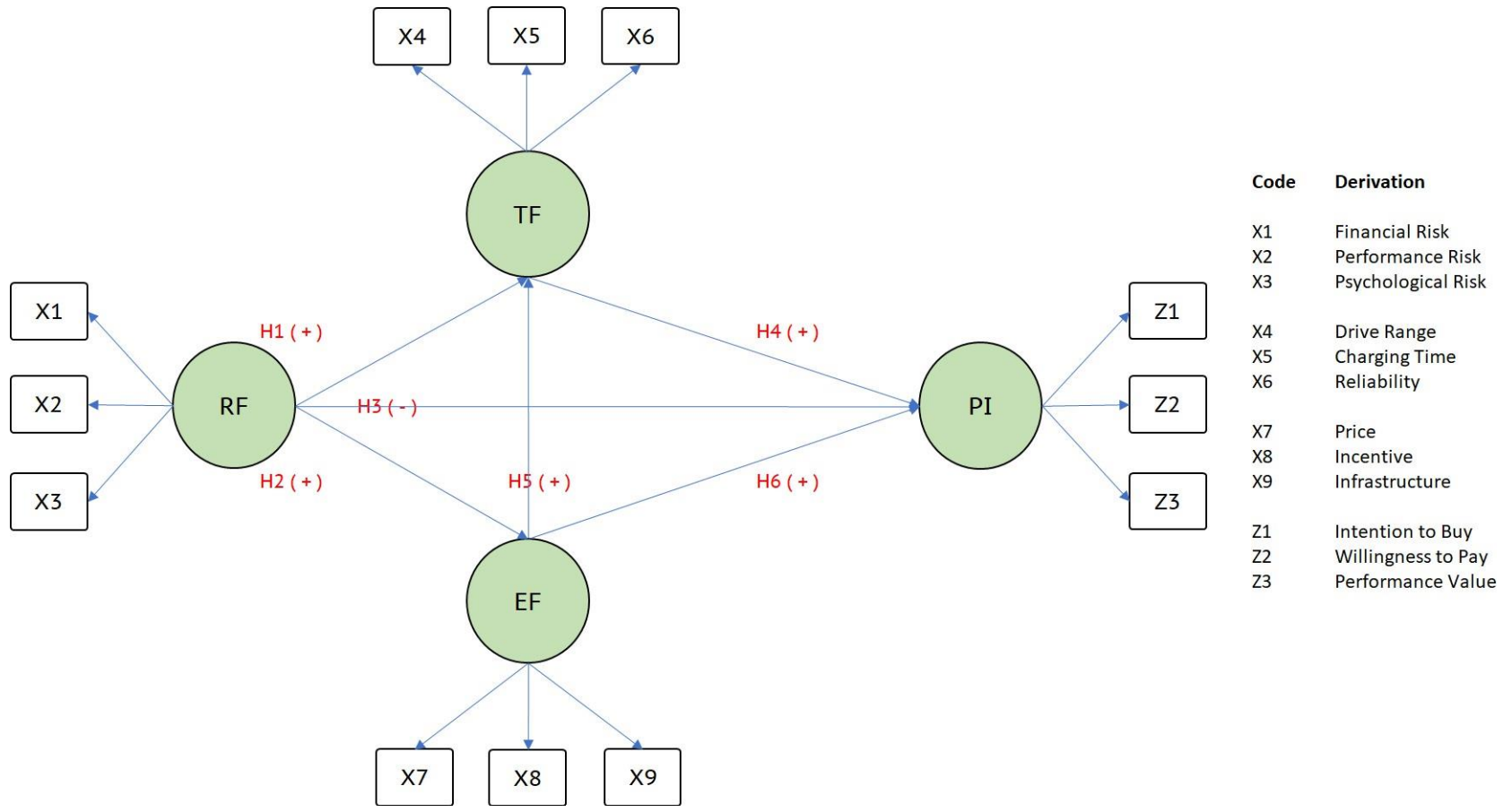
The literature suggests that consumers are willing to pay more for products perceived as safer, better, or of higher quality (Han et al., 2017). Furthermore, the willingness to pay for durable products is closely linked to factors such as brand equity, technology, and value addition. This study hypothesizes that the willingness to pay more, as an interchangeable concept with consumers' purchase intentions, reflects their desire to buy an electric vehicle. Additionally, loyalty, adoption of technologically advanced products, and subjective norms are strong indicators of consumers' willingness to pay premium prices. The financial capability of consumers

is inversely proportional to their willingness to pay a premium (Han et al., 2017). Despite having a purchase intention, some consumers may be deterred by the premium-price effect (Han et al., 2017).

3.5.3. Performance Value

Electric vehicles are mobility platforms designed to transport consumers from point A to point B. Within the consumer purchase framework, vehicle performance is a critical factor. It significantly influences purchase intention and the decision-making process (Kang & Park, 2011). Key attributes such as vehicle quality, reliability, charging time, driving range, driving comfort, and usage convenience play a crucial role in the acceptance of EVs (Zhang et al., 2013). Performance is a primary consideration for both first-time buyers and experienced consumers, and it determines their choice. When the performance of EVs meets the consumers' expectations and utilitarian needs, they are more likely to show a willingness to purchase or adopt the vehicle (Graham-Rowe et al., 2022). Therefore, the performance value of EVs is a fundamental factor influencing purchase intention or willingness to purchase.

Figure 3.4: Conceptualized Model of Electric Vehicle's Purchase Intention from the perspective of India.



Summary of the chapter

This chapter has developed an empirical model of electric vehicle purchase intention, focusing on three key independent determinants: perceived risk, technological factors, and economic factors. The risk factor negatively influences purchase intention, while the other determinants positively impact it.

The model integrates technology benefits with augmented economic and risk variables. Perceived risk encompasses psychological factors related to the fixed and variable costs associated with owning an EV. A thorough understanding of the product and a high level of involvement in the purchase process can decrease perceived risk, directly influencing purchase intention. The product's technology serves as the "engine" driving the purchase intention process.

For consumers with prior experience buying electric vehicles, familiarity, positive experiences, and reduced perceived risks positively influence their intention to purchase. Positive experiences and understanding reduce perceived risks, as previous purchase and usage experiences enhance intention.

Perceived risks have three determinants: financial, psychological, and performance risks. All three determinants negatively influence perceived risks. These determinants focus on limiting alternatives if the consumer has prior knowledge of the product.

CHAPTER IV

PURCHASE INTENTION MODEL OPERATIONALIZATION

4.1 Introduction

This study aims to identify the antecedent variables influencing electric vehicle purchase intention among Indian consumers. Measuring these variables is crucial for effectively validating purchase intentions from the Indian consumer perspective.

The variables influencing the dependent variable, purchase intention, should have multiple measures or indicators. The model incorporates variables that have evolved with consumer preferences, such as technology factors.

The empirical model evaluating purchase intention was conceptualized in the previous chapter, with Purchase Intention as the endogenous construct. This construct will be assessed using durable goods, such as electric vehicles, from the perspective of Indian consumers. Three exogenous constructs will be used to measure the endogenous variable:

1. Perceived Risk
2. Technology Factors
3. Economic Factors

For comprehensiveness, each variable will include as many factors as possible for the pilot study, with a minimum of three for the full-scale study. This approach enhances analytical soundness and provides significant inferences. In empirical testing, the measures used for operationalization will define the domain of the latent unobserved constructs being examined.

In this dissertation, all constructs in the model are treated as latent unobserved constructs with multiple observable indicators. These indicators collectively capture the domain of the latent construct. If a latent construct has orthogonal dimensions, the operationalized model should reflect this. In this study, each construct is specified to have only one dimension. —Multiple measures for a single latent construct should be correlated, as all indicators capture the general factor of the domainl.

The operationalization of the conceptualized model occurs in two stages. First, the domains of the latent constructs are clearly defined. Next, operational measures for the latent constructs are detailed. Where valid measures exist in the literature, they are adopted for this study. These scales, well-developed and validated in existing research, have undergone further validation in two stages for this study. A preliminary pilot study has been conducted, including in-depth interviews with potential buyers, followed by an extensive validation of factors influencing the purchase intention of Indian consumers.

4.2 Domains of the Latent Constructs

This chapter defines the theoretical and empirical domains of all the independent and dependent variables considered in the conceptualized model, drawing from prior validated literature.

The twelve first-order variables are categorized into four factors:

4.2.1 Perceived Risk

4.2.2 Technology Factors

4.2.3 Economic Factors

4.2.4 Purchase Intention

Second-order constructs are differentiated based on their synthesis and approach to estimating and evaluating purchase intention. The definitions, domains, and measures of these constructs are outlined below.

4.2.1. Perceived Risk

The probability of loss that can occur without any external search for information is multiplied by the importance of that loss. In the case of automobiles, potential losses can be financial, performance-related, or psychological (Peter & Tarpey, 1975).

4.2.2. Technology Factors,

The electric vehicle is a product that undergoes technological assessment. Its inherent differentiation lies in the technology it offers to fulfil customers' mobility requirements, particularly its environmentally friendly features. The various technological aspects are thoroughly examined, focusing on how these innovations affect and influence consumers compared to traditional internal combustion engine vehicles (ICEs). Ultimately, the study aims to gauge the impact of these technological advancements on purchase intention or willingness to purchase.

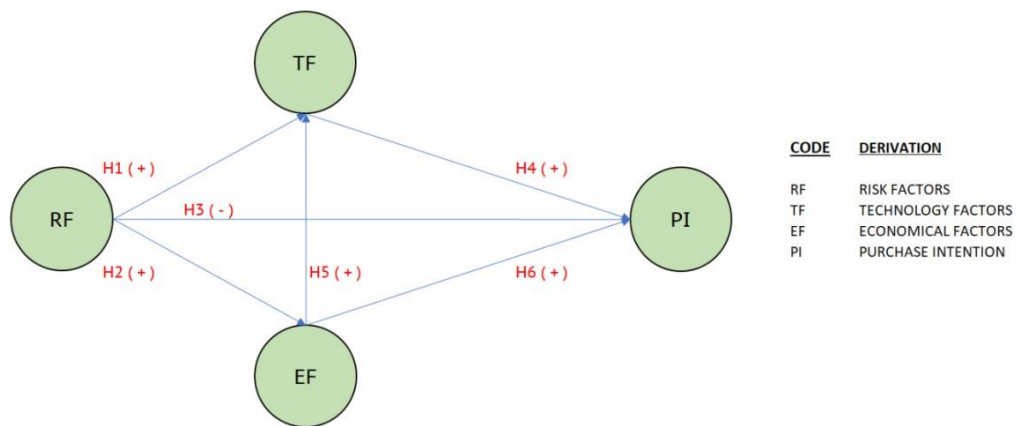
4.2.3. Economic Factors,

Possible costs associated with purchasing electric vehicles may encompass operational costs, time investment, psychological considerations, and unit purchase costs. The tangible price plays a crucial role in shaping purchase intention. The effectiveness of incentives aimed at subsidizing electric vehicle purchases is examined, followed by an analysis of infrastructure from a utilitarian perspective in everyday life.

4.2.4. Purchase Intention

Purchase intention signifies the deliberate, goal-oriented behavioral inclination toward acquiring a product. It encompasses descriptive and evaluative cognitions associated with a specific product or product category. This process initiates when an individual seriously considers making a purchase and concludes upon the actual purchase transaction.

Figure 4.1: Empirical Structural Model (First Order).



4.3 Operational Measures of the Latent Constructs

The conceptual structural model comprises four constructs, with three operational measures in the outer model, resulting in a total of twelve constructs. These constructs are outlined below.

However, the operationalization of willingness to purchase or purchase intention through a single measure limits the validation of —multiple reliable indicators| (Beatty & Smith, 1987; Sweeney & Soutar, 2001). —Recognizing this limitation and drawing from collective insights of prior research, multiple indicators (>three) are employed to operationalize all first and second-level variables of the purchase intention model.

The operational measures of the various outer model constructs are detailed below, with multiple indicators utilized for each. All indicators and measures are adapted from existing literature.

4.3.1. Perceived Risk

X1: Financial

X2: Performance

X3: Psychological

4.3.2. Technological factors

X4: Driving Range

X5: Charging Time

X6: Reliability

4.3.3. Economic factors

X7: Price

X8: Incentives

X9: EV Infrastructure

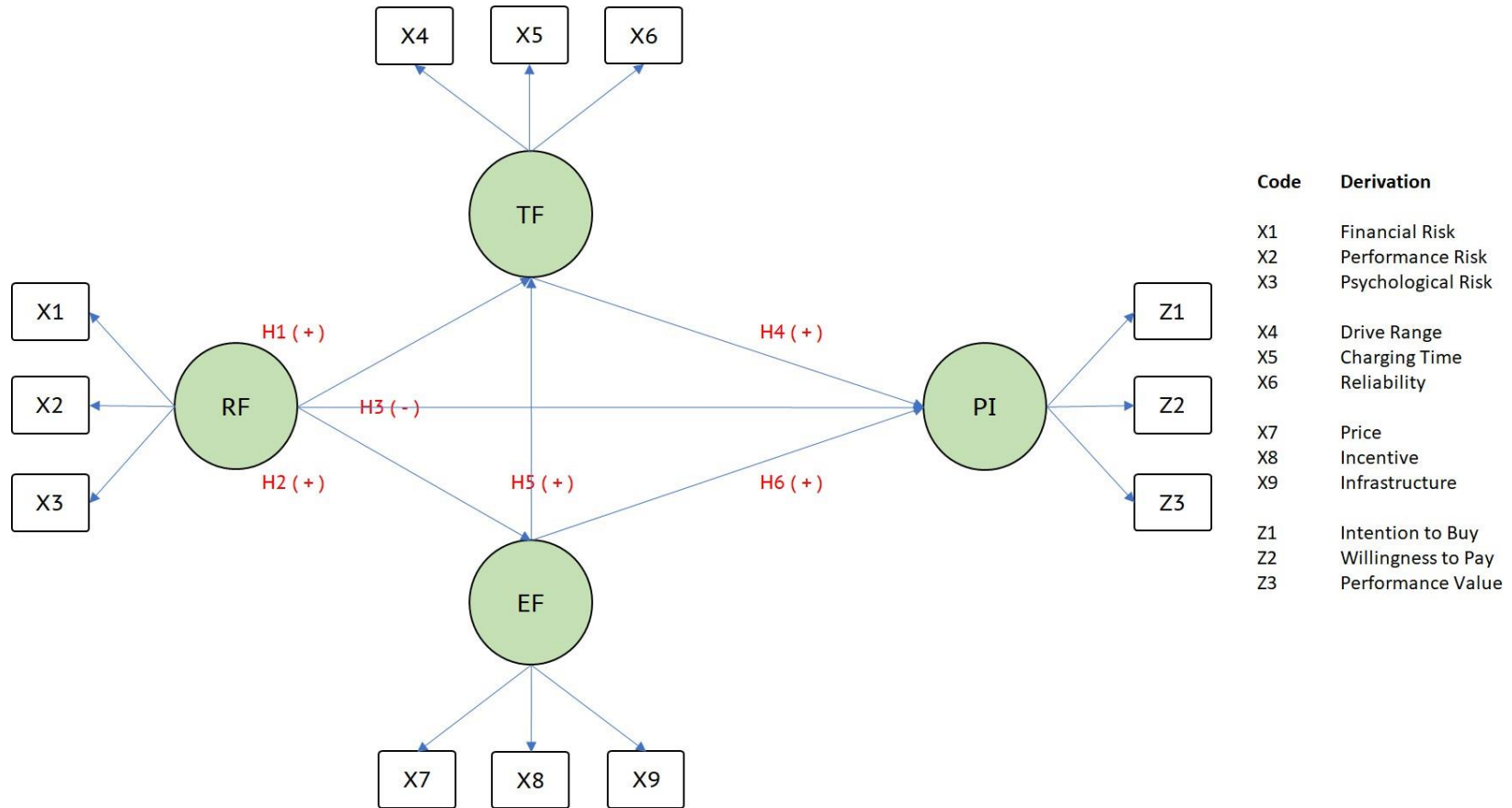
4.3.4. Purchase Intention

Z10: Intention to use EV.

Z11: Willingness to pay.

Z12: Performance Value

Figure (4.2): Operational MODEL OF electric vehicle purchase intention



4.4 Operational Measures of the Second Order Constructs

The preceding section delineated the multiple operational measures of the first-order latent constructs. This segment now delves into the operational measures of the second-order constructs. To effectively capture each construct, each variable will be assessed using a minimum of three measures or indicators.

Independent Variables

Y1: Perceived Risk Factors

- X1 : Financial Risk
- X2 : Performance Risk
- X3 : Psychological Risk

Y2: Technology Factors

- X4 : Drive Range
- X5 : Charging Time
- X6 : Reliability

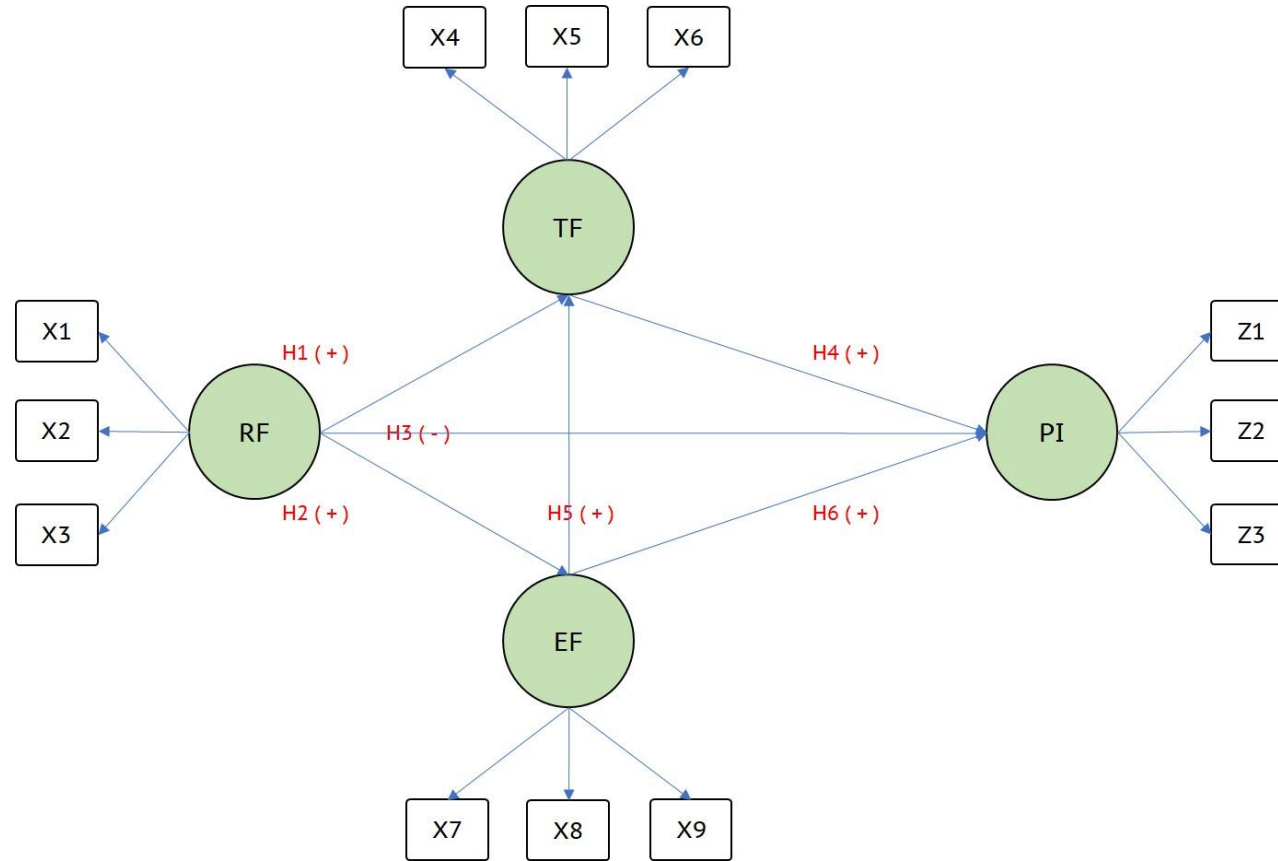
Y3: Economic Factors

- X7 : Price
- X8 : Incentives
- X9 : Infrastructure

Dependent Variable

- Y4 : Purchase Intention
- Z1 : Intention to buy EV
- Z2 : Willingness to Pay
- Z3 : Performance Value

Figure (4.3): Measures Coded Operational MODEL OF electric vehicle purchase intention.



X1: Financial Risk
 X2: Performance
 X3: Psychological

X4: Drive range
 X5: Charging Time
 X6: Reliability

X7: Price
 X8: Incentives
 X9: Infrastructure

Z1: Intention to use EV or Willing to Buy
 Z2: Willingness to Pay
 Z3: PerformanceValue

4.5 Scale Development

The scale development process unfolds in two distinct stages.

In Stage 1, an exhaustive literature review was conducted, and indicators and measures were adapted from existing sources.

Stage 2 entailed a field pilot test of items designed to assess the various constructs. Structural interviews were conducted with prospective buyers intending to purchase a new car within the upcoming six months.

4.5.1 Stage One

For a more comprehensive understanding, chapters three and four have delved into detailed literature reviews. Measures and indicators have been drawn from relevant domains, factorial models, and existing studies, both for the internal and outer models.

The aim of the in-depth literature review is to gather extensive information concerning the domains of all constructs within the model. This includes understanding the experiences and perceptions of new buyers throughout the purchase intention process. Measures have been compiled to characterize purchase activities and other pertinent constructs, with a particular focus on the expressions of interest exhibited by new car buyers, especially from a technological standpoint.

In addition to items extracted from the literature, new items related to various constructs have been added. The combined list served as the basis for evaluation as we transitioned into stage 2.

4.5.2 Stage Two

The pilot study has been conducted to evaluate the validity and reliability of the scales envisioned for this study. After the structured questionnaire was developed, we have administered it to the participant panel and conducted the pilot study in December 2023. The selection of participants have been informed by existing literature, such as (Punj & Staelin, 1983) and Srinivasan & Ratchford (1991), to ensure relevance.

We aimed to employ 5-point Likert-type scales for statements pertaining to most constructs in the dissertation's causal model. Given the expected low response rates in emerging markets, we anticipated conducting the pilot questionnaire survey in a controlled environment, subject to acceptability. Considering the festival season from November to December, we anticipated facilitating a more efficient response rate by conducting the survey in person and distributing questionnaires to willing participants.

We intended to adopt a framework for obtaining actual samples to enhance the reliability of measures. This approach also allows for a fair degree of external validity, as respondents are consumers intending to purchase a new car within the next six months or less.

We opted for convenience sampling over random sampling for two reasons. Firstly, to avoid inclination toward certain brands, price categories, and product segmentation, which requires segmenting consumers based on the unit price of automobiles purchased. Secondly, purchase preferences, criteria, and information search patterns are expected to differ considerably among consumers with varying unit price preferences (e.g., hatchback vs. sedan, personal vs. commercial usage).

Once pilot study data was collected, statistical validation was conducted. This includes Confirmatory Factor Analysis (CFA) to check factor loadings, and Cronbach's alpha to assess internal validity.

Interpretation of factor loadings was conducted using principal component and maximum likelihood methods to estimate factor loadings and specific variances. Factor rotation will be employed to define and validate common factors, initially through exploratory factor analysis followed by confirmatory factor analysis. The determination of the number of parameters involved was guided by Eigenvalues, with a focus on factor loadings of 0.7 or higher, indicative of sufficient variance extraction for Structural Equation Modelling (SEM).

Summary:

In this chapter, the conceptual model of purchase intention from the previous chapter has been translated into operational terms. The domains of the various constructs have been clearly defined, and the operational measures have been explicitly articulated. The process of scale development has been outlined, and the empirical results of the developed scales are presented in chapter 6, demonstrating their validity.

Figure 4.0 depicts a diagrammatic representation of the operational model of external search. Notably, each latent construct is represented by multiple indicators, as observed in the diagram.

CHAPTER V

RESEARCH METHODOLOGY

5.1 Introduction

This study seeks to identify the antecedent variables influencing electric vehicle purchase intention among Indian consumers. Given the significance of measuring consumer purchase intention from the Indian perspective, this chapter outlines the research methodology employed to fulfil the study's objectives. It elaborates on the primary survey, data collection method, and research instrument utilized. Furthermore, it provides detailed descriptions of all constructs under study (refer to Figure 5.0) and the antecedent variables contributing to causation.

5.2 Operational Measures of the Measurement Model

The conceptual structural model comprises four constructs, while the outer model consists of three operational measures, resulting in a total of twelve constructs in the outer model, as described below. However, the reliance on a single measure for willingness to purchase or purchase intention operationalization presents limitations in validating multiple reliable indicators (Beatty & Smith, 1987); Sweeney & Soutar, 2001). To address this limitation, and in line with prior research findings, multiple indicators (> *three*) are employed to operationalize all first and second-level variables of the purchase intention model.

The operational measures for the various outer model constructs are outlined below, with multiple indicators utilized for each. All indicators and measures are adapted from existing literature.

5.2.1. *Perceived Risk*

X1: *Financial*

X2: *Performance*

X3: *Psychological*

5.2.2. *Technological factors*

X4: *Driving Range*

X5: *Charging Time*

X6: *Reliability*

5.2.3. *Economic factors*

X7: *Price*

X8: *Incentives*

X9: *EV Infrastructure*

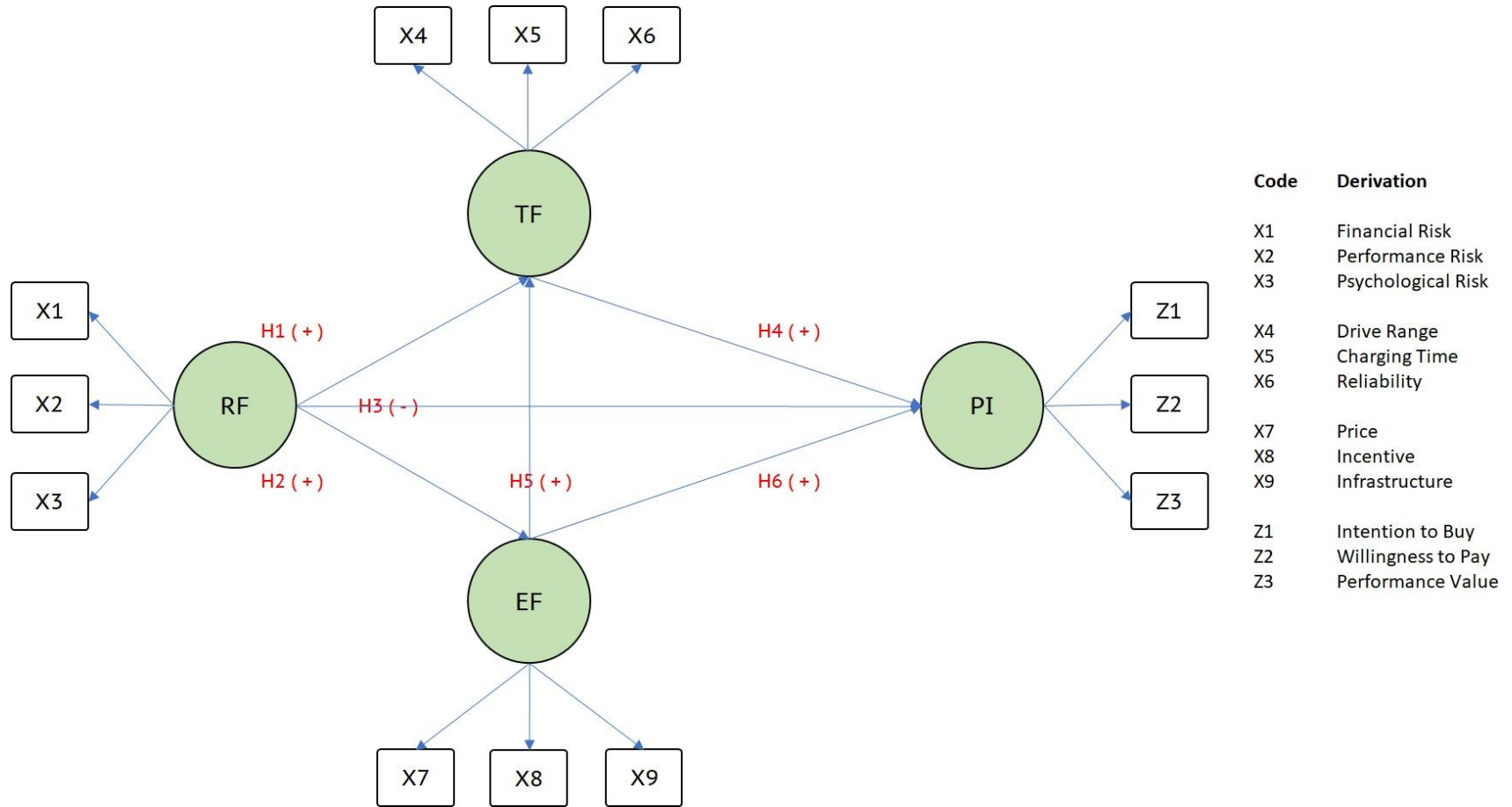
5.2.4. *Purchase Intention*

Z1: *Intention to use EV.*

Z2: *Willingness to pay.*

Z3: *Performance Value*

Figure (5.1): Operational MODEL of electric vehicle purchase intention.



5.3 Questionnaire Development

The scale development process encompasses three stages:

Stage 1:

This stage involves conducting an in-depth literature review and borrowing indicators and measures from existing sources.

Stage 2:

In this stage, scales are structured for all measures. A field pilot test of items tapping into various constructs is conducted, along with structural interviews with prospective buyers intending to purchase a new car within the next six months.

Stage 3:

—The pilot study and data analysis are used to finalize the research instrument. Validation measures include factor loading, composite validity, and average value extracted.

5.3.1. *Stage One – Scales Development*

Chapters three and four are involved in an in-depth literature review to gather comprehensive insights. Measures and indicators have been sourced from relevant domains, factorial models, and existing studies for both the internal and outer models.

The aim of this literature review is to acquire as much information as possible regarding the domains of all constructs within the model, particularly focusing on the experiences and perceptions of new car buyers throughout the purchase intention

process. Measures have been compiled to describe purchase activities and other relevant constructs, with particular emphasis on the expression of interest exhibited by new car buyers, especially from a technological standpoint.

Items related to various constructs have been added to those extracted from the literature. This combined list will serve as the foundation for evaluation as we transition into stage 2 of the research process.

5.3.2. State two – Likert Scales Standardization

The measures obtained from the literature present a mix of Likert scales, with some employing a 5-point scale and others a 7-point scale.

Recent empirical meta-analyses on research instrument scales, as highlighted by Revilla et al. (2014), advocate for the use of the 5-point scale. The authors assert that employing this method minimizes the loss of validity and reliability of the scale. Consequently, we have standardized the instrument by reducing the response categories from 7-point to 5-point scales.

Furthermore, due to anticipated low response rates in emerging markets, we have conducted a pilot questionnaire survey in a controlled environment, pending acceptability. Given that December is a festive season, we anticipated achieving a higher response rate by conducting the survey through online channels. The questionnaire was distributed once participants expressed their willingness to participate.

5.3.3. Stage Three – Pilot Study

Indicators sourced from existing literature have been integrated into a structured questionnaire. Two distinct panels have provided valuable input to refine the questionnaire's components: an industry panel and an academic panel.

Panel_1: Industry Panel

Comprising experts from the automobile industry, including

- *Vaibhav Sinha from Mahindra and Mahindra Ltd.,*
- *Shashikant Vaskar from Ashok Leyland Ltd., and*
- *Sameer Katti from Hyundai Motor India Ltd.,*

This panel offered insights into India's electric vehicle industry and consumer behavior research. Their feedback and suggestions were incorporated into the questionnaire components.

Panel_2: Academic Panel

Consisting of members from the dissertation committee, including

- *Dr. Sanjeev Padashetty and*
- *Dr. Rajeev from the Marketing Department of Alliance University,*

This panel provided valuable feedback that contributed to refining the questionnaire.

The pilot study was conducted from the 1st to the 3rd week of December 2023. Participants were selected based on existing literature derivatives, ensuring alignment with established methodologies.

The study opted for convenience sampling for two reasons: to avoid inclination towards specific brands, price categories, and product segmentation and to account for the diverse purchase preferences and criteria observed among consumers. This segmentation was deemed necessary given the anticipated variations in EV product choices among consumers, ranging from hatchbacks to sedans and from personal to commercial usage.

Data from the pilot study underwent exploratory factor analysis using IBM SPSS. The structural model comprised four constructs, while the measurement model consisted of 12 variables measured by 57 indicators. The sample size (n) was 113, with no missing values observed in the case processing summary. Table 5.1 provides a summary of the findings.

Table 5.1: Case Processing Summary

Data Case Processing Summary						
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
FR_1	113	100.0%	0	0.0%	113	100.0%
FR_2	113	100.0%	0	0.0%	113	100.0%
FR_3	113	100.0%	0	0.0%	113	100.0%
FR_4	113	100.0%	0	0.0%	113	100.0%
FR_5	113	100.0%	0	0.0%	113	100.0%
PR_1	113	100.0%	0	0.0%	113	100.0%
PR_2	113	100.0%	0	0.0%	113	100.0%
PR_3	113	100.0%	0	0.0%	113	100.0%
PSR_1	113	100.0%	0	0.0%	113	100.0%
PSR_2	113	100.0%	0	0.0%	113	100.0%
PSR_3	113	100.0%	0	0.0%	113	100.0%
DR_1	113	100.0%	0	0.0%	113	100.0%

Data Case Processing Summary						
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
DR_2	113	100.0%	0	0.0%	113	100.0%
DR_3	113	100.0%	0	0.0%	113	100.0%
DR_4	113	100.0%	0	0.0%	113	100.0%
CHT_1	113	100.0%	0	0.0%	113	100.0%
CHT_2	113	100.0%	0	0.0%	113	100.0%
CHT_3	113	100.0%	0	0.0%	113	100.0%
RLB_1	113	100.0%	0	0.0%	113	100.0%
RLB_2	113	100.0%	0	0.0%	113	100.0%
RLB_3	113	100.0%	0	0.0%	113	100.0%
RLB_4	113	100.0%	0	0.0%	113	100.0%
RLB_5	113	100.0%	0	0.0%	113	100.0%
RLB_6	113	100.0%	0	0.0%	113	100.0%
RLB_7	113	100.0%	0	0.0%	113	100.0%
PRC_1	113	100.0%	0	0.0%	113	100.0%
PRC_2	113	100.0%	0	0.0%	113	100.0%
PRC_3	113	100.0%	0	0.0%	113	100.0%
PRC_4	113	100.0%	0	0.0%	113	100.0%
PRC_5	113	100.0%	0	0.0%	113	100.0%
PRC_6	113	100.0%	0	0.0%	113	100.0%
INC_1	113	100.0%	0	0.0%	113	100.0%
INC_2	113	100.0%	0	0.0%	113	100.0%
INC_3	113	100.0%	0	0.0%	113	100.0%
INC_4	113	100.0%	0	0.0%	113	100.0%
INC_5	113	100.0%	0	0.0%	113	100.0%
INF_1	113	100.0%	0	0.0%	113	100.0%
INF_2	113	100.0%	0	0.0%	113	100.0%
INF_3	113	100.0%	0	0.0%	113	100.0%
INF_4	113	100.0%	0	0.0%	113	100.0%

Data Case Processing Summary						
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
I2B_1	113	100.0%	0	0.0%	113	100.0%
I2B_2	113	100.0%	0	0.0%	113	100.0%
I2B_3	113	100.0%	0	0.0%	113	100.0%
I2B_4	113	100.0%	0	0.0%	113	100.0%
W2P_1	113	100.0%	0	0.0%	113	100.0%
W2P_2	113	100.0%	0	0.0%	113	100.0%
W2P_3	113	100.0%	0	0.0%	113	100.0%
W2P_4	113	100.0%	0	0.0%	113	100.0%
W2P_5	113	100.0%	0	0.0%	113	100.0%
PV_1	113	100.0%	0	0.0%	113	100.0%
PV_2	113	100.0%	0	0.0%	113	100.0%
PV_3	113	100.0%	0	0.0%	113	100.0%

The normality test assumptions are rigorously examined, encompassing both visual inspection and statistical analysis. Each indicator's Skewness and Kurtosis z-values are meticulously scrutinized, adhering to the statistical literature's guidelines, which stipulate that these values should fall within the range of -1.96 to +1.96 ((Shapiro & Wilk, 1965); Khatun, 2021).

In the pilot study, the Skewness and Kurtosis z-values were found to be within the specified limit, indicating compliance with normality assumptions. Consequently, the analysis proceeded accordingly.

Exploratory Factor Analysis

Principal component analysis with varimax rotation and Kaiser normalization is employed to conduct exploratory factor analysis, elucidating the factor structure and inter-item correlation within the scale. The outcomes of the rotated component (factor) matrix are presented in the subsequent tables.

Table 5.2: Descriptive Statistics

Descriptive Statistics			
	Mean	Std. Deviation	Analysis N
FR_1	2.95	1.451	113
FR_2	3.05	1.209	113
FR_3	3.20	1.127	113
FR_4	3.01	1.214	113
FR_5	3.14	1.141	113
PR_1	3.23	1.282	113
PR_2	3.20	1.143	113
PR_3	3.15	1.128	113
PSR_1	3.30	1.260	113
PSR_2	2.79	1.257	113
PSR_3	2.87	1.206	113
DR_1	3.12	1.078	113
DR_2	2.62	1.352	113
DR_3	3.37	1.120	113
DR_4	3.06	1.136	113

Descriptive Statistics			
	Mean	Std. Deviation	Analysis N
CHT_1	2.65	1.253	113
CHT_2	2.90	1.069	113
CHT_3	2.88	1.087	113
RLB_1	3.04	1.253	113
RLB_2	3.13	1.098	113
RLB_3	3.15	1.096	113
RLB_4	3.18	1.197	113
RLB_5	3.30	1.068	113
RLB_6	3.19	1.098	113
RLB_7	3.27	1.086	113
PRC_1	3.32	1.255	113
PRC_2	2.41	1.334	113
PRC_3	3.25	1.257	113
PRC_4	3.16	1.146	113
PRC_5	3.27	1.054	113
PRC_6	3.45	1.246	113
INC_1	3.16	1.222	113
INC_2	3.45	1.126	113
INC_3	3.18	1.028	113
INC_4	3.22	1.361	113
INC_5	3.16	1.138	113
INF_1	3.27	1.063	113

Descriptive Statistics			
	Mean	Std. Deviation	Analysis N
INF_2	3.28	1.161	113
INF_3	3.37	1.120	113
INF_4	3.18	1.096	113
I2B_1	3.47	1.018	113
I2B_2	3.07	1.108	113
I2B_3	2.86	1.463	113
I2B_4	3.33	1.184	113
W2P_1	3.17	1.051	113
W2P_2	3.21	1.153	113
W2P_3	3.41	1.147	113
W2P_4	2.95	1.201	113
W2P_5	2.94	1.182	113
PV_1	3.28	1.073	113
PV_2	3.16	1.169	113
PV_3	3.16	1.115	113

Table 5.3: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.771
Bartlett's Test of Sphericity	Approx. Chi-Square	3852.906
	Df	1326
	Sig.	.000

The table shows two tests that indicate the suitability of the data for structural detection.

The Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) serves as a statistic assessing the proportion of variance in variables potentially attributed to underlying factors. Typically ranging from 0.5 to 1.0, higher values (approaching 1.0) suggest the potential utility of factor analysis. Conversely, values below 0.50 indicate limited usefulness of factor analysis results.

Bartlett's Test of Sphericity evaluates the hypothesis that the correlation matrix resembles an identity matrix, indicating unrelated variables unsuitable for structure detection. A significance level below 0.05 suggests suitability for factor analysis.

In the pilot study data, the KMO sampling adequacy is 0.771, surpassing the 0.50 threshold, indicating satisfactory sampling adequacy. Bartlett's test of sphericity yields a significance value of 0.000, demonstrating statistical significance ($P < 0.05$) and indicating differentiation from the identity matrix as desired. Thus, both KMO and Bartlett's test satisfy statistical assumptions, affirming the suitability of the model for exploratory factor analysis (EFA).

Total Variance Explained

Utilizing principal component analysis with Eigenvalues greater than one extraction criteria, a total of 12 components were extracted from the data. These components collectively accounted for 70.219 percent of the variance, as detailed in the table below.

