Factors Influencing Electric Vehicle Adoption in South Africa

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ABSTRACT

The automotive industry is undergoing a significant transformation, shifting from internal combustion engine vehicles (ICEVs) to environmentally friendly electric vehicles (EVs). However, while EV adoption is expanding globally to meet the Paris Agreement goals, South Africa is advancing at a slower pace. In 2023, while 532,092 new vehicles were sold in South Africa, EVs constituted only 1.45% of the total vehicle sales. Although the transport sector significantly contributes to the country’s GDP, it is also responsible for around 11% of carbon dioxide emissions. Consequently, to achieve its environmental, regulatory, and economic objectives, South Africa must accelerate its EV adoption.

This study investigates the factors influencing the behavioural intention to adopt EVs using the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) framework. Specifically, it examines the impact of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. This study also posits that government-backed policies and environmental concerns are crucial in accelerating the transition to EVs. Therefore, the influence of government support and environmental concerns was integrated to enhance the theoretical UTAUT2 model, providing a more comprehensive understanding of EV adoption.

This study employed a quantitative research approach using a structured 7-point Likert scale online survey. A total of 309 valid survey responses were analysed using confirmatory factor analysis and structural equation modelling to investigate the empirical fit of the proposed conceptual framework and to test the proposed hypotheses.

The findings revealed that social influence had the strongest impact on South Africans’ behavioural intention to adopt EVs. Environmental concerns and effort expectancy were also found to be statistically significant predictors of the intention to adopt an EV. Factors such as government support, performance expectancy, facilitating conditions, price value, hedonic motivation, and habit were found to have little impact on adoption intentions currently due to barriers such as the current insufficient charging infrastructure, issues with unreliable electricity supply, high import duties, high costs of EVs, limited awareness about EVs, and lack of robust government incentives or policies to support EV adoption. The results also showed an R^2 value of 0.775, indicating that 77.5% of the variance in behavioural intention to adopt EVs in South Africa is explained by the UTAUT2 model, suggesting a strong predictive power of the included factors.

The findings of this study will inform policymakers and industry stakeholders on developing strategies to overcome barriers and leverage enablers to accelerate EV adoption in South Africa, thereby addressing climate change and maintaining economic competitiveness.

This study is also among the first to examine the factors influencing the adoption of EV technology in South Africa using the UTAUT2 model. By doing so, it aims to expand and refine the theoretical understanding of the UTAUT2 framework, offering fresh perspectives on its application in the context of EV adoption and in the context of South Africa. Additionally, this research seeks to contribute to the growing body of knowledge on how government support and environmental concerns influence the adoption of new technologies.

Keywords: electric vehicles, adoption, unified theory of acceptance and use of technology, UTAUT2, behavioural intention, environmental concerns, government support, structural equation modelling, South Africa

DECLARATION

I, Puleng Theodorah Morota, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: **Puleng T. Morota** Signature:

Signed at …**Johannesburg**…………………………………………………………..

On the ……**25th**…………………day of …**February**………………… **2025**………

DEDICATION

I would like to dedicate this research to my late grandmother, Mmaletsiri Elizabeth Thebyane. *Makgampule*, you sacrificed EVERYTHING for this. While I may never know if this is how far you wanted me to go, I know you would have given up everything to make this happen for me. Thank you for teaching me that my dreams are valid and thank you for being the kind of grandmother that would have gone to the depths of the earth to make sure all my dreams come true. *Montshepetšabošego wa bo rare*, I can never thank you enough.

And to my late mother, Rethabile Hilda Morota. *Mom*, you always admired how brave and courageous I've always been when it comes to the things I really want in life. I hope you are also smiling down at this milestone achievement. *Mma waka montedi,* your love keeps me going.

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My praises go to the Most High God! His unmerited favour sustained me during my weakest moments. All my life and through this Master's journey, God proved that His plans truly are to prosper me, to give me hope, and a future. Thank you, Lord.

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LIST OF ACRONYMS

Acronym	Definition
AVE	Average Variance Extracted
BEV	Battery Electric Vehicle
BI	Behavioural Intention
CB-SEM	Covariance-Based Structural Equation Modeling
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CMB	Common Method Bias
CMIN	Chi-Square Minimum Discrepancy
CMIN/DF	Chi-Square Minimum Discrepancy Divided by Degrees of Freedom
CR	Composite Reliability
DOI	Diffusion of Innovations
DTIC	Department of Trade, Industry and Competition
EC	Environmental Concern
EE	Effort Expectancy
EV	Electric Vehicle
FC	Facilitating Conditions
GDP	Gross Domestic Product
GFI	Goodness-of-Fit Index
GS	Government Support
HB	Habit
HEV	Hybrid Electric Vehicle
HM	Hedonic Motivation
HTMT2	Heterotrait-Monotrait Ratio (HTMT) Version 2
ICEV	Internal Combustion Engine Vehicle
NAAMSA	National Association of Automobile Manufacturers of South Africa
NEV	New Energy Vehicle
PC	Personal Computer
PEOU	Perceived Ease of Use

PHEV	Plug-in Hybrid Electric Vehicle
PLS-SEM	Partial Least Squares Structural Equation Modeling
PU	Perceived Usefulness
PV	Price Value
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modeling
SI	Social Influence
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model
TBP	Theory of Planned Behavior
TLI	Tucker-Lewis Index
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Extended Unified Theory of Acceptance and Use of Technology

CHAPTER 1. INTRODUCTION

1.1 Statement of purpose

The purpose of this quantitative study was to investigate the factors influencing potential consumers' behavioural intention to adopt electric vehicles (EVs) in South Africa based on the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model. In addition to the core UTAUT2 constructs, this exploratory study also examined the impact of environmental concerns and government support on consumers' intention to adopt EVs. This study also identified the key barriers and enablers of EV adoption specific to South African consumers.

1.2 Background

The automotive industry worldwide is undergoing a significant transformation driven by technological advancements, stronger government policies, changing consumer preferences, and an increasing emphasis on environmental sustainability (Monye et al., 2023). One of the most profound changes in this industry is the shift from internal combustion engine vehicles (ICEVs) to environmentally friendly battery electric vehicles, as highlighted in South Africa's EV White Paper (2023). This transition is particularly crucial in South Africa, where the transport sector is the third-largest emitter of greenhouse gases, with road transport accounting for over 90% of these emissions (Ntuli et al., 2024). Additionally, the transport sector is a substantial economic contributor, making up 4.3% of the country's gross domestic product (Augustine, 2024).

The transition to EVs in South Africa is imperative not only for reducing the nation's carbon footprint and meeting its net-zero emission targets under the Paris Agreement (2015) but it is also essential for maintaining the competitiveness of South Africa's automotive manufacturing industry and offering more affordable transportation options to South Africans. Globally, the shift towards EVs is accelerating; for instance, in 2024, electric car sales in China were expected to constitute 45% of all car sales, while in the United States, electric car sales in 2024 were projected to increase by 20% compared to the previous year, resulting in nearly half a million additional sales relative to 2023 (Energy Agency, 2024). However, despite these global trends, EVs in South Africa accounted for only 1.45% of total market sales in 2023 (Modiba, 2023).

Despite this growing interest in sustainable transportation solutions, several barriers have hindered widespread EV adoption in South Africa. These include the high purchase price of EVs, insufficient charging infrastructure, and a lack of customer education and awareness, as noted by Mohubedu (2021). Recognising these challenges, South Africa's 2024 budget speech by Finance Minister Enoch Godongwana announced a budget allocation of R964 million and tax incentives to support the country's transition to new energy vehicles (NEVs).

However, Armstrong & Lee (2022) cautioned that although the EV market in developed economies is poised for significant growth with robust government support, this may not be the case in many emerging markets. Therefore, a comprehensive understanding of the factors that influence consumer perceptions and intentions to adopt EVs in South Africa as an emerging market is required. As a relatively new and transformative technology, EVs represent a significant shift in how consumers interact with mobility solutions. Understanding how countries, markets, and consumer segments have adopted new technologies is crucial for identifying their unique challenges and opportunities.

In the South African context, this exploratory study is particularly important given the country's specific socioeconomic, environmental, and energy-related conditions. The findings of this study provide valuable insights for policymakers and industry stakeholders when developing effective strategies to address barriers and leverage enablers to enhance EV adoption.

1.3 Research problem

Despite the global shift towards decarbonisation and the increasing demand for electric vehicles, South Africa's EV adoption rate remains low, posing challenges to the country's environmental and economic goals.

According to Scholtz et al. (2023), while the global market share of electric vehicle sales was 8.6% in 2021, South Africa's market share was only 0.1%. This stark contrast underscores a significant challenge in the South African automotive industry, which is currently experiencing substantial technological disruption as EVs are introduced.

Armstrong & Lee (2022) posited that an early phase of technology disruption is marked by high prices, uncertain profitability due to limited economies of scale, minimal competition, and high risk. These authors emphasised that disruption at an introductory level necessitates comprehensive organisational responses across all levels, from core ideology encompassing purpose, values and vision to strategy development and execution, including how organisations understand and engage with customers.

In any industry, customers are the most critical stakeholders. Therefore, understanding the barriers confronting users and the factors that influence their adoption of new technologies is crucial. To address the low adoption rate of EVs in South Africa, understanding how South African customers perceive EVs and how they make decisions regarding new technologies is essential. This involves assessing consumers' awareness and knowledge about EVs as well as exploring the drivers and barriers to EV adoption to identify the motivations and concerns that shape their decisions.

To systematically explore these factors, the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model was employed as a robust framework for the study. The proposed UTAUT2 model integrates key elements from various technology acceptance models to provide a comprehensive understanding of the determinants of technology acceptance and use. By applying the UTAUT2 model, this study provided valuable insights into the specific factors that drive or hinder the adoption of EVs among South African consumers, thereby informing strategies to enhance EV market penetration in the country.

1.4 Research objectives

In this study, the following research objectives were identified to provide a background for the analysis and discussion of the research topic:

Research Objective 1: To assess the degree of influence that the constructs of the UTAUT2 theoretical framework (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, price value and habit) have on the behavioural intention to adopt EVs in South Africa.

Research Objective 2: To assess the degree of influence that environmental concerns and government support have on the behavioural intention to adopt EVs in South Africa.

Research Objective 3: To identify the key barriers and enablers of EV adoption that are specific to South African consumers.

1.5 Rationale

The objectives of this research were framed around the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model, which hypothesises that the actual use of technology is determined by behavioural intention. According to this model, the perceived likelihood of adopting the technology is dependent on the direct effect of key constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motives, price value, habit, and behavioural intention, as well as demographic factors such as age, gender, experience, and voluntariness of use (Venkatesh et al., 2012)

The transition to electric vehicles is primarily driven by the urgent need to reduce greenhouse gas emissions and combat climate change. To accelerate EV adoption, governments in key markets are implementing a range of supportive policies (Energy Agency, 2024). Therefore, this research included environmental impact and government support as key variables in examining South African car buyers' intention to adopt EVs.

This theory provides a comprehensive framework for understanding and analysing the factors that influence individuals' decisions to adopt and use new technologies. To improve the adoption of EVs in South Africa, it is crucial to understand how South African consumers perceive this new technology and their intentions when adopting and using it. Given the current low EV adoption rates, gaining insights into consumer perception and behaviours helped identify barriers and leverage enablers to increase EV uptake.

Currently, there is notable limited research examining the underlying factors that influence EV adoption in South Africa, specifically through the use of the UTAUT and UTAUT2 technology adoption models. Therefore, this research aimed to significantly enrich the body of knowledge on this identified gap. This research also sought to expand the existing body of knowledge by examining the role of government support and environmental concerns as key factors that shape individuals' behavioural intentions.

1.6 Delimitations

The following delimitations have been identified to enable the conducting of an effective and appropriate study:

i. The study focuses on the UTAUT2 model to explore factors influencing EV adoption. It does not directly consider other theoretical models or frameworks that could offer different perspectives on technology adoption.
ii. This study is limited to South Africa, although some of the literature review may have aspects of reviewing other countries with different economic, social, and environmental contexts.
iii. The study includes all forms of electric vehicles, defined as those powered by one or more electric motors. It does not specify or differentiate between various types of electric vehicles.
iv. The study will also exclude the analyses of unrelated sectors unless they directly intersect with the automotive industry's dynamics or the adoption of EVs.
v. This study excludes potential EV users and buyers under the age of 18.

1.7 Definition of terms

Table 1: Definition of Terms

Term	Definition
Electric Vehicles	According to the US Department of Energy (2024) , electric vehicles are vehicles that have an electric motor instead of an internal combustion engine. These vehicles use a large traction battery pack to power the electric motor and must be plugged into a wall outlet or charging equipment.

Internal Combustion Engine Vehicles	Also known as conventional vehicles, are a type of vehicle powered by an engine that burns fuel, typically gasoline or diesel, to create energy. The combustion process takes place inside the engine's cylinders, where the chemical energy in the fuel is converted into heat energy, which is then used to generate mechanical (kinetic) energy that moves the vehicle.
Technology Adoption	Technology adoption is defined as the successful integration of new technology into a business. This involves more than merely using the technology; adoption signifies that the technology is fully integrated into business processes, utilised to its fullest potential and brings tangible benefits to the organisation (Apty.io, 2023).
UTAUT	The Unified Theory of Acceptance and Use of Technology (UTAUT) is a theoretical framework used to understand and predict user acceptance and usage behaviours of technology. Developed by Venkatesh et al. (2003), UTAUT consolidates several models of technology adoption and use into a unified model. This model includes four key constructs: performance expectancy, effort expectancy, social influence and facilitating factors.
UTAUT2	The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is an extension of UTAUT; a model that helps predict how people will use new technology. It is used to assess a user's behavioural intentions towards a technology by introducing hedonic motivations, price value, and habit as constructs (Venkatesh et al., 2012).
Behavioural Intention	Behavioural intention is the basis for the Theory of Reasoned Action (Fishbein & Ajzen, 1975). It is defined as a person's likelihood of performing a behaviour or using a technology.
Barriers to technology adoption	Barriers to technology adoption refer to the factors that hinder or delay individuals, organisations, or societies from accepting and implementing new technologies. These barriers can be technological, economic, organisational, social, or regulatory in nature.

Environmental Concern	According to Fransson & Gørling (1999), Environmental concern refers to an individual's attitude or evaluation regarding environmental issues, behaviours, or consequences. It may reflect specific intentions to act or a broader value orientation, ranging from self-interest and concern for human health to ecocentric values that prioritise the well-being of the environment.
Government Support	According to Balaskas et al. (2024), government support refers to the regulatory frameworks, policies, and endorsements provided by governmental bodies. This includes actions taken to encourage and assist sectors such as technology, business, health, and education through policy measures, financial incentives, regulation, infrastructure development, and research funding.

1.8 Assumptions

The following assumptions were considered for this study:

i. Although electric vehicles are not a new concept or technology, they are still relatively unpopular in the South African car market. Therefore, this research assumes that the respondents have a basic understanding of EVs and the general concept of the technology. This included their ability to differentiate EVs from traditional ICEVs.
ii. In the context of this research, EVs refers to all forms of vehicles that are powered by one or more electric motors. It does not specify or differentiate between various types of electric vehicles.
iii. The study assumed that the sample of South African consumers participating in the research adequately represented the broader population in terms of socio-economic characteristics and geographic diversity. This includes representation from genders, different income groups, and various age groups. The findings in this study should be interpreted with caution considering potential limitations.

1.9 Report Structure

Table 2: Chapter Outline

Chapter	Content
Chapter 1	**Introduction** – This chapter outlines the background of the study, its purpose, research problem, research objectives, research rationale, delimitations, assumptions, and definitions of key terms used in the study.
Chapter 2	**Literature review** - This chapter reviews existing literature relevant to the study, examining theoretical frameworks, global and local perspectives on electric vehicle adoption and outlines the development of the research hypotheses, based on the constructs of the UTAUT2 model.
Chapter 3	**Research methodology** - This chapter outlines the research methodology employed in the study, detailing the research design, data collection methods, sampling techniques, analysis procedures and statistical tools used to test the research hypotheses.
Chapter 4	**Presentation of Results** - This chapter presents the analysis of the data collected during the study, outlining the methods used to process and interpret the findings.
Chapter 5	**Discussions of Results** - This chapter interprets and discusses the findings from the data analysis, linking them back to the research objectives and hypotheses.
Chapter 6	**Conclusions and Recommendations** – This chapter presents conclusions and recommendations based on the study's findings, offering practical suggestions for policymakers, automotive manufacturers, and stakeholders to enhance the adoption of EVs in South Africa. The chapter also acknowledges the study's limitations and outlines avenues for future research,

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

Understanding the South African automotive industry and its transition to EVs requires a comprehensive analysis of the factors that influence EV adoption. Through a literature review, this exploratory study defines the scope and current state of the South African automotive industry to provide a contextual foundation.

Given the limited literature on the adoption of EVs as a new technology, specifically in South Africa, global studies were utilised to draw relevant insights and parallels. This research explored potential factors such as economic, political, technological, and cultural influences, with a focus on identifying emerging patterns that could shape the future of EV adoption in South Africa. By examining this relatively unexplored area, this study aims to provide new avenues for research and contribute to the evolving discourse on EV transition in emerging markets.

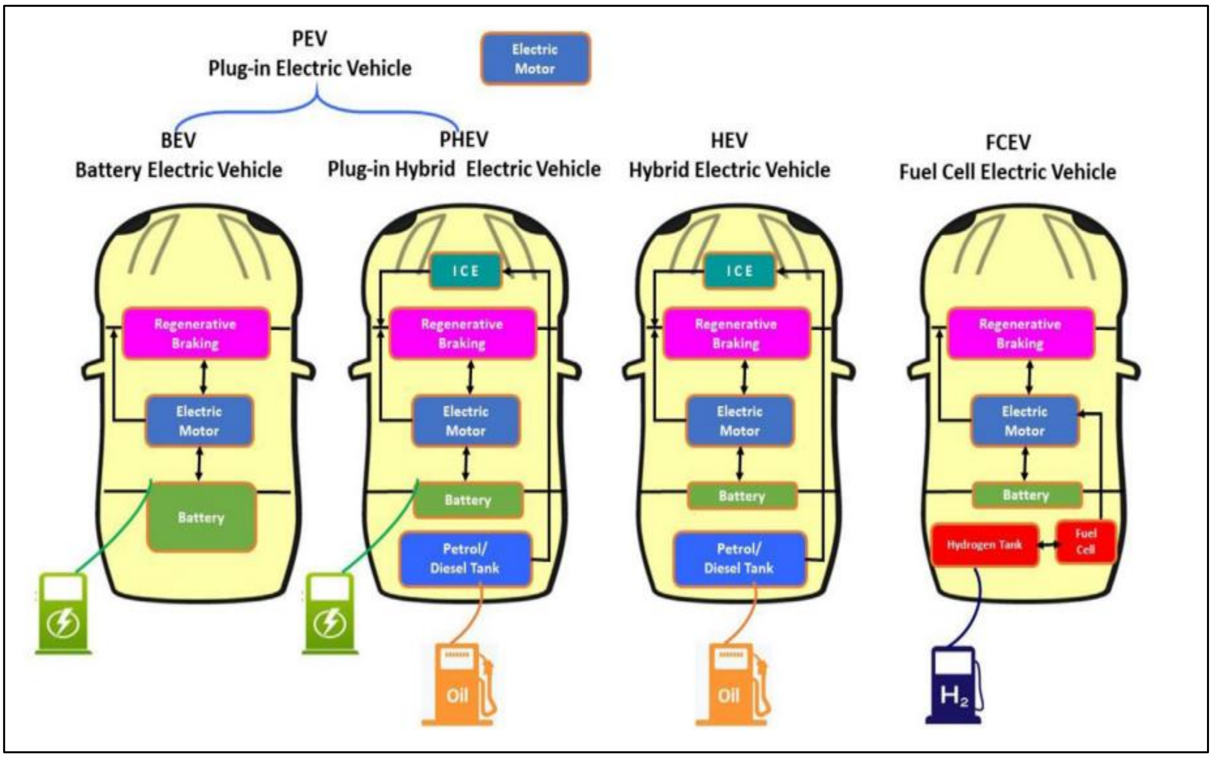
2.2 Definition of Electric Vehicles

Electric vehicles are defined as vehicles that have an electric motor instead of an internal combustion engine and that use a large traction battery pack to power the electric motor (Herrmann & Rothfuss, 2015).

According to Chan (2013), the concept of EVs dates back to the early 19th century, and EVs are 50 years older than ICEVs. Several inventors in Europe and the United States have been given credit for the early inventions and development of EVs (Anderson et al., 2022). Kirsch and Cutcliffe (2001) stated that during the inception of the automotive industry in the late 1890s, steam, gasoline, and electric cars all competed to become the dominant automotive technology. However, the discovery of large petroleum reserves, advancements in internal combustion engine technology, and mass production techniques introduced by Henry Ford led to the dominance of gasoline-powered vehicles by the 1920s (Mom, 2004).