Table 5.4: Total Variance Explained

Total Variance Explained						
Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.648	26.246	26.246	7.301	14.040	14.040
2	5.316	10.223	36.469	3.774	7.257	21.297
3	2.823	5.429	41.898	3.753	7.218	28.515
4	2.577	4.956	46.854	3.499	6.730	35.245
5	2.113	4.064	50.918	3.060	5.884	41.129
6	1.905	3.664	54.582	2.998	5.765	46.894
7	1.699	3.267	57.850	2.761	5.309	52.203
8	1.496	2.877	60.726	2.362	4.542	56.745
9	1.337	2.572	63.298	2.284	4.392	61.137
10	1.256	2.416	65.714	1.733	3.333	64.470
11	1.197	2.301	68.015	1.509	2.902	67.372
12	1.146	2.204	70.219	1.480	2.847	70.219
13	1.060	2.038	72.256			
14	.940	1.808	74.065			
15	.920	1.769	75.834			
16	.866	1.665	77.499			
17	.831	1.597	79.097			
18	.789	1.517	80.614			
19	.771	1.483	82.096			
20	.689	1.326	83.422			

Total Variance Explained

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
21	.631	1.213	84.635			
22	.594	1.142	85.778			
23	.535	1.029	86.806			
24	.517	.995	87.801			
25	.502	.965	88.767			
26	.481	.926	89.692			
27	.445	.856	90.548			
28	.389	.749	91.297			
29	.363	.697	91.994			
30	.358	.688	92.682			
31	.333	.641	93.322			
32	.318	.611	93.933			
33	.308	.593	94.526			
34	.293	.564	95.090			
35	.256	.492	95.582			
36	.238	.457	96.039			
37	.213	.410	96.450			
38	.209	.402	96.852			
39	.184	.353	97.205			
40	.177	.340	97.545			
41	.167	.322	97.867			
42	.157	.303	98.169			
43	.141	.271	98.440			
44	.133	.255	98.695			
45	.127	.243	98.939			
46	.103	.198	99.137			
47	.100	.192	99.329			
48	.088	.169	99.498			
49	.084	.162	99.660			

Total Variance Explained						
Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
50	.078	.149	99.809			
51	.053	.103	99.912			
52	.046	.088	100.000			
Extraction Method: Principal Component Analysis.						

The results of the exploratory factor analysis reveal a solution based on 12 factors that align with our expectations. However, several items exhibit cross-loading on multiple factors and demonstrate lower factor loadings. We have opted to retain only those factors with loadings exceeding 0.5, in line with (Stevens, 2002) guidelines. Consequently, several items have been removed from consideration, including those pertaining to financial risk (FR_3), performance risk (PR_3), psychological risk (PSR_3), driving range (DR_3 & 4), reliability (RLB_1, 4, & 5), price (PRC_1 & 3), incentives (INC_3), infrastructure (INF_4), intention to buy (I2B_4), willingness to pay (W2P_1), and performance value (PV_1).

In total, 15 items have been excluded from the analysis. We conducted further literature review and identified suitable replacements for these items throughout the study. Nonetheless, the twelve-factor solution effectively accounts for 75.965% of the total variance.

Pilot study_2: Data Analysis

Following the findings of the initial pilot study, we conducted an extensive literature review to identify alternative measures that could replace those excluded from the study. This step was crucial to ensure that our measurement framework remained robust and aligned with established methodologies.

Subsequently, a second pilot study was undertaken to gather further data. This phase was designed to expand our sample size, incorporating an additional 55 participants. This iterative approach allowed us to refine our research methods and enhance the reliability of our findings through a broader dataset.

We employed IBM SPSS to conduct exploratory factor analysis on the collected dataset. This analytical approach allowed us to examine the underlying structure of our data by assessing 12 variables across a comprehensive set of 57 indicators. This methodological choice was pivotal in uncovering relationships and patterns within our dataset, providing a deeper understanding of the variables under study. Notably, the case processing summary indicated no missing values, as outlined in Table 5.1.

Table 5.5 Case the summary.

Case Processing Summary						
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
FR_1	55	100.0%	0	0.0%	55	100.0%
FR_2	55	100.0%	0	0.0%	55	100.0%
FR_3	55	100.0%	0	0.0%	55	100.0%
FR_4	55	100.0%	0	0.0%	55	100.0%
PR_1	55	100.0%	0	0.0%	55	100.0%
PR_2	55	100.0%	0	0.0%	55	100.0%
PR_3	55	100.0%	0	0.0%	55	100.0%
PR_4	55	100.0%	0	0.0%	55	100.0%
PSR_1	55	100.0%	0	0.0%	55	100.0%
PSR_2	55	100.0%	0	0.0%	55	100.0%
PSR_3	55	100.0%	0	0.0%	55	100.0%
PSR_4	55	100.0%	0	0.0%	55	100.0%
DR_1	55	100.0%	0	0.0%	55	100.0%

Case Processing Summary						
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
DR_2	55	100.0%	0	0.0%	55	100.0%
DR_3	55	100.0%	0	0.0%	55	100.0%
CHT_1	55	100.0%	0	0.0%	55	100.0%
CHT_2	55	100.0%	0	0.0%	55	100.0%
CHT_3	55	100.0%	0	0.0%	55	100.0%
RLB_1	55	100.0%	0	0.0%	55	100.0%
RLB_2	55	100.0%	0	0.0%	55	100.0%
RLB_3	55	100.0%	0	0.0%	55	100.0%
RLB_4	55	100.0%	0	0.0%	55	100.0%
RLB_5	55	100.0%	0	0.0%	55	100.0%
PR_1	55	100.0%	0	0.0%	55	100.0%
PR_2	55	100.0%	0	0.0%	55	100.0%
PR_3	55	100.0%	0	0.0%	55	100.0%
PR_4	55	100.0%	0	0.0%	55	100.0%
PR_5	55	100.0%	0	0.0%	55	100.0%
PR_5	55	100.0%	0	0.0%	55	100.0%
INC_1	55	100.0%	0	0.0%	55	100.0%
INC_2	55	100.0%	0	0.0%	55	100.0%
INC_3	55	100.0%	0	0.0%	55	100.0%
INC_4	55	100.0%	0	0.0%	55	100.0%
INF_1	55	100.0%	0	0.0%	55	100.0%
INF_2	55	100.0%	0	0.0%	55	100.0%
INF_3	55	100.0%	0	0.0%	55	100.0%
INF_4	55	100.0%	0	0.0%	55	100.0%
I2B_1	55	100.0%	0	0.0%	55	100.0%
I2B_2	55	100.0%	0	0.0%	55	100.0%
I2B_3	55	100.0%	0	0.0%	55	100.0%
I2B_4	55	100.0%	0	0.0%	55	100.0%

Case Processing Summary						
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
I2B_5	55	100.0%	0	0.0%	55	100.0%
W2P_1	55	100.0%	0	0.0%	55	100.0%
W2P_2	55	100.0%	0	0.0%	55	100.0%
W2P_3	55	100.0%	0	0.0%	55	100.0%
W2P_4	55	100.0%	0	0.0%	55	100.0%
PV_1	55	100.0%	0	0.0%	55	100.0%
PV_2	55	100.0%	0	0.0%	55	100.0%
PV_3	55	100.0%	0	0.0%	55	100.0%
SI_1	55	100.0%	0	0.0%	55	100.0%
SI_2	55	100.0%	0	0.0%	55	100.0%
SI_3	55	100.0%	0	0.0%	55	100.0%

Table 5.6: Descriptive statistics

Descriptive Statistics			
	Mean	Std. Deviation	Analysis N
FR_1	4.11	.916	55
FR_2	3.89	.896	55
FR_3	3.53	1.069	55
FR_4	3.93	.790	55
PR_1	2.91	1.206	55
PR_2	3.75	.947	55
PR_3	3.84	.788	55
PR_4	3.09	.948	55
PSR_1	3.89	.916	55
PSR_2	4.09	.776	55
PSR_3	4.13	.747	55
PSR_4	3.16	1.014	55
DR_1	3.11	1.066	55

Descriptive Statistics			
	Mean	Std. Deviation	Analysis N
DR_2	3.62	.805	55
DR_3	3.25	1.092	55
CHT_1	3.82	.611	55
CHT_2	4.24	.607	55
CHT_3	4.24	.637	55
RLB_1	3.58	.712	55
RLB_2	4.16	.462	55
RLB_3	3.51	.791	55
RLB_4	4.04	.637	55
RLB_5	3.64	.778	55
PR_1	3.98	.707	55
PR_2	4.05	.591	55
PR_3	4.13	.883	55
PR_4	4.04	.576	55
PR_5	4.20	.590	55
PR_5	3.96	.607	55
INC_1	3.91	.646	55
INC_2	4.02	.593	55
INC_3	4.38	.527	55
INC_4	3.22	1.031	55
INF_1	4.02	.593	55
INF_2	3.56	.938	55
INF_3	4.16	.601	55
INF_4	4.36	.522	55
I2B_1	3.71	.629	55
I2B_2	3.80	.755	55
I2B_3	3.73	.781	55
I2B_4	4.00	.770	55
I2B_5	4.24	.470	55
W2P_1	3.91	.908	55

Descriptive Statistics			
	Mean	Std. Deviation	Analysis N
W2P_2	4.25	.552	55
W2P_3	3.69	1.086	55
W2P_4	3.44	.856	55
PV_1	3.87	.982	55
PV_2	3.56	.938	55
PV_3	3.67	.747	55
SI_1	3.75	.865	55
SI_2	4.35	.517	55
SI_3	4.09	.519	55

Table 5.7: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.671
Bartlett's Test of Sphericity	Approx. Chi-Square	2785.706
	Df	1119
	Sig.	.000

The Kaiser-Meyer-Olkin (KMO) and Bartlett's tests confirm the adequacy of the sample size for hypothesis measurement, with Bartlett's test showing statistical significance to proceed.

Communalities

The table below summarizes the communalities of the total 52 measures used in the study.

Table 5.8: Communalities of the 52 measures

Communalities		
	Initial	Extraction
FR_1	1.000	.873
FR_2	1.000	.882
FR_3	1.000	.656
FR_4	1.000	.752
PR_1	1.000	.926
PR_2	1.000	.844
PR_3	1.000	.893
PR_4	1.000	.810
PSR_1	1.000	.832
PSR_2	1.000	.908
PSR_3	1.000	.936
PSR_4	1.000	.861
DR_1	1.000	.875
DR_2	1.000	.810
DR_3	1.000	.827
CHT_1	1.000	.796
CHT_2	1.000	.845
CHT_3	1.000	.848
RLB_1	1.000	.861
RLB_2	1.000	.891
RLB_3	1.000	.782
RLB_4	1.000	.874
RLB_5	1.000	.802
PR_1	1.000	.858
PR_2	1.000	.919
PR_3	1.000	.877
PR_4	1.000	.930
PR_5	1.000	.885

Communalities		
	Initial	Extraction
PR_5	1.000	.753
INC_1	1.000	.833
INC_2	1.000	.846
INC_3	1.000	.840
INC_4	1.000	.824
INF_1	1.000	.876
INF_2	1.000	.845
INF_3	1.000	.868
INF_4	1.000	.884
I2B_1	1.000	.885
I2B_2	1.000	.789
I2B_3	1.000	.847
I2B_4	1.000	.905
I2B_5	1.000	.928
W2P_1	1.000	.801
W2P_2	1.000	.820
W2P_3	1.000	.819
W2P_4	1.000	.860
PV_1	1.000	.854
PV_2	1.000	.732
PV_3	1.000	.835
SI_1	1.000	.903
SI_2	1.000	.892
SI_3	1.000	.900
Extraction Method: Principal Component Analysis.		

Total Variance Explained

The principal component analysis was utilized as the extraction method, where Eigenvalues greater than one were extracted from the data. In total, 13 components were extracted, collectively explaining 85.00 percent of the variance. Further details are provided in the table below.

Table 5.9: Total Variance Explained

Total Variance Explained						
Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	14.350	27.595	27.595	10.975	21.105	21.105
2	7.340	14.115	41.710	6.282	12.081	33.186
3	3.991	7.675	49.384	3.811	7.329	40.515
4	3.452	6.639	56.024	3.791	7.290	47.805
5	2.582	4.966	60.989	3.668	7.054	54.859
6	2.359	4.537	65.526	2.491	4.789	59.648
7	1.977	3.801	69.327	2.253	4.333	63.982
8	1.927	3.706	73.034	1.973	3.794	67.776
9	1.537	2.957	75.990	1.949	3.747	71.523
10	1.326	2.550	78.540	1.940	3.731	75.254
11	1.213	2.334	80.874	1.714	3.296	78.550
12	1.121	2.155	83.029	1.677	3.225	81.775
13	1.017	1.956	84.985	1.670	3.211	84.985
14	.888	1.708	86.693			
15	.799	1.537	88.230			
16	.708	1.362	89.592			
17	.656	1.262	90.855			
18	.594	1.143	91.998			
19	.496	.953	92.951			

Total Variance Explained						
Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
20	.478	.919	93.870			
21	.436	.838	94.708			
22	.348	.669	95.377			
23	.336	.647	96.024			
24	.292	.561	96.585			
25	.268	.515	97.100			
26	.218	.419	97.520			
27	.203	.390	97.910			
28	.161	.310	98.219			
29	.144	.276	98.495			
30	.131	.251	98.747			
31	.121	.233	98.979			
32	.103	.199	99.178			
33	.089	.171	99.349			
34	.072	.138	99.487			
35	.061	.117	99.604			
36	.052	.099	99.703			
37	.037	.072	99.775			
38	.030	.058	99.833			
39	.028	.053	99.887			
40	.020	.038	99.924			
41	.014	.027	99.951			
42	.009	.017	99.968			
43	.008	.016	99.984			
44	.005	.010	99.994			
45	.002	.004	99.998			
46	.001	.002	100.000			
47	1.093E-15	2.101E-15	100.000			

Total Variance Explained						
Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
48	5.401E-16	1.039E-15	100.000			
49	1.798E-16	3.458E-16	100.000			
50	-4.890E-16	-9.404E-16	100.000			
51	-6.060E-16	-1.165E-15	100.000			
52	-1.294E-15	-2.489E-15	100.000			
Extraction Method: Principal Component Analysis.						

The Eigenvalue extracts 13 components, which cumulatively explain 84.985 (85%) percent of the variance. Statistically, it is considered to be very good.

Rotated Component Matrix or Rotated Factor Matrix

Following the exploratory factor analysis, we identified a solution composed of 13 factors. Throughout the analysis, it became evident that certain items exhibited cross-loadings, meaning they were associated with multiple factors, and showed lower factor loadings within their intended factors. To maintain the rigor of the analysis, we adhered to Stevens' (2002) recommendation of retaining factors with loadings exceeding 0.6.

As a result, decisions were made to exclude specific items that did not meet this criterion. Notably, infrastructure (INF_1: 0.540) and psychological risk (PSR_4: 0.529) were among the items removed from further consideration in the dataset.

This process led to the elimination of a total of 2 items from the analysis, which was essential for refining the questionnaire's precision and ensuring the reliability of the factors identified through the exploratory factor analysis.

Our primary objective, focusing on identifying the antecedents of pre-purchase intention for electric vehicles, will now advance to confirmatory factor analysis. This method will serve to validate both the measurement and structural models, providing insights into the explained variance (R^2).

As a result, this study is well-positioned to conduct thorough and insightful primary data collection. This approach promises to yield significant insights and contribute valuable empirical evidence to the field of research.

5.4 Final Operational Measures of the Second Order Constructs

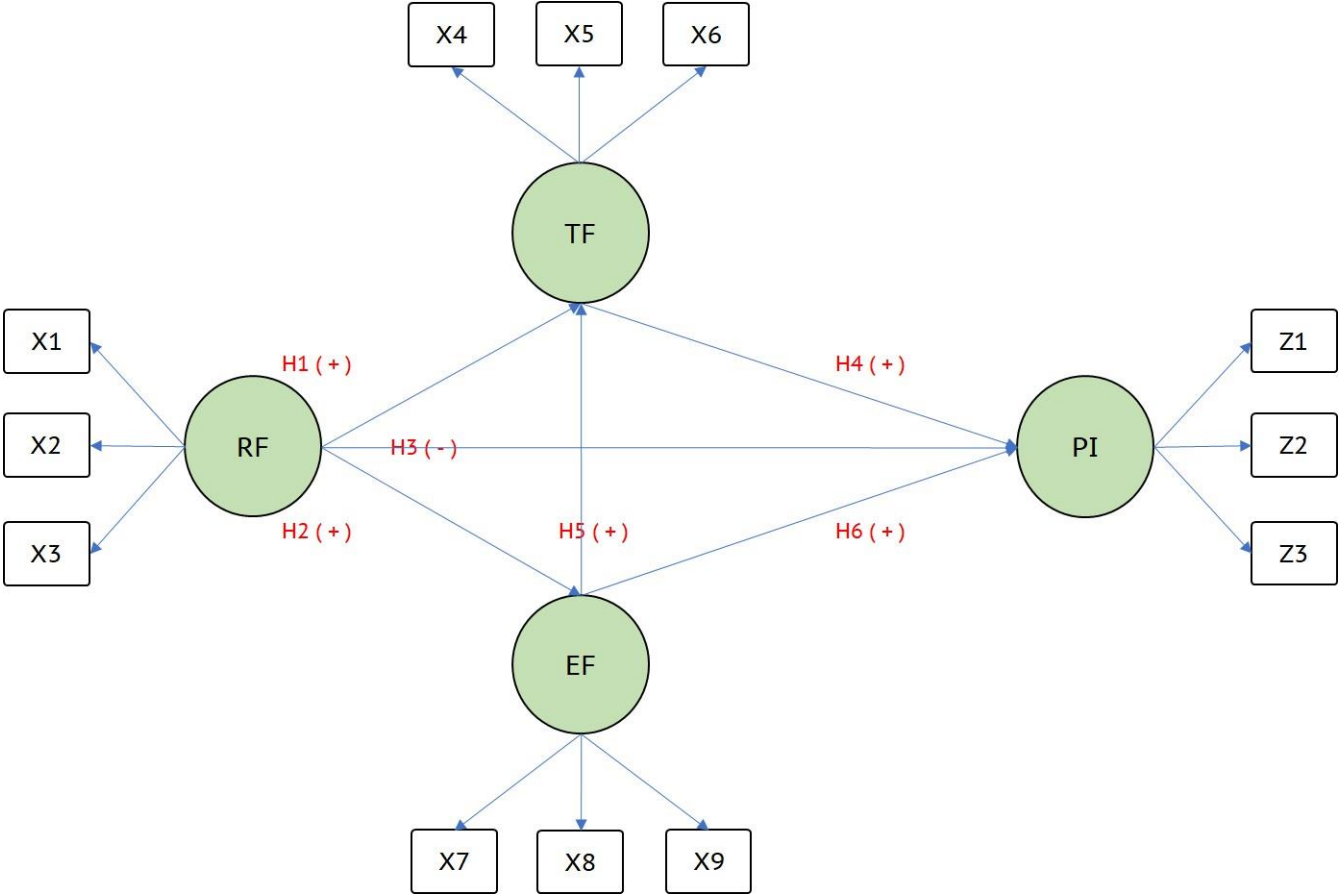
This section delves into the diverse operational measures employed for construct operationalization, providing detailed insights into the operational measures of second-order constructs. Each variable is designed to encompass a minimum of three measures or indicators to capture the constructs within the measurement model comprehensively.

In total, the model encompasses nine independent measurement variables, using the structural independent variables and three variables measuring the dependent variable, reflecting a comprehensive framework for analysis and evaluation.

Table 5.10: The measures in outer model of EV purchase intention

Independent Measures		Dependent Measures	
X1	Financial Risk	Z1	Intention to buy EV.
X2	Performance Risk	Z2	Willingness to Pay
X3	Psychological Risk	Z3	Performance Value
X4	Drive Range	Z4	Social Influence
X5	Charging Time		
X6	Reliability		
X7	Price		
X8	Incentives		
X9	Infrastructure		

Figure (5.2): Measures Coded measurement model electric vehicle purchase intention.



X1: Financial Risk
 X2: Performance
 X3: Psychological

X4: Drive range
 X5: Charging Time
 X6: Reliability

X7: Price
 X8: Incentives
 X9: Infrastructure

Z1: Intention to use EV or Willing to Buy
 Z2: Willingness to Pay
 Z3: Performance Value

The figure (5.2) has theoretically derived causal relations. They are either positive or negative relationships, treated as a hypothesis. The model relations and model have been evaluated using the sequential structural statistical technique.

5.5 Research Design

The overarching insight derived from the literature underscores that research design extends beyond mere data collection and analysis methodologies. Robust research designs share the commonality of delineating the type of data to be utilized and the structural frameworks such as longitudinal, randomized, or non-randomized research. The methodologies encompassing qualitative, quantitative, and mixed methods approaches entail specific design considerations. Moreover, it's noteworthy that all research stages inherently involve elements of 'design.' Crafting instruments for data collection, execution, and analysis constitutes a pivotal aspect of this process (Gorard, 2023).

5.5.1. Data collection method

There are three primary methods for collecting primary data: observation, survey, and experimental methods (Bell, Bryman, & Harley, 2022). Within the survey method, there are four data collection techniques: telephone, structured interviews, in-person surveys, and online surveys (Hulland & Houston, 2020).

While the survey method remains prevalent in consumer behavior research, Meyer et al. (2015) suggest a shift in its effectiveness. Critics argue that traditional survey research is becoming obsolete, advocating for a combination of internet data mining and administrative records (Smith, 2013, p. 218).

Traditional survey methods face challenges, such as the increasing difficulty and cost of telephone surveys (Blumberg & Luke, 2016). Conversely, web-based nonprobability surveys have gained prominence (Stange et al., 2016). In marketing and consumer behavior, survey research is widely utilized (Hulland et al., 2019), with surveys being the most common data collection method in empirical studies.

The survey method offers several advantages, including large sample sizes, ease of data collection, external validity, reliability, generalizability of findings, and cost-effectiveness. Despite recent advancements, surveys remain integral to marketing literature, with e-surveys emerging as the most effective method due to global internet access (Corley, 2023).

E-surveys encompass three methods: point-of-contact, email-based, and online web-based surveys. Web-based surveys are considered the most effective and proactive method. The adoption of technology-based internet tools significantly influences survey research, leading this study to employ a web-based survey approach for data collection.

5.5.2. The sampling population

Web-based surveys present challenges in reaching the public. Couper (2000) outlines various strategies for identifying and selecting participants for web-based surveys, leading to the development of new sampling methods such as respondent-driven sampling, sample matching, and river sampling (Schonlau & Couper, 2017). However, the issue of sampling persists, particularly in nonprobability sampling methods, despite the advancements made in web-based survey techniques. In contrast, probability sampling has shown the effectiveness of web-based surveys as a critical data collection method (Callegaro et al., 2015; Toepoel, 2016).

In alignment with this literature, the sampling population for this study is delineated. The target participants are individuals intending to purchase a new automobile within the next six months, regardless of age, location, income, or profession. They may be prospective buyers with varying levels of experience in evaluating automobiles and may or may not have previous experience with electric vehicles. The primary criterion for inclusion is the intention to purchase a vehicle, serving as the measurement output variable in this study.

5.5.3. The Sampling Frame

Probability and nonprobability sampling methods offer contrasting approaches to address sampling frame challenges, particularly in the context of web-based surveys (Schonlau & Couper, 2017). The selection of a suitable sample frame significantly influences the data collection process, particularly in survey research.

The primary objective of this study is to examine the antecedent variables of electric vehicle purchase intention. The data has been sourced from individuals who have expressed an intent to purchase. Thus, the sampling frame for this study comprises individuals intending to acquire a new electric vehicle, as outlined by Tu and Yang (2020). These individuals may be first-time buyers or repeat purchasers but must possess the intention to acquire an electric vehicle. Moreover, they may belong to any age group, gender, income, profession, and demographic.

5.5.4. The Representative Sampling

Accessing a representative sample from a large, demographically diverse, and geographically scattered population can pose challenges and potentially introduce sampling bias, thereby impacting the validity of study findings. To mitigate this issue,

data collection will focus on Karnataka primarily Bengaluru. Careful consideration will be given to selecting an appropriate sampling method to ensure the sample's representativeness.

Furthermore, it is reasonable to expect that the consumer base intending to purchase electric vehicles (EVs) is concentrated in and around metropolitan areas. Therefore, targeting these regions for data collection will likely yield a more relevant and representative sample for the study.

5.5.5. Sampling method

This study employed non-probability sampling techniques, specifically opting for convenience sampling among other types of sampling methods. The convenience sampling is chosen because it offers a methodological approach in which researchers can gather market research data from a readily accessible group of respondents.

All elements of the population are eligible for inclusion in the sample, with participation largely dependent on the study's proximity and accessibility.

Convenience sampling offers significant advantages for academic marketing research in various ways. Firstly, it is a cost-effective and time-efficient method of data collection. This approach reduces both time and financial expenditures by selecting readily available participants, bypassing the need for more complex sampling procedures. Secondly, it is advantageous for researchers and market practitioners seeking direct input from potential buyers (Habla, Huwe, & Kesternich, 2022).

The very important application factor of convenience sampling in marketing research is, that it is applied statistically to measure the perceptions and intuitions of consumers in the market. Especially data collected from the market is used to

measure and understand the intention or manage opinions of newly launched products. In this case electric vehicles.

However, Convenience sampling encompasses several drawbacks that may diminish the reliability and validity of research findings. Such as bias in sampling, lack of variety, limited external validity, erroneous, and possibility of scholar's bias.

To reduce the biasness in sampling, the study has conducted an effective convenience sampling data using three principal methods (Bryman & Bell, 2020).

- 1) Take multiple samples: We have collected multiple samples beyond what is required to establish statistical power, thereby enhancing the reliability of the results.*
- 2) Repeat the survey: The survey was conducted three times through pilot studies, verifying consistency in sample variance to ensure the results accurately reflect the population.*
- 3) Try cross-validation: The study partitioned the sample into three distinct sets and cross-validated each dataset by comparing its findings with the remainder of the data and with each other.*

The sampling method represents a smaller and more manageable subset of the population, which is crucial for conducting in-depth analysis and drawing statistically sound conclusions about the broader population. This approach is highly effective in gathering comprehensive data and making accurate statistical inferences.

The study specifically targets automobile buyers who have expressed an intention to purchase electric vehicles. By focusing on this specific segment of the population, the

study aims to uncover insights into the factors influencing electric vehicle purchase decisions among consumers.

Given the logistical challenges associated with traveling and gathering data from every city in India, convenience sampling is employed to select a representative city and effectively generalize the study's findings.

5.5.6. The Sample Size

To ensure robust statistical power, validity, and reliability of the constructs, an adequate sample size is crucial. While statistically, a sample size of 167 may suffice for our research design (Carley, Krause, Lane, & Graham, 2023), and (Hair J. , Hult, Ringle, & Sarstedt, 2024). This study has collected data from more than 322 participants.

Summary:

This chapter meticulously outlines the operationalization methods and data collection approaches for the purchase intention model. It meticulously defines the domains of both structural and measurement models, detailing various measures and indicators of constructs. The operational measures are explicitly defined, and the scale development process is described, with empirical results presented in Table (5.0) to demonstrate validity.

Furthermore, Figure 5.0 provides a diagrammatic representation of the operational model of willingness to purchase an electric vehicle, highlighting multiple indicators for each latent construct. The chapter not only defines the methodology but also elaborates on the data collection approach, validating the mode best suited for the study.

Additionally, it succinctly delineates the study's target population and outlines the sample frame, proposing a sampling method to ensure representation and meet the sample frame's requirements.

CHAPTER VI

EMPIRICAL ANALYSIS AND RESULTS

6.1 Introduction

This chapter presents a thorough review of the empirical findings resulting from the model's implementation, as outlined in Chapter IV. It explores the statistical assumptions supporting the multivariate analysis and elucidates the reasoning behind the selection of methodologies utilized to evaluate the efficacy of the structural equation models. The statistical tool employed for measuring the models is SmartPLS (Version 4.0).

The chapter begins with an analysis commenced with a detailed exploration of the model's descriptive statistics. To ensure robustness, the reliability of multiple-item scales was rigorously evaluated using Composite Reliability. This assessment initially involved outlining scale reliability across both pilot and main study frameworks.

Further analysis concentrated on examining the outer loadings of items contributing to higher-order constructs. This step was crucial in understanding how well these items represented their respective constructs. Subsequently, the internal consistency reliabilities of the multiple-item scales were assessed to confirm their reliability and coherence.

Additionally, confirming the underlying factor structure of exogenous variables played a pivotal role in establishing both convergent and discriminant validity. This process was essential for validating that the measurement items effectively captured the intended constructs and demonstrated their distinctiveness from one another, thereby enhancing the overall validity and reliability of the study's outcomes.

The comprehensive testing of the model encompasses the examination of both indicators and latent variables, revealing path coefficients and offering an explanatory narrative of R square. Additionally, the discussion extends to the effect sizes of exogenous variables, culminating in an analysis of the model's goodness of fit. This multifaceted evaluation provides a thorough understanding of the model's causation capabilities and overall validation.

Table 6.1 presents a synthesis of the reliabilities observed for the —scales in both the pilot and main studies. Notably, the reliability metrics for all scales in the main study closely mirror those obtained during the pilot study phase. This consistency underscores the robustness and stability of the measurement instruments across different study iterations.

Table 6.1: Pilot and Main Study Reliability Comparison (Measures)

Measures	# of Items	Composite Reliability	
		Pilot Study	Main Study
Risk Factors	12	0.742	0.756
Technology Factors	11	0.818	1.000
Economic Factors	14	0.708	0.776
Purchase Intention	15	0.747	0.837

6.2 Examining the Data

The method of multivariate analysis is employed to concurrently measure and analyze multiple variables, facilitating the exploration of their interactions. Utilizing various techniques of structural equation modelling enables us to discern both interaction and

causation among these variables. —Consistent with second-generation multivariate analysis, we scrutinized potential drawbacks stemming from the research design and data collection methodologies. Key aspects addressed comprehensively included.

- Analysis of missing data,
- Identification and handling of outliers and
- Testing of the assumption's multivariate analysis techniques.

This meticulous approach ensures the integrity and reliability of the analytical process.

6.2.1 Missing Data Analysis:

The thorough examination of the dataset involved employing rigorous testing methodologies, utilizing both the SPSS descriptive method and Microsoft Excel. To gauge the presence of missing data, we adhered to the methodology delineated by Hair Jr., Black, Babin, and Anderson (2015), calculating the percentage of variables with missing data for each case and the count of cases with missing data for each variable. Remarkably, aside from all cases, the dataset remained devoid of any missing values, attesting to the meticulous approach employed in addressing data integrity concerns, a practice congruent with the principles espoused by Phipps, Butani, and Chun (1995) regarding research instrument design.

It is noteworthy that all questions within the instrument were made obligatory, a strategic decision that significantly bolstered the completion rate and enhanced data quality. The adoption of a 5-point Likert scale, as recommended by (Revilla, Saris, & Krosnick, 2013), further contributed to the near-perfect completeness of data for both cases and causal variables. Comprehensive analyses of missing data, tailored to the

sample frame, are exhaustively documented in Appendices 0.0, providing a detailed account of the dataset's integrity across variable and case-wise modalities.

6.2.2 Outliers Analysis:

The outliers possess the potential to influence the outcomes of empirical analyses significantly. The choice of instrument, featuring a closed 5-point Likert scale, implies that outliers are more likely to occur within responses to open-ended questions, specifically those pertaining to demographic variables like age and profession. However, upon careful statistical scrutiny, we found that instances of outliers were remarkably minimal. This observation serves to reinforce the confidence in the robustness and reliability of our data collection methodology, highlighting its ability to capture and manage potential outliers within the dataset effectively.

6.2.3 Assumptions of multivariate analysis testing:

The initial step in our analysis protocol involves scrutinizing the data distribution and evaluating its adherence to the normality assumption. For this purpose, we employed SPSS (Version 24) to conduct rigorous tests of normality. This comprehensive assessment is conducted through a combination of numbers (statistical) and visual outputs (graphical methods). The statistical significance of the Kolmogorov-Smirnov skewness and kurtosis values should be somewhere between -1.96 and +1.96 (Doane & Seward, 2021). However, skewness and kurtosis values should be as close to zero as possible. The Shapiro-Wilk test's statistical significance p-value should be greater than 0.05 (Shapiro & Wilk, 1965). The graphical methods include histograms, normal quantile-quantile (QQ) plots, and box plots. These should visually indicate that the data are approximately normally distributed. Particularly, it is the case of the independent variable.

The sample characteristics of this study data.

A Shapiro-Wilk test ($p\text{-value} > 0.05$) (Shapiro & Wilk, 1965), (Razali & Wah, 2011), and a visual inspection of the sample histograms, Q-Q plots, and box plots showed that all indicators of both independent and dependent variables are greater than 0.05. The results of these tests revealed that all the indicators exhibit a normal distribution, as indicated by the statistical significance. The null hypothesis for this test of normality is that the data are normally distributed. Hence, in this study, the null hypothesis is accepted as the $p\text{-value}$ of the data is greater than 0.05.

This finding is in line with our anticipated outcome and resonates with established insights from marketing literature. Such insight is critical for contextualizing our analysis within the broader body of research and informing our subsequent analytical approaches. Hence, the normally distributed data helps us choose parametric tests and validate the empirical model.

For a more detailed examination of the statistical tests of normality, please refer to Appendices 0.2, which provides comprehensive insights into our methodology, analysis, and findings.

Additionally, we acknowledge the impact of sample size on the statistical power of our analysis. —It is widely acknowledged that smaller sample sizes, typically 50 or fewer, can compromise statistical power by magnifying the effects of sampling error. Conversely, larger sample sizes, particularly those exceeding 200, tend to mitigate the adverse consequences of non-normality on statistical analyses. This recognition underscores the importance of robust sample sizes in ensuring the reliability and validity of our findings (Hair, Jr., Black, Babin, & Anderson, 2015). In this study, the

total sample size is comprised of 322 participants. Given this substantial sample size, the study analyses are expected to be robust.

6.3 Hierarchical Component Model (HCM)

The model's objective is to delve into higher levels of abstraction by incorporating the lower order of constructs, enabling a more comprehensive examination of complex relationships within the research framework. To facilitate this endeavour, the research instrument employs the Hierarchical Component Modelling (HCM) methodology. This strategic choice is motivated by the methodology's capacity to accommodate the analysis of multilayered structures, aligning seamlessly with the capabilities of SmartPLS SEM. By leveraging this methodological synergy, the study can effectively dissect and evaluate the intricate interplay between variables across different layers of abstraction, thereby enhancing the depth and rigor of the analysis (Hair J. F., Hult, Ringle, & Sarstedt, 2014). The incorporation of Hierarchical Component Modelling (HCM) offers two notable advantages. Firstly, it enables a reduction in the number of relationships within the structural model, thereby enhancing its parsimony and comprehensibility within the Partial Least Squares (PLS) path model. Secondly, HCMs prove particularly valuable in reflective models, especially when variables exhibit high levels of correlation. By leveraging HCMs, potential collinearity issues are mitigated, thereby addressing concerns related to discriminant validity.

The literature in both marketing and econometrics delineates four distinct types of Hierarchical Component Models (HCMs). (Jarvis, MacKenzie, & Podsakoff, 2003), (Wetzel, Odekerken-Schroder, & Van, 2009) and (Hair J., Hult, Ringle, & Sarstedt, 2017). Hierarchical Component Models (HCMs) encompass four distinct

configurations, each delineating unique relationships among constructs. The four types of Hierarchical Component Models (HCMs) are as follows.

1. Reflective – Reflective
2. Reflective – Formative
3. Formative – Reflective
4. Formative – Formative

In this study, guided by theoretical underpinnings and existing scholarly discourse, the second method, the Reflective-Formative HCM, is chosen. This framework comprises two integral components, setting it apart from conventional models. Firstly, the higher-order component (HOC) is designed to measure the overarching abstract entity within the structural model. Secondly, the lower-order components (LOCs) play a crucial role in capturing the nuanced sub-dimensions inherent within these abstract entities.

The SmartPLS-SEM tool adopts the repeated indicators approach to establish the measurement model for LOCs effectively. Consequently, it is essential to meticulously report the loading and reliabilities of LOCs to ensure the robustness and validity of the analytical outcomes. This deliberate approach aligns with best practices in structural equation modelling and enhances the credibility of the study findings. (Hair J., Hult, Ringle, & Sarstedt, 2017).

6.4 Sampling Strategy

This study's primary objective is to conduct an empirical investigation to comprehensively understand and delineate consumers' intention to purchase durable products, such as electric vehicles. More specifically, the research endeavors to

examine various aspects of this behavior, including the latent and mediating variables (as suggested by (Diekmann, Loibl, & Batte, 2009), including the factors contributing to variance in prepurchase behavior and the strategies employed by consumers in their purchase choice (as highlighted by (Park & Agarwal, 2018)). This multifaceted analysis aims to shed light on the nuanced dynamics influencing the intention to purchase across different consumer demographics and geographic settings.

A multitude of factors influence consumers' differentiation of purchase intention. Understanding and contextualizing this facet of consumer search behavior is particularly vital in emerging markets, where economic and market calibration is on exponential growth.

The research instrument was meticulously crafted to precisely capture these dimensions, particularly within the framework of controlled heterogeneity. The study's final sample size consists of 322 participants, representing a robust dataset for analysis. From a statistical perspective, this sample size surpasses the threshold limits outlined in the existing literature (Hair J., Hult, Ringle, & Sarstedt, 2017), thus ensuring ample power to detect meaningful effects and achieve statistical significance. This substantial sample size enhances the study's reliability and strengthens the validity of the findings, providing a solid foundation for drawing meaningful conclusions and making informed interpretations.

The utilization of descriptive statistics provides a robust foundation for the exploration of factors influencing purchase intention for electric vehicles. Through analysis of descriptive data, key insights into the underlying trends, patterns, and distributions of relevant variables can be gleaned. This methodological approach not only facilitates a comprehensive understanding of the antecedents of purchase

intention but also enhances the validity and reliability of subsequent analyses and conclusions drawn from the study. Therefore, descriptive statistics serve as a fundamental tool in substantiating and informing the investigation into the determinants of consumer behavior toward electric vehicles.

The First-order measurement and second-order structural path models are examined. Below is the empirical analysis of the measurement model, followed by the structural model.

6.5 Evaluation of Purchase Intention PLS-SEM Descriptive Statistics

6.5.1 Descriptive Statistics

Descriptive statistics is used to summarize and describe data characteristics. The data is presented in the form of academic tables/figures following the standards of APA style. Three types of descriptive statistics are presented viz. summarizing data in tables/figures (counts, frequencies, percentages). Describing the central tendency (the mode, median, and mean) and finally describing the data variability (min/max values), another well-known method of data variability reporting is the standard deviation. In summary, we might be tempted to believe that descriptive statistics is too simple and not worth doing. However, the first step in almost all quantitative statistical research projects, even the biggest and most complex, is to describe the data. It will provide an overall sense of what the data can tell us.

This study has six categorical demographical variables to understand endogenous variables' sample and control attributes. They are.

- *Genders*
- *Age*
- *Education*
- *Employment*
- *Monthly Income*
- *Native State in India*

The sample demographic characteristics

Table 6.1: Frequency table of demographic variables.

		Gender	Age	Edu	Employment	Monthly Income	Sample State
N	Valid	322	322	322	322	322	322
	Missing	0	0	0	0	0	0
Minimum		1	1	1	1	1	1
Maximum		2	6	6	6	5	17

The investigation encompasses a comprehensive sample size, denoted as N, totalling 322 individuals. Notably, the dataset contains no missing values or incomplete data points. This meticulous attention to detail in data collection enhances the robustness and reliability of the study's findings and analyses.

Table 6.2: Descriptives of Age

Age in Years				
		Frequency	Percent	Cumulative Percent
Valid	18 -25	19	5.9	5.9
	26 - 35	75	23.3	29.2
	36 - 45	157	48.8	78.0
	46 - 55	37	11.5	89.4
	56 - 65	16	5.0	94.4
	> 65	18	5.6	100.0
	Total	322	100.0	

Gender is categorized into two codes: 1 for male and 2 for female. Age, on the other hand, spans six distinct levels: 18 to 25, 26 to 35, 36 to 45, 46 to 55, 56 to 65, and greater than 65.

Table 6.2 provides a comprehensive overview of the age distribution within the sample under study. Among the 322 participants, approximately 6 percent fell within the 18 to 25 age brackets. The subsequent age group, 26-35, exhibited a participation rate of 23 percent, while the 36-45 category represented the highest participation at 49 percent. Participants aged 46-55 accounted for 11 percent, whereas the 56-65 and over 65 age groups each contributed 5 and 6 percent, respectively.

The analysis underscores a notable trend: consumers demonstrate significant purchasing potential, particularly beyond the age of 30. In line with this, individuals aged 36 to 45 exhibited a noteworthy participation rate of 49 percent, followed by those aged 26 to 35 at 23 percent. Notably, when considering individuals aged 25 to 45 collectively, a substantial 72 percent expressed an interest in purchasing an Electric Vehicle (EV). This observation reinforces previous literature highlighting the

significance of purchasing capabilities in the acquisition of durable goods like electric vehicles.

Table 6.3: Descriptives of Education

Education			
	Frequency	Percent	Cumulative Percent
Post Doctoral	10	3.1	100.0
Plus 12	11	3.4	3.4
Ph.D	17	5.3	96.9
Professional Training	18	5.6	9.0
Bachelors	120	37.3	46.3
Masters	146	45.3	91.6
Total	322	100.0	

Data collection within the realm of education encompasses six distinct levels: Plus 12, Professional Degree (ITI & Diploma), Bachelors, Masters, Ph.D., and Post-Doc. Notably, Plus 12 and Professional Degree holders collectively contribute 9 percent to the sample participation. Bachelor’s degree holders constitute the largest segment, representing 37.3 percent, followed closely by Master’s degree holders at 45.3 percent. When combined, bachelor's and master's degree holders account for a substantial 82.6 percent of the participation. Ph.D. holders constitute 5.3 percent of the sample, while Postdoctoral individuals represent 3.1 percent. This diversity underscores the robustness and inclusivity of the sample frame utilized in the study.