Currently, there are various types of EVs classified as HEVs (hybrid electric vehicles), PHEVs (plug-in hybrid electric vehicles), FCEVs (Fuel Cell Electric Vehicles), and BEVs (battery electric vehicles). HEVs and PHEVs are powered by a combination of battery power and alternative fuels, whereas BEVs use only an electric battery for power. FCEVs use a fuel cell to convert hydrogen into electricity (Singh Patyal et al., 2021).

Figure 1: Electric Vehicle Types



Source: (Singh Patyal et al., 2021)

2.3 Background of the SA Automotive Industry

2.3.1 *SA Automotive Industry*

The South African automotive industry is a significant sector of the country’s economy, contributing substantially to GDP, employment, and international trade (International Trade Administration, 2024). According to a Naamsa report (2023), the broader automotive industry’s contribution to GDP was 4.9% in 2022. This industry is home to several multinational automotive manufacturers, including Toyota, BMW, Ford, Mercedes-Benz, Volkswagen, and Nissan. These manufacturers have established production plants across the country in Gauteng, KwaZulu-Natal, and the Eastern Cape provinces (Modiba, 2023).

South Africa produces a range of vehicles, including passenger vehicles, light commercial vehicles, minibuses, medium trucks, buses, and heavy trucks (Modiba, 2023). In 2022, the South African automotive market featured 43 passenger vehicle brands and 2,513 model derivatives, with total revenue from new vehicle sales amounting to R255.7 billion (Modiba, 2023). South African-made vehicles and components are exported to numerous countries, including Europe, North America, and Asia (Monaco & Wuttke, 2023).

According to Monye et al. (2023), the automotive industry in South Africa's automotive industry takes primary responsibility for manufacturing, selling, repairs, and other services of automobile products and is one of the largest employers in the manufacturing sector, providing direct and indirect employment to 112,000 people. In figures released by Naamsa (2023), sales of electric vehicles and new-energy vehicles (NEVs) in South Africa accounted for just 1.45% of the total market sales of 532,092 units. Therefore, there is a need to understand how South Africa is currently navigating the transition towards EVs.

2.3.2 *SA Electric Vehicle Market*

The South African automotive industry is largely dominated by ICEVs, with major manufacturers, such as Toyota, BMW, Volkswagen, Mercedez Benz, Volvo, and Ford, dominating production in both local and export markets. EVs were first introduced into the South African market in 2013 (Moeletsi, 2021), and in 2023, 28 EV models were available in South Africa, with Volvo being the top-selling EV manufacturer in the country (GreenCape, 2024).

Traditional hybrid EVs dominate South Africa's EV market, with sales growing from 4,050 units in 2022 to 6,495 in 2023. However, battery electric vehicles also saw significant growth, surging by 85.46% from 502 units in 2022 to 931 units in 2023 (GreenCape, 2024). Electric vehicles in South Africa generally have higher upfront purchase prices than ICEVs. This price difference is influenced by factors such as battery costs and the lack of local manufacturing of EVs, which attract around 25% in import duties and taxes, making them less accessible for most South Africans (Sustainable Energy Africa, 2022). According to South Africa's EV White Paper (2023), there are about 350 public EV charging stations in the country. This is a stark contrast to countries like the United States, China, and many European nations, where EV infrastructure is far more developed.

Therefore, to support the EV market growth, the South African government is currently implementing policy actions to coordinate national strategies and plans for investment to scale up EVs, as well as to increase the grid capacity to support EV uptake (DTIC, 2023).

2.4 Theoretical Framework

While EVs are well-established in major global markets, they remain a relatively new technology concept in emerging economies like South Africa, where many people have yet to drive or own an EV. Technology adoption theories offer valuable insights into the factors influencing individuals' decisions to embrace new technologies. A strong understanding of these foundational concepts is crucial for analysing EV adoption. This section explores the key theories and models that have shaped the study of technology adoption, with a specific focus on the UTAUT2, the theoretical framework selected for this study. UTAUT2 was built upon a series of earlier technology adoption theories, each contributing key insights to factors that shape behavioural intention and technology adoption (Venkatesh et al., 2012).

2.4.1 *Theory of Reasoned Action*

The foundational model, the Theory of Reasoned Action (TRA), proposed by Fishbein and Ajzen (1975), originated from the authors' research on attitudes and behaviours related to performing certain actions. Ambali and Bakar (2015) 's study of TRA, related to ICT adoption stated that TRA can be used to shed light on the attitudinal behaviours related to acceptance, use, and adoption of technology in organisations. They further explained that according to this model, when positive intention is formed, individuals are more likely to actively engage in the intended behaviour. Otieno et al. (2016) supported this view, asserting that TRA identifies behavioural intention as the most accurate determinant of actual behaviour.

2.4.2 *Theory of Planned Behaviour*

Some studies suggest that behavioural intention does not always translate into actual behaviour (Sheeran & Webb, 2016). This limitation of TRA contributed to the development of the Theory of Planned Behaviour (TPB) by Ajzen (1991), which is now a widely utilised framework for understanding technology adoption and usage. TPB identifies three key determinants of behavioural intention: attitude towards the behaviour, subjective norms, and perceived behavioural control. TPB considers how individual attitudes, social pressure from significant others, and factors such as skills and resources are determinants of behaviour (Ajzen, 1991).

2.4.3 *Technology Acceptance Model*

Although TPB improved upon TRA, it still lacked technology-specific determinants. To address this issue, Davis (1989) developed the Technology Acceptance Model (TAM) to study technology adoption among individuals. This author posited that the primary factors that influence an individual's decision to adopt a new technology are perceived usefulness (PU) and perceived ease of use (PEOU). PU refers to the degree to which an individual believes that using a particular technology will enhance performance or provide significant benefits, while PEOU denotes the extent to which an individual believes that using the technology will be free from effort.

2.4.4 *Diffusion of Innovations*

TAM did not fully consider external factors such as social influence. Therefore, models such as The Diffusion of Innovations theory by Rogers (1962) were developed to make up for this limitation. This model explains how, why, and at what rate new ideas, technologies, and/or products spread through cultures or social systems. According to Rogers (1995), this theory follows the innovation-decision process, which refers to the sequence through which an individual progresses from initially learning about an innovation to developing an opinion about it, then deciding to either adopt or reject it.

2.4.5 *UTAUT*

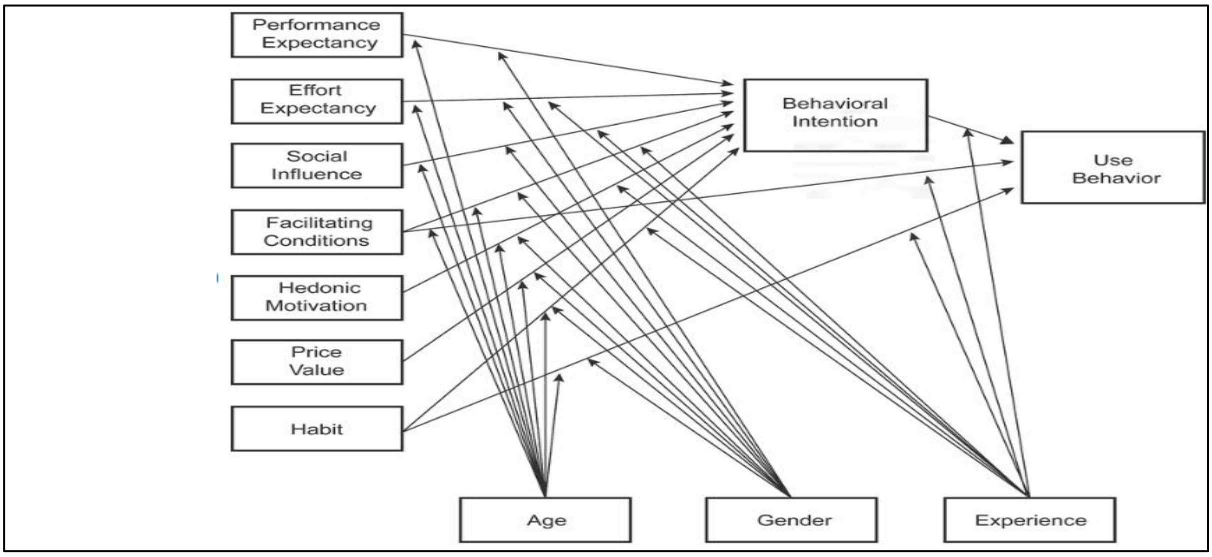
Recognising the fragmented nature of these models, Venkatesh et al. (2003) developed UTAUT by integrating elements from adoption models such as TRA, TPB, TAM, and DOI. Through the UTAUT model, Venkatesh et al. (2003) introduced new constructs to integrate and evaluate various factors that influence behavioural intention and technology adoption. Venkatesh et al. (2003) stated that the actual use of technology is determined by behavioural intention. They further stated that the perceived likelihood of adopting the technology was dependent on the direct effects of four key constructs: performance expectancy, effort expectancy, social influence and facilitating conditions. These authors also stated that the relationships between these factors can also be moderated by four key factors: gender, age, experience, and voluntariness of use.

Marikyan and Papagiannidis (2023) argued that UTAUT has significantly advanced the literature on technology adoption, as it does not only focus on simple systems such as PCs, but also examines the adoption of complex technologies. In this regard, UTAUT demonstrated stronger predictive power than the other adoption models.

2.4.6 *UTAUT2*

Venkatesh et al. (2012) extended UTAUT to form UTAUT2 as a model to study the acceptance and use of technology in a consumer context by incorporating three new constructs: hedonic motivation, price value, and habit. According to Venkatesh et al. (2013), the extensions proposed in UTAUT2 significantly improved the variance explained in behavioural intention, increasing from 56% (using the original UTAUT model) to 74%, and the variance explained increased from 40% with UTAUT to 52% with UTAUT2. The theoretical UTAUT2 model is shown in Figure 2 below.

Figure 2: UTAUT2 Theoretical Model



Source: Venkatesh et al. (2012)

2.5 Prior Studies and Hypothesis Development

The adoption of EVs has emerged as a significant academic topic driven by the growing need to transition towards sustainable transportation. Prior studies on EV adoption consistently emphasise the role of behavioural intention as a precursor to actual adoption. Researchers have identified that individuals' intentions to adopt EVs are shaped by many factors, ranging from personal preferences to external influences.

This section reviews the existing literature on EV adoption and provides insights from studies conducted in different regions and countries. By analysing consumer preferences and identifying the determinants of adoption, this review aims to build on established theoretical frameworks. This review focused more on the UTAUT2 constructs because they provide a comprehensive and robust foundation for understanding behavioural intention.

Performance Expectancy (PE)

The performance expectancy (PE) construct of UTAUT refers to the degree to which using a technology is perceived to enhance job performance or productivity (Venkatesh et al., 2003). This construct is closely related to the perceived usefulness concept in the technology acceptance model by Davis (1989). According to Bajunaied et al. (2023), users who believe that using a technology will significantly improve their performance or efficiency in their tasks are more likely to have a positive intention to use it. In a study on EV adoption in Germany, Chau (2023) found that performance expectancy drives the expansion of the EV market, emphasising that performance expectancy positively affects purchase intentions. Similarly, performance expectancy was found to emphasise the positive effects of perceived performance on EV adoption intentions by Krishnan and Koshy (2021) in India and Cuong et al. (2024) in Vietnam. Based on these findings, it is hypothesised that performance expectancy positively influences behavioural intention to adopt an EV.

> *H1: Performance expectancy positively influences behavioural intention to adopt EVs.*

Effort Expectancy (EE)

The second construct in the UTAUT2 framework, effort expectancy, refers to the perceived ease of use associated with a technology. This reflects how much effort users anticipate they will need to invest in learning and using such technology (Venkatesh et al., 2003).

Samarasinghe et al. (2024) reported that EVs generally meet expectations for ease of use in Sri Lanka, indicating that users in this context may view the technology as accessible and convenient. Supporting this, Manutworakit (2021) identified ease of use as a significant factor in Thai motorists' preference for EVs. According to Charness and Boot (2016), technologies perceived as user-friendly or requiring minimal effort to operate are more likely to be adopted. Based on these findings, it is hypothesised that effort expectancy positively influences behavioural intention to adopt an EV.

H2: Effort expectancy positively influences behavioural intention to adopt EVs.

Social Influence (SI)

Social influence involves the degree to which individuals perceive that important others, such as peers, family, or colleagues, believe they should use a new technology (Venkatesh et al., 2003). Prior studies such as Gitelson & Kerstetter (1995)'s study of the influence of relatives and friends in decision-making stated that other people such as friends and family can affect a person's decision-making process. This author found that friends and relatives shape individual behaviour by between 29 to 39%.

Social influence emerged as a powerful factor in Pyakurel et al. (2025)'s EV study in Nepal. These authors found that people look to their peers and social networks for endorsements when make making decisions to adopt EVs. Similarly, Samarasinghe et al. (2024) agrees with these findings in their study of Sri Lanka. They also found that despite positive attitudes towards EVs, many consumers can remain undecided about purchasing one, partly due to insufficient recommendations from peers.

According to Graf-Vlachy et al. (2018), social influence has been shown to profoundly affect human behavior in general and in technology. In a Chinese study of a similar technology, autonomous vehicles, Zheng & Gao (2021) found social impact to influence adoption. These authors stated that social impact influences individual willingness through personal image symbols, subjective norms, and herd psychology. Based on these studies, it is hypothesised that social influence positively influences behavioural intention to adopt EVs.

H3: Social influence positively influences behavioural intention to adopt EVs.

Facilitating Conditions (FC)

Facilitating conditions are defined as the degree to which an individual believes that organisational and technical infrastructure exists to support the use of technology (Venkatesh et al., 2003). Singh et al. (2023) found that facilitating conditions significantly influenced EV adoption in India. Wang et al. (2023) supported these findings in China, where facilitating conditions have a positive effect on the adoption intention of EVs.

Samarasinghe et al. (2024) also highlighted that adoption is negatively affected when facilitating conditions, such as charging station availability and technical support, are inadequate. Kirana and Nurcahyo (2023) also found that facilitating conditions affect user acceptance of EVs in Indonesia. However, these authors stated that facilitating conditions are influenced by environmental concern, infrastructure readiness, and government policies. Therefore, based on this theory, it is hypothesised that facilitating conditions positively influence behavioural intention to adopt EVs.

H4: Facilitating conditions positively influence behavioural intention to adopt EVs.

Hedonic Motivations (HM)

Venkatesh et al. (2012) define hedonic motivation as the pleasure or enjoyment derived from using technology. These authors incorporated hedonic motivation into UTAUT2 to capture the intrinsic motivational aspects that influence technology adoption. The construct of hedonic motivation recognises that users often engage with technology for not only utilitarian purposes but also for the enjoyment and satisfaction it provides (Tamilmani, Rana, Prakasam, et al., 2019).

In a study exploring consumers' motives for EV adoption, Chaturvedi et al. (2023) found that hedonic motives strongly influence purchase intentions in the South Asian region. Similarly, hedonic motivations, which are explained to include feelings and emotions about a thing by Hoang et al. (2022), were found to be a predictor of BEV adoption in

Vietnam. Based on these findings, this study hypothesised that hedonic motivations can positively influence behavioural intention to adopt EVs.

H5: Hedonic motivation positively influences behavioural intention to adopt EVs.

Price Value (PV)

In UTAUT2, Venkatesh et al. (2012) also included price value (PV) to reflect consumers' cost–benefit analysis when deciding whether to adopt a new technology. These authors argued that price value is a significant predictor of behavioural intention to adopt a technology. Tamilmani et al. (2018) supported this hypothesis and stated that price value is an important addition to UTAUT2 because individuals bear monetary costs when using this technology.

In Germany, Chau (2023) found that low cost of use is a factor that promotes the adoption and use of EVs, and price value positively affects the consumer's purchase intention of electric cars. Similarly, Cuong et al. (2024) found that price value positively affects EV purchase intention in Vietnam. In Thailand, however, Manutworakit (2021) found that the high price of EVs compared to ICE vehicles is a barrier to motivating customers to use EVs. This is similar to Mohubedu (2021), who stated that the high cost of EVs is a significant barrier. Based on the information provided, this study tests whether price value positively influence behavioural intention to adopt an EV with the following hypothesis:

H6: Price Value positively influences behavioural intention to adopt EVs.

Habit (HB)

In UTAUT2, Venkatesh et al. (2012) introduced habit as a construct to reflect the automaticity that users develop over time in performing behaviours related to technology usage. These authors argued that habit is a key predictor of technology use. Habit refers to the extent to which individuals tend to perform behaviours naturally due to learning (Zhou et al., 2021) . This construct emphasises the influence of prior behaviour and experience on the intention to continue using technology.

Srikaanth (2024) highlighted that habit can play a critical role in shaping technology adoption, as frequent use of a technology often leads to it becoming a routine that requires less cognitive effort. According to Tamilmani, Rana, & Dwivedi (2019), habit as a construct is often omitted in UTAUT2-based studies because researchers believe that, in the context of the adoption of new technologies, users have not had sufficient time to develop habitual usage patterns. However, this study tests its influence by hypothesising that habit positively influences behavioural intention to adopt an EV.

H7: Habit positively influences behavioural intention to adopt EVs.

Environmental Concerns (EC)

According to De Groot & Steg (2007), environmental concerns are directly linked to attitudes towards adopting pro-environmental technologies. García de Blanes Sebastián et al. (2023) found that environmental awareness was a key determinant of EV adoption in Spain, suggesting that individuals with greater concern for the environment are more likely to embrace EV technology. Similarly, Cuong et al. (2024) highlighted that environmental concerns positively influenced EV purchase intentions in Vietnam, according to the UTAUT and UTAUT2 models.

In China, He et al. (2021) stated that environmentally conscious consumers increase EV profitability, which may lead manufacturers to stop targeting traditional consumers. Although environmental concerns have not significantly influenced EV purchase decisions in Sri Lanka (Samarasinghe et al., 2024), they remain a relevant factor to explore in this study. Therefore, based on these findings, this study hypothesises that environmental concerns positively influence behavioural intention to adopt EVs.

H8: Environmental concern positively influences behavioural intention to adopt EVs.

Government Support (GS)

Governments in key markets are introducing various supportive policies to accelerate the adoption of EVs. Various researchers, such as Scholtz et al. (2023), have stated that taxation policies affect EV costs. While government support is deemed an insignificant factor in influencing intentions in countries such as Vietnam, Cuong et al. (2024) found it vital in encouraging EV adoption.

Chau (2023) introduced government support in his UTAUT-focused study and found that Germany is showing a serious spirit of promoting the use of EVs by introducing and adding incentives. Phuthong et al. (2024) also studied the impact of supportive government policies in Thailand and found that government incentives for EV purchases play a key role in encouraging people to buy and use EVs.

Government support will therefore be incorporated into this UTAUT2-based study to help understand how government policies, such as taxation incentives, subsidies, and other forms of support, can influence consumers' decisions to adopt EVs. Therefore, based on these findings, this study hypothesises that government support positively influences behavioural intention to adopt EVs.

H9: Government support positively influences behavioural intention to adopt EVs.

The review confirmed that every one of these constructs contributes to forming an intention to adopt electric vehicles, with their influence potentially differing. The developed hypotheses will be employed to assess the impact of these factors on individuals' intentions to adopt electric vehicles.