Table 6.4: Descriptives of Employment

Employment			
	Frequency	Percent	Cumulative Percent
Student	17	5.3	5.3
Not Employed	14	4.3	9.6
Self Employed	37	11.5	21.1
Employed - Private	198	61.5	82.6
Employed - Government	37	11.5	94.1
Retired	19	5.9	100.0
Total	322	100.0	

Employment is segmented into six distinct categories for data collection purposes, as outlined in Table 6.4. Notably, the participation rates vary across these categories. Individuals not currently employed exhibit a participation rate of 4.3 percent, while students show a slightly higher participation at 5.3 percent. Retired individuals participate at a rate of 5.9 percent. Self-employed individuals and those working in government positions both demonstrate a participation rate of 11.5 percent. However, the highest level of participation is observed among privately employed individuals, particularly buyers, with a significant rate of 61.5 percent. This figure serves as a representation of the proportion of consumers intending to purchase electric vehicles within this category.

Table 6.5: Descriptives of Monthly Income

Monthly_Income in Indian Rupees			
	Frequency	Percent	Cumulative Percent
< 30K	35	10.9	10.9
30K to 50K	33	10.2	21.1
50K to 100K	63	19.6	40.7
100K to 150K	54	16.8	57.5
>150K	137	42.5	100.0
Total	322	100.0	

The data collection for monthly income comprises five distinct levels, as outlined in Table 6.5. From least to largest, 10 percent of the sample falls within the 30K to 50K monthly income bracket, denominated in Indian rupees. Additionally, 10.9 percent of the sample earns less than 30K monthly. Buyers with a monthly income ranging from 100K to 150K represent 16.8 percent of the sample, while those earning between 50K to 100K constitute 19.6 percent. Notably, the largest portion of the sample, accounting for 42.5 percent, consists of buyers earning above 150K monthly. This underscores the purchasing power of Indian consumers, particularly in acquiring durable technology products. The robust participation across income brackets within the sample reinforces the validity of the model's inference.

Table 6.6: Descriptives of Sample Participation

Sample_State	Frequency	Percent	Cumulative Percent
Karnataka	210	65.2	65.2
Tamil Nadu	15	4.7	69.9
Andhra Pradesh	34	10.6	80.4
Telangana	12	3.7	84.2
Kerala	11	3.4	87.6
Jharkhand	6	1.9	89.4
Haryana	1	0.3	89.8
Uttar Pradesh	4	1.2	91.0
Chhattisgarh	2	0.6	91.6
Rajasthan	5	1.6	93.2
Delhi	5	1.6	94.7
Assam	6	1.9	96.6
Manipur	2	0.6	97.2
Bihar	2	0.6	97.8
Maharashtra	2	0.6	98.4
Jammu & Kashmir	2	0.6	99.1
Arunachal Pradesh	3	0.9	100.0
Total	322	100.0	

The overarching objective of the data collection initiative is to ensure comprehensive data collection from all geographical regions of India, which encompass its diverse landscape comprising 28 states and 8 union territories. This ambitious scope seeks to

capture the multifaceted socio-economic, cultural, and demographic variations that characterize India's vast expanse. By encompassing every state and union territory, the initiative aims to gather a representative sample that reflects the nation's rich tapestry, thereby facilitating a nuanced understanding of consumer behaviours, preferences, and market dynamics across different regions. Such inclusive data collection endeavours are pivotal for formulating informed strategies, policies, and decisions that resonate with the diverse populace and contribute to the rich development and validation of the equitable antecedents of the empirical model. Such is the sample participation from across the country.

Participation was solely secured from 17 states. Among these, Karnataka exhibited the highest level of engagement, constituting 65.2 percent of the sample. Following Karnataka, Andhra Pradesh contributed 10.6 percent, while Tamil Nadu, Telangana, and Kerala accounted for 4.7 percent, 3.7 percent, and 3.4 percent respectively. Jharkhand and Assam each represented 1.9 percent of the sample, followed by Rajasthan and New Delhi at 1.6 percent each. Uttar Pradesh contributed 1.2 percent, while Arunachal Pradesh, Chhattisgarh, Manipur, Bihar, Maharashtra, Jammu and Kashmir each comprised 0.6 percent of the sample. Lastly, Haryana contributed 0.3 percent.

Though with such a diversified sample size, from the methodological point of view, we would like to put forward that the geographical scope of the study is Karnataka.

The sample size of the study is a critical factor, as it enhances the validity and applicability of the findings across different contexts. In this research, 65% of the participants are from Bengaluru, while the remainder comes from various regions of

India. This proportion is close to a balanced representation and contributes to the robustness of the results.

Beyond sample size, several additional factors impact generalizability, including the sample frame, research design, and methodological rigor, as highlighted by Tsang (2013), Schreier (2018), and Kaplan (2019).

Furthermore, generalizability can be categorized into two types: statistical generalizability and theoretical generalizability, as noted by Bryman (2022). This study validates its findings through both of these lenses.

6.6 Evaluation and Assessment of the PLS_SEM Results

Purchase intention serves as a multifaceted and intricately determined variable influenced by various internal factors and encompasses several dimensions. Within this context, the anticipated emergence of electric vehicles (EVs) stands as a significant driver, poised to offer substantial economic and environmental advantages over conventional internal combustion engine vehicles. Through rigorous technological evaluation, EVs are anticipated to not only mitigate greenhouse gas emissions but also enhance energy security and expand mobility options. However, the multifaceted nature of these advantages complicates direct measurement or observation, as they span across diverse domains.

This study implemented a structured interview survey to navigate this complexity. This methodology was chosen to engage with individuals who harbour intentions to purchase automobiles within the upcoming three months. Specifically, the survey targeted a subset of the population characterized by their expressed interest in acquiring electric vehicles. By honing in on this specific demographic, the study

aimed to delve deeply into the nuanced motivations, considerations, and perceptions driving the purchase intentions within the electric vehicle market segment. Through this approach, the research endeavours to shed light on the underlying dynamics shaping consumer behaviour and preferences in the context of electric vehicle adoption, contributing to a richer understanding of this burgeoning sector. Figure 6.1 elucidates both the measurement and structural models of purchase intention defined in this study.

Fig 6.1 depicts the Structural and measurement models of purchase intention.

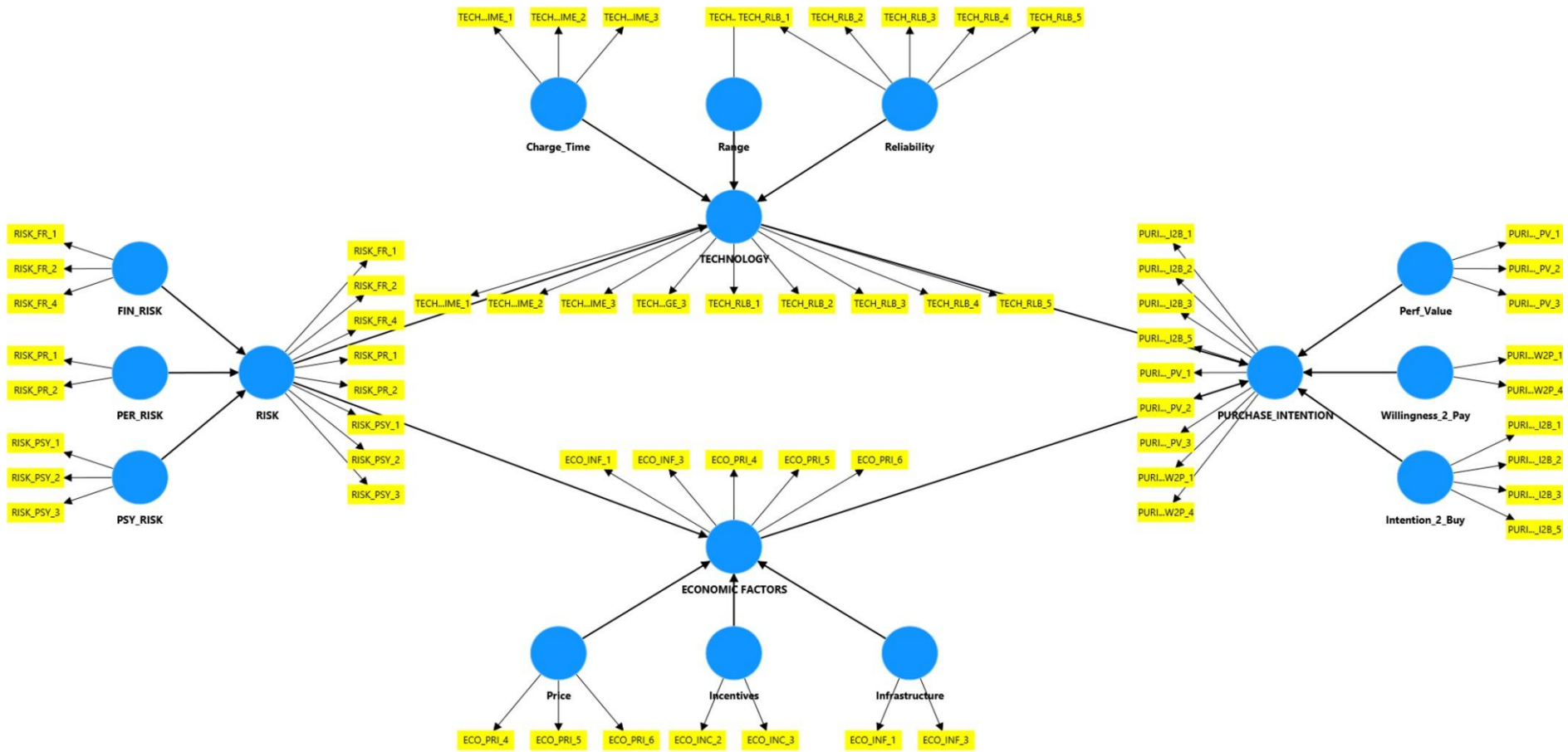


Figure 6.1: Inner and outer model of purchase intention

There is one independent variable, two mediating variables, and a dependent variable in the study. The first independent variable (IV), the —Perceived Riskl (PR), is measured by three first-order constructs with twelve questions in total. The IV and the mediating variable (MV), Technology Factors (TF), are also measured by three outer measurement variables, with eleven indicators in total. The next IV and MV, economic factors (EF), are also measured by three outer model variables, with fourteen indicators in total. Finally, the dependent variable, the —Purchase Intention,l is measured by four outer model constructs, with fifteen indicators in total.

Figure 6.1 delineates the conceptual interconnections and hypothetical relationships among all latent variables. The measurement model elucidates the associations between indicators and latent variables, while the structural model delineates the relationships between exogenous and endogenous variables. In accordance with the theoretical framework, our approach entails employing reflective lower-order and formative higher-order factor specifications in modelling. (Jarvis, MacKenzie, & Podsakoff, 2003).

Model estimation delivers empirical measures to quantify the relationships between the various indicators and constructs encapsulated within both the measurement and structural models. These estimations serve a dual purpose: First, they provide insights into the quality of the measurement process by gauging how well the indicators align with their respective constructs (measurement model). Second, they enable an assessment of the model's overall efficacy in elucidating and forecasting the intended constructs (structural model). By scrutinizing these estimates, we can gauge the reliability and validity of the model, gaining confidence in its ability to represent and predict the research purpose under investigation accurately. In essence, model

estimation serves as a critical step in validating the theoretical framework by empirically evaluating its explanatory and predictive power.

—The structural model estimates are not examined until the reliability and validity of the 1st order constructs have been established. (Hair J., Hult, Ringle, & Sarstedt, 2017). Henceforth, we adhere to the two components outlined in the hierarchical model assessment method proposed by (Henseler, Hubona, & Ray, 2016).

—The model evaluation follows a two-step process,

- 1) the evaluation of the reflective measurement model and
- 2) evaluation of the structural model.

1). Evaluation of Reflective Measurement Model

- (1) Outer Loadings and Significance
- (2) Indicator Reliability
- (3) Internal Consistency Reliability
- (4) Convergent Validity
- (5) Discriminant Validity

2). Evaluation of Structural Model

- (1) Collinearity (VIF)
- (2) Significance of Path Coefficients (Bootstrapped)
- (3) Explanatory Power (Coefficients of Determination R^2)
- (4) Predictive relevance (Q^2)
- (5) Effect sizes (f^2)
- (6) Model Fit.

6.6.1 Evaluation of Reflective Measurement Model

The evaluation of PLS-SEM results commences with a primary emphasis on the measurement model, as pro founded by various scholars (e.g., Chin, 2010; Roldán & Sánchez-Franco, 2012; Tenenhaus et al., 2005). This phase entails processes and assessments often referred to as confirmatory composite analysis (CCA) or confirmatory factor analysis (CFA), as elucidated by Hair, Howard, and Nitzl (2020).

The examination of PLS-SEM estimates facilitates the evaluation of both the reliability and validity of construct measures. This assessment is crucial given that measurement practices often involve the utilization of multiple variables, referred to as multi-items, to assess a construct. The rationale for employing multiple items instead of singular ones in construct measurement is rooted in the anticipation of heightened precision and more accuracy. This improvement stems from the mitigation of overall measurement error inherent in the indicators when multiple indicators are utilized to measure a single concept.

The aim is to minimize measurement error to the greatest extent feasible. Multi-item measures afford a more refined means of identifying and mitigating measurement error, thereby acknowledging its impact on research outcomes. Measurement error pertains to the disparity between the actual value of a variable and the value derived from a measurement process.

6.6.1.1 Outer model loadings and significance

—The evaluation of reflective measurement models encompasses an assessment of the measures' reliability, conducted at both the indicator level (indicator reliability) and the construct level (internal consistency reliability). Validity assessment involves

scrutinizing two types of validity. The first type evaluates the convergent validity of each measure through the average variance extracted (AVE). The second type pertains to discriminant validity, which involves comparing all construct measures within the same model based on the heterotrait-monotrait (HTMT) ratio of correlations. Subsequent sections elaborate on each criterion utilized for evaluating reflective measurement models (Hulland J. , 1999)¶.

The study's data have been assessed through adaptation of the (Hair J., Hult, Ringle, & Sarstedt, 2017) and (Hair J. , Hult, Ringle, & Sarstedt, 2024) reflective measurement model assessment process. Examining the outer loadings of the indicators. At the least, all indicators should exhibit statistically significant outer loadings. A principal guideline indicates that standardized outer loadings should ideally be greater than 0.708. Thus, the standardized outer loading of an indicator, as derived from the PLS-SEM outcomes, ought to be 0.708 or higher, given that the square of this value (0.708^2) equals 0.50. It is noteworthy that in many cases, 0.70 is deemed sufficiently proximate to 0.708 to be deemed acceptable.

In social science research, weaker outer loadings (< 0.70) are frequently encountered (Hulland, 1999). Instead of automatically deleting indicators with outer loadings below 0.70, we meticulously assessed the impact of indicator removal on other measures of reliability and validity. —Indicators with outer loadings ranging between 0.40 and 0.70 are considered for elimination if their removal enhances internal consistency reliability or convergent validity beyond the prescribed threshold value¶. Furthermore, the decision to retain or discard an indicator is also considered based on its effect on content validity. Indicators with weaker outer loadings may still be retained based on their contribution to content validity. However, indicators with very

low outer loadings (below 0.40) are excluded from the construct validity and study (Bagozzi, Yi, & Philipps, 1991; Hair, Ringle, & Sarstedt, 2011), (Hair J. , Hult, Ringle, & Sarstedt, 2024).

Table 6.7 shows the outer loading results of the measurement model.

For clarity, both reliability and validity assessments have been presented within the same table. Internal Consistency Reliability has been assessed via Composite Reliability, while Convergent Validity has been evaluated using Average Variance Extracted (AVE) (Hair J., Hult, Ringle, & Sarstedt, 2017) and (Kay Wong, 2016).

Table 6.7: Evaluation of Reliability and Validity

Indicator	Reliability			Validity
	Outer Loading	Indicator Reliability	Internal Consistency Reliability	Convergent Validity
ECO_INC_2	0.864	0.746	0.808	0.678
ECO_INC_3	0.780	0.608		
ECO_INF_1	0.921	0.848	0.914	0.842
ECO_INF_3	0.915	0.837		
ECO_PRI_4	0.873	0.762	0.857	0.668
ECO_PRI_5	0.856	0.733		
ECO_PRI_6	0.715	0.511		
PURINT_I2B_1	0.863	0.745	0.885	0.658
PURINT_I2B_2	0.833	0.694		

Indicator	Reliability			Validity
	Outer Loading	Indicator Reliability	Internal Consistency Reliability	Convergent Validity
PURINT_I2B_3	0.803	0.645		
PURINT_I2B_5	0.740	0.548		
PURINT_PV_1	0.710	0.504		
PURINT_PV_2	0.845	0.714	0.853	0.661
PURINT_PV_3	0.874	0.764		
PURINT_W2P_1	0.845	0.714		
PURINT_W2P_4	0.846	0.716	0.833	0.714
RISK_FR_1	0.645	0.416		
RISK_FR_2	0.861	0.741	0.856	0.666
RISK_FR_4	0.745	0.555		
RISK_PR_1	0.820	0.672		
RISK_PR_2	0.912	0.832	0.858	0.752
RISK_PSY_1	0.821	0.674		
RISK_PSY_2	0.809	0.654	0.857	0.667
RISK_PSY_3	0.820	0.672		
TECH_CH_TIME_1	0.684	0.468		
TECH_CH_TIME_2	0.864	0.746	0.850	0.656
TECH_CH_TIME_3	0.867	0.752		
TECH_RANGE_3	1.000	1.000	1.000	1.000
TECH_RLB_1	0.697	0.486	0.897	0.636

Indicator	Reliability			Validity
	Outer Loading	Indicator Reliability	Internal Consistency Reliability	Convergent Validity
TECH_RLB_2	0.848	0.719		
TECH_RLB_3	0.773	0.598		
TECH_RLB_4	0.843	0.711		
TECH_RLB_5	0.817	0.667		

Table 6.7: Indicators with outer loadings exceeding 0.70 are retained within the model. Indicators with loadings surpassing 0.40 but falling below 0.70 underwent scrutiny to evaluate the repercussions of their removal on both Composite Reliability and Average Variance Extracted (AVE). Utilizing an iterative approach, indicators are eliminated if their removal leads to an improvement in the aforementioned measures beyond the predetermined threshold; otherwise, they are retained. Indicators with loadings lower than 0.40 are excluded from further consideration.

The measurement model; data iteration reporting.

The Independent Variable: Risk Factors:

The first measurement variable of the lower-order construct (LOC) pertaining to the Risk Factor is financial risk, comprising four indicators. The outer loading relevance testing of the financial risk exceeds the threshold limit of 0.7-factor loading, accompanied by an average variance extracted (AVE) of 0.565. This observation signifies compliance with the validity requirements of the measurement model.

The second lower-order construct (LOC) pertaining to the Risk Factor is the performance risk, which is assessed through four indicators. Among these, PR_1 exhibits a loading of 0.784, while PR_2 displays a loading of 0.874. Conversely, PR_3 and PR_4 demonstrate loadings below the threshold at 0.366 and 0.372, respectively. Consequently, the average variance extracted (AVE) for performance risk is calculated at 0.413 during the initial iteration, necessitating additional iterations to fulfil the statistical assumption for AVE.

The third lower-order construct (LOC) addressing psychological risk encompasses four indicators. The outer loadings for PSY_1, PSY_2, PSY_3, and PSY_4 are 0.820, 0.744, 0.771, and 0.672, respectively. While PSY_4 registers a loading of 0.672, the average variance extracted (AVE) for psychological risk, calculated at 0.579, satisfies the statistical assumption. However, upon considering the reliability and validity of the indicators, the higher-order construct RISK, associated with electric vehicle purchase intention, yields an AVE of 0.372, failing to meet the statistical assumption of at least a 50% variance explanation. Therefore, further iterations are required to address the performance risk LOC.

In the second iteration, PR_3 has been removed from the performance risk construct. Consequently, the average variance extracted (AVE) for performance risk has risen from 0.413 to 0.531. However, the removal of PR_3 has had an adverse effect on the loading of PR_4, diminishing its factor loading from 0.372 to 0.338. Given that this loading falls below the threshold of 0.4, PR_4 is considered a potential candidate for direct deletion. Therefore, it was eliminated to assess its impact on the subsequent AVE of the higher-order construct (HOC) Risk.

In the third iteration focusing on performance risk, PR_4 was removed from the model. This resulted in a notable increase in the average variance extracted (AVE) of performance risk, elevating it from 0.531 to 0.751, indicative of strong AVE at the lower-order level. Despite three iterations, the AVE of the higher-order construct (HOC) Risk remains at 0.423, still falling below the statistical threshold of 0.5. Consequently, attention is directed towards other risk indicators, specifically financial risk and psychological risk, for further iteration to enhance the AVE of HOC risk. Within psychological risk, the indicator PSY_4 exhibits a loading of 0.665 at the LOC level, whereas, at the HOC level, its loading is 0.552. Consequently, it has been deemed suitable for deletion in subsequent iterations.

In the fourth iteration, PSY_4 was eliminated from both the lower-order construct (LOC) and the higher-order construct (HOC) of risk. Despite this adjustment, the AVE of HOC risk remains at 0.443, still below the threshold limit of AVE 0.5. Consequently, attention has shifted to another indicator, financial risk FR_3. Initially, FR_3 exhibited a loading of 0.637 in the first iteration, while in the fourth iteration, its loading increased slightly to 0.641 at the LOC level and 0.573 at the HOC level. However, it was decided to delete it for further iteration.

In the fifth iteration of the higher-order construct (HOC) risk, following the deletion of PSY_4, the average variance extracted (AVE) of risk has reached 0.564. This achievement signifies compliance with the statistical assumption requiring a 50% variance explanation.

Technology Factors:

The higher-order construct (HOC) of technology factors is assessed through three lower-order construct (LOC) factors: driving range, charging time, and reliability.

The lower-order construct (LOC) "driving range" comprises three indicators with loadings of RANGE_1 at 0.381, RANGE_2 at 0.664, and RANGE_3 at 0.802. Similarly, the second LOC, "charging time," is assessed through three indicators with loadings of TIME_1 at 0.685, TIME_2 at 0.864, and TIME_3 at 0.867. The third LOC, "reliability," consists of four indicators with loadings of RLB_1 at 0.696, RLB_2 at 0.847, RLB_3 at 0.775, RLB_4 at 0.843, and RLB_5 at 0.818. The average variance extracted (AVE) of the higher-order construct (HOC) "technology" is 0.401. However, the AVE of LOC "driving range" is 0.412, "charging time" is 0.656, and "reliability" is 0.636. The AVE of LOC "driving range" falls below 0.5, impacting the AVE of HOC technology. Therefore, further iteration is warranted.

In the first iteration, RANGE_1 exhibited a loading of 0.083 on the higher-order construct (HOC). Subsequent to the removal of RANGE_1, the average variance extracted (AVE) of HOC technology increased to 0.441, while the AVE of the lower-order construct (LOC) driving range rose to 0.550, meeting the threshold requirement. However, HOC technology still fell short of meeting the threshold. The remaining two indicators of the LOC driving range, RANGE_2, demonstrated loadings of 0.636, whereas its loadings on HOC were notably lower at 0.324. Considering its loading, it was approaching below 0.4 loading. Hence, it has been deleted. Consequently, Range_3 was loading at 0.833, manifested on HOC technology as a single indicator. The AVE of HOC technology increased to 0.522, surpassing the threshold limit for AVE.

Economic Factors: Iteration

The higher-order construct (HOC) "economic factors" is assessed through three lower-order construct (LOC) variables: Price, Incentives, and Infrastructure. In the

first iteration, the LOC "price" is measured by six indicators with respective factor loadings as follows: PRI_1 at 0.595, PRI_2 at 0.737, PRI_3 at 0.631, PRI_4 at 0.645, PRI_5 at 0.652, and PRI_6 at 0.705. The average variance extracted (AVE) of the "price" variable is calculated at 0.435.

The variable "Incentive" is assessed through four indicators, with corresponding factor loadings as follows: INC_1 (0.589), INC_2 (0.713), INC_3 (0.779), and INC_4 (0.548). The average variance extracted (AVE) for incentives is calculated at 0.441. The third variable, "infrastructure," is evaluated through four indicators, with factor loadings as follows: INF_1 (0.863), INF_2 (0.771), INF_3 (0.867), and INF_4 (0.692). The average variance extracted (AVE) for infrastructure is determined to be 0.642. However, the cumulative AVE of the higher-order construct (HOC) "economic factors" amounts to 0.361, falling short of the AVE threshold. Consequently, further iterations are required.

In the iteration process, one indicator of the LOC "price," PRC_1, exhibited a loading of 0.595, while on the HOC level, its loading was 0.534. Upon removal, the AVE for price increased to 0.474, yet it remained below 0.5. Consequently, the second lowest loading indicator, PRI_3, with a loading of 0.583 at LOC and 0.572 at HOC, was considered for further evaluation. Following the deletion of these two indicators, the AVE of the LOC "price" in the second iteration increased to 0.547, meeting the statistical assumption for AVE. However, the AVE of the LOC "incentive" remained at 0.441, and the AVE of the HOC "economic factors" was 0.378, necessitating further iteration. Consequently, the indicator INC_1, with loadings of 0.584 at LOC and 0.450 at HOC, was removed.

In the third iteration, the AVE of the LOC "incentive" improved to 0.517, yet the AVE of the HOC remained at 0.401 despite the deletion of two indicators. Consequently, the lowest loading factors in the LOC "incentives" were scrutinized. INC_4 exhibited loadings of 0.604 at LOC and 0.481 at HOC, leading to its deletion. However, even after this adjustment, the AVE of the HOC persisted at 0.421, necessitating further iterations. While the AVE of the LOC "infrastructure" stood at 0.643, the fourth indicator INF_4 was loading at 0.603 at HOC, prompting its deletion. Moreover, INF_2, with loadings of 0.579 at HOC, emerged as the least loading factor in the HOC "economic factors," warranting its removal to enhance the AVE. However, despite these adjustments, the AVE remained at 0.449. To further enhance it, PRI_2, with loadings of 0.627 at LOC and 0.617 at HOC, was deleted. Subsequently, the AVE of the HOC improved to 0.550, fulfilling the statistical assumption of AVE exceeding 0.5 or accounting for 50% of variance extraction.

Dependent Variable: Purchase Intention Iteration.

Purchase intention is evaluated through four lower-order construct (LOC) variables: performance value, willingness to pay, intention to buy, and social influence. At the LOC level, performance value is assessed using three indicators, with factor loadings of PV_1 (0.702), PV_2 (0.851), and PV_3 (0.875), while on the HOC side, PV_1 loads at 0.596, PV_2 at 0.723, and PV_3 at 0.704. The second LOC, willingness to pay, is measured through four indicators, with loadings of W2P_1 (0.813), W2P_2 (0.588), W2P_3 (0.711), and W2P_4 (0.747), and on the HOC side, these loadings are 0.704, 0.356, 0.545, and 0.703, respectively. The third LOC, intention to buy, consists of five indicators, with loadings of I2B_1 (0.858), I2B_2 (0.816), I2B_3 (0.774), I2B_4 (0.599), and I2B_5 (0.732), and on the HOC side, these loadings are

0.771, 0.755, 0.666, 0.549, and 0.682, respectively. Lastly, the fourth LOC, social influence, is measured through three indicators, with loadings of SI_1 (0.839), SI_2 (0.531), and SI_3 (0.413), while on the HOC side, the loadings are 0.471, 0.501, and 0.571, respectively.

The average variance extracted (AVE) for performance value is 0.661, for willingness to pay is 0.517, for intention to buy is 0.579, and for social influence is 0.371. However, the AVE for the higher-order construct (HOC) purchase intention is 0.371, falling below the threshold of 0.5. Given that social influence had the maximum negative impact, it was removed from the model. Upon its removal, the AVE for HOC purchase intention improved to 0.431.

In order to enhance the average variance extracted (AVE), an evaluation of indicator loadings at both the higher-order construct (HOC) and lower-order construct (LOC) levels is conducted. For the performance value indicators, all exhibit loadings above 0.7 at both LOC and HOC purchase intention, except for PV_1 on the HOC side, which loads at 0.596. The second LOC, willingness to pay, comprises four indicators, among which W2P_2 has a loading of 0.588. However, this same indicator loads at 0.356 on the HOC side. Consequently, it was removed from the model, and further iterations are being undertaken.

The AVE for the higher-order construct (HOC) has improved to 0.460 from 0.431, yet it remains below the threshold limit of 0.5. Two additional indicators on the HOC side, I2B_4 of intention to buy and W2P_3 of willingness to pay, exhibit loadings below 0.6, at 0.558 and 0.528, respectively. Consequently, they are removed from both the lower-order construct (LOC) and HOC levels. This resulted in an increase in the AVE for the HOC, surpassing the threshold of 0.5.

6.6.1.2 Indicator reliability

The assessment of indicator reliability involves scrutinizing squared outer loadings. Ideally, each indicator's squared loading should equal or exceed 0.4, a benchmark widely recognized as indicative of satisfactory reliability (Henseler, Hubona, & Ray, 2016).

In Table 6.7 of this study, it is observed that the reliability of nearly all indicators surpasses 0.6. This exceeds the threshold limit of 0.4 recommended by (Hair J. , Hult, Ringle, & Sarstedt, 2024), indicating a high level of reliability for the indicators. Hence, the indicators demonstrate a sophisticated level of reliability.

6.6.1.3 Internal Consistency Reliability, Assessment

Cronbach's alpha, a widely used traditional method, serves to evaluate the reliability of internal consistency. Its underlying assumption is that all indicators contribute equally to this reliability. However, in the context of Partial Least Squares Structural Equation Modelling (PLS-SEM), indicators are given priority based on their individual reliability levels, acknowledging that not all indicators may be equally reliable. Additionally, Cronbach's alpha can be influenced by the number of items within a scale, potentially affecting the assessment of internal consistency reliability. Recognizing these intricacies and limitations, PLS-SEM opts for a more tailored approach: composite reliability, which provides a more nuanced evaluation of internal consistency reliability by considering the specific contributions of each indicator (Hair, Sarstedt, Ringle, & Mena, 2012), (Hair J. , Hult, Ringle, & Sarstedt, 2024).

Reliability measurements serve as a fundamental aspect of research evaluation, representing a spectrum from 0 to 1. Higher values denote stronger reliability, while lower values suggest less dependable measurements. Typically, a threshold of 0.6 or higher is deemed acceptable across various research paradigms, spanning both exploratory and advanced studies.

Within the context of this dissertation, an in-depth analysis reveals that composite reliability figures surpass 0.872 (almost 9) for all variables, underscoring the presence of robust internal consistency reliability throughout the study. This notable consistency is evidenced in Table 6.7, illustrating the meticulous attention to reliability assessment within the research framework.

6.6.1.4 Convergent Validity Assessment

Convergent validity provides insights into the degree to which individual indicators within a construct exhibit positive correlations with other indicators within the same construct. At the core of assessing convergent validity lies the Average Variance Extracted (AVE), a metric utilized to quantify this aspect. Calculating the AVE involves summing the squared loading scores of each indicator and subsequently dividing this sum by the total number of indicators within the variable. This process offers a comprehensive understanding of how well the indicators converge, reinforcing the construct's validity.

In order to validate the variance, an AVE value of 0.50 or higher is considered acceptable (Henseler, Ringle, & Sinkovics, 2009). If the AVE falls below 0.40, it is recommended for elimination (Hair, Ringle, & Sarstedt, 2011). Previous studies indicate that a latent variable should elucidate a significant portion of each

indicator's variance, typically around 50% or 0.50. Therefore, the outer loading of each indicator is expected to exceed 0.708, as its square equals 0.50.

In the present study, the Average Variance Extracted (AVE) surpasses 0.50 across all cases. Specifically, none are less than 0.650. The convergent column in Table 6.7 affirms this, providing validation of the measurement model's convergent validity.

6.6.1.5 Discriminant Validity Assessment

Within the realm of marketing research, discriminant empirical analysis plays a pivotal role in determining the degree of distinctiveness exhibited by a particular variable in relation to others. This underscores the variable's capacity to encapsulate unique facets that are not encompassed by any other variables within the model. In their work, (Hair, Sarstedt, Ringle, & Mena, 2012) outline two primary methodologies for evaluating discriminant validity: (1) The loading method and (2) the Fornel-Larcker criterion. Notably, scholarly discourse leans towards the latter approach due to its more conservative stance on validity analysis when compared to the former.

However, in 2015 (Henseler, Ringle, & Sarstedt, 2015) proposed a significant contribution by introducing a fresh method to assess the discriminant validity of latent variables. Through a critical examination of existing methodologies like Cross Loading and the Fornel-Larcker criteria, they identified limitations in effectively pinpointing shortcomings in discriminant validity. To bridge this gap, they introduced a new technique named the "Heterotrait Monotrait ratio of correlations" (HTMT), presenting an alternative avenue for scrutinizing discriminant validity. Their empirical investigation demonstrated the superiority of the HTMT approach over

traditional criteria. Consequently, the HTMT method emerges as a recommended and superior means for gauging discriminant validity.

In this study, we embrace a dual approach encompassing both the Fornel-Larcker method and the Heterotrait Monotrait ratio (HTMT) method. Our intention is to rigorously assess discriminant validity to ensure the thorough identification of any potential ambiguities.

*(2) **The Fornel-Larcker Method:** A comparison is conducted by computing the square root of Average Variance Extracted (AVE) values along with the correlations among latent variables. The underlying premise is that a construct should exhibit significantly stronger relationships or variances with its associated indicators compared to those with any other construct. Specifically, the square root of AVE should exceed its highest correlation with any other construct. Table 6.8 illustrates the application of the Fornell-Larcker criterion within the model.*

	ChargeTime	FinRisk	Incentives	Infrastructure	Intention 2Buy	PerRisk	PsyRisk	PerfValue	Price	Range	Reliability	Willingness 2Pay
ChargeTime	0.810											
FinRisk	0.254	0.816										
Incentives	0.386	0.376	0.823									
Infrastructure	0.215	0.470	0.374	0.918								
Intention2Buy	0.388	0.365	0.610	0.339	0.811							
PerRisk	0.121	0.516	0.349	0.545	0.281	0.867						
PsyRisk	0.251	0.504	0.303	0.591	0.210	0.534	0.817					
PerfValue	0.501	0.215	0.511	0.264	0.605	0.252	0.110	0.813				
Price	0.505	0.233	0.627	0.348	0.620	0.165	0.216	0.515	0.817			
Range	0.251	0.257	0.258	0.248	0.402	0.305	0.282	0.324	0.317	1.000		
Reliability	0.593	0.291	0.551	0.255	0.604	0.215	0.166	0.746	0.601	0.362	0.798	
Willingness2Pay	0.484	0.282	0.501	0.307	0.670	0.243	0.267	0.573	0.539	0.394	0.668	0.845

Table 6.8: Fornell-Larcker Analysis of the Model

A notable observation emerges regarding the relationship between the square root of the Average Variance Extracted (AVE) for each latent variable and the correlations among these latent variables. Specifically, it becomes evident that the square root of the AVE values consistently exceeds the correlations among the latent variables. This comparative analysis is visually presented in the form of table 6.8, where both horizontal and vertical depictions help elucidate the relationship. Moreover, the findings of the Fornell-Larcker Analysis provide further validation, confirming that the model meets the criterion of discriminant validity.

(2) Heterotrait - Monotrait Ratio (HTMT) Method

The assessment criterion of HTMT results is: —If the HTMT value is below 0.90, discriminant validity is established between two reflective constructs.‖ (Henseler, Ringle, & Sarstedt, 2015), (Chakraborty, Sana, & Azam, 2022).

Table 6.9: HTMT Assessment of the Model

Relationship	HeteroTrait-MonoTrait ratio (HTMT)
ECONOMIC FACTORS <-> Charge_Time	0.624
FIN_RISK <-> Charge_Time	0.348
FIN_RISK <-> ECONOMIC FACTORS	0.546
Incentives <-> Charge_Time	0.622
Incentives <-> ECONOMIC FACTORS	0.467
Incentives <-> FIN_RISK	0.621
Infrastructure <-> Charge_Time	0.279
Infrastructure <-> ECONOMIC FACTORS	0.279
Infrastructure <-> FIN_RISK	0.600

Relationship	HeteroTrait-MonoTrait ratio (HTMT)
Infrastructure <-> Incentives	0.587
Intention_2_Buy <-> Charge_Time	0.505
Intention_2_Buy <-> ECONOMIC FACTORS	0.784
Intention_2_Buy <-> FIN_RISK	0.467
Intention_2_Buy <-> Incentives	0.570
Intention_2_Buy <-> Infrastructure	0.420
PER_RISK <-> Charge_Time	0.176
PER_RISK <-> ECONOMIC FACTORS	0.570
PER_RISK <-> FIN_RISK	0.702
PER_RISK <-> Incentives	0.578
PER_RISK <-> Infrastructure	0.717
PER_RISK <-> Intention_2_Buy	0.354
PSY_RISK <-> Charge_Time	0.340
PSY_RISK <-> ECONOMIC FACTORS	0.605
PSY_RISK <-> FIN_RISK	0.663
PSY_RISK <-> Incentives	0.480
PSY_RISK <-> Infrastructure	0.741
PSY_RISK <-> Intention_2_Buy	0.262
PSY_RISK <-> PER_RISK	0.693
PURCHASE_INTENTION <-> Charge_Time	0.646
PURCHASE_INTENTION <->	0.795

Relationship	HeteroTrait-MonoTrait ratio (HTMT)
ECONOMIC FACTORS	
PURCHASE_INTENTION <-> FIN_RISK	0.425
PURCHASE_INTENTION <-> Incentives	0.570
PURCHASE_INTENTION <-> Infrastructure	0.423
PURCHASE_INTENTION <-> Intention_2_Buy	0.262
PURCHASE_INTENTION <-> PER_RISK	0.376
PURCHASE_INTENTION <-> PSY_RISK	0.286
Perf_Value <-> Charge_Time	0.691
Perf_Value <-> ECONOMIC FACTORS	0.672
Perf_Value <-> FIN_RISK	0.295
Perf_Value <-> Incentives	0.839
Perf_Value <-> Infrastructure	0.343
Perf_Value <-> Intention_2_Buy	0.777
Perf_Value <-> PER_RISK	0.347
Perf_Value <-> PSY_RISK	0.204
Perf_Value <-> PURCHASE_INTENTION	0.262
Price <-> Charge_Time	0.685
Price <-> ECONOMIC FACTORS	0.262
Price <-> FIN_RISK	0.320
Price <-> Incentives	0.262
Price <-> Infrastructure	0.447

Relationship	HeteroTrait-MonoTrait ratio (HTMT)
Price <-> Intention_2_Buy	0.805
Price <-> PER_RISK	0.263
Price <-> PSY_RISK	0.295
Price <-> PURCHASE_INTENTION	0.819
Price <-> Perf_Value	0.703
RISK <-> Charge_Time	0.345
RISK <-> ECONOMIC FACTORS	0.658
RISK <-> FIN_RISK	0.262
RISK <-> Incentives	0.638
RISK <-> Infrastructure	0.782
RISK <-> Intention_2_Buy	0.414
RISK <-> PER_RISK	0.262
RISK <-> PSY_RISK	0.262
RISK <-> PURCHASE_INTENTION	0.413
RISK <-> Perf_Value	0.314
RISK <-> Price	0.339
Range <-> Charge_Time	0.292
Range <-> ECONOMIC FACTORS	0.404
Range <-> FIN_RISK	0.295
Range <-> Incentives	0.352
Range <-> Infrastructure	0.275
Range <-> Intention_2_Buy	0.443
Range <-> PER_RISK	0.367

Relationship	HeteroTrait-MonoTrait ratio (HTMT)
Range <-> PSY_RISK	0.314
Range <-> PURCHASE_INTENTION	0.463
Range <-> Perf_Value	0.382
Range <-> Price	0.370
Range <-> RISK	0.367
Reliability <-> Charge_Time	0.742
Reliability <-> ECONOMIC FACTORS	0.685
Reliability <-> FIN_RISK	0.364
Reliability <-> Incentives	0.815
Reliability <-> Infrastructure	0.305
Reliability <-> Intention_2_Buy	0.718
Reliability <-> PER_RISK	0.288
Reliability <-> PSY_RISK	0.200
Reliability <-> PURCHASE_INTENTION	0.883
Reliability <-> Perf_Value	0.262
Reliability <-> Price	0.752
Reliability <-> RISK	0.324
Reliability <-> Range	0.396
TECHNOLOGY <-> Charge_Time	0.262
TECHNOLOGY <-> ECONOMIC FACTORS	0.737
TECHNOLOGY <-> FIN_RISK	0.411
TECHNOLOGY <-> Incentives	0.810

Relationship	HeteroTrait-MonoTrait ratio (HTMT)
TECHNOLOGY <-> Infrastructure	0.345
TECHNOLOGY <-> Intention_2_Buy	0.722
TECHNOLOGY <-> PER_RISK	0.313
TECHNOLOGY <-> PSY_RISK	0.306
TECHNOLOGY <-> PURCHASE_INTENTION	0.882
TECHNOLOGY <-> Perf_Value	0.262
TECHNOLOGY <-> Price	0.796
TECHNOLOGY <-> RISK	0.397
TECHNOLOGY <-> Range	0.535
TECHNOLOGY <-> Reliability	0.262
Willingness_2_Pay <-> Charge_Time	0.712
Willingness_2_Pay <-> ECONOMIC FACTORS	0.800
Willingness_2_Pay <-> FIN_RISK	0.421
Willingness_2_Pay <-> Incentives	0.895
Willingness_2_Pay <-> Infrastructure	0.440
Willingness_2_Pay <-> Intention_2_Buy	0.262
Willingness_2_Pay <-> PER_RISK	0.371
Willingness_2_Pay <-> PSY_RISK	0.394
Willingness_2_Pay <-> PURCHASE_INTENTION	0.440
Willingness_2_Pay <-> Perf_Value	0.858

Relationship	HeteroTrait-MonoTrait ratio (HTMT)
Willingness_2_Pay <-> Price	0.812
Willingness_2_Pay <-> RISK	0.456
Willingness_2_Pay <-> Range	0.509
Willingness_2_Pay <-> Reliability	0.262
Willingness_2_Pay <-> TECHNOLOGY	0.440

Table 6.9 presents the findings of the HTMT analysis. Notably, all HTMT "original sample" values are below the threshold of 0.90. On average, the values across the study remain below 0.480.