2.6 Conceptual Framework

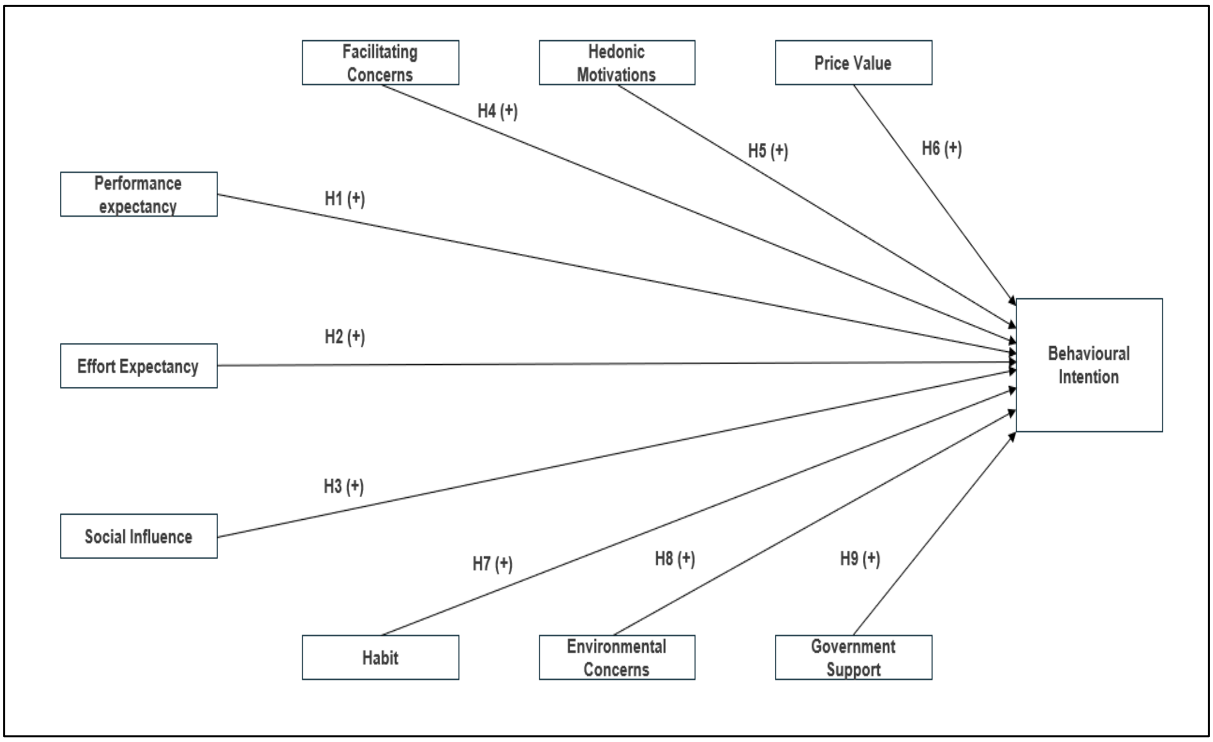
According to Luft et al. (2022), a conceptual framework outlines the researcher's understanding of the key concepts being studied. These authors stated that a conceptual framework aims to highlight the proposed relationships between these concepts and to address the research gaps identified in the literature review. A conceptual framework also serves as a visual or descriptive representation of how different elements within a study are connected (Miles & Huberman, 1994).

Unlike other technologies, the adoption of EVs is heavily influenced by sustainability and environmental awareness, and factors such as government incentives, policies, and infrastructure development significantly impact EV adoption. Therefore, modifications to the standard UTAUT2 framework were found necessary to study the influence of environmental concerns and government support have on the behavioural intention to adopt EVs. Other studies on EV adoption, such as those conducted in Germany and Thailand, have highlighted the growing influence of environmental concerns and government policy measures on behavioural intentions. As a result, these studies modified UTAUT2 to incorporate these two critical constructs, reflecting their increasing significance in shaping consumer decisions regarding EV adoption. The same approach was adopted in this study.

The standard UTAUT2 framework also includes age, gender, and experience as moderating variables. This study did not include these variables as part of the conceptual framework because EV adoption is still in its early stages in South Africa, and market barriers and other macroenvironmental factors may be stronger determinants of adoption than variations in user demographics.

Figure 3 below represents the hypothesised relationships between performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, price value, habit, environmental concerns, government support, and the behavioural intention to adopt EVs in South Africa.

Figure 3: Research Conceptual Model



Source: Author's own compilation

2.7 Conclusion of Literature Review

The literature review in this chapter has provided a comprehensive examination of the South African automotive industry’s current state and its transition towards electric vehicles, alongside an analysis of global trends in EV adoption. The review of prior studies on EV adoption across different regions has revealed commonalities and differences in factors influencing consumer intentions in Spain, Germany, China, Thailand, India, Indonesia, and Vietnam. However, the relative importance of these factors varies across socioeconomic and cultural contexts.

The findings of this literature review provide a robust foundation for the subsequent empirical analysis. By integrating insights from global studies and tailoring them to the South African context, this research formulated the hypothesised relationships between the identified factors and EV adoption intention. The conceptual framework developed in this chapter guides the examination of these relationships to provide a nuanced understanding of the complex interplay of factors influencing EV adoption in South Africa.

CHAPTER 3. RESEARCH METHODOLOGY

The primary objective of this research was to examine the factors influencing the behavioural intention to adopt EVs in South Africa. This chapter elaborates on the research paradigm, research approach, research design, population and sampling, data collection methods, data analysis procedures, quality assurance, and ethical considerations followed in this study.

3.1 Research Paradigm

According to Kivunja & Kuyini (2017), a research paradigm is a set of beliefs and practices that guide researchers' inquiry. The research paradigm for this study on the factors influencing the adoption of EVs in South Africa is rooted in the positivist paradigm.

The positivist paradigm, also known as empiricism, is characterised by the belief that reality is objective and can be observed and measured through empirical evidence (Williamson et al., 2002). According to Park et al. (2020), the key objective of positivist research is to establish explanatory connections or causal relationships that enable the prediction and regulation of the phenomena under study. Positivism paradigm is suitable for this study because it allows for a systematic investigation of quantifiable data to understand the factors influencing EV adoption in South Africa using hypothesis testing and statistical analysis

3.2 Research approach

To gain a comprehensive understanding of the factors influencing the adoption of EVs in South Africa, an in-depth analysis is essential. This study adopts a quantitative research approach, which, according to Watson (2015), involves systematically investigating phenomena through the collection of quantifiable data. Creswell (2004) further explained that a quantitative approach transforms human experiences into numerical data, enabling objective analysis of various variables. This approach emphasises statistical, mathematical, or numerical analysis of information gathered through tools such as surveys, questionnaires, and polls (Babbie, 2010).

Xiong (2022) also supported the use of this approach for research and stated that quantitative methods facilitate objective data collection and can minimise research bias through the use of standardized surveys. Queirós et al. (2017) also stated that surveys which are often used in quantitative research provide high representativeness but are also cost-effective, making them an efficient method for gathering large amounts of data.

Overall, the quantitative approach enables a rigorous, unbiased, and cost-effective investigation, ensuring that the findings can be generalised and applied to a wide population, which is crucial for understanding the adoption of EVs in South Africa.

3.3 Research design

A research design serves as a blueprint for the study, guiding the collection and analysis of data (Leedy, 1997). In quantitative research, various designs are employed to gather data. For this research, which aims to explore the attitudes and opinions of South Africans regarding the adoption of EVs, a descriptive research design was found to be most appropriate. A descriptive research design is a type of research methodology that seeks to describe a population, situation, or phenomenon accurately and systematically and uses a wide variety of research methods to investigate one or more variables (McCombes, 2019). According to this author, for descriptive research designs, the researcher does not control or manipulate any of the variables, but only observes and measures them.

Common method of the descriptive research design includes surveys and questionnaire, observational methods, case studies and content analysis. For this research, the survey method was selected. According to Brant et al. (2015), survey research designs allows for the systematic collection of data by obtaining information from a sample of individuals through their responses to questions.

The survey research design begins by identifying the population of interest, followed by implementing recruitment strategies to ensure adequate representation of that population. Brant et al. (2015) stated that data can be gathered using methods such as self-administered questionnaires or those administered by an interviewer. In this study, a self-administered survey was chosen. Participants provided their responses independently from the researcher. While this ensures anonymity and protects the privacy of each person involved in the study, self-administered surveys have disadvantages such as response bias, potential for respondents to misunderstand questions, low response rates and incomplete surveys.

However, self-administered surveys also offer several advantages, such as scalability, efficiency, and cost-effectiveness, making them an ideal choice for this study (Marcano Belisario et al., 2015). This method allows for the collection of large amounts of data quickly, which is crucial given the broad geographic and demographic scope of the target population for this study.

3.4 Data collection method

An online questionnaire was administered using Qualtrics Survey Software. Qualtrics offers efficient electronic data storage, facilitates streamlined data analysis, and enables a broad geographic reach, thereby supporting the collection of diverse and potentially representative responses from the target population. According to Kuphanga (2024), questionnaires are an effective and flexible tool for data collection, providing standardisation in the collection, organisation, and analysis of data. Eungoo & Hwang (2023) further highlight that online questionnaires promote respondent anonymity, a critical factor in ensuring candid and unbiased responses, free from the social desirability or interviewer effects that can influence qualitative methods.

A key advantage of online surveys is their convenience for participants, who can respond at a time that suits them. Additionally, they enable the rapid collection of large volumes of data within a relatively short timeframe and at a reduced cost (Regmi et al., 2016). However, as Taherdoost (2021) notes, researchers must remain aware of potential limitations, such as low response rates, non-response bias, and issues surrounding the representativeness of the sample.

In this study, a digital survey link was generated using Qualtrics and distributed to participants via various social media platforms, offering a practical and cost-effective approach to data collection. The initial participants, who were personally known to the researcher, received a message including the study title, its objectives, and the survey link. This message was shared through WhatsApp (both individual and group chats), Microsoft Teams, Facebook, and LinkedIn. The link was sent directly to approximately

100 contacts across these platforms. Furthermore, the survey was shared within a community WhatsApp group comprising 363 members residing in the Modderfontein area. To expand local outreach, the questionnaire was also disseminated 18 times via QR code to individuals within the same community.

3.5 Population and Sampling

This section outlines the target population, sample size, and sampling approach used in the study. Defining the population ensures clarity regarding the group of individuals to whom the research findings will be applicable (Eldredge et al., 2014). The sample size determines the number of participants required for the study, while the sampling process determines the subset of participants selected for analysis (Martínez-Mesa et al., 2016). According to Eungoo & Hwang (2023), a well-defined sampling strategy is crucial for obtaining reliable and generalisable results.

3.5.1 *Population*

According to Stats SA (2024), South Africa had an estimated population of approximately 63.02 million as of mid-2024. Approximately 45.34 million people are active internet users (Statista.com, 2024).

This study, which explores the factors influencing EV adoption in South Africa, targeted potential EV buyers and drivers aged 18 years and older (the legal driving age in South Africa), residing in the country, and willing to participate in an online survey. To complete the online survey, participants needed access to a cell phone, laptop, or other device with internet access. There were no restrictions based on gender, ethnicity, socioeconomic status, or other demographic factors, as the goal was to obtain a broad and inclusive representation of the adult population.

Based on these criteria, the total estimated population for this study consisted of adults with internet access. Since approximately 65%–70% of South Africa’s population is aged 18 years or older, this equates to roughly 42.22 million adults (Statista.com, 2024). Considering that most internet users fall within this demographic, the estimated number of internet-using adults who could participate in the study was approximately 40 million.

3.5.2 *Sample*

In research, selecting an appropriate sample size is crucial for ensuring the accuracy and reliability of findings (Andrade, 2020). In this case, given a total population of 40 million adults in South Africa, a 95% confidence level, a 5% margin of error, and an assumed population proportion of 0.5, the required sample size was determined using the standard formula for sample size calculation:

n= Sample size
N= 40 million adults in SA
Z= 1.96Z (Z-value for 95% confidence)
p= 0.5p (estimated proportion, used when you don't have an estimate)
E= 0.05 (margin of error)

Figure 4: Sample Size Formular

$$n = \frac{N \cdot Z^2 \cdot p \cdot (1-p)}{(E^2 \cdot (N-1)) + (Z^2 \cdot p \cdot (1-p))}$$

n ≈384

Therefore, a sample size of approximately **384** participants was determined to be suitable for a 95% confidence level with a 5% margin of error.

This calculation follows well-established statistical principles in survey sampling. A sample size of 384 is widely recognised as sufficient for producing statistically reliable results when estimating proportions in large populations (Krejcie & Morgan, 1970).

3.5.3 *Sampling method*

This study employed a non-probability sampling approach, specifically convenience sampling combined with elements of snowball sampling. Non-probability sampling refers to a research method in which participants are selected based on convenience or specific criteria, rather than through random selection (Ahmed, 2024). This study identified the factors that influence South Africans' adoption of electric vehicles. Pandey and Pandey

(2021) stated that this technique can be used in studies in which the goal is to explore or gain insights into a specific phenomenon.

Convenience sampling is a non-probability sampling technique in which samples are selected from the population because they are conveniently available to the researcher (Creswell, 2004). For this study, the initial participants, who were people known to the researcher, were sent a message containing the title of the study, the objectives of the survey, and a link to the Qualtrics online survey to complete. The message was shared through WhatsApp chats, WhatsApp groups, Teams Chat, Facebook, and LinkedIn. While this method allowed for easy data collection and cost-effectiveness, Golzar and Tajik (2022) cautioned researchers to be mindful of biases and limitations, such as the sample not being representative enough and the lack of generalisability of the research findings.

The initial participants were also encouraged to share the survey link with their networks, including their friends, colleagues, and other potential electric vehicle buyers or drivers. Therefore, snowball sampling was also incorporated to enhance the diversity of responses and ensure broad participation. Snowball sampling involves recruiting research participants through referrals from existing participants (Nikolopoulou, 2022). This method helped increase participation from individuals who may not have been reached through the initial outreach.

3.6 Research instrument

An online survey questionnaire was the research instrument used to conduct this study. The questionnaire was designed based on the conceptual framework developed by the author that integrates UTAUT2 constructs with environment concerns and government support. The questionnaire was divided into three sections.

Section A: Demographics

This section aimed to gather essential demographic information. Understanding the demographic profile of respondents is crucial for analysing how different groups of people perceive and adopt electric vehicles.

- age, gender, highest level of education, employment status, monthly household income and current vehicle ownership

Section B: UTAUT2 Constructs measurement items (including environmental concerns and government support).

This section examined the various factors that influenced consumers' behavioural intention to adopt and use electric vehicles, based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model.

A total of 41 measurement items were employed in the survey. *Sections B1 to B7* included items corresponding to the seven core constructs of the UTAUT2 model: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. *Section B8* contained items related to environmental concerns, while *Section B9* addressed perceptions of government support. Finally, *Section B10* focused on items measuring behavioural intention.

Section C: Open-end questions

This section asked survey participants 2 open-ended, non-mandatory questions.

- **Question 1:** What do you think are the biggest challenges or barriers to adopting electric vehicles in South Africa?
- **Question 2:** In your opinion, what could be done to encourage more people to switch to electric vehicles in South Africa?

The survey questionnaire has been added under APPENDIX *B – Research Instrument.*

3.7 Procedure for data collection

Data collection for this study was conducted through an online survey administered via the Qualtrics platform. The survey included forty-one 7-point Likert scale statements and two open-ended questions to allow participants to express their views in depth. As mentioned in 3.5.3, convenience sampling was initially used to select participants, which included individuals known to the researcher. A message containing the survey link was distributed through various communication channels. The survey was made accessible online, and the Qualtrics link was provided to participants along with a brief description of the study's objectives.

The link was shared with approximately 100 WhatsApp, Facebook, and LinkedIn contacts. The survey link was also shared in a community WhatsApp group consisting of 363 members living in the Modderfontein area and distributed 18 times via QR code to people in the Modderfontein area. Participants were encouraged to share the survey link within their networks. This helped broaden the participant pool, ensuring the collection of data from a more diverse demographic. Through this snowball method, additional participants were recruited, further enhancing the study's representativeness, and increasing the sample size.

The survey remained open for a period of four weeks to allow time for participants to respond. During this time, reminders were sent weekly to encourage the initial participants to complete the survey and share the link with other willing participants.

To ensure ethical compliance, all participants were informed of the study's purpose and their rights prior to completing the survey. Informed consent was obtained from all respondents. While no personally identifiable information was explicitly collected, complete anonymity could not be guaranteed due to the use of online distribution methods and the potential for metadata collection (e.g., IP addresses) by the survey platform. However, all responses were handled with strict confidentiality. Data were stored securely within the Qualtrics system, and only the researcher had access to the raw data. All responses were anonymised during analysis, and results were reported in a manner that ensured individuals could not be identified.

3.8 Data analysis strategies and interpretation

Analysis of the quantitative collected data was be performed using IBM SSPS v29 and IBM SPSS Amos v29. Analysis of the qualitative data collected for the two open-ended questions were analysed using Python, Scikit-learn library, and Excel.

3.8.1 *Data Cleaning and Screening*

The data screening process involved exporting the data collected on Qualtrics into and IBM SPSS file. On IBM SPSS, data was analysed to assess overall completeness before using it to for quantitative analysis. In SPSS, the survey responses were screened for missing values and outliers. Additionally, checks were conducted for non-response bias and non-normal variables. Of the 417 responses collected, 104 were excluded due to issues such as straight-lining behavior (5 cases), ineligibility due to age (4 participants under 18), and incomplete responses.

3.8.2 *Frequency Analysis*

Frequency analysis of demographic characteristics involved examining how often different demographic variables (age, gender, highest level of education, employment status, monthly household income and current vehicle ownership) collected in the questionnaire appeared in the dataset. This step helped in understanding the composition of the study sample and ensuring that the analysis accounts for the diversity and representativeness of the participants. The frequency analysis was performed using IBM SPSS v29.

3.8.3 *Descriptive Analysis*

To assess the factors influencing the adoption intention of EVs in South Africa using the Unified Theory of Acceptance and Use of Technology (UTAUT2), descriptive statistics were employed to analyse the data collected through the Likert scale questionnaire. The Likert scale data captured respondents' attitudes towards EV adoption, with responses ranging from 1 (Strongly Disagree) to 7 (Strongly Agree).

Descriptive statistics such as the mean and standard deviation were calculated for each measurement item to provide insights into the central tendencies and variabilities in attitudes towards EV adoption. This approach helped us understand the general sentiments and perceived factors affecting EV adoption intentions within the South African context, while ensuring that the ordinal nature of the Likert scale data was appropriately considered in the analysis.

3.8.4 *Structural Equation Modelling*

Subsequently, Structural Equation Modelling (SEM) was be employed to analyse the relationships between the UTAUT constructs and EV adoption intention. Structural Equation Modelling (SEM) is a statistical methodology that takes a confirmatory (hypothesis testing) approach to analyse data representing some phenomena (Kline, 2005). Christ et al. (2014) stated that SEM allows for the examination of complex relationships and can be used to test theories of causal relationships. Tarhini et al. (2015) also stated that SEM has two key advantages over traditional statistics like regression. These authors say that SEM can test multiple relationships between independent and dependent variables at the same time and SEM accounts for measurement errors, improving the accuracy of reliability estimates and overall model fit.

This study has 9 dependent variables and 1 independent variables whose relationships require evaluation. According to Fan et al. (2016), this technique can be used to test and evaluate multivariate causal relationships that involve multiple dependent variables, latent variables, or indirect effects. SEM was found to be suitable for this study as it allows for the simultaneous testing of multiple relationships within a single model, whereas regression would require a series of separate analyses.

SEM also allows for the inclusion of latent variables that are not directly observed but are inferred from multiple observed indicators (Hair et al., 2021). This is particularly relevant for constructs in the UTAUT2 framework, which are often conceptualised as latent variables. According to (Hair et al., 2021), regression models do not accommodate latent variables because they only consider observed variables, which can limit their ability to analyse abstract concepts like attitudes or intentions effectively.

There are two commonly employed techniques in Structural Equation Modelling (SEM): Covariance-Based SEM (CB-SEM) and Partial Least Squares SEM (PLS-SEM). According to Dash and Paul (2021), CB-SEM is most appropriate when the research objective is theory testing and validation, whereas PLS-SEM is better suited for research focused on prediction and theory development. This study used CB-SEM because its primary objective was to test and validate the conceptual UTAUT2 framework. Using SPSS and Amos v29, SEM was applied to analyse the complex relationships among the variables. The analysis process began by specifying latent variables and their observed indicators, followed by Common Method Bias (CMB) testing using Harman's Single Factor Test.

Several studies have demonstrated the suitability of SEM for analysing consumer adoption of EVs. For instance, Champahom et al. (2025) employed SEM to examine EV adoption intentions in Thailand using the UTAUT2 framework, incorporating government participation as a key factor. Similarly, Irfanto & Apriliantty (2022) also used SEM to analyse questionnaire data in their study of EV adoption in Indonesia also based on the UTAUT2 model. Given its effectiveness in analysing UTAUT2-focused studies, SEM was found well-suited for this study.

Confirmatory factor analysis was also conducted to assess model fit using indices such as CMIN/DF, RMSEA, GFI, CFI, and TLI. Reliability and validity were evaluated using Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT2) to ensure distinctiveness between constructs. The structural model analysis confirmed the acceptable model fit and evaluated the relationships between the latent variables. With the structural model validated, hypothesis testing was conducted to determine the significance of the relationships between the nine independent variables and behavioural intention.

3.8.5 *Text Analysis*

Open-ended questions assessing RO3 and RO4 in this research were analysed using a thematic analysis process. Thematic analysis is the process of identifying patterns or themes in qualitative data (Maguire & Delahunt, 2017). The responses from Qualtrics were downloaded into an Excel file and pre-processed to remove null values to eliminate incomplete responses and resolve data type inconsistencies for compatibility with text analysis tools. Additional cleaning steps included removing irrelevant characters, symbols, and extraneous spaces, as well as standardising text by converting all responses to lowercase.