Summary

The results above suggest that the measurement model satisfactorily meets all evaluation criteria. Consequently, we move forward to assess the structural model.

6.6.2 Evaluation of Structural Model

—The evaluation of a structural model enables the assessment of the degree to which empirical findings align with the theoretical constructs proposed within the model. (Hair J., Hult, Ringle, & Sarstedt, 2017) The following delineates systematic methodologies designed to comprehensively evaluate the structural model, ensuring a thorough examination of its components and relationships.

- *Prepping the data for Collinearity Issues (VIF analysis)*
- *Significance of path coefficients,*
- *Assess the R^2 variance,*
- *Effect sizes of f^2 ,*
- *Effect sizes of Q^2 and finally,*
- *Model fit.*

6.6.2.1 Prepping the data for Collinearity Issues (VIF analysis)

The variance inflation factor (VIF) analysis serves as a critical tool for assessing collinearity within the formative model, offering insights into the interrelationships among predictor variables. When VIF values surpass five, it raises a flag for potential collinearity issues, indicating a heightened probability of multicollinearity among the predictors (Becker, Ringle, Sarstedt, & Volckner, 2024). In their guidance, the authors advocate for striving towards VIF values below three, which signifies an optimal scenario with minimal collinearity concerns. However, they propose that VIF values falling within the range of 3 to 5 are still generally acceptable but warrant careful consideration and further investigation into the model's robustness.

Table 6.10: Variance Inflation Factor (VIF) of the model

	VIF
<i>Economic Factors -> Purchase_Intention</i>	<i>1.987</i>
<i>Economic Factors -> Technology</i>	<i>1.383</i>
<i>Risk -> Economic Factors</i>	<i>1.000</i>
<i>Risk -> Purchase_Intention</i>	<i>1.385</i>
<i>Risk -> Technology</i>	<i>1.383</i>
<i>Technology -> Purchase_Intention</i>	<i>1.649</i>

Table 6.10 showcases the VIF output of the model, illustrating the interrelationships among predictor variables. This provides valuable insights into the complex interplay among predictor variables. Notably, each VIF value remains comfortably below the threshold of two, a finding that resonates closely with the guidance provided by the (Becker, Ringle, Sarstedt, & Volckner, 2024). This observation carries significant weight, indicating a favourable condition where collinearity concerns among predictors are notably mitigated, thereby bolstering the credibility and robustness of the model's outcomes.

6.6.2.2 Structural Model Path Coefficients

After confirming the reliability and validity of the construct measures, the next crucial step is to delve into assessing the results of the structural model. This assessment primarily revolves around estimating path coefficients, which serve as key indicators of the relationships within the model. Path coefficients typically span from -1 to +1, where a coefficient of 1 denotes a strong and positive relationship, while -1 signifies a negative correlation. Positive relationships often approach statistical significance, while negative ones exhibit a similar trend in the opposite direction. Hence, the structural model's evaluation entails scrutinizing these coefficients to comprehend the dynamics of the relationships under study. Below, we present the hypothesis-tested model specifically focusing on pre-purchase intention, offering insights into the extent of factors influencing this crucial aspect of consumer behaviour.

In SmartPLS-SEM, the bootstrapping procedure is employed to test the significance of path coefficients. —This method is widely endorsed for evaluating significance levels and obtaining confidence intervals. (Henseler, Ringle, & Sinkovics, 2009) & (Hair, Sarstedt, Ringle, & Mena, 2012). The bootstrapping procedure is instrumental

in generating T-statistics, a crucial metric to ascertain the significance of both measurement and structural model path coefficients.

The complete bootstrapping option, employing 10,000 subsamples, is utilized to compute the T-statistics. (Hair J., Hult, Ringle, & Sarstedt, 2017). The analytical method is followed as specified by Hair J., Hult, Ringle, & Sarstedt (2024). Figure 6.1 and Table 6.13 provide the determinants of the coefficient t-statistics along with their corresponding p-values, denoting the study's hypothesis's significance and support.

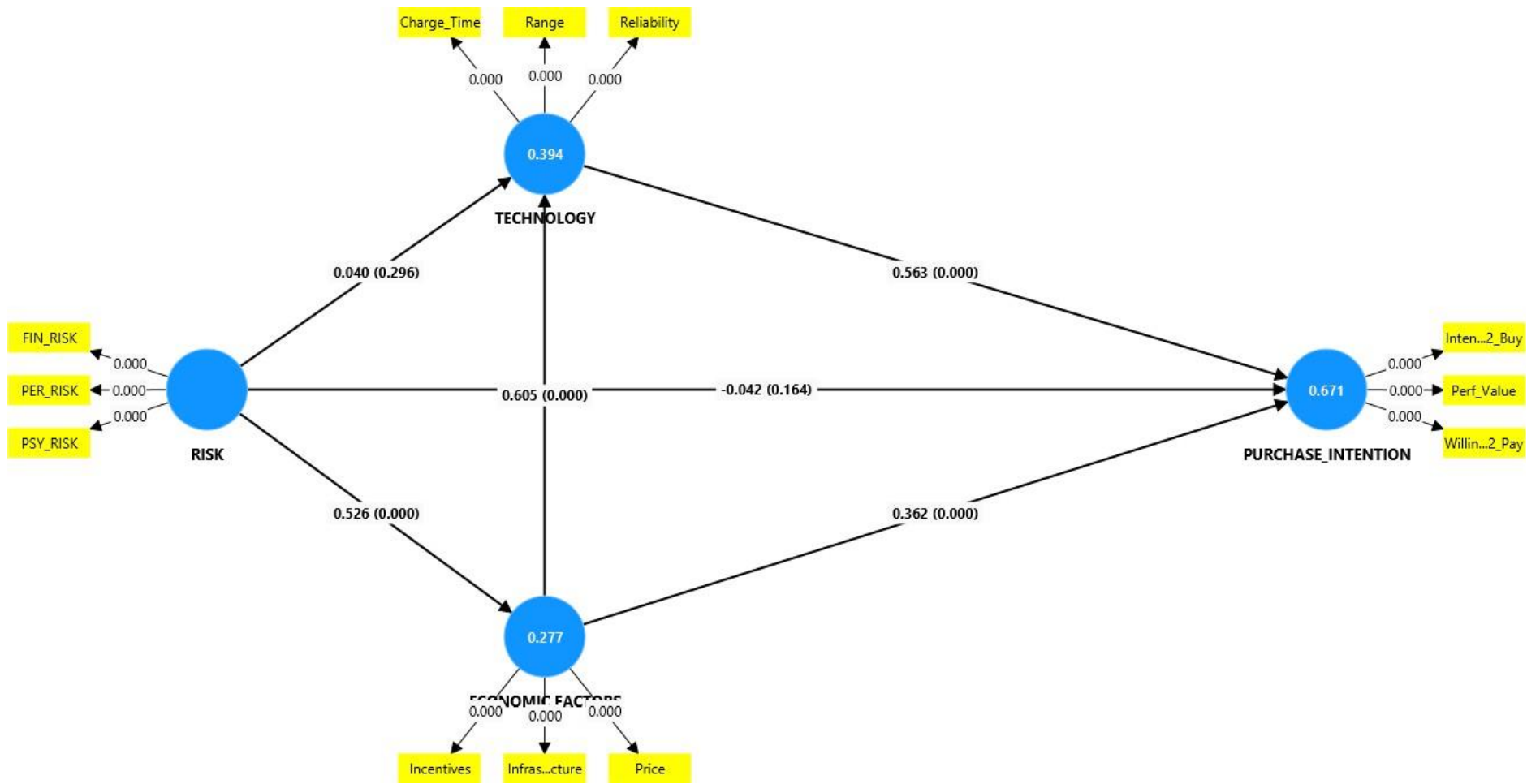


Figure 6.2: Models Path Coefficients and (p-values).

Ledger: *p-value <0.05. **p-value <0.03. ***p-value <0.001

Table 6.11: Path Coefficients of Structural Model

<i>Path Relationship</i>	<i>Path coefficients</i>
<i>Economic Factors -> Purchase_Intention</i>	0.362
<i>Economic Factors -> Technology</i>	0.605
<i>Risk -> Economic Factors</i>	0.526
<i>Risk -> Purchase_Intention</i>	-0.042
<i>Risk -> Technology</i>	0.040
<i>Technology -> Purchase_Intention</i>	0.563

Table 6.12: Path Coefficients of Structural Model: T statistics

<i>Path Relationship</i>	<i>Original Sample</i>	<i>Sample mean</i>	<i>Standard deviation</i>	<i>T statistics</i>	<i>P values</i>
<i>Economic Factors => Purchase_Intention</i>	0.362	0.361	0.055	6.628	0.000
<i>Economic Factors => Technology</i>	0.605	0.605	0.056	10.760	0.000
<i>Risk => Economic Factors</i>	0.526	0.526	0.056	9.442	0.000
<i>Risk => Purchase_Intention</i>	-0.042	-0.041	0.043	0.978	0.164
<i>Risk => Technology</i>	0.040	0.044	0.074	0.536	0.296
<i>Technology => Purchase_Intention</i>	0.563	0.562	0.043	13.239	0.000

Table 6.13: T-Statistics of Path Coefficients, Structural Model

Proposed Hypothesis		Path Coefficient	T-Statistics	P Values (<0.05) (2-tailed)	Support (Yes/No)
H1	Perceived Risk has a positive influence on Technology.	0.040	0.536	0.296	No
H2	Perceived Risk has a positive influence on Economic Factors.	0.526	9.442	0.000	Yes
H3	Perceived Risk has a negative influence on EV purchase Intention.	-0.042	0.978	0.164	No
H4	Technology has a positive influence on EV Purchase Intention.	0.563	13.239	0.000	Yes
H5	Economic Factor has a positive influence on EV Technology.	0.605	10.760	0.000	Yes
H6	Economic Factor has a positive influence on EV Purchase Intention.	0.362	6.628	0.000	Yes

Path coefficient sizes and statistical significance.

The structural path model depicted in Figure 6.2 unveils several noteworthy relationships, shedding light on the dynamics within the studied framework. Firstly, it reveals that Economic Factors exert the most substantial influence on Technology Factors, as evidenced by a coefficient of 0.605 and a statistically significant p-value of 0.000. This finding underscores the pivotal role of economic determinants in shaping technological aspects within the model.

Furthermore, the analysis indicates that Technology Factors wield considerable influence over the endogenous variable, purchase intention, with a coefficient of 0.563 and a p-value of 0.000. This highlights the intricate interplay between technological advancements and consumer behavioural intentions, elucidating their mutually reinforcing relationship.

Moreover, the model underscores the significant impact of perceived risk on Economic factors, with a coefficient of 0.526 and a p-value of 0.000. This suggests that perceptions of risk play a vital role in shaping economic decisions and behaviours, underscoring the need to consider risk perceptions within the broader economic context.

Lastly, the structural path model elucidates that Economic Factors directly influence purchase intention, showcasing a coefficient of 0.362 and a p-value of 0.000. This direct link emphasizes the importance of economic factors in shaping consumer intentions and purchasing behaviours, emphasizing the need for a comprehensive understanding of economic influences on consumer decision-making processes.

H1: The hypothesized path relationship between Perceived Risk and Technology is not statistically significant. (P-value: 0.296)

H2: The hypothesized path relationship between Perceived Risk and Economic Factor is statistically significant. (P-value: 0.000)

H3: The hypothesized path relationship between Perceived Risk and Purchase Intention is not statistically significant. (P-value: 0.164)

H4: The hypothesized path relationship between the Technology Factor and Purchase Intention is statistically significant. (P-value: 0.000)

H5: The hypothesized path relationship between The Economic Factors and Technology is statistically significant. (P-value: 0.000).

H6: The hypothesized path relationship between The Economic Factors and Purchase Intention is statistically significant. (P-value: 0.000).

As depicted in Figure 6.2 and summarized in Table 6.13, four out of six hypotheses are supported by the market's primary data. Significance testing was conducted using commonly adopted thresholds for two-tailed tests, including values of (1) 2.57 (significance level at 1%), (2) 1.96 (significance level at 5%), and (3) 1.65 (significance level at 10%). Within marketing literature, a significance level of 5% is typically considered standard practice. Thus, the significance levels of path coefficients were assessed using a T-statistic of 1.96 (corresponding to a significance level of 5%) and a p-value of <0.05. This approach is somewhat conservative, as exploratory studies often adopt a significance level of 10% (Hair J. F., Hult, Ringle, & Sarstedt, 2014).

6.6.2.3 Coefficients of Determination (R^2)

R^2 serves as a metric for predictive accuracy, evaluating the correlation between endogenous constructs' actual and predicted values. Additionally, it estimates the proportion of variance in endogenous constructs explained by their related exogenous constructs. Ranging from 0 to 1, an R^2 value of 1 indicates a higher level of explained variance, while lower values suggest less variance explained. The variability of R^2 depends on the intricacies of the models under consideration (Hair J., Hult, Ringle, & Sarstedt, 2017).

In realm of marketing literature, researchers often prioritize delving into the theoretical interconnections among constructs over solely emphasizing predictive accuracy. This approach recognizes that certain latent variables crucial to understanding behavioural phenomena cannot be directly observed or measured. As such, researchers strive to develop models that effectively capture and explain the underlying data and achieve this with a parsimonious selection of exogenous constructs. This balancing act ensures that the resulting models provide meaningful insights into the intricate dynamics of human behaviour while maintaining simplicity and interpretability, (Tenenhaus, Esposito, Chatelin, & Lauro, 2005) (Hair, Sarstedt, Ringle, & Mena, 2012). The term "parsimonious" is used to describe these structural models, indicating their characteristic of being concise and economical while still effectively capturing and explaining the underlying relationships among variables.

In this empirical validation of the model, the coefficient of determination R^2 for the endogenous variable Purchase Intention is recorded as 0.671, as depicted in Figure 6.2. This signifies that the latent variables Perceived Risk, Economic Factor, and Technology Factor collectively account for 67.1% of the variance observed in the Purchase Intention of Electric Vehicles.

6.6.2.4 Effect of Control Variables

This section explores how control variables, such as demographic factors, impact the endogenous variable, Purchase Intention. The combined influence of all latent variables provides insight into 67.1% of the variability observed in Electric Vehicle (EV) Purchase Intention. In this study, control variables encompass a range of factors, including gender, age, education level, employment status, monthly income, and the participants' native state.

A notable observation emerged upon integrating these variables into the endogenous variable, Purchase Intention: the six control variables exhibited no impact on purchase intention. Despite their inclusion, the model's explanatory power—both before and after incorporating the control variables—remained consistent at 67.1%. This indicates that the control variables did not significantly alter the model's ability to explain variance in Purchase Intention.

Please refer to Figure 6.3 for a comprehensive breakdown of the model specifications incorporating control variables on the endogenous variable.

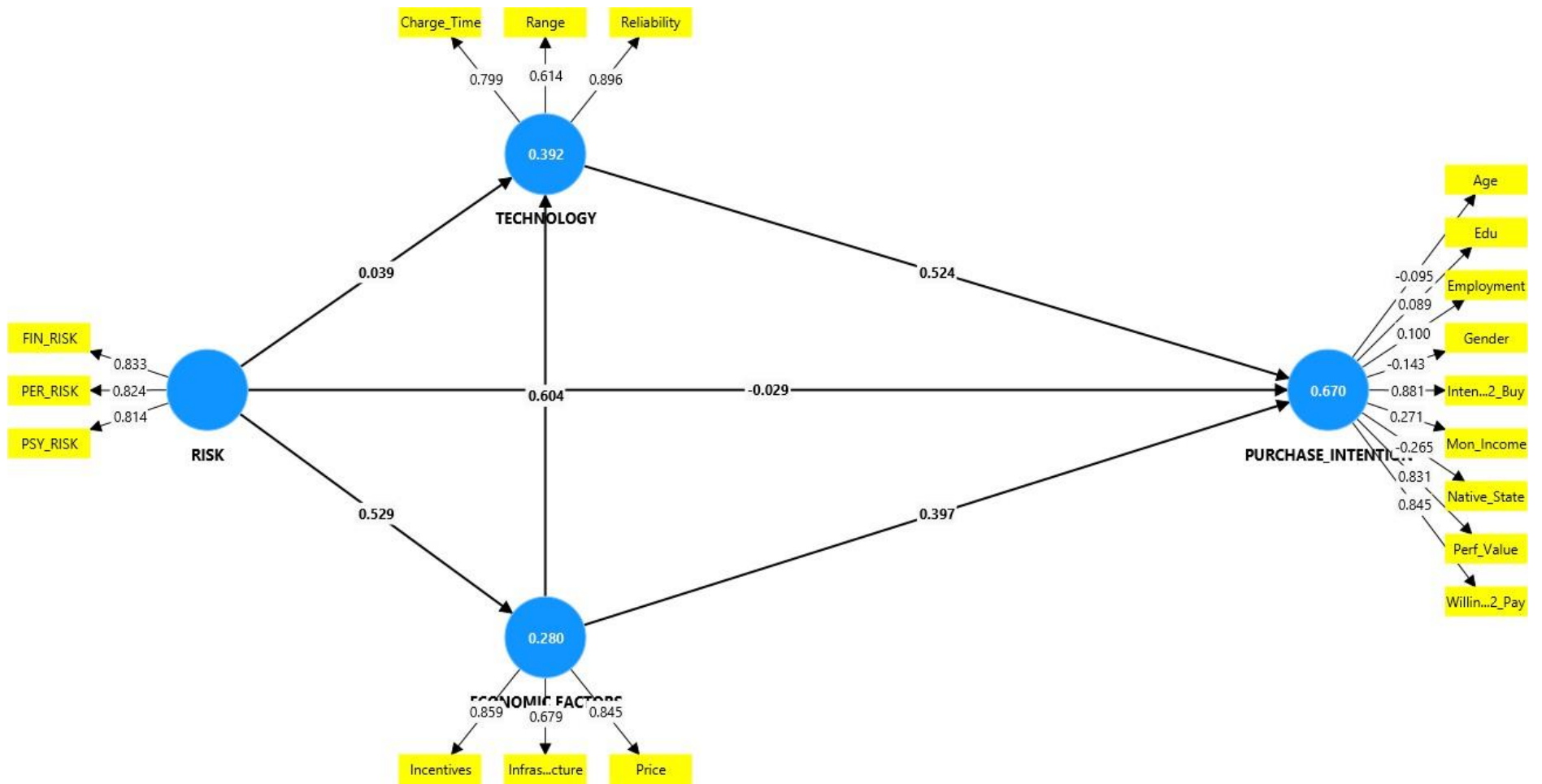


Figure 6.3: Control Variables' effect on the model.

6.6.2.5 f^2 effect sizes

Contemporary researchers are increasingly skeptical of relying solely on P-values and alpha levels, turning instead to focus on effect sizes, denoted by f^2 . While a p-value may indicate a statistically significant relationship (typically <0.05), its effect size on endogenous variables may be comparatively minimal. Through f^2 analysis, researchers gain insight into the substantive significance of the observed effects, discerning whether the significance represents a meaningful impact.

f^2 serves as a metric for evaluating effect sizes as a quality criterion. By examining the change in the R^2 value when a specific exogenous variable is excluded from the structural model, researchers can gauge whether the omitted variable holds substantive significance for the endogenous variable. —These effect sizes of the latent variables are denoted as f^2 values. Typically, f^2 effect size values of 0.02, 0.15, and 0.35 are categorized as small, moderate, and large, respectively. (Henseler, Ringle, & Sinkovics, 2009).

Table 6.14: f^2 effect sizes

Latent Variable	f-square	Effect Size
<i>Economic Factors -> Purchase_Intention</i>	<i>0.200</i>	<i>Medium</i>
<i>Economic Factors -> Technology</i>	<i>0.437</i>	<i>Large</i>
<i>Risk -> Economic Factors</i>	<i>0.383</i>	<i>Large</i>
<i>Risk -> Purchase_Intention</i>	<i>0.004</i>	<i>Small</i>
<i>Risk -> Technology</i>	<i>0.002</i>	<i>Small</i>
<i>Technology -> Purchase_Intention</i>	<i>0.585</i>	<i>Large</i>

The study encompasses six path relationships, each revealing varying effect sizes. Among them, two exhibit small effects: the relationship of Perceived Risk with Technology and Perceived Risk with Purchase Intention. Additionally, one path relationship demonstrates a moderate effect: Economic Factor with Purchase Intention. Notably, the remaining three paths demonstrate large effects, with one path showing a very high effect size: Economic Factors with Technology, Risk with Economic Factors, and Technology with Purchase Intention.

6.6.2.6 Predictive Relevance (Q^2)

The blindfolding technique is employed to assess the structural model's predictive relevance (Q^2). Q -square quantifies the model's predictive capability, determining whether it holds any predictive relevance. A Q^2 value greater than 0 is indicative of good predictive relevance (Tenenhaus, Esposito, Chatelin, & Lauro, 2005). Thus, if the model yields any value above zero, it signifies predictive relevance, suggesting that the reconstructed values are accurate and the model holds predictive utility (Henseler, et al., 2014); (Dijkstra & Henseler, 2015)..

—The blindfolding procedure computes Stone Geisser's Q^2 value (Stone, 1974) to cross-validate the structural model's predictive relevance. Researchers seek to extend their understanding of the model's predictive accuracy beyond the R^2 criterion, prompting an investigation into Stone-Geisser's Q^2 value. The blindfolding procedure necessitates specifying an omission distance (D), with recommended values between 5 and 12. (Hair J., Hult, Ringle, & Sarstedt, 2017). The value for D selected in this study is 10, as recommended.

The evaluation criterion for Q^2 mirrors that of f^2 estimation, providing a consistent framework for assessing predictive relevance (Lohmöller, 1989). Within this framework, values of 0.02, 0.15, and 0.30 serve as benchmarks, indicating whether the exogenous variable's predictive relevance is small, moderate, or large, respectively. It is important to note that these assessments are made within the context of the specified omission distance (D), ensuring a comprehensive understanding of the model's predictive capabilities. (Hair J., Hult, Ringle, & Sarstedt, 2017).

Table 6.15: Predictive relevance (Q^2) of variables

Variable	PLS Predict LV Summary	
	Loading	Estimation
Economic Factor	0.268	Medium
Purchase Intention	0.212	Medium
Technology	0.217	Medium

Table 6.15 offers a comprehensive overview of the Stone Geisser's Q^2 findings, shedding light on the predictive capabilities of the study's dependent variables within cross-validated commonality. Remarkably, the analysis highlights the presence of three dependent variables, all of which exhibit notable medium predictive capabilities. Each variable showcases a value of 0.15 or higher, underscoring their substantial predictive potential within the structural model.

6.6.2.7 Goodness of Fit Index

The model fit criteria encompass a comprehensive set of four key metrics utilized to assess the adequacy of a structural model. These metrics include:

6.6.2.7.1. SRMR (Standardized Root Mean Square Residual):

—The SRMR is defined as the variance between the observed correlation and the correlation matrix implied by the model (Hair J., Hult, Ringle, & Sarstedt, 2017), (Henseler, et al., 2014).

SRMR —value less than 0.10 or 0.08 are considered a good fit. (Hu & Bentler, 1998).

Table 6.16: SRMR summary

Fit Measure	Saturated Model	Estimated Model
SRMR	0.063	0.063

Both the saturated and estimated model's SRMR is 0.063. It indicates that SRMR values are less than 0.08, meeting the threshold limit specified by the literature (Hu & Bentler, 1998).

6.6.2.7.2. d_ULS (delta-Unweighted Least Squares):

—The Bollen-Stine bootstrapping procedure yields d_ULS outcomes in Partial Least Squares Structural Equation Modeling (PLS-SEM). This method examines the numerical incongruence between the empirical covariance matrix and the covariance matrix derived from the composite factor model. d_ULS denotes various approaches for computing the model's disparity (Dijkstra & Henseler, 2015).

Interpreting d_ULS results deviates from conventional statistical approaches. It necessitates comparing the original model values with the confidence intervals derived from the sampling distribution generated by the bootstrapping method.

Table 6.17: d_LS summary of the model

Fit Measure	Original Sample	CI: 97.5%	T-Statistics	P-Values
Saturated Model	1.931	0.750	7.521	0.000
Estimated Model	2.340	0.917	5.396	0.000

In Table 6.17, the d_LS values for the saturated model are meticulously detailed, with the original sample yielding 1.931 and the estimated model producing 2.340. Notably, the latter surpasses the former, which is consistent with the principles of the d_LS approach for evaluating model fit. Additionally, the T-statistics exceed the critical threshold of 1.96 at a significance level of 5%, accompanied by P-values below 0.05, providing robust evidence of statistical significance.

6.6.2.7.3. The Geodesic Distance (d_G)

In Partial Least Squares Structural Equation Modeling (PLS-SEM), researchers utilize the bootstrapping procedure to generate d_G results. This analytical approach scrutinizes the mathematical discordance between the empirical covariance matrix and the covariance matrix derived from the composite factor model. By conducting d_G analysis, researchers can discern the extent of discrepancy between the observed data and the model's theoretical assumptions, thereby enabling a comprehensive evaluation of model adequacy.

Table 6.18: d_G summary of the model

	Original Sample	CI: 97.5%	P-Values
Saturated Model	0.350	0.876	0.000
Estimated Model	0.432	0.932	0.000

The interpretation of d_G results closely parallels that of d_LS. Within Table 6.18, the d_G value attributed to the saturated model stands at 0.350, contrasting with the estimated model's value of 0.432. This discrepancy between the two values adheres to the principle of the d_G approach for evaluating model fit, which stipulates that the latter value should surpass the former. Such consistency underscores the robustness of the assessment process and ensures alignment with established standards for model adequacy, (Dijkstra & Henseler, 2015). Through consistent evaluation methods, the confirmation of these findings is reinforced by the alignment of confidence intervals. Additionally, the T-statistics surpass the critical threshold of 1.96 at a significance level of 5%, coupled with P-values falling below 0.05. These observations collectively affirm the statistical significance of the results, further bolstering their reliability and validity.

CHAPTER VII

DISCUSSION OF THE RESULTS

7.1 Introduction

The thesis delves into the empirical findings of the purchase intention model specifically crafted for the electric vehicle domain. It showcases the model's exceptional structural design and empirical efficacy, highlighting its superiority over existing frameworks. Notably, this distinctive model stands alone in its evaluation of consumer behaviour within the Indian context, making it a pioneering contribution to the field.

In this study, the indicators employed have demonstrated reliability and validity beyond mere acceptability, as evidenced by both Composite Reliability and Cronbach's Alpha measures. Each latent variable is represented by multiple indicators with significant loadings, affirming their alignment with the intended constructs. Moreover, the measurement errors remain below 50% across all cases, establishing construct validity. This robust validation framework ensured that the structural model's evaluation was conducted on a firm footing, devoid of concerns regarding the potential distortion of results by measurement errors. —This ensured a robust foundation for evaluating the structural model, free from concerns of measurement error biasing the results. Consequently, the model outcomes are directly inferred, paving the way for a comprehensive discussion of the findings and a deeper understanding of the study's implications.

7.2 Analysis of the Model Results

The purchase intention model encompasses three endogenous variables and one exogenous variable. The endogenous variables comprise Technology Factors, Economic Factors, and Purchase Intention, each validated through a set of ten lower-order variables and measured via a cumulative total of forty indicators. The exogenous variable, Perceived Risk, is validated through three constructs at the lower order and measured with twelve indicators.

Path Coefficient Model

Table 7.1: Hypothesized Path Coefficient Model, with Empirical Evidence

Hypothesis		Hypothesized Sign	Path-Coefficients	Sig. (Yes/No)	P-Value (<0.05)
H1	PR -> TF	Positive	No	No	0.296
H2	PR -> EF	Positive	Yes	Yes***	0.000
H3	PR -> PI	Negative	No	No	0.164
H4	TF -> PI	Positive	Yes	Yes***	0.000
H5	EF -> TF	Positive	Yes	Yes***	0.000
H6	EF -> PI	Positive	Yes	Yes***	0.000

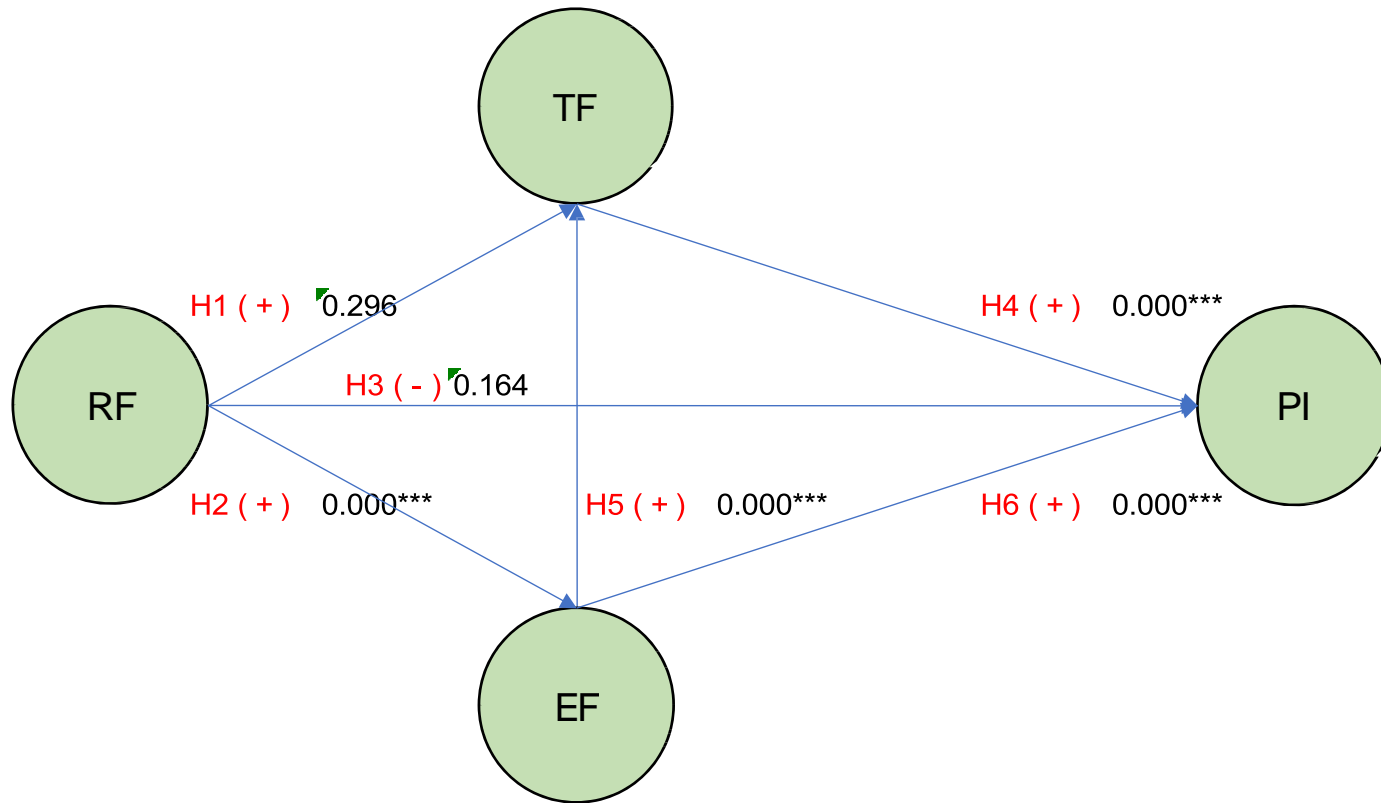


Figure: 7.1: Hypothesized Path Relationships & Empirical Estimation

Table and Figure: 7.1. provides a concise overview of the empirically validated relationships among the latent variables within the model, maintaining consistency with the presentation sequence in the preceding chapters. The statistical significance of each structural link is rigorously established, underpinning the reliability of the model's findings.

Four of the six structural path hypotheses proposed within the model have demonstrated significant outcomes. Notably, all four of these relationships exhibit exceedingly high levels of significance ($p > 0.001$).

The empirically supported structural relationships are as follows:

- (1) Perceived Risk > Economic Factors,*
- (2) Technology Factors > Purchase Intention,*
- (3) Economic Factors > Technology, and*
- (4) Economic Factors > Purchase Intention.*

These findings underscore the robustness of the identified associations within the model, highlighting key dynamics shaping purchase intentions in the context under study.

The following discussion examines each relationship in the same sequence as outlined in Table 7.1. The p-values, which are enclosed in parentheses and were derived from the standardized solution of the SmartPLS bootstrapped run applied to the complete model, serve as the basis for further analysis. For a comprehensive understanding of the findings from the 1st-order factor analysis, refer to (Appendix - 1). Additionally, the outcomes of the 2nd-order structural model are elaborated upon in (Appendix - 2).

Specific Indirect Effect

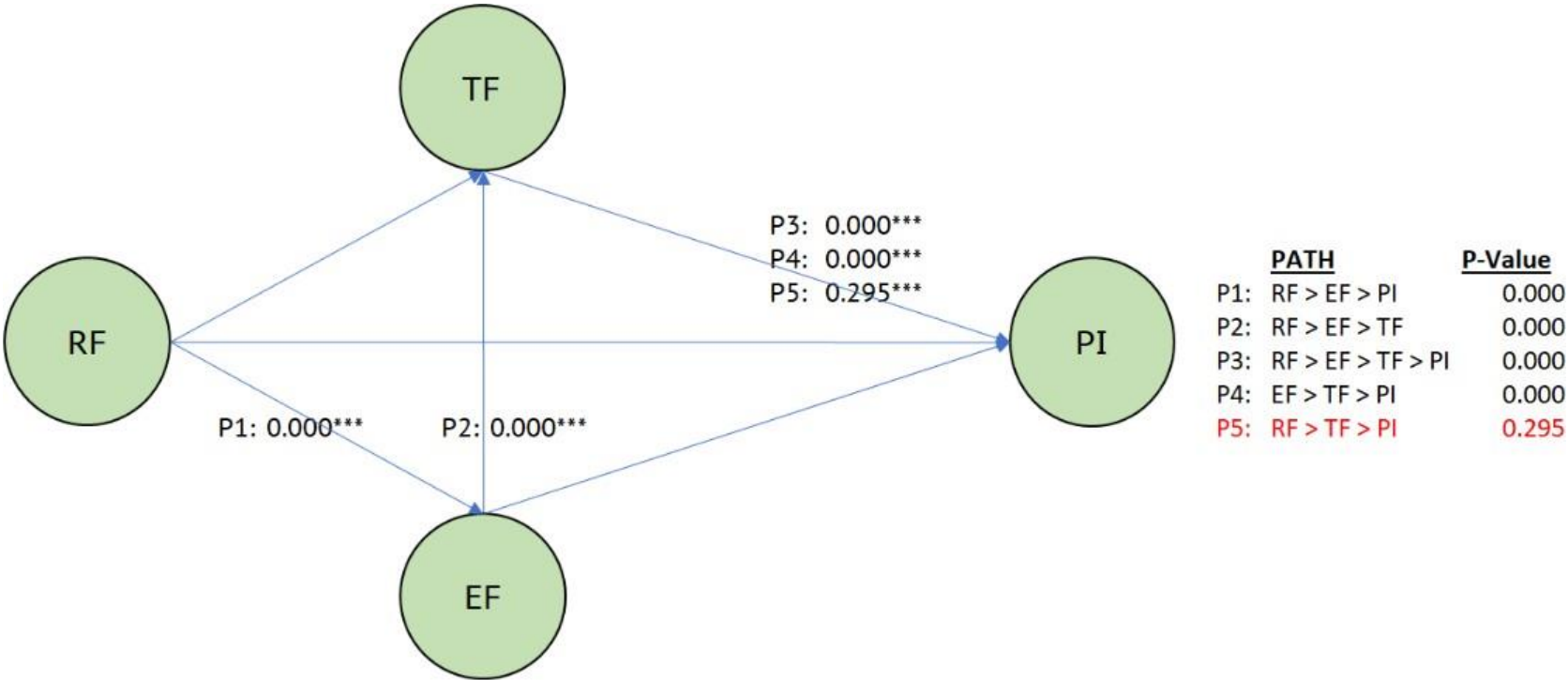


Figure 7.2: Specific Indirect Relationships of the Intention.

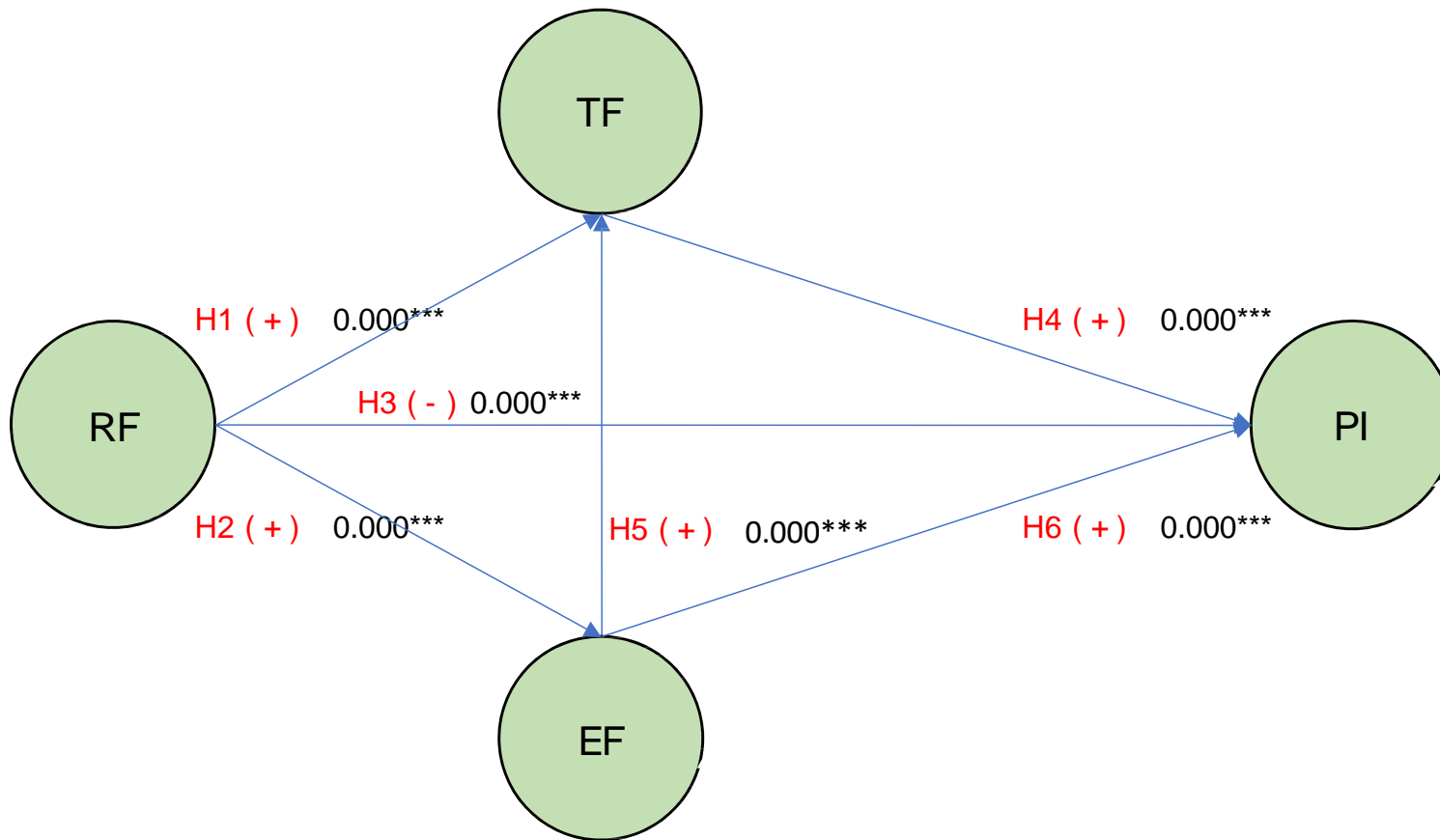


Figure 7.3: Total Effect of Relationships in the Intention.

7.2.1 Perceived Risk Effect

The risk construct exhibits three path relationships within the model. As hypothesized, the effect of Perceived Risk on Technology Factors appears to be negative, although the statistical significance (P-value: 0.296) indicates a lack of robustness in the relationship. This suggests that a higher degree of performance, financial, and/or psychological risk associated with a purchase may tend to increase the inclination towards conservatism in adopting a new technology product category, although not strongly supported by the data. —Regarding the latent variable loadings of Perceived Risk, the financial risk (0.833) is slightly higher than both performance (0.823) and psychological (0.814) risk, aligning with expectations. Furthermore, the influence of risk on any other construct maintains a consistent relative impact, regardless of the statistical significance of the relationship with Technology Factors. The analysis reveals an intriguing interplay regarding Perceived Risk in relation to both technology and purchase intention. At first, Perceived Risk displays a statistically negative specific indirect effect on the technology factor > purchase intention. This indicates that heightened perceptions of risk concerning the technology dampen consumers' inclination to purchase (Indirect Effect: 0.295). However, the more notable observation emerges when considering the total effect of Perceived Risk on technology, which is found to be statistically significant and positive (Total Effect: 0.000). This empirical discovery implies that despite perceiving the new technology product as risky in its entirety, consumers exhibit a paradoxical behaviour—they delve deeper into specific technological aspects (Roehm & Brady, 2007). This deeper examination suggests that consumers are not deterred by the overarching risk perception but rather engage in a nuanced evaluation, particularly focusing on utilitarian criteria when contemplating a purchase. This nuanced approach indicates

a willingness among consumers to critically assess the functional benefits of the technology despite overarching risk perceptions, showcasing a complex decision-making process influenced by both risk aversion and intrinsic evaluation.

The second path relationship in focus pertains to perceived risk and its association with economic factors. As anticipated, perceived risk exerts a positive influence (P value: 0.000) on Economic Factors. The hypothesis suggests that mitigating risk is perceived as a potential benefit within the economic realm, as highlighted by its significant impact. The premise posits that reducing risk is inherently linked to economic advantages associated with a product. Consequently, perceived risk emerges as a precursor to the perceived economic benefits, underscoring its role as an influential independent antecedent factor shaping consumer perceptions within the economic domain. (Conchar, Zinkhan, Peters, & Olavarrieta, 2004). A pivotal discovery in this study underscores the statistically significant and specific indirect effects of perceived risk on all its path relationships with endogenous variables.

These effects are observed as follows:

- (1) Risk -> Economic Factors -> Purchase Intention (P-value: 0.000),*
- (2) Risk -> Economic Factors -> Technology -> Purchase Intention (P-value: 0.000), and*
- (3) Risk -> Economic Factors -> Technology (P-value: 0.000).*

Moreover, when considering total effects, perceived risk also demonstrates a significant overall impact on economic factors (P-value: 0.000). This statistical analysis highlights the pervasive influence of perceived risk across various

dimensions of consumer decision-making processes, emphasizing its role as a critical determinant in shaping attitudes and intentions towards electric vehicle purchases.

The third hypothesis under examination in this study pertains to the relationship between perceived risk and purchase intention. H3 posits that Perceived Risk negatively influences Purchase Intention (P-value: 0.164). Given that all purchasers of electric vehicles face inherent risks, this hypothesis seeks to understand how such risks affect consumer behaviour. If a consumer perceives a higher level of risk associated with an electric vehicle, it tends to have a detrimental impact on their intention to make a purchase. This underscores the complex interplay between perceived risk and purchase behaviour, highlighting the nuanced role of risk perception in shaping consumer decision-making processes.

The study's empirical findings show that the total effects of the product that Perceived risk has a positive total effect on purchase intention (total effect, p-value: 0.000). It suggests that rather than deterring purchases outright, perceived risk actually enhances consumers' product knowledge. It achieves this by prompting consumers to broaden their awareness of new and unfamiliar electric vehicle products to mitigate perceived risks.

The positive association of total effects (P-value: 0.000) signifies Perceived Risk's significant and substantial impact. This suggests that the considerable magnitude of Perceived Risk plays a crucial role, indicating purposeful activity by the mediating variables. Specifically, these mediating variables serve to effectively mediate and mitigate the risks associated with the intention to purchase electric vehicles.

7.2.2 Effect of Technology Factors

The Technology Factor is represented by a single path relationship within the model, specifically with the endogenous variable, Purchase Intention. The proposed hypothesis suggests a positive relationship between the Technology Factor and Purchase Intention. Empirical validation confirms this hypothesis, revealing a direct and statistically significant positive influence of technological factors on purchase intention (P-value: 0.000), positioning it as a significant antecedent variable in the electric vehicle purchase intention decision-making process. The Technology Factor stands out as a critical factor driving consumers' purchase intentions, with a notably positive impact (P-value: 0.000). This factor encompasses three key latent variables: drive range, reliability, and charging time. These variables hold significant sway in consumers' evaluations of electric vehicles, influencing their overall perception and desirability. Upon closer inspection of the loadings associated with these variables, an interesting trend emerges. While all factors contribute substantially to consumers' decision-making processes, Reliability (P-value: 0.819) exhibits a slightly stronger influence compared to both Charging Time (0.800) and drive range (P-value: 0.710). This finding aligns with theoretical expectations, highlighting the pivotal role of reliability in consumer preferences. Reliability is a cornerstone in shaping purchase intentions, underscoring the importance of trustworthiness and dependability when consumers assess electric vehicles and form a purchase intention.

7.2.3 Effect of Economic Factors on Purchase Intention

In this study's conceptual framework, Economic Factors are positioned as antecedent variables influencing both Technology Factors and Purchase Intention. Within this framework, Economic Factors manifest two distinct path relationships: one with the

mediating variable, the Technology Factor, and another with the output variable, Purchase Intention. As posited in the theoretical framework, Economic Factors yield a significant positive influence on both Technology Factors (P-value: 0.000) and Purchase Intention (P-value: 0.000).

Furthermore, Economic Factors encompass three latent variables: Price, Incentives, and charging infrastructure. Among these variables, Incentives emerge as notably influential in shaping purchase intentions, evidenced by their high factor loading of 0.860. Close behind, the fixed purchase cost and variable maintenance prices of electric vehicles also wield considerable influence, with a factor loading of 0.848. Lastly, charging infrastructure emerges as the third most influential latent factor in driving purchase intention, boasting a factor loading of 0.700. These findings underscore the intricate and multifaceted impact of Economic Factors on consumer decision-making processes concerning electric vehicle purchases.

The economic factor exerts a highly significant positive direct influence (P-value: 0.000) on both the technology factors and purchase intention, consistent with the theoretical framework proposed in the study. Additionally, it demonstrates very significant positive total indirect effects on "Economic Factors -> Purchase Intention" (P-value: 0.000) and specific indirect effects on "Economic Factors -> Technology -> Purchase Intention" (P-value: 0.000).

In total, the economic factors exhibit significant total effects on:

- 1. Economic Factors -> Purchase Intention with a P-value of 0.000.*
- 2. Economic Factors -> Technology with a P-value of 0.000.*

The profound impact of economic factors across all relationships highlights their central role in shaping purchase intentions. Key determinants like unit price, maintenance cost, government incentives, and the availability of charging infrastructure emerge as crucial drivers influencing consumer decision-making processes regarding purchase intentions. These factors collectively underscore the intricate interplay between economic considerations and consumer behaviour, emphasizing the multifaceted nature of purchasing decisions in relation to electric vehicles.

The examination of "Specific Indirect Effects" within the structural model unveils a detailed understanding of the intricate pathways and interdependencies at play.

- *Risk -> Economic Factors -> Purchase Intention with a P-value of 0.000.*
- *Risk -> Economic Factors -> Technology -> Purchase Intention with a P-value of 0.000.*
- *Risk -> Economic Factors -> Technology, with a P-value of 0.000.*
- *Economic Factors -> Technology -> Purchase Intention with a P-value of 0.000.*
- *Risk -> Technology -> Purchase Intention, with a P-value of 0.000.*

The "Total Effects" analysis within the structural model reveals a comprehensive understanding of the intricate pathways and interdependencies that influence the observed outcomes.

- *Economic Factors -> Purchase Intention with a p-value of 0.000.*
- *Economic Factors -> Technology, with a p-value of 0.000.*
- *Risk -> Economic Factors, with a p-value of 0.000.*
- *Risk -> Purchase Intention, with a p-value of 0.000.*
- *Risk -> Technology with a p-value of 0.000.*
- *Technology -> Purchase Intention, with a p-value of 0.000.*

These findings offer clarity on the complex pathways through which diverse factors intertwine within the structural model, revealing the nuanced dynamics that influence consumer decision-making processes concerning purchase intentions. Notably, all constructs demonstrate statistical significance across the hypothesized relationships. The path coefficients for direct, indirect, and total effects are all significant, underscoring the robustness of the model's theoretical estimation.

CHAPTER VIII

SUMMARY AND CONCLUSIONS

8.1 Introduction

This chapter provides a comprehensive summary of the dissertation, beginning with an exploration of the study's motivation and the significance and relevance of the research topic. It identifies the specific research gap addressed by this dissertation, establishing the context and necessity for the investigation.

The chapter then delineates the research objectives, clearly stating the aims of the study. It details the data collection procedures, explaining the methods and strategies employed to gather the necessary information. This includes a thorough description of the data, offering insights into its nature, scope, and relevance to the research objectives.

Next, the methodology used for data analysis is discussed, providing a detailed account of the analytical techniques and processes used to derive meaningful results. This section ensures that the reader understands the rigor and systematic approach applied to the analysis.

The chapter then presents the study's findings, summarizing the key results and their implications. This is followed by an in-depth discussion of the research's major contributions, highlighting how the study advances knowledge in the field and its potential impact on future research and practice.

Finally, the chapter addresses the study's limitations, acknowledging any constraints or challenges encountered during the research process. It concludes with an overview

of the scope for future work, suggesting areas for further investigation and how subsequent studies can build upon this dissertation's findings.

8.2 Research Objectives

The objectives of this study are:

8.2.1 Developing indicators and measures that influence the purchase intention of electric vehicles from the perspective of consumers in emerging markets, with a specific focus on India.

8.2.2 Conceptualizing a hypothetical pre-purchase intention model.

8.2.3 Operationalizing a hierarchical model of purchase intention.

8.2.4 Empirically validating the model with primary data using primary data collected from consumers intending to purchase a new electric vehicle.

8.2.5 Identifying and empirically validating antecedent variables of purchase intention and evaluating their impact on the development of electric vehicle product strategies for India and other emerging markets.

8.3 Research Design

The foundation of this thesis rests upon established measures sourced from existing literature. Employing a survey as the chosen method for data collection, indicators have been curated from studies spanning Western and Chinese consumer markets. Initial observations from the first pilot study revealed certain indicators exhibiting inadequate loading on latent variables, prompting a restructuring of the instrument. This involved supplementing new indicators identified through an additional literature

review. Subsequent validation of the instrument was pursued through a second pilot study involving a sample size of 54. Finally, validation for the main study was achieved, with data collection via survey yielding a substantial sample size of 322 participants. Microsoft Forms was the instrument used to conduct the survey to collect data for the study.

8.4 Method of Analysis

A sophisticated hierarchical model is meticulously constructed to delve into the nuanced intricacies underlying consumers' purchase intentions regarding electric vehicles (more info @chapter 5). This endeavor unfolds within the structured framework of controlled heterogeneity, strategically designed to unravel the diverse factors shaping individuals' attitudes and behaviours toward adopting electric vehicles. Employing the robust statistical methodology of "Structural Equation Modelling" (SEM), the research meticulously dissects the multifaceted interplay between various determinants and purchase intention. Notably, the study adopts a principled stance by abstaining from any form of manipulation, thereby ensuring the integrity and transparency of both the measurement and structural models employed. This conscientious approach not only enhances the credibility of the findings but also fosters a deeper understanding of the complex dynamics at play in the realm of electric vehicle adoption. The study relies on the sophisticated analytical capabilities of the SmartPLS (Version 4.0) software tool to validate the soundness of the constructed hierarchical model. Through rigorous validation procedures, this software serves as a reliable partner in confirming the robustness and validity of the proposed model, thus bolstering confidence in the research findings and their implications.

8.5 Results Summary

—Directly, four of the six hypothesized relationships and a total of six of the six hypothesized relationships exhibited statistical significance (P-value < 0.00) in the model.

Based on bootstrapped model t-statistics, the rank ordering of the determinants of the Purchase Intention, in decreasing order of importance, is as follows.

Specific indirect effects: Purchase Intention determinants.

T-statistics: 5.005

RISK -> ECONOMIC FACTORS -> PURCHASE_INTENTION.

T-statistics: 6.380

RISK -> ECONOMIC FACTORS -> TECHNOLOGY -> PURCHASE_INTENTION.

T-statistics: 7.057

RISK -> ECONOMIC FACTORS -> TECHNOLOGY.

T-statistics: 8.034

ECONOMIC FACTORS -> TECHNOLOGY -> PURCHASE_INTENTION.

The empirical rank order of determinants indicates variations in effect size. We identified two constructs acting as mediators between the independent and dependent variables. Both economic and technological factors have a statistically significant impact on purchase intention. However, technological factors (T-statistics-8.034)

exert a greater influence on purchase intention compared to economic factors (T-statistics -7.057). This suggests that factors such as the driving range of the electric vehicle, charging time, and technology reliability significantly affect purchase intention, surpassing considerations like unit price, maintenance cost, governmental incentives, and charging infrastructure availability.

However, the model reveals divergent conclusions regarding the total effects observed. It produces results that are diametrically opposed. In summary, Economic Factors (with a T-statistic of 14.061) are shown to exert a more significant influence on electric vehicle purchase intention compared to technology factors (with a T-statistic of 13.239). This suggests that, despite the prominence of technology-related considerations in individual determinants, the aggregate effect of economic factors outweighs that of technological factors when assessing their impact on consumer intentions towards electric vehicle purchases.

Looking back, we found that a variety of economic and technological factors play crucial roles in shaping purchase intention. Economic considerations such as the initial cost of purchasing a vehicle, ongoing maintenance expenses, available incentives for vehicle acquisition, and the accessibility of charging infrastructure all weigh heavily in consumer decision-making. Additionally, technological factors such as the driving range achievable on a single charge, the time required for charging, and the overall reliability of the vehicle are significant determinants.

However, it's noteworthy that existing literature emphasizes the importance of perceived risk as a central factor influencing purchase intention. Interestingly, our study confirms this assertion, albeit demonstrating that perceived risk follows economic and technological factors in significance. This finding underscores the

complex interplay of various influences on consumer decision-making in the context of electric vehicle adoption.

Furthermore, it's worth highlighting that this pattern contrasts with the dynamics observed in the purchase intention of internal combustion engine vehicles, suggesting that the determinants of purchase intention may vary considerably between different types of vehicles.

The study rigorously adhered to the requirements of the SmartPLS methodology, and comprehensive details regarding reliability and validity assessments are provided. The conceptualized model of external information search effectively accounts for 67% of the variance in electric vehicle purchase intention. This represents a notable advancement in understanding the pre-purchase search process of consumers in emerging markets. Additionally, it surpasses the explanatory power of other existing models of electric vehicle pre-purchase intention found in marketing literature, marking a significant improvement in this field.

In summary, the model regarding the intention to purchase electric vehicles demonstrates empirical validity, supported by primary data. Both the measurement and structural models produce meaningful and statistically significant results. Furthermore, two additional noteworthy findings emerge: Firstly, the antecedents and determinants of purchase intention among consumers in emerging markets like India differ from those in developed countries. Secondly, within emerging markets, the processes and determinants of purchase intention among Indian consumers of electric vehicles vary from those observed in China.

8.6 Study Contributions

—By synthesizing literature from three distinct domains, this study has made significant contributions to elucidating the antecedents of purchase intention, a critical aspect in comprehending consumer decision-making concerning electric vehicles.

This comprehensive review of the literature on consumer pre-purchase intention yields novel empirical insights, enriching our understanding of the diverse dimensions of both traditional and modern antecedents influencing consumer behavior.

Here are the quantified contributions derived from this study, offering a clear delineation of its impact:

- 1) Incorporation of technological factors into the realms of economics and perceived risk literature, culminating in the development of an integrated model for pre-purchase intention regarding electric vehicles.
- 2) The conceptual model of pre-purchase intention is robust and offers richer model specifications than those currently available in marketing literature and economics literature.
- 3) Specified and highlighted the richness of technological factors and their comprehensive latent dimensions in the purchase intention process for durable goods.
- 4) Providing empirical evidence for the effects of both conventional and contemporary data sources on pre-purchase intention.
- 5) Quantified the pre-purchase antecedents and strategies specific to emerging market consumers from the context of India regarding electric vehicles.

- 6) The process of scale optimization and adoption has resulted in a collection of reliable scales for variables related to both technology and economic factors. The utilization of Hierarchical Component Modelling in conjunction with the repeated indicators approach of SmartPLS enhances the rigor and robustness of the empirical models.

Theoretical implications of this research manifest in various ways. The findings hold significant relevance for behavioural researchers across economics and marketing domains. By shedding light on a pivotal aspect of consumer information search behavior, this study contributes to a deeper understanding of this critical phenomenon. Notably, this study stands out as the first of its kind to comprehensively measure risk, technology, and economic variables for durable goods simultaneously. It was observed that the direct, indirect, and total effects significantly diverge from those observed for electric vehicle purchase intention in India (Bronnenberg & Dube ´, 2018).

Moreover, the empirically validated model introduces several novel theoretical relationships that have not been previously examined. For instance, the influence of the risk factor on individuals' need for information technology presents an intriguing finding for both marketing scholars and economics researchers. This study identifies and confirms the theoretical significance of this variable in consumer behavior, especially in the pre-purchase intention for durable goods.

Moreover, this study represents the first investigation into the direct causal relationship between economic factors and technology, thereby adding to the current literature in this field.

Furthermore, this study corroborates previously explored relationships, such as the positive association between perceived risk and technology. Notably, the key finding of this model contradicts the economics of information theory proposed by (Stigler, 1961), underscoring the impact of purchase intention on decision-making processes.

Generalizability: The scale development, research instrument validation, and study antecedents are robust, allowing the model estimation to apply not only to electric vehicle (EV) purchases but also to other durable, technology-driven products, such as two-wheeler EVs, electric trucks, buses, and similar innovation product.

8.7 Managerial Implications of the study

This study gives marketing practitioners valuable insights into the various individual and comprehensive variables influencing consumers' pre-purchase intentions. The model can be readily utilized by practitioners by providing an understanding of the entire spectrum of antecedents rather than focusing solely on specific aspects. The findings highlight which antecedents consumers perceive as risks and strategies, indicating their significance in decision-making.

In marketing, particularly for advertisers, it is now evident that consumers intending to purchase a new electric vehicle are predominantly motivated by technological considerations, closely followed by economic factors.

Understanding purchase intention is crucial as it signifies the primary stage of need assessment and processing in the consumer decision-making process. By identifying their target segment, marketers can tailor their communication strategies to highlight the technological and economic benefits of electric vehicles, both in the short and long term.

For instance, if marketers aim to position or promote a product effectively, they could emphasize the technological advantages to capitalize on the eventual positive environmental impact. Similarly, focusing on the economic benefits of choosing electric vehicles on various platforms can also be advantageous.

8.8 Limitations

When one is not the author, it is often easier to pinpoint limitations within a study. However, it is crucial to recognize that every study, including this one, has its own set of limitations.

The primary method of data collection utilized in this study was the survey method, in line with established prior literature and theoretical frameworks.

It is important to highlight that the sample was drawn exclusively from Karnataka. While the model is intended to be applicable to the search behaviour in emerging markets for durable goods, any significant deviations in population characteristics from those represented in the sample may restrict the generalizability of the results.

Moreover, data was collected exclusively from individuals who held significant decision-making authority or were key decision-makers in the purchasing process. This presents a limitation as it does not capture the dynamics of joint decision-making or the support received from family members or other stakeholders. Although attempts were made to incorporate measures for this aspect, constraints in the length of the instrument necessitated their exclusion.

Furthermore, there is a need for further refinement and conceptualization of technological factors, along with subsequent scale validation. Additionally, exploring the conceptualization of cost-benefit analysis is imperative, particularly considering

the higher cost associated with electric vehicles compared to internal combustion engine vehicles.

8.9 Directions for Future Work

The conceptualized models of pre-purchase intention are intended to be applicable across a spectrum of durable goods. It is crucial to test the generalizability of these models by applying them to durable goods beyond cars, capital-intensive products, or other high-involvement items. Replication studies would further bolster their validity. Ideally, durables characterized by minimal involvement or joint decision-making processes would be most suitable for the application of these models.

Consumers with prior purchase experience may employ varying approaches to evaluate products, with some potentially demonstrating brand loyalty based on previous usage. Further investigation is needed to evaluate the impact of these factors on purchase intention.

While surveys serve as a well-established method of validation, it is essential to address the nature, pattern, and quality of search from a managerial perspective, particularly as consumer behaviour continues to evolve. Given that framing a purchase intention for durable products is a multifaceted process, it is imperative to track consumers throughout the entire search journey to adequately capture the role of antecedents and how expectations evolve over time, ultimately shaping consumer choice. Longitudinal studies offer a more effective means of comprehending the search process.

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Appendix - 0

Missing Value Summary

Valid N	Cases		Missing		Total	
	N	Percent	N	Percent	N	Percent
Gender	322	100.0%	0	0.0%	322	100.0%
Age	322	100.0%	0	0.0%	322	100.0%
Edu	322	100.0%	0	0.0%	322	100.0%
Employment	322	100.0%	0	0.0%	322	100.0%
Mon_Income	322	100.0%	0	0.0%	322	100.0%
Sample_State	322	100.0%	0	0.0%	322	100.0%
RISK_FR_1	322	100.0%	0	0.0%	322	100.0%
RISK_FR_2	322	100.0%	0	0.0%	322	100.0%
RISK_FR_3	322	100.0%	0	0.0%	322	100.0%
RISK_FR_4	322	100.0%	0	0.0%	322	100.0%
RISK_PR_1	322	100.0%	0	0.0%	322	100.0%
RISK_PR_2	322	100.0%	0	0.0%	322	100.0%
RISK_PR_3	322	100.0%	0	0.0%	322	100.0%
RISK_PR_4	322	100.0%	0	0.0%	322	100.0%
RISK_PSY_1	322	100.0%	0	0.0%	322	100.0%
RISK_PSY_2	322	100.0%	0	0.0%	322	100.0%
RISK_PSY_3	322	100.0%	0	0.0%	322	100.0%
RISK_PSY_4	322	100.0%	0	0.0%	322	100.0%
TECH_RANGE_1	322	100.0%	0	0.0%	322	100.0%
TECH_RANGE_2	322	100.0%	0	0.0%	322	100.0%
TECH_RANGE_3	322	100.0%	0	0.0%	322	100.0%
TECH_CH_TIME_1	322	100.0%	0	0.0%	322	100.0%
TECH_CH_TIME_2	322	100.0%	0	0.0%	322	100.0%
TECH_CH_TIME_3	322	100.0%	0	0.0%	322	100.0%
TECH_RLB_1	322	100.0%	0	0.0%	322	100.0%
TECH_RLB_2	322	100.0%	0	0.0%	322	100.0%
TECH_RLB_3	322	100.0%	0	0.0%	322	100.0%
TECH_RLB_4	322	100.0%	0	0.0%	322	100.0%
TECH_RLB_5	322	100.0%	0	0.0%	322	100.0%
ECO_PRI_1	322	100.0%	0	0.0%	322	100.0%
ECO_PRI_2	322	100.0%	0	0.0%	322	100.0%
ECO_PRI_3	322	100.0%	0	0.0%	322	100.0%
ECO_PRI_4	322	100.0%	0	0.0%	322	100.0%
ECO_PRI_5	322	100.0%	0	0.0%	322	100.0%
ECO_PRI_6	322	100.0%	0	0.0%	322	100.0%

ECO_INC_1	322	100.0%	0	0.0%	322	100.0%
ECO_INC_2	322	100.0%	0	0.0%	322	100.0%
ECO_INC_3	322	100.0%	0	0.0%	322	100.0%
ECO_INC_4	322	100.0%	0	0.0%	322	100.0%
ECO_INF_1	322	100.0%	0	0.0%	322	100.0%
ECO_INF_2	322	100.0%	0	0.0%	322	100.0%
ECO_INF_3	322	100.0%	0	0.0%	322	100.0%
ECO_INF_4	322	100.0%	0	0.0%	322	100.0%
PURINT_PV_1	322	100.0%	0	0.0%	322	100.0%
PURINT_PV_2	322	100.0%	0	0.0%	322	100.0%
PURINT_PV_3	322	100.0%	0	0.0%	322	100.0%
PURINT_W2P_1	322	100.0%	0	0.0%	322	100.0%
PURINT_W2P_2	322	100.0%	0	0.0%	322	100.0%
PURINT_W2P_3	322	100.0%	0	0.0%	322	100.0%
PURINT_W2P_4	322	100.0%	0	0.0%	322	100.0%
PURINT_I2B_1	322	100.0%	0	0.0%	322	100.0%
PURINT_I2B_2	322	100.0%	0	0.0%	322	100.0%
PURINT_I2B_3	322	100.0%	0	0.0%	322	100.0%
PURINT_I2B_4	322	100.0%	0	0.0%	322	100.0%
PURINT_I2B_5	322	100.0%	0	0.0%	322	100.0%
PURINT_SI_1	322	100.0%	0	0.0%	322	100.0%
PURINT_SI_2	322	100.0%	0	0.0%	322	100.0%
PURINT_SI_3	322	100.0%	0	0.0%	322	100.0%

Pre-Purchase Behavior of Electric Vehicles (Cars)

Hello,

We are trying to understand the buying behavior of new car buyers (Electric Vehicles). So, please tell us what you think by answering below questions. The survey doesn't ask any personal questions or collects personal details. It is completely anonymous and will be used only for academic research.

The survey might take around 10 minutes. It can be much quicker too, So please participate and provide your thoughts.

For any questions or feedback, you are welcome to contact me at dsunilphd19@bus.alliance.edu.in

Thank you in advance!

* Required

Descriptive Indicators

The demographic information of the sample frame.

1. Gender *

Male

Female

2. Age (Bracket) *

- 18 -25
- 26 - 35
- 36 - 45
- 46 - 55
- 56 - 65
- More than 65

3. Education *

- Plus 12
- Professional Training
- Bachelor's Degree
- Post Graduate Degree
- Doctorate - PhD
- Post Doctoral

4. Are you considering to buy an Electric Vehicle (EV) in near future *

Yes

No

5. Employment *

Student

Not Employed

Employed - Government

Employed - Private

Self Employed

Retired

6. Your native state *

- Karnataka
- Andhra Pradesh
- Telangana
- Tamil Nadu
- Kerala
- Arunachal Pradesh
- Assam
- Bihar
- Chhattisgarh
- Goa
- Gujarat
- Haryana
- Himachal Pradesh
- Jammu and Kashmir
- Jharkhand
- Madhya Pradesh
- Maharashtra
- Manipur

- Meghalaya
- Mizoram
- Nagaland
- Orissa
- Punjab
- Rajasthan
- Sikkim
- Tripura
- Uttarakhand
- Uttar Pradesh
- West Bengal
- Andaman and Nicobar Islands
- Chandigarh
- Dadra and Nagar Haveli
- Daman and Diu
- Delhi
- Lakshadweep
- Pondicherry
- I am not an Indian

7. Monthly Income *

- Less than Rs. 30000
- From Rs. 30001 to 50000
- From Rs. 50001 to 100000
- From Rs. 100001 to 150000
- More than 1.5 Lakh

8. Currently, do you own any car? *

- Yes
- No

9. Do you currently own an Electric Vehicle (EV) *

- Yes
- No

10. Driving Experience (Any Car) *

- 0-2 year
- 2-4 years
- 4-6 years
- 6-8 years
- 8-10 years
- More than 10 Years

11. In a year, how many Kilometers do you drive (Average) *

- Up to 5,000 KM
- Up to 10,000 KM
- Up to 15,000 KM
- Up to 20,000 KM
- More than 20,000 KM

Perceived Risk of a Buyer

This section refers to an individual's subjective evaluation of his/her risk of any adverse outcome in terms of financial, performance, and time risk in relation to electric vehicles performance on purchase

12. The Electric Vehicles (EV) are expensive, so there is a risk of losing money if the EV does not last many years *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

13. EV Battery is costly, there will be hidden costs with owning an EV *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

14. Replacing or repair of a battery makes EV most costly than conventional (Petrol/Diesel) vehicles *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

15. EV require regular service checks to maintain optimal battery performance. It will increase maintenance cost *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

16. EVs can only go to specialist repair showrooms, it might cost a lot *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

17. Driving outside of my town with my EV would add frustration to my life if I have difficulty finding recharge stations *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

18. Driving outside my town with my EV would add range anxiety to my life due to the lack of charging stations *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

19. EV drives short distances with limited mileage overall *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

20. Driving outside my town with my EV would add stress to my life if I have difficulty recharging *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

21. Electric cars give me anxiety about safety and reliability *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

22. EVs have potential fire risk and emission of gases during the charging process *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Technology of Electric Cars

An electric vehicle uses a batteries to store electrical energy. It's a new technology compared to conventional vehicles such as petrol. This section covers on these technological aspects.

23. I feel uncomfortable with the limited driving range of EVs *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

24. The average driving range of EVs are not satisfactory *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

25. The driving range of EVs is sufficient for my mobility needs in everyday life *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

26. Due to the limited driving range of EVs, I would feel that my freedom to travel is restricted *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

27. I do not mind if it takes longer to charge battery than to refuel. *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

28. I could integrate the charging of the batteries in my everyday life without any problems *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

29. I do not mind if EVs needs to be charged often/every night *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

30. I would be as safe in an EV as in a conventional (petrol/diesel) car *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

31. The safety in EVs is a given (well considered) *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

32. An EV will take me safely to my destination *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

33. I rely on the new technology of EVs *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

34. Electric Vehicles are reliable *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

35. I can depend on an EV to reliably get where I need to go *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

36. I can depend on the EV to reliably take me every time from one place to another *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Economic factors

37. Electric Vehicles are expensive *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

38. Electric Vehicles are unaffordable *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

39. The overall price of EVs is higher than that of similar combustion (Petrol/Diesel) engine vehicle *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

40. The price of Electric Vehicles is higher than what I expected *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

41. Compared to the price that I need to pay, EVs offer value for money *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

42. Electric Vehicles are considered to be a good buy. *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

43. It is easier to receive subsidies for the purchase of EVs than for the rest of the vehicles. *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

44. The purchase of an EV is more cost-effective when monetary incentives are in place *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

45. I am aware of the subsidies available for the purchase of EVs *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

46. Government incentives for electric cars are very unpredictable in India *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

47. Future political support for electric cars is very uncertain in India *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

48. It is hard to find a charging station where an EV can be charged. *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

49. It is hard to find an repair shop that services EVs *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

50. Using an EV for longer distances is difficult due to a lack of charging stations along the highway *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

51. When driving an electric car, I'm always (would always be) worried about running out of charge *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Purchase Intention

52. I intend to buy an electric vehicle in the near future *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

53. I will recommend my friend and relatives to buy an electric vehicle *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

54. Comparing with conventional (Petrol/Diesel) vehicles, electric vehicles are more attractive *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

55. I am willing to drive an EV in the near future *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

56. My financial situation permits me to purchase an electric vehicle *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

57. My preference for electric vehicles is higher than that for petrol vehicles *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

58. My desire to purchase an electric vehicle is based on its environmental friendliness *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

59. If I do not have cash on hand, I am willing to lease an electric vehicle *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

60. I would pay one third more for an EV than for a comparable conventional vehicle *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

61. The electric vehicles possess a consistent quality *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

62. The electric vehicles in current market are well made *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

63. The electric vehicles in current market have an acceptable standard of quality *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

THANK YOU

Thank you so much for your time in completing our survey. It is greatly appreciated, as we will use your response to understand the buying behaviour of Electric Vehicles.

Pre-Purchase Behavior of Electric Vehicles (Cars)

Hello,

We are trying to understand the buying behavior of new car buyers (Electric Vehicles). Electric Vehicles are Battery Electric Vehicles, Hybrid Electric Vehicles, and Plug-in Hybrid Electric Vehicles. Please provide your valuable insights by answering the following questions. The survey doesn't ask any personal questions or collect personal details. The data collected will be anonymous and used only for academic research.

The survey might take around 7 minutes. So please participate and provide your thoughts.

For any questions or feedback, please contact me at dsunilphd19@bus.alliance.edu.in
Thank you in advance!

* Required

Descriptive Indicators

1. Gender *

Male

Female

2. Age (Bracket) *

- 18 -25
- 26 - 35
- 36 - 45
- 46 - 55
- 56 - 65
- More than 65

3. Education *

- Plus 12
- Professional Training
- Bachelor's Degree
- Post Graduate Degree
- Doctorate PhD
- Post Doctoral

4. Are you considering to buy an Electric Vehicle (EV) in near future *

Yes

No

5. Employment *

Student

Not Employed

Employed Government

Employed - Private

Self Employed

Retired

6. Your native state *

- Karnataka
- Andhra Pradesh
- Telangana
- Tamil Nadu
- Kerala
- Arunachal Pradesh
- Assam
- Bihar
- Chhattisgarh
- Goa
- Gujarat
- Haryana
- Himachal Pradesh
- Jammu and Kashmir
- Jharkhand
- Madhya Pradesh
- Maharashtra
- Manipur



- Meghalaya
- Mizoram
- Nagaland
- Orissa
- Punjab
- Rajasthan
- Sikkim
- Tripura
- Uttarakhand
- Uttar Pradesh
- West Bengal
- Andaman and Nicobar Islands
- Chandigarh
- Dadra and Nagar Haveli
- Daman and Diu
- Delhi
- Lakshadweep
- Pondicherry
- I am not an Indian

7. Monthly Income *

- Less than Rs. 30000
- From Rs. 30001 to 50000
- From Rs. 50001 to 100000
- From Rs. 100001 to 150000
- More than 1.5 Lakh

8. Currently, do you own any car? *

- Yes
- No

9. Do you currently own an Electric Vehicle (EV) *

- Yes
- No

10. Driving Experience (Any Car) *

- 0-2 year
- 2-4 years
- 4-6 years
- 6-8 years
- 8-10 years
- More than 10 Years

11. In a year, how many Kilometers do you drive (Average) *

- Up to 5,000 KM
- Up to 10,000 KM
- Up to 15,000 KM
- Up to 20,000 KM
- More than 20,000 KM

12. The Electric Vehicles (EV) are expensive, so there is a risk of losing money if the EV does not last many years *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

13. EV Battery is costly, there will be hidden costs with owning an EV *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

14. I feel uncomfortable with the limited driving range of EVs *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

15. Replacing or repair of a battery makes EV most costly than conventional (Petrol/Diesel) vehicles *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

16. EV require regular service checks to maintain optimal battery performance. It will increase maintenance cost *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

17. The driving range of EVs is sufficient for my mobility needs in everyday life *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

18. EVs can only go to specialist repair showrooms, it might cost a lot *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

19. Driving outside of my town with my EV would add frustration to my life if I have difficulty finding recharge stations *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

20. I do not mind if it takes longer to charge battery than to refuel. *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

21. Driving outside my town with my EV would add range anxiety to my life due to the lack of charging stations *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

22. EV drives short distances with limited mileage overall *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

23. Driving outside my town with my EV would add stress to my life if I have difficulty recharging *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

24. Electric cars give me anxiety about safety and reliability *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

25. EVs have potential fire risk and emission of gases during the charging process *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

26. The average driving range of EVs are not satisfactory *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

27. Due to the limited driving range of EVs, I would feel that my freedom to travel is restricted *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

28. I could integrate the charging of the batteries in my everyday life without any problems *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

29. I do not mind if EVs needs to be charged often/every night *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

30. I would be as safe in an EV as in a conventional (petrol/diesel) car *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

31. The safety in EVs is a given (well considered) *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

32. Electric Vehicles are expensive *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

33. An EV will take me safely to my destination *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

34. I rely on the new technology of EVs *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

35. The overall price of EVs is higher than that of similar combustion (Petrol/Diesel) engine vehicle *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

36. Electric Vehicles are reliable *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

37. I can depend on an EV to reliably get where I need to go *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

38. It is easier to receive subsidies for the purchase of EVs than for the rest of the vehicles. *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

39. I can depend on the EV to reliably take me every time from one place to another *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

40. Electric Vehicles are unaffordable *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

41. The price of Electric Vehicles is higher than what I expected *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

42. I intend to buy an electric vehicle in the near future *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

43. Compared to the price that I need to pay, EVs offer value for money *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

44. Electric Vehicles are considered to be a good buy. *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

45. The purchase of an EV is more cost-effective when monetary incentives are in place *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

46. I am aware of the subsidies available for the purchase of EVs *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

47. My financial situation permits me to purchase an electric vehicle *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

48. Government incentives for electric cars are very unpredictable in India *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

49. I will recommend my friend and relatives to buy an electric vehicle *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

50. Future political support for electric cars is very uncertain in India *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

51. It is hard to find a charging station where an EV can be charged. *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

52. It is hard to find an repair shop that services EVs *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

53. Using an EV for longer distances is difficult due to a lack of charging stations along the highway *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

54. The electric vehicles possess a consistent quality *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

55. When driving an electric car, I'm always (would always be) worried about running out of charge *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

56. Comparing with conventional (Petrol/Diesel) vehicles, electric vehicles are more attractive *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

57. I am willing to drive an EV in the near future *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

58. My preference for electric vehicles is higher than that for petrol vehicles *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

59. My desire to purchase an electric vehicle is based on its environmental friendliness *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

60. If I do not have cash on hand, I am willing to lease an electric vehicle *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

61. I would pay one third more for an EV than for a comparable conventional vehicle *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

62. The electric vehicles in current market are well made *

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

63. The electric vehicles in current market have an acceptable standard of quality *

Strongly
Disagree

Disagree

Neither

Agree

Strongly
Agree

THANK YOU

Thank you so much for your time in completing our survey. It is greatly appreciated, as we will use your response to understand the buying behaviour of Electric Vehicles.