The cleaned data were then processed using Scikit-learn to generate a word cloud, with measures such as the iterative introduction of stop words (e.g., "and" "the" and "of") and the application of a 50-word limit to focus on the most significant terms. The process involved multiple runs to refine the stop-word list to exclude irrelevant terms. This iterative approach ensured that the final word cloud highlighted key terms in the dataset, providing a foundation for the subsequent thematic analysis of the responses. This approach ensured a comprehensive and rigorous interpretation of the qualitative responses.

3.9 Limitations

i. The sample size of this study (384) may not be representative of the larger population, and external validity may be compromised.
ii. Reliance on convenience and snowball sampling introduces selection bias because participants were initially drawn from personal networks. This may result in a sample that does not adequately represent the broader South African population.
iii. Despite efforts to ensure representativeness across different demographic groups and geographic regions, bias may be present and may lead to skewed results. The study's reliance on self-reported data may introduce response biases, such as social desirability bias, affecting the accuracy of responses.
iv. Snowball sampling relies on participants recruiting others from their networks, which may result in a sample with similar demographic, socioeconomic, or attitudinal characteristics. This may limit the diversity of perspectives captured in the study.

3.10 Quality Assurance

3.10.1 *External Validity*

External validity refers to the extent to which the findings of the study can be generalised beyond the specific context of the research (Andrade, 2018). According to Findley et al. (2021) ignoring external validity can lead to biased or misleading conclusions about the broader applicability of research findings.

In this study, external validity was supported by the sufficiently large sample size of that aimed to collect 384 responses, which exceeds the minimum requirements suggested by Boomsma (1985). However, it is acknowledged that the generalisability of the findings may still be limited by factors such as the demographic characteristics of the sample, potential selection bias, and the specific context in which the data was collected. Additionally, the study's reliance on self-reported survey responses may introduce response biases, further impacting external validity. To strengthen generalisability, future research could replicate the study in different populations and geographic regions.

3.10.2 *Internal Validity*

Internal validity refers to the degree to which a study accurately establishes a causal relationship between variables, minimizing the influence of confounding factors. In this study, internal validity is strengthened by designing survey questions based on established constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT) framework (Venkatesh et al., 2012). By relying on previously validated constructs, the study ensures that the measurement instruments are theoretically sound and aligned with prior research, reducing the risk of measurement errors.

Furthermore, internal validity is maintained by carefully structuring the survey to avoid leading questions, ambiguous wording, or response biases that could distort the results.

3.10.3 *Reliability*

According to Kubai (2019), reliability can be defined as the degree to which the measure of a construct is consistent or reliable. To ensure reliability a consistent data collection tool, Qualtrics Survey Software was used to administer the questionnaire to ensure that a standardised format is shared across all participants, minimizing variability in data collection.

The findings of this study were also tested against The Cronbach's Alpha to ensure reliability and to ensure that the constructs have adequate internal consistency. According to Taber (2018), Cronbach's alpha is a statistic commonly quoted by authors to demonstrate that tests and scales that have been constructed or adopted for research projects are fit for purpose.

The study also included confirmatory factor analysis (CFA), where reliability measures such as composite reliability (CR) and average variance extracted (AVE) where included to ensure reliability. Potential threats to reliability include measurement errors (Mohajan, 2017), ambiguous survey items, and participant fatigue when answering long questionnaires (Cobern & Adams, 2020).

3.11 Ethical considerations

Ethics were carefully considered throughout the research process. The study adhered to ethical guidelines for research involving human subjects, including the protection of participants' privacy and rights.

Participants were informed that submitting the completed survey constitutes their consent to participate in the study. No individual identifying information, such as names or identity numbers, was collected. Only individuals aged 18 and over were eligible to participate. Informed consent was obtained from all participants, ensuring voluntary participation and confidentiality of responses. Collected data was stored on a password-protected personal laptop, which had authentication controls to restrict access. The data was anonymised to protect the identities of respondents and will be destroyed one year after the study's conclusions.

3.12 Consistency table

RO#	**Research Objective**	**Literature Survey**	**Source of Data**	**Type of data**	**Analysis**
RO1	To assess the degree of influence that the constructs of the UTAUT2 theoretical framework (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, price value and habit) have on the behavioural intention to adopt EVs in South Africa.	Venkatesh et al. (2003),(Venkatesh et al., 2012), Chau (2023),Zhang (2024)	Survey questionnaire Section B1-B7	Quantitative	Descriptive statistics, CFA, SEM
RO2	To assess the degree of influence that environmental concerns and government support have on the	Chau (2023),	Survey questionnaire	Quantitative	Descriptive statistics, CFA, SEM

	behavioural intention to adopt EVs in South Africa.		Section B8-B9		
RO3	To identify the key barriers and enablers of EV adoption that are specific to South African consumers.		Survey questionnaire Section C: Q1 & Q2	Qualitative	Thematic analysis

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

For data collection, a survey was created and administered through Qualtrics, a widely used online survey tool known for its user-friendly interface and robust data collection features. Participants were recruited using a mix of convenience and snowball non-probability sampling methods. Digital platforms (WhatsApp, LinkedIn, Microsoft Teams, and Facebook) were used to share a digital survey link with participants within personal networks, accompanied by a message encouraging participants to share the survey link with their networks. This cascading referral process facilitated broader outreach and increased the overall number of survey participants. The survey was active for 4 weeks in November 2024.

4.2 Data Screening

The data screening process was conducted using Qualtrics and IBM SPSS v29 to ensure accuracy, completeness, and reliability of the data. Initially, 417 responses were collected through Qualtrics, which provided an automated quality check, recording an overall survey response quality of 97%. Within Qualtrics, responses were first examined for straight-lining behaviour, resulting in the removal of 5 cases. Additionally, 4 respondents were under the age of 18 and were automatically filtered out as they did not meet the eligibility criteria.

The remaining dataset was then exported to IBM SPSS v29, where further screening was conducted. This involved identifying and removing incomplete responses, as well as checking for missing data and potential outliers. After applying these screening procedures, a total of 309 valid and complete responses were retained for analysis.

4.3 Respondents’ Profile

The 309 valid responses underwent frequency analysis based on the following demographic variables: age, gender, highest level of education, employment status, monthly household income, and car ownership.

The frequency results of the demographic sample are presented in Table 3.

Table 3: Demographic Information of Respondents

Demographic	Frequency	Percentage
Age		
18-24	16	5,2
25-34	182	58,9
35-44	91	29,4
45-54	18	5,8
55 and older	2	0,6
Gender		
Male	152	49,2
Female	154	49,8
Non-binary / third gender	1	0,3
Prefer not to say.	2	0,6
Education Level		
Primary education	2	0,6
Secondary education	22	7,1
Tertiary education (Diploma, bachelor’s degree)	124	40,1
Postgraduate education (honours, master’s degree, Ph.D.)	161	52,1
Employment Status		
Employed full-time	262	84,8
Employed part-time	13	4,2
Self-employed	19	6,1
Unemployed	7	2,3
Student	8	2,6

Retired	0	0
Monthly Household Income		
Less than R10,000	15	4.9
R10,000 - R19,999	21	6.8
R20,000 - R29,999	38	1.3
R30,000 - R39,999	46	14.9
R40,000 - R49,999	33	10.7
R50,000 and above	115	37.2
Prefer not to say.	41	13.3
Car Ownership		
Yes, I own a fuel/diesel/hybrid engine powered vehicle.	254	82.2
No, I do not own a vehicle.	55	17.8
Yes, I own an electric vehicle/s.	0	0
Yes, I own both fuel/diesel/hybrid engine powered and electric vehicles.	0	0

4.3.1 *Age*

Frequency analysis of age revealed that this demographic profile predominantly represented younger and middle-aged individuals, potentially reflecting a key segment of the study population. The age distribution of respondents revealed that the majority (58.9%) of participants were between the ages of 25 and 34 years, followed by 29.4% in the 35 to 44 age group. Younger respondents aged 18 to 24 accounted for 5.2%, while 5.8% of participants fell within the 45 to 54 age range. Only 0.6% of respondents were aged 55 and older.

4.3.2 *Gender*

The gender distribution of respondents was nearly evenly split between males and females. 49,2% of males completed the survey, whereas females accounted for 49.8% of the valid responses. A small proportion of participants identified as non-binary or third gender (0.3%), whereas 0.6% preferred not to disclose their gender. There was a balanced representation of male and female respondents, providing a diverse perspective on gender-related factors that may influence EV adoption in South Africa.

4.3.3 *Education Level*

A majority (52.1%) of participants reported having completed postgraduate education, including honours, master's, or Ph.D. qualifications, while 40.1% had attained tertiary education such as diplomas or bachelor's degrees. 7.1% of respondents had completed secondary education as their highest level of education. 0.6% respondents indicated primary education as their highest qualification.

The high educational attainment of the respondents showed that the study predominantly reflects the perspectives of a well-educated population. However, this limits the representation of individuals with lower education levels, potentially underrepresenting barriers such as affordability, lack of awareness, and accessibility.

4.3.4 *Employment Status*

Given South Africa's high unemployment rate, understanding respondents' employment status was a key aspect of this study. For this survey, most respondents (84.8%) were employed full-time, reflecting a predominantly economically active participant base. In addition, 6.1% of respondents were self-employed, and 4.2% were employed part-time. A small proportion of participants identified themselves as students (2.6%) or unemployed (2.3%).

The limited representation of students and unemployed individuals highlighted a potential underrepresentation of barriers related to lower incomes or economic inactivity, which could affect the generalisability of the findings on EV adoption in South Africa.

4.3.5 *Monthly Household Income*

The monthly household income distribution of respondents showed a wide range of income levels. 37.2% of respondents reported a monthly household income of R50,000 and above, while 14.9% earned between R30,000 and R39,999, and 12.3% earned between R20,000 and R29,999. Smaller proportions reported earnings between R10,000 and R19,999 (6.8%) or less than R10,000 (4.9%). A total of 13.3% of the participants chose not to disclose their income. This range shows that the study captures perspectives across various income brackets, although the prominence of higher-income respondents may influence findings related to affordability and access to electric vehicles.

4.3.6 *Car Ownership*

In the survey, respondents were given the option to indicate whether they owned an EV. However, none of the participants selected this option. This indicates that none of the respondents currently owned an EV. Despite this, a majority (82.2%) reported owning a fuel, diesel, or hybrid engine-powered vehicle, while 17.8% indicated that they did not own a car.