Annexure 1: Path Coefficients of Measurement Model

	Path coefficients
Charge_Time -> TECHNOLOGY	0.364
ECONOMIC FACTORS -> PURCHASE_INTENTION	0.004
FIN_RISK -> RISK	0.440
Incentives -> ECONOMIC FACTORS	0.011
Infrastructure -> ECONOMIC FACTORS	0.514
Intention_2_Buy -> PURCHASE_INTENTION	0.507
PER_RISK -> RISK	0.327
PSY_RISK -> RISK	0.445
Perf_Value -> PURCHASE_INTENTION	0.370
Price -> ECONOMIC FACTORS	0.682
RISK -> ECONOMIC FACTORS	0.013
RISK -> TECHNOLOGY	0.001
Range -> TECHNOLOGY	0.138
Reliability -> TECHNOLOGY	0.679
TECHNOLOGY -> PURCHASE_INTENTION	0.002
Willingness_2_Pay -> PURCHASE_INTENTION	0.270

Annexure 2: Indirect effects

Specific indirect effects

	Specific indirect effects
FIN_RISK -> RISK -> TECHNOLOGY	0.000
RISK -> TECHNOLOGY -> PURCHASE_INTENTION	0.000
Range -> TECHNOLOGY -> PURCHASE_INTENTION	0.000
Reliability -> TECHNOLOGY -> PURCHASE_INTENTION	0.001
PER_RISK -> RISK -> TECHNOLOGY	0.000
Incentives -> ECONOMIC FACTORS -> PURCHASE_INTENTION	0.000
PSY_RISK -> RISK -> TECHNOLOGY	0.000
Infrastructure -> ECONOMIC FACTORS -> PURCHASE_INTENTION	0.002
FIN_RISK -> RISK -> TECHNOLOGY -> PURCHASE_INTENTION	0.000
PSY_RISK -> RISK -> TECHNOLOGY -> PURCHASE_INTENTION	0.000
PER_RISK -> RISK -> TECHNOLOGY -> PURCHASE_INTENTION	0.000
Price -> ECONOMIC FACTORS -> PURCHASE_INTENTION	0.003
RISK -> ECONOMIC FACTORS -> PURCHASE_INTENTION	0.000
FIN_RISK -> RISK -> ECONOMIC FACTORS	0.006
Charge_Time -> TECHNOLOGY -> PURCHASE_INTENTION	0.001
PER_RISK -> RISK -> ECONOMIC FACTORS	0.004
PSY_RISK -> RISK -> ECONOMIC FACTORS	0.006
PER_RISK -> RISK -> ECONOMIC FACTORS -> PURCHASE_INTENTION	0.000
PSY_RISK -> RISK -> ECONOMIC FACTORS -> PURCHASE_INTENTION	0.000
FIN_RISK -> RISK -> ECONOMIC FACTORS -> PURCHASE_INTENTION	0.000

Annexure 3: Total effects

	Total effects
Charge_Time -> PURCHASE_INTENTION	0.001
Charge_Time -> TECHNOLOGY	0.364
ECONOMIC FACTORS -> PURCHASE_INTENTION	0.004
FIN_RISK -> ECONOMIC FACTORS	0.006
FIN_RISK -> PURCHASE_INTENTION	0.000
FIN_RISK -> RISK	0.440
FIN_RISK -> TECHNOLOGY	0.000
Incentives -> ECONOMIC FACTORS	0.011
Incentives -> PURCHASE_INTENTION	0.000
Infrastructure -> ECONOMIC FACTORS	0.514
Infrastructure -> PURCHASE_INTENTION	0.002
Intention_2_Buy -> PURCHASE_INTENTION	0.507
PER_RISK -> ECONOMIC FACTORS	0.004
PER_RISK -> PURCHASE_INTENTION	0.000
PER_RISK -> RISK	0.327
PER_RISK -> TECHNOLOGY	0.000
PSY_RISK -> ECONOMIC FACTORS	0.006
PSY_RISK -> PURCHASE_INTENTION	0.000
PSY_RISK -> RISK	0.445
PSY_RISK -> TECHNOLOGY	0.000
Perf_Value -> PURCHASE_INTENTION	0.370
Price -> ECONOMIC FACTORS	0.682
Price -> PURCHASE_INTENTION	0.003
RISK -> ECONOMIC FACTORS	0.013
RISK -> PURCHASE_INTENTION	0.000
RISK -> TECHNOLOGY	0.001
Range -> PURCHASE_INTENTION	0.000
Range -> TECHNOLOGY	0.138
Reliability -> PURCHASE_INTENTION	0.001
Reliability -> TECHNOLOGY	0.679
TECHNOLOGY -> PURCHASE_INTENTION	0.002
Willingness_2_Pay -> PURCHASE_INTENTION	0.270

Annexure 4: Outer loadings

	Outer loadings
ECO_INC_2 <- Incentives	0.864
ECO_INC_3 <- Incentives	0.780
ECO_INF_1 <- ECONOMIC FACTORS	0.713
ECO_INF_1 <- Infrastructure	0.921
ECO_INF_3 <- Infrastructure	0.915
ECO_INF_3 <- ECONOMIC FACTORS	0.687
ECO_PRI_4 <- ECONOMIC FACTORS	0.715
ECO_PRI_4 <- Price	0.873
ECO_PRI_5 <- ECONOMIC FACTORS	0.747
ECO_PRI_5 <- Price	0.856
ECO_PRI_6 <- ECONOMIC FACTORS	0.667
ECO_PRI_6 <- Price	0.715
PURINT_I2B_1 <- Intention_2_Buy	0.863
PURINT_I2B_1 <- PURCHASE_INTENTION	0.788
PURINT_I2B_2 <- Intention_2_Buy	0.833
PURINT_I2B_2 <- PURCHASE_INTENTION	0.774
PURINT_I2B_3 <- PURCHASE_INTENTION	0.699
PURINT_I2B_3 <- Intention_2_Buy	0.803
PURINT_I2B_5 <- PURCHASE_INTENTION	0.703
PURINT_I2B_5 <- Intention_2_Buy	0.740
PURINT_PV_1 <- Perf_Value	0.710
PURINT_PV_1 <- PURCHASE_INTENTION	0.616
PURINT_PV_2 <- PURCHASE_INTENTION	0.707
PURINT_PV_2 <- Perf_Value	0.845
PURINT_PV_3 <- Perf_Value	0.874
PURINT_PV_3 <- PURCHASE_INTENTION	0.708
PURINT_W2P_1 <- PURCHASE_INTENTION	0.696
PURINT_W2P_1 <- Willingness_2_Pay	0.845
PURINT_W2P_4 <- Willingness_2_Pay	0.846
PURINT_W2P_4 <- PURCHASE_INTENTION	0.698
RISK_FR_1 <- RISK	0.645
RISK_FR_1 <- FIN_RISK	0.838
RISK_FR_2 <- FIN_RISK	0.861
RISK_FR_2 <- RISK	0.690
RISK_FR_4 <- RISK	0.697
RISK_FR_4 <- FIN_RISK	0.745
RISK_PR_1 <- PER_RISK	0.820
RISK_PR_1 <- RISK	0.562
RISK_PR_2 <- RISK	0.785

RISK_PR_2 <- PER_RISK	0.912
RISK_PSY_1 <- RISK	0.771
RISK_PSY_1 <- PSY_RISK	0.821
RISK_PSY_2 <- PSY_RISK	0.809
RISK_PSY_2 <- RISK	0.614
RISK_PSY_3 <- PSY_RISK	0.820
RISK_PSY_3 <- RISK	0.658
TECH_CH_TIME_1 <- TECHNOLOGY	0.539
TECH_CH_TIME_1 <- Charge_Time	0.684
TECH_CH_TIME_2 <- Charge_Time	0.864
TECH_CH_TIME_2 <- TECHNOLOGY	0.676
TECH_CH_TIME_3 <- TECHNOLOGY	0.718
TECH_CH_TIME_3 <- Charge_Time	0.867
TECH_RANGE_3 <- Range	1.000
TECH_RANGE_3 <- TECHNOLOGY	0.476
TECH_RLB_1 <- Reliability	0.697
TECH_RLB_1 <- TECHNOLOGY	0.685
TECH_RLB_2 <- Reliability	0.848
TECH_RLB_2 <- TECHNOLOGY	0.821
TECH_RLB_3 <- Reliability	0.773
TECH_RLB_3 <- TECHNOLOGY	0.712
TECH_RLB_4 <- Reliability	0.843
TECH_RLB_4 <- TECHNOLOGY	0.797
TECH_RLB_5 <- TECHNOLOGY	0.745
TECH_RLB_5 <- Reliability	0.817

Annexure 5: Latent variables

Observations	Charge_Tim e	ECONOMIC FACTORS	FIN_RISK	Incentives	Infrastructu re	Intention_2 _Buy	PER_RISK	PSY_RISK	PURCHASE_I NTENTION	Perf_Value	Price	RISK	Range	Reliability	TECHNOLO GY	Willingness _2_Pay
0	-1.078	0.668	0.733	1.517	0.978	0.953	0.995	0.179	0.510	-0.329	0.252	0.728	0.508	-0.324	-0.543	0.554
1	-1.745	0.435	1.365	1.097	0.496	1.491	0.995	0.476	0.786	0.024	0.230	1.134	0.508	0.403	-0.289	0.037
2	-1.078	-0.599	0.733	0.474	0.496	-1.435	0.616	0.506	-0.856	0.001	-1.286	0.750	0.508	-1.245	-1.168	-0.479
3	-1.078	0.439	1.365	0.272	1.523	0.050	1.587	0.891	-0.229	0.082	-0.517	1.517	1.422	-1.051	-0.910	-1.053
4	1.012	-0.104	-1.291	0.257	-1.557	1.221	-1.324	-1.216	1.377	1.626	1.026	-1.543	1.422	0.369	0.814	0.554
5	-0.700	0.192	0.353	-0.771	0.978	0.096	0.616	0.803	-0.512	-0.329	-0.540	0.709	-1.320	-0.767	-0.952	-1.570
6	-1.078	-1.964	-1.291	-1.611	-1.557	-1.705	-1.324	-1.216	-1.846	-1.484	-1.661	-1.543	-1.320	-1.506	-1.599	-1.570
7	0.185	-0.099	-1.671	0.257	-2.039	1.808	-1.324	-1.840	1.801	1.178	1.374	-1.987	1.422	2.041	1.650	1.616
8	2.057	0.167	-2.302	1.517	-2.039	1.515	-2.294	-2.226	1.821	1.626	1.772	-2.754	1.422	2.041	2.332	1.616
9	1.781	-0.383	-1.291	0.054	-1.494	0.638	-1.916	-2.226	0.936	0.825	0.651	-2.185	1.422	1.780	2.053	1.071
10	-1.848	-1.964	-1.567	-1.611	-1.557	-1.705	-1.324	-1.216	-1.846	-1.484	-1.661	-1.665	-1.320	-2.210	-2.358	-1.570
11	0.909	-0.153	0.181	0.054	0.496	-0.264	0.616	0.179	0.188	0.825	-0.521	0.361	-0.406	0.420	0.555	0.037
12	-0.989	1.465	-0.738	0.474	0.978	0.953	1.587	1.188	0.650	0.047	1.397	0.721	1.422	0.072	-0.096	0.554
13	-1.078	-3.036	-1.567	-2.654	-2.102	-2.584	-1.324	-1.216	-2.720	-1.837	-2.806	-1.665	-1.320	-1.751	-1.766	-2.632
14	0.358	-0.357	1.113	-0.568	0.014	0.075	1.587	0.861	-0.085	-0.329	-0.517	1.396	-0.406	-0.324	-0.151	0.037
15	-1.457	-0.612	-1.015	-1.191	-0.950	-0.195	-1.324	-1.602	-0.340	-0.213	-0.168	-1.596	-0.406	0.949	0.054	-0.537
16	-0.700	0.198	0.733	-0.148	0.496	0.367	0.616	0.773	-0.376	-1.130	-0.142	0.864	-1.320	-0.324	-0.653	-0.508
17	-0.700	0.761	0.837	0.272	1.523	1.538	1.587	1.812	1.648	1.155	-0.164	1.692	1.422	-0.092	-0.119	1.616
18	-0.976	0.351	-1.187	-0.786	0.496	-1.414	-1.324	1.100	-0.981	-0.741	0.248	-0.468	0.508	-1.232	-1.121	0.037
19	1.012	0.133	0.733	1.517	-1.557	1.808	-1.324	-1.216	1.824	1.626	1.397	-0.650	0.508	1.103	1.189	1.100
20	-0.976	-1.410	-1.187	-1.611	0.559	-1.976	-1.324	-0.207	-1.120	0.082	-2.408	-1.046	0.508	-1.082	-1.015	-0.508
21	-0.412	-1.429	0.077	-1.409	-0.530	-1.976	-0.140	-0.118	-1.411	-1.095	-1.661	-0.062	-1.320	-0.764	-0.858	0.037
22	-0.559	-0.370	-1.671	1.517	-1.557	-0.832	-2.294	-2.226	-1.138	-0.423	0.578	-2.478	-2.234	1.265	0.329	-2.115
23	-0.322	-0.874	0.249	0.474	-0.048	-0.243	0.024	-0.237	-0.543	-0.777	-1.286	0.003	-1.320	-0.585	-0.689	-0.508
24	-0.425	0.351	0.605	-0.786	0.496	-1.414	-1.703	-0.831	-1.847	-1.519	0.248	-0.663	0.508	-1.091	-0.825	-2.087
25	0.620	0.654	-0.451	-1.409	1.041	-0.513	-1.538	-0.178	-0.917	-1.402	0.275	-0.776	-0.406	-0.477	-0.148	-0.479
26	-0.425	-0.631	0.629	0.474	-0.530	-1.144	-1.324	-1.246	-1.427	-0.777	-0.517	-0.713	0.508	-1.133	-0.849	-2.087
27	0.198	-0.945	0.733	0.474	-0.111	-0.534	0.995	-0.772	-0.544	-0.365	-1.290	0.310	0.508	0.159	0.238	-0.508
28	-1.078	0.207	0.837	0.474	1.041	0.367	1.587	1.188	-0.064	-0.683	-0.540	1.419	1.422	-0.545	-0.570	0.037
29	-0.700	-2.799	0.985	-1.611	-2.102	-1.387	0.024	-0.265	-1.706	-1.896	-2.435	0.312	-1.320	-1.312	-1.324	-1.025
30	1.012	0.617	0.022	1.097	0.496	-0.583	-0.567	0.476	0.184	0.825	0.647	0.041	0.508	0.858	1.022	0.554
31	-0.790	-1.656	0.353	-0.989	-1.620	-0.832	-0.567	-1.186	-0.699	-0.812	-1.259	-0.560	1.422	-0.923	-0.726	0.037
32	1.287	1.759	0.353	1.517	0.978	0.997	1.587	1.812	1.665	1.979	1.772	1.473	1.422	1.780	1.873	1.616
33	-0.527	-0.370	0.733	0.054	-1.557	1.246	-0.140	0.803	0.944	0.436	0.628	0.634	0.508	0.858	0.462	0.583
34	0.749	-1.680	-1.542	-0.351	-0.593	-1.117	-0.567	-0.148	-0.684	-0.294	-2.033	-0.923	-1.320	0.601	0.487	0.009
35	-1.470	-1.614	-1.542	-0.351	-1.557	-0.874	0.238	-0.118	-0.978	-0.718	-1.282	-0.645	-1.320	-1.506	-1.737	-1.053
36	-0.700	0.729	-0.279	0.474	0.496	0.637	0.616	-0.831	0.798	0.471	0.605	-0.290	0.508	0.131	-0.090	1.100

37	-0.700	-1.168	-0.175	-1.191	-0.048	-0.555	-1.538	1.188	-0.255	0.059	-1.661	-0.046	-0.406	-0.585	-0.706	0.009
38	-1.354	0.435	0.077	0.474	0.496	0.075	0.995	0.803	-0.524	-1.130	0.230	0.709	0.508	-1.272	-1.289	-0.479
39	2.057	-0.402	-2.302	1.517	-2.584	1.808	-2.294	-2.226	2.097	1.979	1.397	-2.754	1.422	2.041	2.332	1.616
40	1.012	0.701	0.733	0.474	0.496	0.637	0.024	0.803	0.783	0.825	0.628	0.686	0.508	0.858	1.022	0.554
41	0.461	0.701	-0.027	1.517	0.496	0.637	0.616	-0.445	0.925	0.825	0.628	-0.010	0.508	0.858	0.821	1.071
42	-0.193	-0.735	-1.187	-0.786	-1.620	-1.684	-1.324	-0.831	-0.993	-0.388	0.248	-1.319	0.508	-0.134	-0.094	0.037
43	-0.527	0.192	1.745	1.517	0.978	-0.805	1.587	0.921	-0.404	1.178	-0.540	1.702	-1.320	0.559	0.007	-1.570
44	1.012	0.701	0.022	0.474	0.496	0.637	0.616	0.209	0.783	0.825	0.628	0.313	0.508	0.858	1.022	0.554
45	-0.700	-0.948	0.249	-0.568	-1.012	-1.997	-0.354	-0.772	-1.705	-1.072	-0.521	-0.347	-0.406	-1.700	-1.463	-1.053
46	0.461	0.701	0.733	0.474	0.496	0.637	-0.189	-1.216	1.227	1.626	0.628	-0.281	0.508	0.664	0.689	1.100
47	-0.976	0.351	-0.254	-0.786	0.496	-1.414	-1.324	1.100	-1.425	-1.542	0.248	-0.053	-1.320	-0.724	-1.029	-0.508
48	-0.033	-0.096	-0.003	-0.568	0.496	-0.243	-0.354	-0.207	-0.231	-0.329	-0.517	-0.210	0.508	-0.324	-0.163	0.037
49	-0.193	-0.127	0.224	0.677	-2.039	-0.832	-0.732	-1.008	-1.539	-1.896	1.397	-0.609	-1.320	-2.040	-1.642	-1.570
50	1.012	0.663	0.022	0.474	-0.048	1.538	0.830	-0.118	1.104	0.471	0.999	0.239	1.422	0.858	1.148	0.554
51	0.069	-0.869	-0.175	-2.234	-0.530	-1.976	-0.354	0.090	-1.411	-1.095	-0.888	-0.154	0.508	-0.779	-0.432	0.037
52	0.531	0.724	0.457	1.517	0.978	0.415	1.587	-0.683	0.629	1.979	0.256	0.427	0.508	1.547	1.307	-1.082
53	0.069	0.435	0.733	1.097	0.496	0.637	0.616	0.179	0.649	0.082	0.230	0.606	0.508	0.624	0.525	1.071
54	0.633	-0.412	0.249	-1.394	-1.494	0.616	-0.354	-0.118	-0.244	-0.741	0.624	-0.059	0.508	-0.249	0.125	-1.053
55	1.012	-0.105	-0.254	0.474	-0.048	0.637	-0.732	0.447	0.350	0.436	-0.119	-0.149	0.508	0.169	0.553	-0.508
56	-0.252	-1.708	0.224	-0.351	-0.468	-0.243	-0.140	-1.216	-0.541	-0.388	-2.037	-0.500	-1.320	-1.264	-1.133	-1.025
57	0.185	-0.631	-0.224	-0.568	-0.530	-0.534	1.208	0.564	-0.251	-1.130	-0.517	0.542	1.422	-0.518	-0.089	1.616
58	-1.078	-1.964	-1.291	-1.611	-1.557	0.123	-1.324	-1.216	-0.074	-0.317	-1.661	-1.543	-1.320	-1.506	-1.599	0.066
59	-2.123	-1.988	-0.500	-2.234	-0.530	-0.486	-0.732	-1.158	-0.956	-1.095	-2.435	-0.980	-0.406	-0.387	-1.096	-1.025
60	1.390	-0.954	-1.947	-1.611	-0.530	-1.754	-1.324	-0.948	-1.849	-1.484	-0.919	-1.722	-1.320	-1.312	-0.563	-1.570
61	-0.816	-1.666	0.605	-0.351	-0.530	-1.456	-0.732	-0.592	-0.862	0.024	-2.033	-0.248	-0.406	-0.997	-1.021	-0.508
62	-0.687	0.701	0.457	0.894	0.496	0.637	0.616	0.179	0.354	-0.329	0.628	0.483	-1.320	-0.324	-0.657	0.554
63	-0.193	0.351	-1.187	-0.786	0.496	-1.414	-1.324	1.100	-0.981	-0.741	0.248	-0.468	0.508	0.584	0.394	0.037
64	-0.610	-1.932	1.389	-2.031	-0.530	-1.393	1.587	0.504	-1.247	-1.072	-2.431	1.360	1.422	-0.403	-0.278	-0.537
65	-1.745	0.701	-1.094	0.474	0.496	0.637	-0.519	0.803	0.783	0.825	0.628	-0.292	-2.234	-1.955	-2.266	0.554
66	0.229	0.198	-0.358	-0.771	0.496	0.367	0.616	0.803	0.639	0.825	-0.142	0.401	0.508	0.471	0.482	0.554
67	-0.527	0.705	1.113	-0.771	1.523	0.955	0.024	0.476	0.623	0.790	-0.168	0.713	0.508	1.107	0.629	-0.537
68	-0.527	0.109	-0.935	-1.191	-0.530	0.637	0.238	-0.623	0.930	0.825	0.624	-0.622	0.508	0.226	0.031	1.100
69	1.012	0.701	0.101	0.474	0.496	0.637	0.616	0.803	0.486	0.024	0.628	0.603	0.508	0.363	0.685	0.554
70	0.461	0.701	0.378	-0.989	0.496	0.075	0.403	-0.088	0.212	0.471	0.628	0.267	1.422	1.093	1.105	0.037
71	1.012	1.199	-0.910	0.474	0.978	0.637	0.616	-0.445	1.074	1.214	0.999	-0.391	1.422	1.780	1.773	1.100
72	1.230	0.354	-1.291	-0.351	1.523	1.808	-1.324	-1.216	2.097	1.979	-0.548	-1.543	-1.320	1.459	1.257	1.616
73	0.358	-0.854	-1.567	0.054	-0.468	-1.435	0.024	0.270	-1.122	-1.095	-0.888	-0.581	0.508	-1.064	-0.529	0.037
74	0.461	-0.132	0.733	1.097	-1.557	1.517	-0.140	-1.840	1.647	1.178	0.999	-0.537	0.508	2.041	1.625	1.616
75	-0.527	0.701	0.733	-0.366	0.496	0.637	0.995	0.506	-0.221	-0.718	0.628	0.873	-0.406	0.155	-0.143	-1.025
76	-0.149	0.108	0.181	-0.568	0.978	-1.144	0.024	0.209	-0.973	-0.329	-0.521	0.183	0.508	-0.518	-0.332	-1.025
77	-0.976	-1.106	-1.187	-1.409	-0.530	0.048	-1.324	-1.513	-0.533	-0.400	-1.259	-1.624	-1.320	-1.700	-1.689	-1.541
78	-0.033	0.351	-1.947	-0.786	0.496	-2.024	-0.140	-0.148	-1.861	-1.130	0.248	-0.970	-1.320	-1.040	-0.905	-1.570
79	-1.457	-1.186	-1.922	0.054	-1.012	-1.705	0.238	0.209	-1.562	-0.718	-0.892	-0.672	-0.406	-0.743	-1.097	-1.570

80	-1.457	0.678	-1.187	0.894	0.014	-0.874	-1.111	-1.246	-1.427	-1.166	0.999	-1.439	-1.320	-1.700	-1.873	-2.087
81	-0.309	-0.096	0.101	0.054	0.496	-0.243	0.995	1.812	-0.373	-0.329	-0.517	1.175	0.508	-0.779	-0.574	-0.479
82	0.345	-0.659	0.353	0.054	-0.530	0.637	0.616	-0.415	0.641	0.825	-0.494	0.176	0.508	0.624	0.625	0.037
83	-0.976	0.464	0.733	0.474	0.496	0.367	1.208	0.891	0.354	0.059	0.256	1.118	0.508	0.624	0.145	0.554
84	-1.078	-0.893	0.733	0.474	0.496	0.367	0.238	0.209	-0.503	-1.484	-1.661	0.498	0.508	-1.312	-1.215	-0.479
85	-0.687	-1.665	-0.634	-0.989	-2.039	-1.366	0.024	-0.889	-1.401	-0.718	-0.888	-0.667	-1.320	-0.623	-0.860	-1.541
86	-1.078	-1.936	-0.738	1.517	-1.557	0.976	-0.732	0.239	-0.627	-2.638	-1.684	-0.452	0.508	-1.945	-1.646	-0.450
87	-1.341	-0.607	0.654	-2.031	-1.557	0.685	-0.946	-1.158	-0.053	-1.060	0.256	-0.528	-0.406	0.060	-0.511	0.066
88	-0.412	-1.172	-1.567	-0.366	-1.075	-1.754	-0.567	0.861	-1.579	-0.365	-0.915	-0.492	0.508	-0.532	-0.446	-2.115
89	0.126	0.478	1.469	-0.351	0.559	0.006	0.616	1.485	-0.109	0.825	0.256	1.508	1.422	0.662	0.695	-1.599
90	0.736	0.701	-0.199	0.474	0.496	0.637	0.238	0.803	0.783	0.825	0.628	0.341	-0.406	0.858	0.796	0.554
91	-1.457	0.351	-1.567	-0.786	0.496	-1.414	-1.111	0.861	-1.563	-1.519	0.248	-0.667	0.508	-0.560	-0.842	-1.053
92	-2.123	-3.296	-2.302	-2.654	-2.584	-2.877	-2.294	-2.226	-3.161	-2.638	-2.806	-2.754	-2.234	-2.689	-2.909	-2.632
93	-0.527	-0.631	-1.947	-0.568	-0.530	-1.144	1.587	-0.415	-0.516	0.919	-0.517	-0.524	-1.320	-0.716	-0.859	-1.053
94	-1.078	0.961	0.629	1.517	0.978	0.928	0.616	-0.060	1.078	0.825	0.628	0.458	-1.320	0.858	0.009	1.071
95	-1.078	0.701	0.101	0.474	0.496	0.637	0.616	0.803	0.354	-0.329	0.628	0.603	0.508	-0.324	-0.543	0.554
96	-0.136	-0.299	-0.806	-0.568	-1.494	0.096	-1.324	-1.216	0.522	0.507	0.632	-1.324	-0.406	0.715	0.376	1.100
97	-0.963	-1.116	0.261	-1.191	-1.075	-1.684	-1.916	-0.148	-1.396	-1.072	-0.911	-0.576	-0.406	-0.006	-0.414	-0.508
98	1.390	1.493	1.009	1.517	0.978	1.517	0.616	-1.069	1.944	1.979	1.374	0.180	0.508	1.119	1.343	1.616
99	-1.078	-1.376	-1.291	-1.611	-1.557	-1.705	-1.324	-1.216	-1.846	-1.484	-0.911	-1.543	-1.320	-1.506	-1.599	-1.570
100	1.287	0.351	0.629	-0.786	0.496	-1.414	0.616	-1.513	-0.973	0.059	0.248	-0.196	-1.320	-1.312	-0.605	-1.025
101	-0.206	-0.208	-2.302	-0.163	-1.138	0.048	-1.703	-1.245	0.354	1.626	0.647	-2.128	-2.234	0.915	0.243	-1.053
102	-0.033	0.147	1.113	0.054	0.014	0.096	0.995	0.803	0.048	-0.777	0.252	1.173	0.508	0.365	0.307	1.100
103	-0.206	-0.171	-1.474	-0.786	-0.593	1.246	-1.111	-1.216	1.227	1.626	0.275	-1.553	-2.234	0.864	0.209	-0.020
104	-0.700	-1.423	-1.187	-1.611	-1.012	-0.147	-0.732	-0.919	-0.256	0.001	-1.263	-1.172	0.508	-1.686	-1.327	-0.537
105	1.390	0.427	0.733	1.517	-1.557	1.517	-1.324	-1.216	1.797	1.979	1.772	-0.650	1.422	1.792	1.926	1.071
106	0.082	0.090	-0.175	-0.786	0.014	-1.414	-0.354	-0.504	-0.511	0.530	0.248	-0.413	-0.406	0.339	0.201	0.037
107	0.229	-0.844	-0.254	-0.366	-1.557	-1.165	-1.324	-0.623	-1.140	-0.741	-0.115	-0.821	-1.320	-1.119	-0.849	-1.053
108	0.345	-0.096	-0.254	-0.148	0.496	0.637	0.616	0.209	0.651	0.471	-0.517	0.191	0.508	0.380	0.458	0.554
109	1.287	0.407	-0.303	-0.366	0.496	0.075	0.995	-0.148	0.486	0.825	0.252	0.120	1.422	0.349	0.902	0.554
110	-1.078	0.430	0.733	1.517	0.978	0.928	0.616	-0.445	1.078	0.825	-0.168	0.332	0.508	0.858	0.261	1.071
111	0.576	1.530	-0.224	1.517	1.523	0.907	1.587	0.625	1.216	0.825	1.003	0.694	0.508	1.806	1.504	1.616
112	-0.322	-0.077	-0.175	0.474	-0.048	0.367	0.995	0.803	0.355	0.825	-0.142	0.604	0.508	-0.090	-0.100	-0.479
113	-1.848	-1.475	-1.542	-0.989	-1.620	0.415	-1.916	-2.226	-0.357	-0.306	-0.892	-2.290	-2.234	-1.213	-1.806	-1.570
114	-0.149	-0.096	0.101	-0.771	0.496	-0.534	-0.354	0.120	-0.390	-0.329	-0.517	-0.017	0.508	-0.079	-0.033	0.009
115	-0.803	0.938	-1.187	0.054	0.496	-0.874	-1.324	-1.543	-1.428	-1.931	0.999	-1.639	0.508	-0.790	-0.756	-1.053
116	-0.687	-1.642	0.629	-1.611	-1.557	-0.486	0.616	-0.889	-0.805	-1.072	-1.259	0.078	-1.320	-1.479	-1.440	-0.508
117	-1.457	0.345	-1.567	-1.814	0.978	-0.853	-0.946	-1.543	-1.100	-1.449	-0.150	-1.687	-0.406	-1.700	-1.747	-0.537
118	-1.078	-1.144	-1.922	-1.611	-1.075	0.367	-1.324	-1.216	0.360	0.471	-0.888	-1.819	-1.320	-1.506	-1.599	0.009
119	-0.193	-1.693	-1.187	0.474	-2.039	0.117	-1.324	1.100	0.337	-0.011	-0.915	-0.468	0.508	0.584	0.394	1.071
120	0.633	-1.703	0.378	-0.989	-1.075	-1.144	0.403	-1.275	-1.247	-0.683	-1.661	-0.273	-0.406	0.584	0.569	-1.541
121	0.255	0.961	1.745	1.517	0.978	0.637	1.587	1.812	0.783	0.825	0.628	2.090	0.508	0.858	0.737	0.554
122	-0.296	0.701	0.022	0.474	0.496	0.637	0.616	0.803	0.783	0.825	0.628	0.572	0.508	-0.495	-0.379	0.554

123	-0.193	0.198	-1.119	-0.148	0.496	0.637	0.616	-0.118	0.509	0.471	-0.142	-0.344	0.508	0.403	0.267	0.037
124	1.012	0.692	0.733	0.474	-0.048	1.538	-1.324	-1.216	1.525	0.825	1.026	-0.650	0.508	1.352	1.356	1.616
125	0.518	0.967	-0.426	0.474	0.496	-0.901	1.587	1.485	-1.276	-0.777	1.026	0.996	1.422	-1.011	-0.302	-2.087
126	-0.918	-0.166	-0.806	-0.989	-1.075	-1.144	0.403	-1.275	-0.969	-1.095	0.624	-0.793	-0.406	-0.269	-0.570	0.037
127	0.461	0.668	-0.107	0.894	0.978	0.638	0.238	0.149	1.061	1.201	0.252	0.095	0.508	0.899	0.847	1.100
128	1.012	0.426	-0.738	0.474	-0.048	0.928	0.616	-0.445	0.794	0.825	0.628	-0.317	0.508	0.471	0.758	0.037
129	1.012	0.701	0.733	0.474	0.496	0.637	0.616	0.803	0.783	0.825	0.628	0.879	0.508	0.858	1.022	0.554
130	-0.963	1.265	1.745	-0.771	1.523	0.637	0.995	0.476	0.625	0.766	0.654	1.304	0.508	0.652	0.155	0.066
131	2.057	2.033	1.745	1.517	1.523	1.491	1.587	1.812	1.942	1.979	1.772	2.090	0.508	1.307	1.705	1.616
132	1.012	-0.124	0.022	0.894	-1.138	0.951	0.024	0.803	0.330	-0.812	0.628	0.379	0.508	-0.052	0.400	0.554
133	-0.180	0.501	-1.567	-0.148	1.041	0.590	0.238	-0.683	-0.266	-1.578	-0.164	-0.905	-2.234	-0.640	-0.822	0.009
134	-0.322	-1.168	0.733	-0.771	-0.048	-0.220	0.616	-0.237	0.056	0.825	-1.661	0.416	0.508	-0.269	-0.223	-0.479
135	0.852	0.198	0.353	-0.351	0.496	0.050	0.616	-0.387	-0.216	0.118	-0.142	0.192	0.508	0.571	0.768	-1.053
136	-1.354	-0.064	1.745	-0.351	1.523	-1.435	1.587	1.100	-1.549	-1.072	-1.286	1.771	-2.234	-1.272	-1.667	-1.570
137	-0.527	0.379	0.733	0.474	0.496	1.221	0.616	-0.445	0.680	0.118	0.275	0.332	0.508	0.100	-0.053	0.066
138	0.185	0.515	0.181	0.474	0.978	-1.120	1.587	0.564	-0.825	-0.683	-0.138	0.852	0.508	-0.389	-0.127	0.037
139	-1.078	0.701	1.113	0.474	0.496	0.637	0.616	0.179	0.646	0.825	0.628	0.776	0.508	0.664	0.129	0.066
140	-1.078	0.668	0.733	1.517	0.978	0.953	0.995	0.179	0.510	-0.329	0.252	0.728	0.508	-0.324	-0.543	0.554
141	-0.527	0.458	-0.254	-0.771	0.978	0.074	1.587	0.564	-0.218	-0.329	-0.142	0.667	0.508	-0.997	-0.800	-0.479
142	-1.078	-1.216	1.089	-1.394	0.496	0.341	0.616	0.476	-0.197	-0.271	-2.063	0.889	0.508	-0.534	-0.687	-0.996
143	-0.700	-1.424	0.329	-0.973	0.496	-1.976	0.616	-1.216	-1.533	-0.660	-2.408	-0.206	-1.320	-1.521	-1.466	-0.996
144	-1.078	0.668	0.733	1.517	0.978	0.953	0.995	0.179	0.510	-0.329	0.252	0.728	0.508	-0.324	-0.543	0.554
145	1.012	-0.105	0.457	-0.568	-0.048	0.050	0.616	0.803	0.047	0.413	-0.119	0.757	0.508	0.858	1.022	-0.479
146	0.461	-0.332	-0.303	-0.989	-1.012	-0.512	1.587	0.564	-0.388	0.059	0.256	0.633	0.508	-0.546	-0.130	-0.508
147	-1.078	0.701	1.113	0.474	0.496	0.637	0.616	0.179	0.646	0.825	0.628	0.776	0.508	0.664	0.129	0.066
148	-1.297	0.701	1.009	1.097	0.496	0.367	1.208	0.179	0.639	0.825	0.628	0.921	1.422	0.471	0.043	0.554
149	-1.078	0.668	0.733	1.517	0.978	0.953	0.995	0.179	0.510	-0.329	0.252	0.728	0.508	-0.324	-0.543	0.554
150	2.057	0.435	-0.175	0.474	0.496	0.928	0.995	-0.178	0.951	0.471	0.230	0.171	1.422	1.119	1.707	1.100
151	-1.078	0.701	1.113	0.474	0.496	0.637	0.616	0.179	0.646	0.825	0.628	0.776	0.508	0.664	0.129	0.066
152	-0.322	0.407	-0.910	-0.568	0.496	0.050	0.238	0.803	-0.098	-0.741	0.252	0.034	0.508	-0.052	-0.077	0.554
153	-1.078	0.668	0.733	1.517	0.978	0.953	0.995	0.179	0.510	-0.329	0.252	0.728	0.508	-0.324	-0.543	0.554
154	1.024	1.474	-0.910	-0.148	1.523	1.808	0.616	-0.148	1.537	0.471	0.999	-0.261	1.422	0.569	0.949	1.616
155	1.287	1.502	-0.027	0.272	1.523	1.221	1.587	0.534	1.080	0.825	1.026	0.740	0.508	0.277	0.726	0.554
156	1.012	-0.109	0.077	-0.148	-1.075	0.637	0.616	0.179	0.488	0.413	0.628	0.313	1.422	0.403	0.837	0.037
157	-1.078	0.701	1.113	0.474	0.496	0.637	0.616	0.179	0.646	0.825	0.628	0.776	0.508	0.664	0.129	0.066
158	-1.078	0.668	0.733	1.517	0.978	0.953	0.995	0.179	0.510	-0.329	0.252	0.728	0.508	-0.324	-0.543	0.554
159	-1.078	0.701	1.113	0.474	0.496	0.637	0.616	0.179	0.646	0.825	0.628	0.776	0.508	0.664	0.129	0.066
160	-2.123	1.740	0.985	1.517	1.523	0.637	1.587	0.564	0.646	0.825	1.397	1.202	1.422	0.858	0.006	0.066
161	-0.527	0.169	-0.530	0.474	0.496	0.367	0.616	-0.445	-0.087	-1.130	-0.168	-0.220	0.508	0.624	0.303	0.554
162	-1.078	1.740	-0.175	-0.366	1.523	1.808	-0.567	-0.919	1.372	0.024	1.397	-0.673	1.422	0.087	-0.133	1.616
163	0.069	0.435	0.733	1.097	0.496	0.637	0.616	0.179	0.649	0.082	0.230	0.606	0.508	0.624	0.525	1.071
164	-0.033	-0.096	-0.003	-0.568	0.496	0.074	-0.354	-0.207	-0.076	-0.329	-0.517	-0.210	0.508	-0.324	-0.163	0.037
165	0.229	0.198	-0.358	-0.771	0.496	0.367	0.616	0.803	0.639	0.825	-0.142	0.401	0.508	0.471	0.482	0.554

166	-0.976	0.464	0.733	0.474	0.496	0.367	1.208	0.891	0.354	0.059	0.256	1.118	0.508	0.624	0.145	0.554
167	-1.078	0.430	0.733	1.517	0.978	1.245	0.616	-0.445	1.233	0.825	-0.168	0.332	0.508	0.858	0.261	1.071
168	0.461	0.701	0.378	-0.989	0.496	-0.241	0.403	-0.088	0.056	0.471	0.628	0.267	1.422	1.093	1.105	0.037
169	-0.033	0.147	1.113	0.054	0.014	0.096	0.995	0.803	0.048	-0.777	0.252	1.173	0.508	0.365	0.307	1.100

170	-0.700	0.761	0.837	0.272	1.523	1.538	1.587	1.812	1.648	1.155	-0.164	1.692	1.422	-0.092	-0.119	1.616
171	1.287	0.407	-0.303	-0.366	0.496	-0.241	0.995	-0.148	0.330	0.825	0.252	0.120	1.422	0.104	0.735	0.554
172	-2.123	-3.296	-2.302	-2.654	-2.584	-2.877	-2.294	-2.226	-3.161	-2.638	-2.806	-2.754	-2.234	-2.689	-2.909	-2.632
173	-0.309	-0.096	0.101	0.054	0.496	0.074	0.995	1.812	-0.218	-0.329	-0.517	1.175	0.508	-0.779	-0.574	-0.479
174	0.358	-0.357	1.113	-0.568	0.014	-0.241	1.587	0.861	-0.241	-0.329	-0.517	1.396	-0.406	-0.324	-0.151	0.037
175	-1.341	-1.433	-1.671	-0.568	-1.557	-1.098	-2.294	-2.226	-1.553	-1.130	-0.915	-2.478	-2.234	-0.712	-1.290	-2.115
176	0.576	1.530	-0.224	1.517	1.523	0.907	1.587	0.625	1.216	0.825	1.003	0.694	0.508	1.806	1.504	1.616
177	-0.309	-1.191	-1.291	-1.191	-0.530	-0.534	-1.324	-1.216	-0.532	-0.329	-1.290	-1.543	-1.320	-0.518	-0.647	-0.508
178	0.345	-0.096	-0.254	-0.148	0.496	0.637	0.616	0.209	0.651	0.471	-0.517	0.191	0.508	0.624	0.625	0.554
179	-1.848	-1.475	-1.542	-0.989	-1.620	-0.219	-1.916	-2.226	-0.668	-0.306	-0.892	-2.290	-2.234	-1.702	-2.140	-1.570
180	1.012	0.701	0.733	0.474	0.496	0.637	0.024	0.803	0.783	0.825	0.628	0.686	0.508	0.858	1.022	0.554
181	0.345	-0.659	0.353	0.054	-0.530	0.637	0.616	-0.415	0.641	0.825	-0.494	0.176	0.508	0.624	0.625	0.037
182	1.012	0.663	0.022	0.474	-0.048	1.538	0.830	-0.118	1.104	0.471	0.999	0.239	1.422	0.858	1.148	0.554
183	-0.322	-0.077	-0.175	0.474	-0.048	0.367	0.995	0.803	0.355	0.825	-0.142	0.604	0.508	-0.090	-0.100	-0.479
184	-1.078	0.207	0.837	0.474	1.041	0.367	1.587	1.188	-0.064	-0.683	-0.540	1.419	1.422	-0.545	-0.570	0.037
185	1.012	1.199	-0.910	0.474	0.978	0.637	0.616	-0.445	1.074	1.214	0.999	-0.391	1.422	1.780	1.773	1.100
186	1.287	1.759	0.353	1.517	0.978	0.997	1.587	1.812	1.665	1.979	1.772	1.473	1.422	1.780	1.873	1.616
187	-0.149	0.108	0.181	-0.568	0.978	-0.827	0.024	0.209	-0.818	-0.329	-0.521	0.183	0.508	-0.518	-0.332	-1.025
188	-1.078	-1.144	-1.922	-1.611	-1.075	0.367	-1.324	-1.216	0.360	0.471	-0.888	-1.819	-1.320	-1.506	-1.599	0.009
189	0.461	0.701	0.733	0.474	0.496	0.637	-0.189	-1.216	1.227	1.626	0.628	-0.281	0.508	0.664	0.689	1.100
190	0.531	0.724	0.457	1.517	0.978	-0.219	1.587	-0.683	0.318	1.979	0.256	0.427	0.508	1.547	1.307	-1.082
191	-1.078	-0.893	0.733	0.474	0.496	0.367	0.238	0.209	-0.503	-1.484	-1.661	0.498	0.508	-1.312	-1.215	-0.479
192	-1.078	0.961	0.629	1.517	0.978	1.245	0.616	-0.060	1.233	0.825	0.628	0.458	-1.320	0.858	0.009	1.071
193	0.255	0.961	1.745	1.517	0.978	0.637	1.587	1.812	0.783	0.825	0.628	2.090	0.508	0.858	0.737	0.554
194	-1.457	-0.612	-1.015	-1.191	-0.950	-0.512	-1.324	-1.602	-0.495	-0.213	-0.168	-1.596	-0.406	0.705	-0.113	-0.537
195	0.461	0.701	-0.027	1.517	0.496	0.637	0.616	-0.445	0.925	0.825	0.628	-0.010	0.508	0.858	0.821	1.071
196	-0.527	0.701	0.733	-0.366	0.496	0.637	0.995	0.506	-0.221	-0.718	0.628	0.873	-0.406	-0.090	-0.310	-1.025
197	1.012	0.133	0.733	1.517	-1.557	1.808	-1.324	-1.216	1.824	1.626	1.397	-0.650	0.508	0.858	1.022	1.100
198	0.198	-0.945	0.733	0.474	-0.111	-0.534	0.995	-0.772	-0.544	-0.365	-1.290	0.310	0.508	0.403	0.405	-0.508
199	1.012	0.701	0.101	0.474	0.496	0.637	0.616	0.803	0.486	0.024	0.628	0.603	0.508	0.363	0.685	0.554
200	-1.078	-1.964	-1.291	-1.611	-1.557	-1.412	-1.324	-1.216	-1.411	-1.095	-1.661	-1.543	-1.320	-1.506	-1.599	-1.025
201	2.057	-0.402	-2.302	1.517	-2.584	1.808	-2.294	-2.226	2.097	1.979	1.397	-2.754	1.422	2.041	2.332	1.616
202	0.461	-0.132	0.733	1.097	-1.557	1.200	-0.140	-1.840	1.492	1.178	0.999	-0.537	0.508	2.041	1.625	1.616
203	-0.527	-0.370	0.733	0.054	-1.557	0.930	-0.140	0.803	0.788	0.436	0.628	0.634	0.508	0.858	0.462	0.583
204	-0.322	-0.874	0.249	0.474	-0.048	0.074	0.024	-0.237	-0.388	-0.777	-1.286	0.003	-1.320	-0.585	-0.689	-0.508
205	-1.078	0.701	0.101	0.474	0.496	0.637	0.616	0.803	0.354	-0.329	0.628	0.603	0.508	-0.324	-0.543	0.554
206	0.736	0.701	-0.199	0.474	0.496	0.637	0.238	0.803	0.783	0.825	0.628	0.341	-0.406	0.858	0.796	0.554
207	-0.687	-0.631	-0.634	-0.568	-0.530	-0.534	-0.354	-0.207	-0.532	-0.329	-0.517	-0.486	-0.406	-1.245	-1.156	-0.508
208	-1.078	-1.936	-0.738	1.517	-1.557	0.659	-0.732	0.239	-0.782	-2.638	-1.684	-0.452	0.508	-1.700	-1.479	-0.450

209	-0.252	-1.708	0.224	-0.351	-0.468	0.074	-0.140	-1.216	-0.386	-0.388	-2.037	-0.500	-1.320	-1.508	-1.300	-1.025
210	-0.412	-1.429	0.077	-1.409	-0.530	-1.976	-0.140	-0.118	-1.411	-1.095	-1.661	-0.062	-1.320	-0.520	-0.692	0.037
211	-0.687	0.701	0.457	0.894	0.496	0.637	0.616	0.179	0.354	-0.329	0.628	0.483	-1.320	-0.324	-0.657	0.554
212	-0.700	0.198	0.733	-0.148	0.496	0.367	0.616	0.773	-0.376	-1.130	-0.142	0.864	-1.320	-0.324	-0.653	-0.508
213	1.390	0.427	0.733	1.517	-1.557	1.200	-1.324	-1.216	1.642	1.979	1.772	-0.650	1.422	1.547	1.759	1.071
214	1.012	0.692	0.733	0.474	-0.048	1.538	-1.324	-1.216	1.525	0.825	1.026	-0.650	0.508	1.352	1.356	1.616
215	1.012	0.701	0.022	0.474	0.496	0.637	0.616	0.209	0.783	0.825	0.628	0.313	0.508	0.858	1.022	0.554
216	1.390	1.493	1.009	1.517	0.978	1.200	0.616	-1.069	1.789	1.979	1.374	0.180	0.508	1.119	1.343	1.616
217	-1.354	0.435	0.077	0.474	0.496	-0.241	0.995	0.803	-0.679	-1.130	0.230	0.709	0.508	-1.272	-1.289	-0.479
218	-0.610	-1.932	1.389	-2.031	-0.530	-0.760	1.587	0.504	-0.936	-1.072	-2.431	1.360	1.422	-0.403	-0.278	-0.537
219	0.229	-0.844	-0.254	-0.366	-1.557	-1.165	-1.324	-0.623	-1.140	-0.741	-0.115	-0.821	-1.320	-1.119	-0.849	-1.053
220	-0.193	0.351	-1.187	-0.786	0.496	-1.098	-1.324	1.100	-0.826	-0.741	0.248	-0.468	0.508	0.584	0.394	0.037
221	-0.425	0.351	0.605	-0.786	0.496	-1.098	-1.703	-0.831	-1.692	-1.519	0.248	-0.663	0.508	-0.846	-0.658	-2.087
222	-0.193	-1.693	-1.187	0.474	-2.039	0.434	-1.324	1.100	0.492	-0.011	-0.915	-0.468	0.508	0.584	0.394	1.071
223	0.620	0.654	-0.451	-1.409	1.041	-0.197	-1.538	-0.178	-0.761	-1.402	0.275	-0.776	-0.406	-0.232	0.019	-0.479
224	0.069	-0.869	-0.175	-2.234	-0.530	-1.976	-0.354	0.090	-1.411	-1.095	-0.888	-0.154	0.508	-0.779	-0.432	0.037
225	0.518	0.967	-0.426	0.474	0.496	0.366	1.587	1.485	-0.654	-0.777	1.026	0.996	1.422	-1.011	-0.302	-2.087
226	-0.976	-1.106	-1.187	-1.409	-0.530	0.681	-1.324	-1.513	-0.222	-0.400	-1.259	-1.624	-1.320	-1.700	-1.689	-1.541
227	-0.033	0.351	-1.947	-0.786	0.496	-1.391	-0.140	-0.148	-1.550	-1.130	0.248	-0.970	-1.320	-1.040	-0.905	-1.570
228	1.287	0.351	0.629	-0.786	0.496	-1.098	0.616	-1.513	-0.818	0.059	0.248	-0.196	-1.320	-1.312	-0.605	-1.025
229	-0.193	-0.735	-1.187	-0.786	-1.620	-1.368	-1.324	-0.831	-0.838	-0.388	0.248	-1.319	0.508	-0.623	-0.428	0.037
230	-0.527	0.109	-0.935	-1.191	-0.530	0.637	0.238	-0.623	0.930	0.825	0.624	-0.622	0.508	0.471	0.198	1.100
231	-1.457	0.678	-1.187	0.894	0.014	-0.557	-1.111	-1.246	-1.271	-1.166	0.999	-1.439	-1.320	-1.700	-1.873	-2.087
232	-0.527	-0.631	-1.947	-0.568	-0.530	-0.827	1.587	-0.415	-0.361	0.919	-0.517	-0.524	-1.320	-1.205	-1.193	-1.053
233	-0.976	0.351	-1.187	-0.786	0.496	-1.098	-1.324	1.100	-0.826	-0.741	0.248	-0.468	0.508	-1.232	-1.121	0.037
234	-0.816	-1.666	0.605	-0.351	-0.530	-1.773	-0.732	-0.592	-1.017	0.024	-2.033	-0.248	-0.406	-0.752	-0.854	-0.508
235	-1.470	-1.614	-1.542	-0.351	-1.557	-0.557	0.238	-0.118	-0.823	-0.718	-1.282	-0.645	-1.320	-1.506	-1.737	-1.053
236	-0.700	-2.799	0.985	-1.611	-2.102	-2.020	0.024	-0.265	-2.017	-1.896	-2.435	0.312	-1.320	-1.312	-1.324	-1.025
237	-0.976	-1.410	-1.187	-1.611	0.559	-1.976	-1.324	-0.207	-1.120	0.082	-2.408	-1.046	0.508	-1.571	-1.349	-0.508
238	-0.193	-0.127	0.224	0.677	-2.039	0.118	-0.732	-1.008	-1.073	-1.896	1.397	-0.609	-1.320	-2.040	-1.642	-1.570
239	-0.700	-1.168	-0.175	-1.191	-0.048	-0.872	-1.538	1.188	-0.411	0.059	-1.661	-0.046	-0.406	-0.585	-0.706	0.009
240	-0.918	-0.166	-0.806	-0.989	-1.075	-0.827	0.403	-1.275	-0.814	-1.095	0.624	-0.793	-0.406	-0.025	-0.403	0.037
241	0.082	0.090	-0.175	-0.786	0.014	-1.098	-0.354	-0.504	-0.355	0.530	0.248	-0.413	-0.406	0.584	0.368	0.037
242	-0.803	0.938	-1.187	0.054	0.496	-0.557	-1.324	-1.543	-1.273	-1.931	0.999	-1.639	0.508	-0.790	-0.756	-1.053
243	1.390	-0.954	-1.947	-1.611	-0.530	-1.120	-1.324	-0.948	-1.538	-1.484	-0.919	-1.722	-1.320	-1.312	-0.563	-1.570
244	-1.457	-1.186	-1.922	0.054	-1.012	-1.705	0.238	0.209	-1.562	-0.718	-0.892	-0.672	-0.406	-1.232	-1.431	-1.570
245	-0.136	-0.299	-0.806	-0.568	-1.494	0.096	-1.324	-1.216	0.522	0.507	0.632	-1.324	-0.406	0.471	0.209	1.100
246	-0.687	-1.642	0.629	-1.611	-1.557	-1.120	0.616	-0.889	-1.117	-1.072	-1.259	0.078	-1.320	-1.479	-1.440	-0.508
247	0.358	-0.854	-1.567	0.054	-0.468	-1.435	0.024	0.270	-1.122	-1.095	-0.888	-0.581	0.508	-0.819	-0.362	0.037
248	-0.425	-0.631	0.629	0.474	-0.530	-0.827	-1.324	-1.246	-1.271	-0.777	-0.517	-0.713	0.508	-1.378	-1.016	-2.087
249	0.633	-0.412	0.249	-1.394	-1.494	0.299	-0.354	-0.118	-0.399	-0.741	0.624	-0.059	0.508	-0.739	-0.209	-1.053
250	-1.457	0.345	-1.567	-1.814	0.978	-0.219	-0.946	-1.543	-0.789	-1.449	-0.150	-1.687	-0.406	-1.700	-1.747	-0.537
251	-1.457	0.351	-1.567	-0.786	0.496	-1.098	-1.111	0.861	-1.408	-1.519	0.248	-0.667	0.508	-1.049	-1.176	-1.053

252	0.633	-1.703	0.378	-0.989	-1.075	-0.827	0.403	-1.275	-1.091	-0.683	-1.661	-0.273	-0.406	0.584	0.569	-1.541
253	-0.790	-1.656	0.353	-0.989	-1.620	0.118	-0.567	-1.186	-0.232	-0.812	-1.259	-0.560	1.422	-0.923	-0.726	0.037
254	-0.700	-1.423	-1.187	-1.611	-1.012	-1.097	-0.732	-0.919	-0.723	0.001	-1.263	-1.172	0.508	-1.441	-1.160	-0.537
255	-0.687	-1.665	-0.634	-0.989	-2.039	-1.683	0.024	-0.889	-1.556	-0.718	-0.888	-0.667	-1.320	-0.623	-0.860	-1.541
256	0.749	-1.680	-1.542	-0.351	-0.593	-1.750	-0.567	-0.148	-0.995	-0.294	-2.033	-0.923	-1.320	1.091	0.821	0.009
257	-1.341	-0.607	0.654	-2.031	-1.557	0.052	-0.946	-1.158	-0.364	-1.060	0.256	-0.528	-0.406	-0.429	-0.844	0.066
258	-0.976	0.351	-0.254	-0.786	0.496	-1.098	-1.324	1.100	-1.270	-1.542	0.248	-0.053	-1.320	-0.480	-0.862	-0.508
259	-0.412	-1.172	-1.567	-0.366	-1.075	-1.120	-0.567	0.861	-1.268	-0.365	-0.915	-0.492	0.508	-0.777	-0.613	-2.115
260	-0.963	-1.116	0.261	-1.191	-1.075	-1.368	-1.916	-0.148	-1.240	-1.072	-0.911	-0.576	-0.406	0.238	-0.247	-0.508
261	-2.123	-1.988	-0.500	-2.234	-0.530	-1.120	-0.732	-1.158	-1.267	-1.095	-2.435	-0.980	-0.406	0.102	-0.762	-1.025
262	-0.700	-0.948	0.249	-0.568	-1.012	-2.313	-0.354	-0.772	-1.861	-1.072	-0.521	-0.347	-0.406	-1.700	-1.463	-1.053
263	-0.527	0.192	1.745	1.517	0.978	-0.805	1.587	0.921	-0.404	1.178	-0.540	1.702	-1.320	0.559	0.007	-1.570
264	-0.700	0.729	-0.279	0.474	0.496	0.637	0.616	-0.831	0.798	0.471	0.605	-0.290	0.508	0.131	-0.090	1.100
265	-0.193	0.198	-1.119	-0.148	0.496	0.637	0.616	-0.118	0.509	0.471	-0.142	-0.344	0.508	0.403	0.267	0.037
266	0.185	-0.631	-0.224	-0.568	-0.530	-0.534	1.208	0.564	-0.251	-1.130	-0.517	0.542	1.422	-0.518	-0.089	1.616
267	0.736	0.938	0.733	1.517	0.496	0.320	-0.140	0.803	-0.080	-1.461	0.999	0.634	-1.320	0.190	0.213	1.071
268	0.633	0.967	-1.291	1.517	0.496	-0.262	0.995	-0.562	0.759	1.590	1.026	-0.500	-2.234	0.858	0.502	1.071
269	1.403	0.938	0.733	0.894	0.496	0.637	-0.140	0.803	0.781	0.436	0.999	0.634	-1.320	1.093	1.066	1.071
270	1.012	0.426	0.378	0.474	-0.048	-0.219	0.024	0.032	0.351	0.825	0.628	0.182	-1.320	0.858	0.770	0.554
271	0.909	0.170	0.378	0.677	0.496	0.076	-0.781	0.831	0.374	0.494	-0.119	0.285	-2.234	1.558	1.080	0.554
272	1.012	0.435	-0.530	-0.148	0.496	-0.264	0.024	-0.592	0.330	0.825	0.230	-0.489	-0.406	0.664	0.764	0.554
273	1.012	0.701	0.733	0.894	0.496	0.320	-0.140	0.803	0.358	-0.294	0.628	0.634	-1.320	-0.293	-0.012	1.100
274	1.781	0.701	1.009	0.474	0.496	0.611	0.616	1.188	0.628	0.413	0.628	1.176	-1.320	0.430	0.760	0.554
275	1.781	1.227	1.009	0.474	0.978	0.637	1.208	1.812	0.777	0.413	1.026	1.643	0.508	0.885	1.323	1.100
276	1.012	0.701	0.733	0.474	0.496	0.637	0.616	0.803	0.783	0.825	0.628	0.879	0.508	0.624	0.864	0.554
277	2.057	0.938	1.745	0.894	0.496	0.928	1.208	1.427	1.057	0.766	0.999	1.793	0.508	1.806	2.048	1.071
278	1.012	0.407	0.733	0.474	0.496	0.637	0.024	0.417	0.495	0.047	0.252	0.511	-0.406	0.624	0.738	0.554
279	1.012	0.701	0.353	0.474	0.496	0.637	0.024	0.417	0.630	0.413	0.628	0.341	-0.406	0.858	0.896	0.554
280	0.736	0.701	0.733	0.894	0.496	-0.220	-0.140	0.803	0.330	0.401	0.628	0.634	0.508	0.186	0.464	1.100
281	1.781	1.264	1.113	0.894	1.523	0.320	-0.519	1.812	0.216	-0.294	0.605	1.130	0.508	0.650	1.161	0.583
282	1.506	0.701	1.365	0.474	0.496	1.245	0.451	1.515	1.244	1.237	0.628	1.422	1.422	0.681	1.208	0.554
283	0.736	0.407	0.733	0.474	0.496	0.074	-0.140	0.803	0.200	0.413	0.252	0.634	0.508	0.420	0.622	0.037
284	0.736	0.701	0.353	0.474	0.496	0.637	-0.732	0.803	0.783	0.825	0.628	0.270	0.508	0.624	0.763	0.554
285	-0.643	-0.990	-2.302	1.517	-2.584	-1.610	-0.781	-2.226	-0.109	1.979	0.647	-2.263	-1.320	2.041	0.976	-0.020
286	1.506	1.740	1.745	1.517	1.523	1.491	0.073	0.803	1.073	1.178	1.397	1.151	0.508	0.900	1.232	-0.479
287	1.665	0.905	1.009	1.517	0.978	0.928	-0.140	1.427	1.089	1.237	0.624	1.030	0.508	0.369	0.931	0.554
288	1.403	1.474	1.745	0.894	1.523	1.491	0.073	1.812	1.636	1.155	0.999	1.599	0.508	-0.053	0.544	1.616
289	1.506	1.768	1.365	0.272	1.523	0.611	-0.519	1.812	0.346	0.401	1.374	1.235	1.422	-0.312	0.535	-0.450
290	1.012	0.701	1.365	0.474	0.496	0.637	-0.140	0.803	0.783	0.825	0.628	0.910	0.508	0.664	0.890	0.554
291	1.012	0.701	1.009	0.272	0.496	0.637	-0.140	0.803	0.631	1.178	0.628	0.756	0.508	0.610	0.854	-0.479
292	1.012	0.701	1.009	0.474	0.496	0.637	-0.140	0.803	0.783	0.825	0.628	0.756	0.508	0.858	1.022	0.554
293	1.390	1.530	1.365	0.894	1.523	1.517	0.073	1.515	1.508	1.567	1.003	1.299	0.508	0.610	0.997	0.583
294	0.461	-0.040	1.113	-0.771	0.496	0.003	-0.519	0.803	-0.523	-1.484	-0.513	0.682	0.508	-1.245	-0.608	0.066

295	1.403	1.479	1.469	0.474	1.041	0.637	-0.140	1.130	0.930	0.825	1.397	1.102	-0.406	1.123	1.213	1.100
296	1.781	0.961	0.758	0.474	0.978	0.611	-0.567	1.427	0.060	-1.130	0.578	0.784	1.422	0.226	0.997	0.583
297	0.736	0.938	0.298	1.517	0.496	0.320	-1.324	0.476	-0.080	-1.461	0.999	-0.082	-1.320	0.190	0.213	1.071
298	1.012	0.967	-1.291	1.097	0.496	-0.262	0.616	-0.562	0.759	1.590	1.026	-0.623	1.422	0.664	1.016	1.071
299	0.736	0.701	0.733	0.474	0.496	0.637	0.238	0.803	0.783	0.825	0.628	0.756	-0.406	0.858	0.796	0.554
300	1.012	0.938	0.733	0.894	0.496	0.637	-0.140	0.803	0.781	0.436	0.999	0.634	-1.320	1.093	0.928	1.071
301	1.012	0.426	0.077	0.474	-0.048	-0.219	-0.567	0.803	0.351	0.825	0.628	0.200	-1.320	0.858	0.770	0.554

302	1.012	0.701	-0.659	0.474	0.496	0.637	0.024	0.803	0.783	0.825	0.628	0.069	-1.320	0.858	0.770	0.554
303	1.012	0.701	0.733	0.474	0.496	0.637	-0.140	0.803	0.783	0.825	0.628	0.634	0.508	0.858	1.022	0.554
304	1.012	0.701	0.733	0.474	0.496	0.367	-0.140	0.803	0.639	0.825	0.628	0.634	0.508	0.858	1.022	0.554
305	1.012	0.701	0.733	0.474	0.496	0.637	-0.140	0.803	0.211	0.047	0.628	0.634	0.508	0.858	1.022	-0.479
306	1.012	0.435	-0.530	-0.148	0.496	-0.264	0.024	-0.592	0.330	0.825	0.230	-0.489	-0.406	0.664	0.764	0.554
307	1.012	0.701	0.733	0.894	0.496	0.320	-0.140	0.803	0.358	-0.294	0.628	0.634	-1.320	-0.293	-0.012	1.100
308	1.781	0.701	1.009	0.474	0.496	0.611	0.616	1.188	0.628	0.413	0.628	1.176	-1.320	0.430	0.760	0.554
309	1.781	1.227	1.009	0.474	0.978	0.637	1.208	1.812	0.930	0.825	1.026	1.643	0.508	0.885	1.323	1.100
310	1.390	0.938	0.733	0.474	0.496	0.050	-0.354	0.803	-0.078	-0.683	0.999	0.563	-1.320	0.434	0.623	0.554
311	1.114	2.033	1.745	1.517	1.523	0.050	1.208	1.041	0.071	-1.060	1.772	1.618	-2.234	0.695	0.576	1.616
312	1.012	0.701	0.733	0.474	0.496	0.637	-0.140	0.803	0.783	0.825	0.628	0.634	0.508	0.858	1.022	0.554
313	1.012	0.113	0.733	0.894	0.496	-0.264	-0.354	1.100	0.045	0.059	-0.123	0.693	-1.320	0.186	0.313	0.554
314	1.506	0.477	1.365	0.272	0.434	0.048	0.616	1.812	0.616	0.378	0.234	1.604	0.508	0.173	0.733	1.616
315	0.736	0.995	0.733	0.474	0.496	-0.220	-0.732	0.803	0.056	0.825	1.003	0.441	0.508	-0.242	0.174	-0.479
316	1.781	1.227	1.009	0.474	0.978	0.637	1.208	1.812	0.777	0.413	1.026	1.643	0.508	0.885	1.323	1.100
317	1.012	0.701	0.733	0.474	0.496	0.637	0.616	0.803	0.783	0.825	0.628	0.879	0.508	0.624	0.864	0.554
318	2.057	0.938	1.745	0.894	0.496	0.928	1.208	1.427	1.057	0.766	0.999	1.793	0.508	1.806	2.048	1.071
319	1.012	0.407	0.733	-0.148	0.496	0.637	0.024	0.417	0.495	0.047	0.252	0.511	-0.406	0.624	0.738	0.554
320	1.012	0.701	0.353	0.474	0.496	0.637	0.024	0.417	0.630	0.413	0.628	0.341	-0.406	0.858	0.896	0.554
321	0.736	0.701	0.733	0.894	0.496	-0.220	-0.140	0.803	0.330	0.401	0.628	0.634	0.508	0.186	0.464	1.100

Annexure 6: Correlations of Measurement Model

	Charge_Time	Eco Factor	FIN_RISK	Incentives	Infrastructure	Intention_2_Buy	PER_RISK	PSY_RISK	PURCHASE_INTENTION	Perf_Value	Price	RISK	Range	Reliability	TECHNOLOGY	Willingness_2_Pay
Charge_Time	1.000	0.461	0.254	0.386	0.215	0.388	0.121	0.251	0.517	0.501	0.505	0.263	0.251	0.593	0.802	0.484
ECONOMIC FACTORS	0.461	1.000	0.414	0.635	0.763	0.613	0.408	0.464	0.645	0.498	0.870	0.523	0.351	0.552	0.592	0.538
FIN_RISK	0.254	0.414	1.000	0.376	0.470	0.365	0.516	0.504	0.342	0.215	0.233	0.833	0.257	0.291	0.327	0.282
Incentives	0.386	0.635	0.376	1.000	0.374	0.610	0.349	0.303	0.638	0.511	0.627	0.415	0.258	0.551	0.550	0.501
Infrastructure	0.215	0.763	0.470	0.374	1.000	0.339	0.545	0.591	0.356	0.264	0.348	0.649	0.248	0.255	0.286	0.307
Intention_2_Buy	0.388	0.613	0.365	0.610	0.339	1.000	0.281	0.210	0.915	0.605	0.620	0.347	0.402	0.604	0.607	0.670
PER_RISK	0.121	0.408	0.516	0.349	0.545	0.281	1.000	0.534	0.302	0.252	0.165	0.792	0.305	0.215	0.232	0.243
PSY_RISK	0.251	0.464	0.504	0.303	0.591	0.210	0.534	1.000	0.221	0.110	0.216	0.841	0.282	0.166	0.244	0.267
PURCHASE_INTENTION	0.517	0.645	0.342	0.638	0.356	0.915	0.302	0.221	1.000	0.835	0.655	0.348	0.432	0.766	0.769	0.825
Perf_Value	0.501	0.498	0.215	0.511	0.264	0.605	0.252	0.110	0.835	1.000	0.515	0.226	0.324	0.746	0.734	0.573
Price	0.505	0.870	0.233	0.627	0.348	0.620	0.165	0.216	0.655	0.515	1.000	0.253	0.317	0.601	0.636	0.539
RISK	0.263	0.523	0.833	0.415	0.649	0.347	0.792	0.841	0.348	0.226	0.253	1.000	0.339	0.273	0.329	0.323
Range	0.251	0.351	0.257	0.258	0.248	0.402	0.305	0.282	0.432	0.324	0.317	0.339	1.000	0.362	0.476	0.394
Reliability	0.593	0.552	0.291	0.551	0.255	0.604	0.215	0.166	0.766	0.746	0.601	0.273	0.362	1.000	0.945	0.668
TECHNOLOGY	0.802	0.592	0.327	0.550	0.286	0.607	0.232	0.244	0.769	0.734	0.636	0.329	0.476	0.945	1.000	0.685
Willingness_2_Pay	0.484	0.538	0.282	0.501	0.307	0.670	0.243	0.267	0.825	0.573	0.539	0.323	0.394	0.668	0.685	1.000

Annexure 7: Covariance of Measurement Model

	Charge_Time	ECONOMIC FACTORS	FIN_RISK	Incentives	Infrastructure	Intention_2_Buy	PER_RISK	PSY_RISK	PURCHASE_INTENTION	Perf_Value	Price	RISK	Range	Reliability	TECHNOLOGY	Willingness_2_Pay
Charge_Time	1.000	0.461	0.254	0.386	0.215	0.388	0.121	0.251	0.517	0.501	0.505	0.263	0.251	0.593	0.802	0.484
ECONOMIC FACTORS	0.461	1.000	0.414	0.635	0.763	0.613	0.408	0.464	0.645	0.498	0.870	0.523	0.351	0.552	0.592	0.538
FIN_RISK	0.254	0.414	1.000	0.376	0.470	0.365	0.516	0.504	0.342	0.215	0.233	0.833	0.257	0.291	0.327	0.282
Incentives	0.386	0.635	0.376	1.000	0.374	0.610	0.349	0.303	0.638	0.511	0.627	0.415	0.258	0.551	0.550	0.501
Infrastructure	0.215	0.763	0.470	0.374	1.000	0.339	0.545	0.591	0.356	0.264	0.348	0.649	0.248	0.255	0.286	0.307
Intention_2_Buy	0.388	0.613	0.365	0.610	0.339	1.000	0.281	0.210	0.915	0.605	0.620	0.347	0.402	0.604	0.607	0.670
PER_RISK	0.121	0.408	0.516	0.349	0.545	0.281	1.000	0.534	0.302	0.252	0.165	0.792	0.305	0.215	0.232	0.243
PSY_RISK	0.251	0.464	0.504	0.303	0.591	0.210	0.534	1.000	0.221	0.110	0.216	0.841	0.282	0.166	0.244	0.267
PURCHASE_INTENTION	0.517	0.645	0.342	0.638	0.356	0.915	0.302	0.221	1.000	0.835	0.655	0.348	0.432	0.766	0.769	0.825
Perf_Value	0.501	0.498	0.215	0.511	0.264	0.605	0.252	0.110	0.835	1.000	0.515	0.226	0.324	0.746	0.734	0.573
Price	0.505	0.870	0.233	0.627	0.348	0.620	0.165	0.216	0.655	0.515	1.000	0.253	0.317	0.601	0.636	0.539
RISK	0.263	0.523	0.833	0.415	0.649	0.347	0.792	0.841	0.348	0.226	0.253	1.000	0.339	0.273	0.329	0.323
Range	0.251	0.351	0.257	0.258	0.248	0.402	0.305	0.282	0.432	0.324	0.317	0.339	1.000	0.362	0.476	0.394
Reliability	0.593	0.552	0.291	0.551	0.255	0.604	0.215	0.166	0.766	0.746	0.601	0.273	0.362	1.000	0.945	0.668
TECHNOLOGY	0.802	0.592	0.327	0.550	0.286	0.607	0.232	0.244	0.769	0.734	0.636	0.329	0.476	0.945	1.000	0.685
Willingness_2_Pay	0.484	0.538	0.282	0.501	0.307	0.670	0.243	0.267	0.825	0.573	0.539	0.323	0.394	0.668	0.685	1.000

Annexure 8: Descriptives of Measurement Model

	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	No of observations	Cramér-von Mises test statistic	Cramér-von Mises p value
Charge_Time	0.000	-0.149	-2.123	2.057	1.000	-0.958	0.086	322.000	0.715	0.000
ECONOMIC FACTORS	0.000	0.351	-3.296	2.033	1.000	0.157	-0.731	322.000	1.519	0.000
FIN_RISK	0.000	0.224	-2.302	1.745	1.000	-0.654	-0.475	322.000	1.099	0.000
Incentives	0.000	0.272	-2.654	1.517	1.000	-0.545	-0.327	322.000	0.852	0.000
Infrastructure	0.000	0.496	-2.584	1.523	1.000	-0.429	-0.705	322.000	3.015	0.000
Intention_2_Buy	0.000	0.310	-2.877	1.808	1.000	-0.447	-0.492	322.000	1.183	0.000
PER_RISK	0.000	0.024	-2.294	1.587	1.000	-0.764	-0.280	322.000	0.682	0.000
PSY_RISK	0.000	0.179	-2.226	1.812	1.000	-0.683	-0.252	322.000	0.589	0.000
PURCHASE_INTENTION	0.000	0.127	-3.161	2.097	1.000	-0.353	-0.284	322.000	0.449	0.000
Perf_Value	0.000	0.047	-2.638	1.979	1.000	-0.538	-0.127	322.000	0.601	0.000
Price	0.000	0.252	-2.806	1.772	1.000	0.024	-0.762	322.000	1.540	0.000
RISK	0.000	0.174	-2.754	2.090	1.000	0.020	-0.488	322.000	0.349	0.000
Range	0.000	0.508	-2.234	1.422	1.000	-0.687	-0.535	322.000	4.154	0.000
Reliability	0.000	0.164	-2.689	2.041	1.000	-0.627	-0.196	322.000	0.606	0.000
TECHNOLOGY	0.000	0.014	-2.909	2.332	1.000	-0.405	-0.161	322.000	0.190	0.007
Willingness_2_Pay	0.000	0.037	-2.632	1.616	1.000	-0.497	-0.394	322.000	0.836	0.000

Annexure 10: Outer Model Descriptives (Measurement Model)

	Mean	Median	Observed min	Observed max	deviation	ss kurtosis	Skewness	Observations	Cramér-von Mises test statistic	Cramér-von Mises p value
ECO_INC_2	0.000	-0.006	-1.542	1.474	0.503	0.892	0.008	322.000	3.005	0.000
ECO_INC_3	0.000	0.007	-1.832	1.916	0.625	0.892	-0.008	322.000	3.005	0.000
ECO_INF_1	0.000	0.031	-2.327	2.518	0.701	1.903	-0.397	322.000	1.667	0.000
ECO_INF_1	0.000	0.073	-1.367	1.405	0.390	2.620	-0.092	322.000	4.668	0.000
ECO_INF_3	0.000	-0.076	-1.458	1.418	0.404	2.620	0.092	322.000	4.668	0.000
ECO_INF_3	0.000	0.062	-2.441	1.929	0.726	1.753	-0.879	322.000	1.627	0.000
ECO_PRI_4	0.000	0.046	-2.077	2.224	0.699	0.833	-0.096	322.000	0.645	0.000
ECO_PRI_4	0.000	0.000	-1.894	1.276	0.488	1.499	-0.575	322.000	1.352	0.000
ECO_PRI_5	0.000	-0.136	-1.752	1.967	0.665	0.009	0.421	322.000	0.901	0.000
ECO_PRI_5	0.000	-0.060	-1.269	1.696	0.518	0.449	0.283	322.000	0.818	0.000
ECO_PRI_6	0.000	0.176	-1.749	1.870	0.745	0.135	-0.287	322.000	0.706	0.000
ECO_PRI_6	0.000	0.158	-1.775	1.740	0.699	0.322	-0.360	322.000	0.799	0.000
PURINT_I2B_1	0.000	-0.054	-1.627	2.852	0.504	3.365	0.720	322.000	0.878	0.000
PURINT_I2B_1	0.000	-0.099	-1.621	2.307	0.616	1.096	0.646	322.000	0.743	0.000
PURINT_I2B_2	0.000	-0.041	-2.548	2.314	0.554	2.908	-0.063	322.000	1.182	0.000
PURINT_I2B_2	0.000	-0.011	-2.159	2.005	0.634	1.761	0.049	322.000	0.829	0.000
PURINT_I2B_3	0.000	-0.036	-2.538	2.471	0.715	1.751	-0.048	322.000	0.451	0.000
PURINT_I2B_3	0.000	-0.119	-1.718	2.117	0.597	1.663	0.238	322.000	0.896	0.000
PURINT_I2B_5	0.000	0.141	-2.426	1.901	0.712	1.372	-0.454	322.000	1.168	0.000
PURINT_I2B_5	0.000	0.107	-2.402	2.007	0.673	1.099	-0.177	322.000	0.773	0.000
PURINT_PV_1	0.000	0.003	-2.106	2.115	0.704	1.021	0.042	322.000	0.718	0.000
PURINT_PV_1	0.000	0.104	-2.300	2.239	0.787	0.409	-0.156	322.000	0.266	0.001
PURINT_PV_2	0.000	0.147	-2.262	1.976	0.707	0.546	-0.477	322.000	0.815	0.000
PURINT_PV_2	0.000	0.003	-1.690	1.879	0.534	1.379	-0.236	322.000	1.037	0.000
PURINT_PV_3	0.000	-0.006	-1.258	1.940	0.486	2.504	0.624	322.000	1.236	0.000
PURINT_PV_3	0.000	0.065	-1.984	2.043	0.706	0.418	0.194	322.000	0.244	0.001
PURINT_W2P_1	0.000	-0.027	-2.881	1.795	0.718	1.440	-0.511	322.000	0.502	0.000
PURINT_W2P_1	0.000	-0.141	-1.529	1.631	0.536	0.783	0.248	322.000	1.759	0.000
PURINT_W2P_4	0.000	0.141	-1.625	1.524	0.534	0.783	-0.248	322.000	1.759	0.000
PURINT_W2P_4	0.000	0.103	-2.248	1.656	0.716	0.244	-0.524	322.000	0.907	0.000
RISK_FR_1	0.000	0.096	-2.203	1.731	0.764	-0.284	0.034	322.000	0.309	0.000
RISK_FR_1	0.000	-0.051	-1.779	1.798	0.546	0.728	0.175	322.000	0.490	0.000
RISK_FR_2	0.000	-0.020	-1.350	1.894	0.509	2.034	0.694	322.000	1.443	0.000
RISK_FR_2	0.000	0.050	-1.780	2.140	0.724	0.591	0.197	322.000	0.411	0.000
RISK_FR_4	0.000	0.104	-1.852	1.536	0.717	-0.074	-0.534	322.000	0.503	0.000
RISK_FR_4	0.000	0.067	-2.259	1.832	0.667	0.904	-0.679	322.000	0.611	0.000
RISK_PR_1	0.000	0.038	-1.892	1.976	0.573	1.356	-0.238	322.000	3.540	0.000
RISK_PR_1	0.000	0.107	-2.731	2.607	0.827	0.613	-0.507	322.000	0.287	0.000

RISK_PR_2	0.000	0.034	-2.351	1.832	0.620	1.265	-0.413	322.000	0.543	0.000
RISK_PR_2	0.000	-0.028	-1.415	1.355	0.410	1.356	0.238	322.000	3.540	0.000
RISK_PSY_1	0.000	-0.030	-1.858	1.968	0.637	0.718	-0.167	322.000	0.539	0.000
RISK_PSY_1	0.000	-0.217	-2.290	1.831	0.571	1.616	0.008	322.000	1.463	0.000
RISK_PSY_2	0.000	0.133	-2.146	1.598	0.588	1.574	-0.551	322.000	2.032	0.000
RISK_PSY_2	0.000	0.110	-2.066	1.946	0.790	0.076	-0.157	322.000	0.247	0.001
RISK_PSY_3	0.000	0.135	-2.105	1.816	0.572	1.512	-0.200	322.000	1.618	0.000
RISK_PSY_3	0.000	0.143	-2.587	2.197	0.753	0.969	-0.328	322.000	0.525	0.000
TECH_CH_TIME_1	0.000	0.116	-2.368	2.445	0.842	0.036	-0.217	322.000	0.338	0.000
TECH_CH_TIME_1	0.000	0.065	-1.873	2.184	0.729	0.257	0.000	322.000	0.597	0.000
TECH_CH_TIME_2	0.000	-0.049	-1.439	2.193	0.503	1.999	0.397	322.000	0.742	0.000
TECH_CH_TIME_2	0.000	0.093	-2.085	2.046	0.737	0.126	-0.264	322.000	0.272	0.001
TECH_CH_TIME_3	0.000	0.044	-2.498	2.227	0.696	0.536	-0.211	322.000	0.297	0.000
TECH_CH_TIME_3	0.000	-0.051	-1.267	2.121	0.498	1.567	0.493	322.000	0.858	0.000
TECH_RANGE_3	0.000	0.000	0.000	0.000	0.000	-0.687	0.535	322.000	4.154	0.000
TECH_RANGE_3	0.000	0.130	-2.748	1.855	0.879	0.040	-0.491	322.000	0.349	0.000
TECH_RLB_1	0.000	0.099	-2.710	2.217	0.717	1.025	0.031	322.000	0.752	0.000
TECH_RLB_1	0.000	0.024	-2.326	2.153	0.729	0.607	0.165	322.000	0.315	0.000
TECH_RLB_2	0.000	0.008	-1.507	1.601	0.530	0.642	-0.080	322.000	0.805	0.000
TECH_RLB_2	0.000	0.035	-1.683	1.936	0.570	0.815	-0.098	322.000	0.327	0.000
TECH_RLB_3	0.000	0.082	-2.040	1.699	0.634	0.864	-0.487	322.000	0.766	0.000
TECH_RLB_3	0.000	0.074	-2.233	1.815	0.702	0.380	-0.365	322.000	0.486	0.000
TECH_RLB_4	0.000	0.021	-2.237	1.430	0.538	1.580	-0.382	322.000	1.024	0.000
TECH_RLB_4	0.000	0.036	-2.100	1.511	0.604	0.826	-0.329	322.000	0.548	0.000
TECH_RLB_5	0.000	0.029	-2.548	3.027	0.667	2.192	0.034	322.000	0.547	0.000
TECH_RLB_5	0.000	-0.006	-2.346	2.673	0.576	3.497	0.010	322.000	1.468	0.000

Annexure 11: Quality Criteria of Measurement Model

R-square

	R-square	R-square adjusted
ECONOMIC FACTORS	0.999	0.999
PURCHASE_INTENTION	1.000	1.000
RISK	1.000	1.000
TECHNOLOGY	1.000	1.000

f-square

	f-square
Charge_Time -> TECHNOLOGY	4211.717
ECONOMIC FACTORS -> PURCHASE_INTENTION	0.117
FIN_RISK -> RISK	5113.995
Incentives -> ECONOMIC FACTORS	0.053
Infrastructure -> ECONOMIC FACTORS	129.375
Intention_2_Buy -> PURCHASE_INTENTION	1568.435
PER_RISK -> RISK	2703.913
PSY_RISK -> RISK	5071.912
Perf_Value -> PURCHASE_INTENTION	830.807
Price -> ECONOMIC FACTORS	244.314
RISK -> ECONOMIC FACTORS	0.079
RISK -> TECHNOLOGY	0.013
Range -> TECHNOLOGY	768.614
Reliability -> TECHNOLOGY	13673.955
TECHNOLOGY -> PURCHASE_INTENTION	0.020
Willingness_2_Pay -> PURCHASE_INTENTION	447.085

Annexure 12: Construct reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Charge_Time	0.733	0.756	0.850	0.656
ECONOMIC FACTORS	0.749	0.747	0.833	0.499
FIN_RISK	0.747	0.746	0.856	0.666
Incentives	0.529	0.545	0.808	0.678
Infrastructure	0.813	0.813	0.914	0.842
Intention_2_Buy	0.825	0.829	0.885	0.658
PER_RISK	0.678	0.729	0.858	0.752
PSY_RISK	0.752	0.759	0.857	0.667
PURCHASE_INTENTION	0.877	0.878	0.902	0.506
Perf_Value	0.739	0.749	0.853	0.661
Price	0.747	0.753	0.857	0.668
RISK	0.832	0.841	0.873	0.464
Reliability	0.855	0.861	0.897	0.636
TECHNOLOGY	0.860	0.869	0.891	0.481
Willingness_2_Pay	0.600	0.600	0.833	0.714

Annexure 13 :Discriminant validity

	Heterotrait-monotrait ratio (HTMT)
ECONOMIC FACTORS <-> Charge_Time	0.624
FIN_RISK <-> Charge_Time	0.348
FIN_RISK <-> ECONOMIC FACTORS	0.546
Incentives <-> Charge_Time	0.622
Incentives <-> ECONOMIC FACTORS	0.994
Incentives <-> FIN_RISK	0.621
Infrastructure <-> Charge_Time	0.279
Infrastructure <-> ECONOMIC FACTORS	0.975
Infrastructure <-> FIN_RISK	0.600
Infrastructure <-> Incentives	0.587
Intention_2_Buy <-> Charge_Time	0.505
Intention_2_Buy <-> ECONOMIC FACTORS	0.784
Intention_2_Buy <-> FIN_RISK	0.467
Intention_2_Buy <-> Incentives	0.942
Intention_2_Buy <-> Infrastructure	0.420
PER_RISK <-> Charge_Time	0.176
PER_RISK <-> ECONOMIC FACTORS	0.570
PER_RISK <-> FIN_RISK	0.702
PER_RISK <-> Incentives	0.578
PER_RISK <-> Infrastructure	0.717
PER_RISK <-> Intention_2_Buy	0.354
PSY_RISK <-> Charge_Time	0.340
PSY_RISK <-> ECONOMIC FACTORS	0.605
PSY_RISK <-> FIN_RISK	0.663

PSY_RISK <-> Incentives	0.480
PSY_RISK <-> Infrastructure	0.741
PSY_RISK <-> Intention_2_Buy	0.262
PSY_RISK <-> PER_RISK	0.693
PURCHASE_INTENTION <-> Charge_Time	0.646
PURCHASE_INTENTION <-> ECONOMIC FACTORS	0.795
PURCHASE_INTENTION <-> FIN_RISK	0.425
PURCHASE_INTENTION <-> Incentives	0.952
PURCHASE_INTENTION <-> Infrastructure	0.423
PURCHASE_INTENTION <-> Intention_2_Buy	1.075
PURCHASE_INTENTION <-> PER_RISK	0.376
PURCHASE_INTENTION <-> PSY_RISK	0.286
Perf_Value <-> Charge_Time	0.691
Perf_Value <-> ECONOMIC FACTORS	0.672
Perf_Value <-> FIN_RISK	0.295
Perf_Value <-> Incentives	0.839
Perf_Value <-> Infrastructure	0.343

Perf_Value <-> Intention_2_Buy	0.777
Perf_Value <-> PER_RISK	0.347
Perf_Value <-> PSY_RISK	0.204
Perf_Value <-> PURCHASE_INTENTION	1.043
Price <-> Charge_Time	0.685
Price <-> ECONOMIC FACTORS	1.168
Price <-> FIN_RISK	0.320
Price <-> Incentives	0.979
Price <-> Infrastructure	0.447
Price <-> Intention_2_Buy	0.805
Price <-> PER_RISK	0.263

Price <-> PSY_RISK	0.295
Price <-> PURCHASE_INTENTION	0.819
Price <-> Perf_Value	0.703
RISK <-> Charge_Time	0.345
RISK <-> ECONOMIC FACTORS	0.658
RISK <-> FIN_RISK	1.059
RISK <-> Incentives	0.638
RISK <-> Infrastructure	0.782
RISK <-> Intention_2_Buy	0.414
RISK <-> PER_RISK	1.024
RISK <-> PSY_RISK	1.055
RISK <-> PURCHASE_INTENTION	0.413
RISK <-> Perf_Value	0.314
RISK <-> Price	0.339
Range <-> Charge_Time	0.292
Range <-> ECONOMIC FACTORS	0.404
Range <-> FIN_RISK	0.295
Range <-> Incentives	0.352
Range <-> Infrastructure	0.275
Range <-> Intention_2_Buy	0.443
Range <-> PER_RISK	0.367
Range <-> PSY_RISK	0.314
Range <-> PURCHASE_INTENTION	0.463
Range <-> Perf_Value	0.382
Range <-> Price	0.370
Range <-> RISK	0.367
Reliability <-> Charge_Time	0.742
Reliability <-> ECONOMIC FACTORS	0.685
Reliability <-> FIN_RISK	0.364
Reliability <-> Incentives	0.815
Reliability <-> Infrastructure	0.305

Reliability <-> Intention_2_Buy	0.718
Reliability <-> PER_RISK	0.288
Reliability <-> PSY_RISK	0.200
Reliability <-> PURCHASE_INTENTION	0.883
Reliability <-> Perf_Value	0.937
Reliability <-> Price	0.752

Reliability <-> RISK	0.324
Reliability <-> Range	0.396
TECHNOLOGY <-> Charge_Time	1.022
TECHNOLOGY <-> ECONOMIC FACTORS	0.737
TECHNOLOGY <-> FIN_RISK	0.411
TECHNOLOGY <-> Incentives	0.810
TECHNOLOGY <-> Infrastructure	0.345
TECHNOLOGY <-> Intention_2_Buy	0.722
TECHNOLOGY <-> PER_RISK	0.313
TECHNOLOGY <-> PSY_RISK	0.306
TECHNOLOGY <-> PURCHASE_INTENTION	0.882
TECHNOLOGY <-> Perf_Value	0.919
TECHNOLOGY <-> Price	0.796
TECHNOLOGY <-> RISK	0.397
TECHNOLOGY <-> Range	0.535
TECHNOLOGY <-> Reliability	1.089
Willingness_2_Pay <-> Charge_Time	0.712
Willingness_2_Pay <-> ECONOMIC FACTORS	0.800
Willingness_2_Pay <-> FIN_RISK	0.421
Willingness_2_Pay <-> Incentives	0.895
Willingness_2_Pay <-> Infrastructure	0.440
Willingness_2_Pay <-> Intention_2_Buy	0.950
Willingness_2_Pay <-> PER_RISK	0.371
Willingness_2_Pay <-> PSY_RISK	0.394

Willingness_2_Pay <-> PURCHASE_INTENTION	1.131
Willingness_2_Pay <-> Perf_Value	0.858
Willingness_2_Pay <-> Price	0.812
Willingness_2_Pay <-> RISK	0.456
Willingness_2_Pay <-> Range	0.509
Willingness_2_Pay <-> Reliability	0.930
Willingness_2_Pay <-> TECHNOLOGY	0.944

Annexure 14 : Fornell-Larcker criterion (FL Criterion) of Measurement Model

	Charge_Time	ECONOMIC FACTORS	FIN_RISK	Incentives	Infrastructure	Intention_2_Buy	PER_RISK	PSY_RISK	PURCHASE_INTENTION	Perf_Value	Price	RISK	Range	Reliability	TECHNOLOGY	Willingness_2_Pay
Charge_Time	0.810															
ECONOMIC FACTORS	0.461	0.707														
FIN_RISK	0.254	0.414	0.816													
Incentives	0.386	0.635	0.376	0.823												
Infrastructure	0.215	0.763	0.470	0.374	0.918											
Intention_2_Buy	0.388	0.613	0.365	0.610	0.339	0.811										
PER_RISK	0.121	0.408	0.516	0.349	0.545	0.281	0.867									
PSY_RISK	0.251	0.464	0.504	0.303	0.591	0.210	0.534	0.817								
PURCHASE_INTENTION	0.517	0.645	0.342	0.638	0.356	0.915	0.302	0.221	0.711							
Perf_Value	0.501	0.498	0.215	0.511	0.264	0.605	0.252	0.110	0.835	0.813						
Price	0.505	0.870	0.233	0.627	0.348	0.620	0.165	0.216	0.655	0.515	0.817					
RISK	0.263	0.523	0.833	0.415	0.649	0.347	0.792	0.841	0.348	0.226	0.253	0.681				
Range	0.251	0.351	0.257	0.258	0.248	0.402	0.305	0.282	0.432	0.324	0.317	0.339	1.000			
Reliability	0.593	0.552	0.291	0.551	0.255	0.604	0.215	0.166	0.766	0.746	0.601	0.273	0.362	0.798		
TECHNOLOGY	0.802	0.592	0.327	0.550	0.286	0.607	0.232	0.244	0.769	0.734	0.636	0.329	0.476	0.945	0.694	
Willingness_2_Pay	0.484	0.538	0.282	0.501	0.307	0.670	0.243	0.267	0.825	0.573	0.539	0.323	0.394	0.668	0.685	0.845

Annexure 15: FL Collinearity VIF of Measurement Model

Outer model - List

	VIF
ECO_INC_2	1.149
ECO_INC_3	1.149
ECO_INF_1	1.968
ECO_INF_1	1.882
ECO_INF_3	1.882
ECO_INF_3	1.905
ECO_PRI_4	2.081
ECO_PRI_4	2.077
ECO_PRI_5	2.067
ECO_PRI_5	1.965
ECO_PRI_6	1.285
ECO_PRI_6	1.234
PURINT_I2B_1	2.267
PURINT_I2B_1	2.417
PURINT_I2B_2	1.978
PURINT_I2B_2	2.297
PURINT_I2B_3	1.972
PURINT_I2B_3	1.773
PURINT_I2B_5	1.623
PURINT_I2B_5	1.451
PURINT_PV_1	1.243
PURINT_PV_1	1.488
PURINT_PV_2	2.169

PURINT_PV_2	1.816
PURINT_PV_3	1.950
PURINT_PV_3	2.070
PURINT_W2P_1	1.764
PURINT_W2P_1	1.225
PURINT_W2P_4	1.225
PURINT_W2P_4	1.611
RISK_FR_1	2.017
RISK_FR_1	1.932
RISK_FR_2	1.997
RISK_FR_2	2.127
RISK_FR_4	1.603
RISK_FR_4	1.237
RISK_PR_1	1.356
RISK_PR_1	1.445
RISK_PR_2	2.336
RISK_PR_2	1.356
RISK_PSY_1	2.093

RISK_PSY_1	1.394
RISK_PSY_2	1.601
RISK_PSY_2	1.765
RISK_PSY_3	1.598
RISK_PSY_3	1.731
TECH_CH_TIME_1	1.287
TECH_CH_TIME_1	1.222
TECH_CH_TIME_2	1.845
TECH_CH_TIME_2	2.000

TECH_CH_TIME_3	2.107
TECH_CH_TIME_3	1.812
TECH_RANGE_3	1.000
TECH_RANGE_3	1.253
TECH_RLB_1	1.617
TECH_RLB_1	1.715
TECH_RLB_2	2.372
TECH_RLB_2	2.511
TECH_RLB_3	1.759
TECH_RLB_3	1.837
TECH_RLB_4	2.634
TECH_RLB_4	2.882
TECH_RLB_5	2.439
TECH_RLB_5	2.385

Annexure 16: Path Coefficients of Structural Model

	Path coefficients
ECONOMIC FACTORS -> PURCHASE_INTENTION	0.362
ECONOMIC FACTORS -> TECHNOLOGY	0.605
RISK -> ECONOMIC FACTORS	0.526
RISK -> PURCHASE_INTENTION	-0.042
RISK -> TECHNOLOGY	0.040
TECHNOLOGY -> PURCHASE_INTENTION	0.563

Annexure 17: Indirect Effects of Structural Model

RISK -> ECONOMIC FACTORS -> PURCHASE_INTENTION
RISK -> ECONOMIC FACTORS -> TECHNOLOGY -> PURCHASE_INTENTION
RISK -> ECONOMIC FACTORS -> TECHNOLOGY
ECONOMIC FACTORS -> TECHNOLOGY -> PURCHASE_INTENTION
RISK -> TECHNOLOGY -> PURCHASE_INTENTION

Specific indirect effects	
	0.190
	0.179
	0.319
	0.341
	0.022

Annexure 18: Total Effect of Structural Model

	Total effects
ECONOMIC FACTORS -> PURCHASE_INTENTION	0.702
ECONOMIC FACTORS -> TECHNOLOGY	0.605
RISK -> ECONOMIC FACTORS	0.526
RISK -> PURCHASE_INTENTION	0.350
RISK -> TECHNOLOGY	0.358
TECHNOLOGY -> PURCHASE_INTENTION	0.563

Annexure 19: Outer loadings of Structural Model

	Outer loadings
Charge_Time <- TECHNOLOGY	0.800
FIN_RISK <- RISK	0.833
Incentives <- ECONOMIC FACTORS	0.860
Infrastructure <- ECONOMIC FACTORS	0.675
Intention_2_Buy <- PURCHASE_INTENTION	0.877
PER_RISK <- RISK	0.823
PSY_RISK <- RISK	0.814
Perf_Value <- PURCHASE_INTENTION	0.844
Price <- ECONOMIC FACTORS	0.848
Range <- TECHNOLOGY	0.610
Reliability <- TECHNOLOGY	0.897
Willingness_2_Pay <- PURCHASE_INTENTION	0.866

Annexure 20: Latent Variables of Structural Model

	ECONOMIC FACTORS	PURCHASE_INTENTION	RISK	TECHNOLOGY
0	1.139	0.447	0.780	-0.447
1	0.771	0.592	1.171	-0.312
2	-0.181	-0.731	0.757	-0.953
3	0.430	-0.355	1.562	-0.562
4	0.022	1.318	-1.551	1.047
5	-0.242	-0.698	0.704	-1.110
6	-2.009	-1.838	-1.551	-1.666
7	0.007	1.775	-1.957	1.637
8	0.750	1.839	-2.762	2.379
9	-0.213	0.980	-2.171	2.127
10	-2.009	-1.838	-1.672	-2.358
11	-0.032	0.238	0.390	0.465
12	1.176	0.595	0.755	0.090
13	-3.178	-2.721	-1.672	-1.800
14	-0.480	-0.087	1.440	-0.163
15	-0.945	-0.365	-1.578	-0.183
16	0.045	-0.500	0.859	-0.867
17	0.586	1.663	1.684	0.115
18	-0.069	-0.816	-0.618	-0.905
19	0.754	1.752	-0.665	1.165
20	-1.595	-0.917	-1.119	-0.823
21	-1.557	-1.169	-0.067	-0.994
22	0.391	-1.299	-2.485	-0.223
23	-0.373	-0.594	0.028	-0.860
24	-0.069	-1.940	-0.722	-0.609
25	-0.146	-0.931	-0.870	-0.143
26	-0.202	-1.546	-0.722	-0.633
27	-0.397	-0.543	0.416	0.324

28	0.341	-0.114	1.445	-0.284
29	-2.544	-1.669	0.339	-1.409
30	0.955	0.316	-0.031	1.031
31	-1.573	-0.622	-0.523	-0.377
32	1.812	1.781	1.472	1.931
33	-0.245	0.871	0.574	0.421
34	-1.267	-0.538	-0.954	0.216
35	-1.274	-1.021	-0.627	-1.821
36	0.656	0.852	-0.199	-0.047
37	-1.289	-0.185	-0.225	-0.725
38	0.490	-0.600	0.732	-1.077
39	0.393	2.090	-2.762	2.379
40	0.666	0.781	0.638	1.031
41	1.136	0.980	0.059	0.812
42	-0.814	-0.780	-1.358	0.008

43	0.788	-0.449	1.740	-0.313
44	0.666	0.781	0.332	1.031
45	-0.843	-1.588	-0.326	-1.338
46	0.666	1.306	-0.219	0.706
47	-0.069	-1.341	-0.209	-1.196
48	-0.310	-0.208	-0.220	-0.033
49	0.206	-1.668	-0.576	-1.608
50	0.639	0.985	0.290	1.315
51	-1.586	-1.169	-0.181	-0.242
52	1.141	0.519	0.561	1.218
53	0.771	0.688	0.631	0.528
54	-0.877	-0.462	-0.075	0.272
55	0.144	0.218	-0.227	0.652

56	-1.225	-0.640	-0.423	-1.205
57	-0.671	-0.025	0.592	0.232
58	-2.009	-0.052	-1.551	-1.666
59	-2.271	-1.011	-0.950	-1.181
60	-1.319	-1.857	-1.736	-0.581
61	-1.245	-0.741	-0.250	-0.998
62	0.855	0.327	0.510	-0.861
63	-0.069	-0.816	-0.618	0.403
64	-2.178	-1.159	1.424	-0.020
65	0.666	0.781	-0.375	-2.461
66	-0.235	0.678	0.393	0.508
67	0.114	0.467	0.679	0.557
68	-0.446	0.991	-0.555	0.073
69	0.666	0.466	0.594	0.759
70	0.007	0.228	0.290	1.226
71	1.000	1.144	-0.327	1.822
72	0.135	2.090	-1.551	0.878
73	-0.534	-0.963	-0.573	-0.284
74	0.389	1.664	-0.439	1.462
75	0.288	-0.435	0.905	-0.250
76	-0.142	-0.960	0.169	-0.185
77	-1.379	-0.733	-1.619	-1.732
78	-0.069	-1.821	-0.964	-0.995
79	-0.727	-1.537	-0.668	-1.112
80	0.850	-1.596	-1.433	-1.922
81	-0.030	-0.407	1.129	-0.392
82	-0.381	0.581	0.237	0.638
83	0.501	0.377	1.137	0.114
84	-0.348	-0.628	0.494	-0.990
85	-1.556	-1.397	-0.609	-1.026
86	-0.611	-0.839	-0.519	-1.337

87	-1.349	-0.130	-0.529	-0.625
88	-0.948	-1.627	-0.579	-0.297
89	0.152	-0.290	1.454	0.856
90	0.666	0.781	0.314	0.637

91	-0.069	-1.542	-0.792	-0.727
92	-3.347	-3.148	-2.762	-3.014
93	-0.671	-0.481	-0.388	-1.013
94	1.306	1.091	0.494	-0.367
95	0.666	0.327	0.594	-0.447
96	-0.502	0.660	-1.339	0.212
97	-1.318	-1.259	-0.695	-0.511
98	1.636	1.979	0.274	1.324
99	-1.677	-1.838	-1.551	-1.666
100	-0.069	-0.911	-0.063	-0.622
101	-0.187	0.251	-2.154	-0.275
102	0.141	0.155	1.186	0.346
103	-0.441	1.106	-1.548	-0.303
104	-1.641	-0.263	-1.159	-1.045
105	0.920	1.769	-0.665	1.978
106	-0.239	-0.316	-0.409	0.092
107	-0.764	-1.141	-0.870	-0.935
108	-0.121	0.641	0.211	0.504
109	0.121	0.566	0.201	1.145
110	0.953	1.091	0.392	0.202
111	1.664	1.293	0.765	1.379
112	0.134	0.279	0.622	-0.019
113	-1.411	-0.567	-2.281	-2.095
114	-0.402	-0.329	-0.049	0.056
115	0.641	-1.498	-1.631	-0.594
116	-1.831	-0.802	0.176	-1.496

117	-0.539	-1.102	-1.649	-1.638
118	-1.497	0.328	-1.827	-1.666
119	-0.909	0.453	-0.618	0.403
120	-1.559	-1.298	-0.165	0.445
121	1.306	0.781	2.081	0.731
122	0.666	0.781	0.559	-0.231
123	0.045	0.442	-0.293	0.303
124	0.651	1.533	-0.665	1.302
125	0.843	-1.453	1.006	0.093
126	-0.547	-0.852	-0.683	-0.638
127	0.859	1.139	0.104	0.835
128	0.475	0.692	-0.252	0.818
129	0.666	0.781	0.870	1.031
130	0.479	0.569	1.337	0.135
131	2.004	1.969	2.081	1.691
132	0.280	0.257	0.327	0.531
133	0.227	-0.392	-0.854	-1.119
134	-1.100	0.056	0.472	-0.117
135	-0.046	-0.341	0.248	0.810
136	-0.192	-1.573	1.809	-1.931
137	0.510	0.537	0.392	0.004
138	0.497	-0.681	0.918	0.018

139	0.666	0.592	0.798	0.096
140	1.139	0.447	0.780	-0.447
141	-0.066	-0.286	0.728	-0.598
142	-1.367	-0.361	0.901	-0.562
143	-1.330	-1.396	-0.080	-1.524
144	1.139	0.447	0.780	-0.447
145	-0.325	-0.003	0.750	1.031
146	-0.688	-0.368	0.707	0.041

147	0.666	0.592	0.798	0.096
148	0.947	0.678	0.985	0.188
149	1.139	0.447	0.780	-0.447
150	0.490	0.963	0.246	1.873
151	0.666	0.592	0.798	0.096
152	0.030	-0.059	0.003	0.002
153	1.139	0.447	0.780	-0.447
154	0.912	1.497	-0.213	1.161
155	1.113	1.003	0.816	0.821
156	-0.167	0.419	0.344	1.065
157	0.666	0.592	0.798	0.096
158	1.139	0.447	0.780	-0.447
159	0.666	0.592	0.798	0.096
160	1.838	0.592	1.270	0.073
161	0.314	-0.091	-0.161	0.292
162	0.990	1.321	-0.652	0.063
163	0.771	0.688	0.631	0.528
164	-0.310	-0.087	-0.220	-0.033
165	-0.235	0.678	0.393	0.508
166	0.501	0.377	1.137	0.114
167	0.953	1.212	0.392	0.202
168	0.007	0.108	0.290	1.226
169	0.141	0.155	1.186	0.346
170	0.586	1.663	1.684	0.115
171	0.121	0.446	0.201	1.010
172	-3.347	-3.148	-2.762	-3.014
173	-0.030	-0.286	1.129	-0.392
174	-0.480	-0.207	1.440	-0.163
175	-1.209	-1.678	-2.485	-1.618
176	1.664	1.293	0.765	1.379
177	-1.294	-0.529	-1.551	-0.818

178	-0.121	0.641	0.211	0.638
179	-1.411	-0.809	-2.281	-2.363
180	0.666	0.781	0.638	1.031
181	-0.381	0.581	0.237	0.638
182	0.639	0.985	0.290	1.315
183	0.134	0.279	0.622	-0.019
184	0.341	-0.114	1.445	-0.284
185	1.000	1.144	-0.327	1.822
186	1.812	1.781	1.472	1.931

187	-0.142	-0.840	0.169	-0.185
188	-1.497	0.328	-1.827	-1.666
189	0.666	1.306	-0.219	0.706
190	1.141	0.277	0.561	1.218
191	-0.348	-0.628	0.494	-0.990
192	1.306	1.212	0.494	-0.367
193	1.306	0.781	2.081	0.731
194	-0.945	-0.486	-1.578	-0.317
195	1.136	0.980	0.059	0.812
196	0.288	-0.435	0.905	-0.385
197	0.754	1.752	-0.665	1.031
198	-0.397	-0.543	0.416	0.458
199	0.666	0.466	0.594	0.759
200	-2.009	-1.364	-1.551	-1.666
201	0.393	2.090	-2.762	2.379
202	0.389	1.543	-0.439	1.462
203	-0.245	0.750	0.574	0.421
204	-0.373	-0.473	0.028	-0.860
205	0.666	0.327	0.594	-0.447
206	0.666	0.781	0.314	0.637
207	-0.671	-0.529	-0.496	-1.083

208	-0.611	-0.959	-0.519	-1.203
209	-1.225	-0.519	-0.423	-1.339
210	-1.557	-1.169	-0.067	-0.860
211	0.855	0.327	0.510	-0.861
212	0.045	-0.500	0.859	-0.867
213	0.920	1.648	-0.665	1.844
214	0.651	1.533	-0.665	1.302
215	0.666	0.781	0.332	1.031
216	1.636	1.858	0.274	1.324
217	0.490	-0.721	0.732	-1.077
218	-2.178	-0.918	1.424	-0.020
219	-0.764	-1.141	-0.870	-0.935
220	-0.069	-0.695	-0.618	0.403
221	-0.069	-1.820	-0.722	-0.475
222	-0.909	0.574	-0.618	0.403
223	-0.146	-0.811	-0.870	-0.008
224	-1.586	-1.169	-0.181	-0.242
225	0.843	-0.971	1.006	0.093
226	-1.379	-0.492	-1.619	-1.732
227	-0.069	-1.579	-0.964	-0.995
228	-0.069	-0.790	-0.063	-0.622
229	-0.814	-0.660	-1.358	-0.260
230	-0.446	0.991	-0.555	0.208
231	0.850	-1.475	-1.433	-1.922
232	-0.671	-0.360	-0.388	-1.282
233	-0.069	-0.695	-0.618	-0.905
234	-1.245	-0.862	-0.250	-0.863

235	-1.274	-0.900	-0.627	-1.821
236	-2.544	-1.910	0.339	-1.409
237	-1.595	-0.917	-1.119	-1.092

238	0.206	-1.306	-0.576	-1.608
239	-1.289	-0.306	-0.225	-0.725
240	-0.547	-0.731	-0.683	-0.504
241	-0.239	-0.196	-0.409	0.227
242	0.641	-1.377	-1.631	-0.594
243	-1.319	-1.615	-1.736	-0.581
244	-0.727	-1.537	-0.668	-1.381
245	-0.502	0.660	-1.339	0.078
246	-1.831	-1.044	0.176	-1.496
247	-0.534	-0.963	-0.573	-0.150
248	-0.202	-1.425	-0.722	-0.767
249	-0.877	-0.583	-0.075	0.003
250	-0.539	-0.860	-1.649	-1.638
251	-0.069	-1.421	-0.792	-0.995
252	-1.559	-1.178	-0.165	0.445
253	-1.573	-0.260	-0.523	-0.377
254	-1.641	-0.625	-1.159	-0.911
255	-1.556	-1.518	-0.609	-1.026
256	-1.267	-0.779	-0.954	0.485
257	-1.349	-0.371	-0.529	-0.894
258	-0.069	-1.220	-0.209	-1.062
259	-0.948	-1.386	-0.579	-0.432
260	-1.318	-1.139	-0.695	-0.377
261	-2.271	-1.252	-0.950	-0.912
262	-0.843	-1.709	-0.326	-1.338
263	0.788	-0.449	1.740	-0.313
264	0.656	0.852	-0.199	-0.047
265	0.045	0.442	-0.293	0.303
266	-0.671	-0.025	0.592	0.232
267	1.300	-0.040	0.574	-0.015
268	1.312	0.938	-0.390	0.026

269	1.020	0.827	0.574	0.745
270	0.475	0.454	0.187	0.461
271	0.427	0.437	0.177	0.520
272	0.210	0.437	-0.450	0.639
273	0.855	0.430	0.574	-0.171
274	0.666	0.609	1.139	0.531
275	1.012	0.829	1.610	1.350
276	0.666	0.781	0.870	0.902
277	1.020	1.068	1.785	1.966
278	0.500	0.475	0.490	0.617
279	0.666	0.619	0.324	0.746
280	0.855	0.498	0.574	0.552
281	1.207	0.231	0.978	1.221
282	0.666	1.174	1.355	1.414

283	0.500	0.205	0.574	0.681
284	0.666	0.781	0.175	0.793
285	0.060	0.157	-2.168	0.455
286	1.838	0.847	1.100	1.250
287	1.304	1.053	0.934	1.021
288	1.381	1.645	1.487	0.685
289	1.267	0.217	1.088	0.868
290	0.666	0.781	0.850	0.924
291	0.575	0.521	0.694	0.894
292	0.666	0.781	0.694	1.031
293	1.383	1.419	1.207	1.044
294	-0.400	-0.557	0.591	-0.343
295	1.199	0.991	1.021	1.047
296	0.814	0.013	0.656	1.273
297	1.300	-0.040	-0.207	-0.015
298	1.123	0.938	-0.539	1.209

299	0.666	0.781	0.722	0.637
300	1.020	0.827	0.574	0.590
301	0.475	0.454	0.119	0.461
302	0.666	0.781	0.029	0.461
303	0.666	0.781	0.574	1.031
304	0.666	0.678	0.574	1.031
305	0.666	0.077	0.574	1.031
306	0.210	0.437	-0.450	0.639
307	0.855	0.430	0.574	-0.171
308	0.666	0.609	1.139	0.531
309	1.012	0.991	1.610	1.350
310	0.831	-0.036	0.490	0.378
311	2.004	0.225	1.637	0.128
312	0.666	0.781	0.574	1.031
313	0.523	0.136	0.603	0.092
314	0.379	0.790	1.534	0.850
315	0.832	0.056	0.341	0.317
316	1.012	0.829	1.610	1.350
317	0.666	0.781	0.870	0.902
318	1.020	1.068	1.785	1.966
319	0.220	0.475	0.490	0.617
320	0.666	0.619	0.324	0.746
321	0.855	0.498	0.574	0.552

Annexure 21: Correlations of Structural Model

	ECONOMIC FACTORS	PURCHASE_INTENTION	RISK	TECHNOLOGY
ECONOMIC FACTORS	1.000	0.692	0.526	0.626
PURCHASE_INTENTION	0.692	1.000	0.350	0.774
RISK	0.526	0.350	1.000	0.358
TECHNOLOGY	0.626	0.774	0.358	1.000

Annexure 22: Covariance of Structural Model

	ECONOMIC FACTORS	PURCHASE_INTENTION	RISK
ECONOMIC FACTORS	1.000	0.692	0.526
PURCHASE_INTENTION	0.692	1.000	0.350
RISK	0.526	0.350	1.000
TECHNOLOGY	0.626	0.774	0.358

TECHNOLOGY
0.626
0.774
0.358
1.000

Annexure 23: Descriptives of Structural Model

	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Observation	Cramér-von Mises test statistic	Cramér-von Mises p value
ECONOMIC FACTORS	0.000	0.135	-3.347	2.004	1.000	0.168	-0.672	322.000	0.765	0.000
PURCHASE_INTENTION	0.000	0.181	-3.148	2.090	1.000	-0.360	-0.268	322.000	0.431	0.000
RISK	0.000	0.176	-2.762	2.081	1.000	0.011	-0.496	322.000	0.372	0.000
TECHNOLOGY	0.000	0.068	-3.014	2.379	1.000	-0.181	-0.200	322.000	0.094	0.136

Annexure 24: Inner Model Correlation (Structural Model)

	Charge_Time	FIN_RISK	Incentives	Infrastructure	Intention_2_Buy	PER_RISK	PSY_RISK	Perf_Value	Price	Range	Reliability	Willingness_2_Pay
Charge_Time	1.000	0.023	-0.061	-0.019	-0.083	-0.180	0.155	0.026	0.081	-0.499	-0.472	0.050
FIN_RISK	0.023	1.000	0.101	-0.168	0.139	-0.543	-0.542	-0.052	0.087	-0.119	0.098	-0.075
Incentives	-0.061	0.101	1.000	-0.545	0.031	0.050	-0.160	0.039	-0.376	-0.089	0.150	-0.072
Infrastructure	-0.019	-0.168	-0.545	1.000	-0.030	0.049	0.133	-0.025	-0.572	0.153	-0.137	0.056
Intention_2_Buy	-0.083	0.139	0.031	-0.030	1.000	-0.067	-0.084	-0.528	0.003	0.170	-0.092	-0.373
PER_RISK	-0.180	-0.543	0.050	0.049	-0.067	1.000	-0.411	0.160	-0.103	0.101	0.074	-0.111
PSY_RISK	0.155	-0.542	-0.160	0.133	-0.084	-0.411	1.000	-0.103	0.009	0.028	-0.180	0.192
Perf_Value	0.026	-0.052	0.039	-0.025	-0.528	0.160	-0.103	1.000	-0.011	-0.177	0.154	-0.591
Price	0.081	0.087	-0.376	-0.572	0.003	-0.103	0.009	-0.011	1.000	-0.082	0.004	0.009
Range	-0.499	-0.119	-0.089	0.153	0.170	0.101	0.028	-0.177	-0.082	1.000	-0.528	0.032
Reliability	-0.472	0.098	0.150	-0.137	-0.092	0.074	-0.180	0.154	0.004	-0.528	1.000	-0.082
Willingness_2_Pay	0.050	-0.075	-0.072	0.056	-0.373	-0.111	0.192	-0.591	0.009	0.032	-0.082	1.000

Annexure 25: Inner Model Descriptives (Structural Model)

	Mean	Median	erved min	erved max	deviation	ss kurtosis	Skewness	tions used	Cramér-von Mises test statistic	Cramér-von Mises p value
Charge_Time	0.000	0.011	-2.181	1.855	0.600	0.654	-0.093	322.000	0.145	0.027
FIN_RISK	0.000	0.044	-1.623	1.287	0.553	0.250	-0.225	322.000	0.450	0.000
Incentives	0.000	-0.071	-1.350	2.042	0.511	1.254	0.356	322.000	0.418	0.000
Infrastructure	0.000	0.047	-2.849	1.653	0.738	2.516	-1.122	322.000	1.362	0.000
Intention_2_Buy	0.000	-0.029	-1.747	1.711	0.481	0.865	0.017	322.000	0.246	0.001
PER_RISK	0.000	-0.008	-1.415	1.907	0.568	0.168	-0.031	322.000	0.204	0.005
PSY_RISK	0.000	0.003	-1.482	1.603	0.581	0.593	0.270	322.000	0.132	0.041
Perf_Value	0.000	0.042	-1.930	1.847	0.536	1.472	-0.054	322.000	0.290	0.000
Price	0.000	0.063	-1.366	1.400	0.531	0.391	0.014	322.000	0.521	0.000
Range	0.000	0.037	-2.551	1.765	0.792	0.228	-0.429	322.000	0.140	0.032
Reliability	0.000	-0.012	-1.094	1.633	0.442	0.660	0.400	322.000	0.179	0.010
Willingness_2_Pay	0.000	0.025	-1.531	1.637	0.500	0.767	-0.122	322.000	0.310	0.000

Annexure 26: Quality Criteria of Structural Model

	R-square	R-square adjusted
ECONOMIC FACTORS	0.277	0.275
PURCHASE_INTENTION	0.671	0.668
TECHNOLOGY	0.394	0.390

f-square

	f-square
ECONOMIC FACTORS -> PURCHASE_INTENTION	0.200
ECONOMIC FACTORS -> TECHNOLOGY	0.437
RISK -> ECONOMIC FACTORS	0.383
RISK -> PURCHASE_INTENTION	0.004
RISK -> TECHNOLOGY	0.002
TECHNOLOGY -> PURCHASE_INTENTION	0.585

Annexure 27: Construct Reliability and Validity (Structural Model)

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ECONOMIC FACTORS	0.710	0.731	0.839	0.638
PURCHASE_INTENTION	0.828	0.828	0.897	0.744
RISK	0.763	0.766	0.863	0.678
TECHNOLOGY	0.669	0.746	0.818	0.606

Annexure 28: Discriminant validity – HTMT (Structural Model)

	monotrait ratio (HTMT)
PURCHASE_INTENTION <-> ECONOMIC FACTORS	0.888
RISK <-> ECONOMIC FACTORS	0.748
RISK <-> PURCHASE_INTENTION	0.438
TECHNOLOGY <-> ECONOMIC FACTORS	0.872
TECHNOLOGY <-> PURCHASE_INTENTION	1.007
TECHNOLOGY <-> RISK	0.521

Annexure 29: Fornell-Larcker criterion (FL Criterion) of Structural Model

	ECONOMIC FACTORS	PURCHASE_INTENTION	RISK	TECHNOLOGY
ECONOMIC FACTORS	0.798			
PURCHASE_INTENTION	0.692	0.863		
RISK	0.526	0.350	0.824	
TECHNOLOGY	0.626	0.774	0.358	0.778

Annexure 30: FL Collinearity VIF of Structural Model

Outer model - List

	VIF
Charge_Time	1.546
FIN_RISK	1.513
Incentives	1.726
Infrastructure	1.192
Intention_2_Buy	2.088
PER_RISK	1.579
PSY_RISK	1.555
Perf_Value	1.715
Price	1.689
Range	1.154
Reliability	1.667
Willingness_2_Pay	1.973

Inner model - List

	VIF
ECONOMIC FACTORS -> PURCHASE INTENTION	1.987
ECONOMIC FACTORS -> TECHNOLOGY	1.383
RISK -> ECONOMIC FACTORS	1.000
RISK -> PURCHASE_INTENTION	1.385
RISK -> TECHNOLOGY	1.383
TECHNOLOGY -> PURCHASE_INTENTION	1.649

Model fit

	Saturated model	Estimated model
SRMR	0.106	0.106
d_ULS	0.881	0.881

d_G	0.350	0.350
Chi-square	612.165	612.165
NFI	0.686	0.686

Annexure 31: Path Coefficients of Bootstrapped Model

Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV)	P values
ECONOMIC FACTORS -> PURCHASE INTENTION	0.362	0.361	0.055	6.628	0.000
ECONOMIC FACTORS -> TECHNOLOGY	0.605	0.605	0.056	10.760	0.000
RISK -> ECONOMIC FACTORS	0.526	0.526	0.056	9.442	0.000
RISK -> PURCHASE_INTENTION	-0.042	-0.041	0.043	0.978	0.164
RISK -> TECHNOLOGY	0.040	0.044	0.074	0.536	0.296
TECHNOLOGY -> PURCHASE_INTENTION	0.563	0.562	0.043	13.239	0.000

Annexure 32: Indirect Effects of Bootstrapped Model

Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
ECONOMIC FACTORS -> PURCHASE_INTENTION	0.341	0.341	0.042	8.034	0.000
RISK -> PURCHASE_INTENTION	0.392	0.394	0.061	6.383	0.000
RISK -> TECHNOLOGY	0.319	0.319	0.045	7.057	0.000

Annexure 33: Specific Indirect Effect of Bootstrapped Model

Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
RISK -> ECONOMIC FACTORS -> PURCHASE_INTENTION	0.190	0.191	0.038	5.005	0.000
RISK -> ECONOMIC FACTORS -> TECHNOLOGY -> PURCHASE_INTENTION	0.179	0.179	0.028	6.380	0.000
RISK -> ECONOMIC FACTORS -> TECHNOLOGY	0.319	0.319	0.045	7.057	0.000
ECONOMIC FACTORS -> TECHNOLOGY -> PURCHASE_INTENTION	0.341	0.341	0.042	8.034	0.000
RISK -> TECHNOLOGY -> PURCHASE_INTENTION	0.022	0.024	0.042	0.539	0.295

Annexure 34: Total Effect of Bootstrapped Model

Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV)	P values
ECONOMIC FACTORS -> PURCHASE INTENTION	0.702	0.702	0.050	14.061	0.000
ECONOMIC FACTORS -> TECHNOLOGY	0.605	0.605	0.056	10.760	0.000
RISK -> ECONOMIC FACTORS	0.526	0.526	0.056	9.442	0.000
RISK -> PURCHASE_INTENTION	0.350	0.353	0.068	5.174	0.000
RISK -> TECHNOLOGY	0.358	0.362	0.074	4.836	0.000
TECHNOLOGY -> PURCHASE_INTENTION	0.563	0.562	0.043	13.239	0.000

Annexure 35: Outer Loadings of Bootstrapped Model

Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Charge_Time <- TECHNOLOGY	0.800	0.799	0.029	27.141	0.000
FIN_RISK <- RISK	0.833	0.834	0.021	39.264	0.000
Incentives <- ECONOMIC FACTORS	0.860	0.860	0.019	46.150	0.000
Infrastructure <- ECONOMIC FACTORS	0.675	0.671	0.059	11.531	0.000
Intention_2_Buy <- PURCHASE_INTENTION	0.877	0.877	0.015	56.751	0.000
PER_RISK <- RISK	0.823	0.821	0.025	33.200	0.000
PSY_RISK <- RISK	0.814	0.812	0.030	26.747	0.000
Perf_Value <- PURCHASE_INTENTION	0.844	0.844	0.018	47.179	0.000
Price <- ECONOMIC FACTORS	0.848	0.848	0.018	47.914	0.000
Range <- TECHNOLOGY	0.610	0.608	0.054	11.313	0.000
Reliability <- TECHNOLOGY	0.897	0.897	0.011	83.196	0.000
Willingness_2_Pay <- PURCHASE_INTENTION	0.866	0.866	0.016	54.577	0.000

Annexure 36: Quality Criteria of Bootstrapped Model

R-square

Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV))	P values
ECONOMIC FACTORS	0.277	0.280	0.058	4.808	0.000
PURCHASE_INTENTION	0.671	0.675	0.033	20.076	0.000
TECHNOLOGY	0.394	0.403	0.045	8.764	0.000

R-square adjusted Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV))	P values
ECONOMIC FACTORS	0.275	0.278	0.058	4.754	0.000
PURCHASE_INTENTION	0.668	0.672	0.034	19.796	0.000
TECHNOLOGY	0.390	0.399	0.045	8.625	0.000

f-square

Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV))	P values
ECONOMIC FACTORS	0.731	0.734	0.030	24.565	0.000
PURCHASE_INTENTION	0.828	0.828	0.019	43.411	0.000
RISK	0.766	0.771	0.028	27.680	0.000
TECHNOLOGY	0.746	0.747	0.030	24.916	0.000

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV))	P values
ECONOMIC FACTORS -> PURCHASE_INTE	0.200	0.206	0.067	2.999	0.001
ECONOMIC FACTORS -> TECHNOLOGY	0.437	0.451	0.110	3.988	0.000
RISK -> ECONOMIC FACTORS	0.383	0.398	0.113	3.378	0.000
RISK -> PURCHASE_INTENTION	0.004	0.008	0.010	0.405	0.343
RISK -> TECHNOLOGY	0.002	0.009	0.012	0.152	0.440
TECHNOLOGY -> PURCHASE_INTENTION	0.585	0.590	0.121	4.854	0.000

Average variance extracted (AVE)

Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O /STDEV)	P values
ECONOMIC FACTORS	0.638	0.638	0.027	23.411	0.000
PURCHASE_INTENTION	0.744	0.744	0.021	35.469	0.000
RISK	0.678	0.677	0.025	26.792	0.000
TECHNOLOGY	0.606	0.606	0.026	23.733	0.000

Composite reliability (rho c)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O /STDEV)	P values
ECONOMIC FACTORS	0.839	0.839	0.017	49.605	0.000
PURCHASE_INTENTION	0.897	0.897	0.010	87.802	0.000
RISK	0.863	0.862	0.014	62.420	0.000
TECHNOLOGY	0.818	0.817	0.017	47.478	0.000

Composite reliability (rho a) Cronbach's alpha

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O /STDEV)	P values
ECONOMIC FACTORS	0.710	0.709	0.036	19.465	0.000
PURCHASE_INTENTION	0.828	0.827	0.019	43.277	0.000
RISK	0.763	0.761	0.027	27.866	0.000
TECHNOLOGY	0.669	0.667	0.038	17.701	0.000

Annexure 37: Outer Loadings of Control Variable

	Outer loadings
Age <- PURCHASE_INTENTION	-0.095
Charge_Time <- TECHNOLOGY	0.799
Edu <- PURCHASE_INTENTION	0.089
Employment <- PURCHASE_INTENTION	0.100
FIN_RISK <- RISK	0.833
Gender <- PURCHASE_INTENTION	-0.143
Incentives <- ECONOMIC FACTORS	0.859
Infrastructure <- ECONOMIC FACTORS	0.679
Intention_2_Buy <- PURCHASE_INTENTION	0.881
Mon_Income <- PURCHASE_INTENTION	0.271
Native_State <- PURCHASE_INTENTION	-0.265
PER_RISK <- RISK	0.824
PSY_RISK <- RISK	0.814
Perf_Value <- PURCHASE_INTENTION	0.831
Price <- ECONOMIC FACTORS	0.845
Range <- TECHNOLOGY	0.614
Reliability <- TECHNOLOGY	0.896
Willingness_2_Pay <- PURCHASE_INTENTION	0.845

Annexure 38: Quality Criteria of Control Variable

R-square

	R-square
ECONOMIC FACTORS	0.280
PURCHASE_INTENTION	0.670
TECHNOLOGY	0.392

f-square

	f-square
ECONOMIC FACTORS -> PURCHASE_INTENTION	0.240
ECONOMIC FACTORS -> TECHNOLOGY	0.432
RISK -> ECONOMIC FACTORS	0.389
RISK -> PURCHASE_INTENTION	0.002
RISK -> TECHNOLOGY	0.002
TECHNOLOGY -> PURCHASE_INTENTION	0.505

R-square adjusted
0.278
0.667
0.388

Annexure 39: PLS Predict LV Summary

PLS-SEM

	Q ² predict	RMSE	MAE
ECONOMIC FACTORS	0.269	0.860	0.675
PURCHASE_INTENTION	0.111	0.950	0.755
TECHNOLOGY	0.114	0.947	0.757