The absence of EV ownership in the sample indicates that participants did not have direct exposure to or practical experience with the technology. This lack of familiarity could influence respondents' perceptions, attitudes, and reported barriers to adoption, potentially skewing the study towards theoretical or second-hand knowledge about EVs rather than lived experiences.

4.4 Descriptive Analysis

Descriptive analysis was conducted on the questionnaire responses to understand the participants' perceptions regarding factors influencing their intention to adopt EVs. The tables below present the descriptive statistics for the UTAUT2 construct-based questions, highlighting the mean and standard deviation (SD) values.

According to Rahman Othman et al. (2011), descriptive statistics involving mean, and variance can be used for construct validation in a questionnaire. A 7-point Likert scale was used in this study. The mean and standard deviation can provide insights into the central tendency and variability of responses (Rahman Othman et al., 2011). IBM SPSS v29 was used to extract the mean and standard deviations of the collected data.

4.4.1 *Performance Expectancy*

Table 4 : Descriptive Analysis – Performance expectancy

Item	Statement	Frequency	%
PE1	I am satisfied with current average driving range of Electric Vehicles (around 350km per full charge).	3.93	1.778
PE2	I think the current charging time of Electric Vehicles needs to be improved.	5.34	1.539
PE3	With the fuel price increasing significantly, I think using an Electric Vehicle could lower my fuel expense.	5.15	1.668
PE4	With the current performance of electric vehicles like driving range, charging time, and saving of fuel cost, I think that an Electric Vehicle could enhance my driving experience.	4.59	1.691
PE5	I think that the distance that an Electric Vehicle can run is enough to meet the needs of everyday use.	5.02	1.679

The mean responses of the statements based on performance expectancy revealed a mix of perceptions and concerns. Respondents were generally neutral or slightly dissatisfied with the current driving range of EVs, with some variation in how people felt about the 350 km range. However, the respondents agreed that the current charging times need to be improved. Additionally, respondents somewhat agreed that EVs could help lower fuel expenses, especially as fuel prices rise, making them an attractive option for cost-conscious consumers. Respondents also believe that the driving range of EVs is adequate for their everyday needs, although opinions on this are not entirely uniform.

Although there is optimism about potential cost savings and sufficient range, the overall driving experience with EVs generated more mixed feelings. Many respondents believed that current EV performance could enhance their driving experience, but this sentiment was not overwhelmingly strong. The variation in responses indicated diverse opinions on EV adoption, with some individuals embracing the advantages of lower fuel costs and adequate range, while others remain concerned about issues like charging time and overall vehicle performance.

4.4.2 *Effort Expectancy*

Table 5 : Descriptive Analysis – Effort expectancy

Item	Statement	Frequency	%
EE1	Using an Electric Vehicle would be easy for me, as there is no big difference between using Electric Vehicles and using traditional vehicles.	4.33	1.848
EE2	I think it would be easy for me to learn how to use an Electric Vehicle.	5.93	1.289
EE3	I think it would be easy for me to become skillful at using an Electric Vehicle.	5.82	1.326
EE4	I think I have the necessary resources to use an Electric Vehicle.	4.24	1.904

Respondents were generally neutral but somewhat agreed that using an EV would be easy, as they saw little difference between operating an EV and a traditional vehicle. The relatively high standard deviation indicates a range of opinions, suggesting that some participants were more uncertain about the similarities between driving EVs and conventional cars. In contrast, respondents expressed a stronger consensus regarding their ability to learn how to use an EV, with a lower standard deviation reflecting greater agreement on this point.

Similarly, they were confident in their ability to become skilled at driving an EV, though there was slightly less agreement about having the necessary resources to operate an EV. The variation in responses regarding resource availability suggests some respondents were uncertain or concerned about the practical aspects of using an EV. Overall, while respondents were more confident about learning the skills required to operate an EV, they showed some reservations about the resources needed for smooth usage.

4.4.3 *Social Influence*

Table 6 : Descriptive Analysis – Social influence

Item	Statement	Frequency	%
SI1	Buying and using an Electric Vehicle is a social trend in South Africa.	3.36	1.668
SI2	People around me will support my decision if I choose to buy an Electric Vehicle.	4.54	1.652
SI3	If people around me buy and use Electric Vehicle, I would also consider buying one.	4.11	1.801
SI4	Other people will be impressed if I purchase an Electric Vehicle.	4.31	1.711

The results indicate that respondents generally do not perceive buying and using EVs as a widespread social trend in South Africa, as reflected by the lower agreement with SI1. However, they expressed a neutral to slightly positive stance regarding social support, indicating that friends and family would likely endorse their decision to purchase an EV. Additionally, respondents showed a moderate inclination to consider purchasing an EV if others in their social circles did the same. Furthermore, they somewhat agreed that owning an EV could leave a positive impression on others. Overall, social influence appears to play a role in shaping EV adoption decisions, particularly through perceived social support and the influence of peers.

4.4.4 *Facilitating Conditions*

Table 7 : Descriptive Statistics - Facilitating conditions

Item	Statement	Frequency	%
FC1	I think charging stations and service centres are important for Electric Vehicle buyers.	6.44	1.137
FC2	In South Africa, there is currently 350 charging stations. I think the charging infrastructure in SA is sufficient for Electric Vehicle users.	2.61	1.623
FC3	I think it is easy to charge and find support for an Electric Vehicle when it has issues.	3.06	1.548
FC4	I have access to reliable maintenance and repair services for Electric Vehicles.	3.30	1.526
FC5	I believe I can get help from others when I have difficulties using an Electric Vehicle.	3.41	1.662

The results highlighted concerns about the adequacy of infrastructure and support systems for EV adoption in South Africa. Respondents generally agreed on the importance of having charging stations and service centres for EV buyers, showing strong consensus on this point. However, there was a clear disagreement regarding the sufficiency of the existing charging infrastructure in the country, with many expressing doubts about its adequacy.

Additionally, respondents were not confident about the ease of charging EVs or finding support when they encountered issues, indicating that current systems are not well-developed. Similarly, respondents perceived a lack of reliable maintenance and repair services, with respondents showing moderate disagreement on the availability of such services. Overall, the findings reflect a mixed view of the facilitating conditions for EVs, with more favourable opinions about the need for infrastructure and less favourable views on the current state of support systems.

4.4.5 *Hedonic Motivations*

Table 8 : Descriptive Statistics - Hedonic motivations

Item	Statement	Frequency	%
HM1	I think that I would find driving an Electric Vehicle to be an enjoyable experience.	5.30	1.541
HM2	I think driving an Electric Vehicle is interesting due to its smoothness, high acceleration, and high technology.	5.36	1.429
HM3	I believe that I would feel free to travel with an Electric Vehicle even if it runs for a limited distance.	3.91	1.863
HM4	I believe I would be satisfied with the distance travelled using an Electric Vehicle.	3.90	1.735

The results revealed that respondents generally find the idea of driving an EV appealing. Respondents agreed that driving an EV would be an enjoyable experience, and that they would appreciate the smooth driving experience, the high acceleration, and the advanced technology associated with EVs. However, there were mixed feelings about the practical aspects of owning and using an EV.

The respondents expressed uncertainty about feeling comfortable with the limited travel distance of an EV, indicating some concerns about range anxiety. Furthermore, they were not fully satisfied with the distance that an EV can travel on a single charge, indicating that this factor could be a deterrent for adoption.

4.4.6 *Price Value*

Table 9 : Descriptive Statistics - Price Value

Item	Statement	Frequency	%
PV1	I believe the long-term savings on fuel and maintenance justify the higher initial cost of Electric Vehicles.	4.35	1.751

PV2	I would be willing to pay more upfront for an Electric Vehicle because of the future cost savings.	4.04	1.785
PV3	I believe the overall value I would get from buying an Electric Vehicle is worth the investment.	4.32	1.720
PV4	I think that Electric Vehicles are reasonably priced.	3.31	1.653

Respondents agreed that the long-term savings on fuel and maintenance justify the higher initial cost of EVs, as shown by a mean of 4.35. However, a standard deviation of 1.751 indicated considerable variability in responses. Similar responses were recorded for the statement “I believe the overall value I would get from buying an Electric Vehicle is worth the investment.” with a mean of 4.32 and a standard deviation of 1.720.

The perception of EVs being reasonably priced was the lowest, with a mean of 3.31 and a standard deviation of 1.653, suggesting that many respondents view current EV pricing as a barrier to adoption. Respondent’s willingness to pay more upfront for an EV due to future cost savings received neutral responses with a mean of 4.04 and a standard deviation of 1.785, indicating some hesitation and diverse opinions on this matter.

4.4.7 *Habit*

Table 10 : Descriptive Statistics - Habit

Item	**Statement**	**Frequency**	**%**
HB1	The use of Electric Vehicles can become a habit for me.	4.76	1.586
HB2	I believe that using Electric Vehicles can become natural for me.	4.93	1.537
HB3	I believe I could get addicted to using an Electric Vehicle.	4.09	1.806

The results indicated that respondents generally see the potential for using EVs to become a regular part of their routines. Respondents somewhat agreed that adopting EVs could become a habitual activity and that using them could feel natural as part of their daily lives.

However, when it came to the idea of becoming "addicted" to using an EV, there was less agreement, with more variation in opinions. This indicated that although EV adoption is seen as something that could easily fit into respondents' habits, the notion of becoming overly reliant or attached to EVs was less convincing for many. Overall, the findings show moderate support for EVs becoming a natural habit, but with some scepticism about developing an extreme attachment to them.

4.4.8 *Environmental Concerns*

Table 11 : Descriptive Statistics - Environmental concerns

Item	Statement	Frequency	%
EC1	I think I would prefer to buy and use an Electric Vehicle as it helps with environmental issues such as reducing air pollution and saving natural energy.	4.97	1.803
EC2	By buying and using Electric Vehicles, I believe I can help save the environment for the next generation.	5.01	1.661
EC3	Electric Vehicles cause less pollution.	5.04	1.694
EC4	I want to preserve energy and the environment.	5.79	1.224

The results for EC show that respondents generally agree with the environmental benefits EVs. Respondents agreed on their preference for purchasing and using EVs because of their potential to address environmental issues, such as reducing air pollution and conserving natural energy.

There was also agreement that by choosing EVs, they could help protect the environment for future generations. Respondents also agreed that EVs could help reduce pollution, reflecting a positive perception of their environmental impact. The strongest agreement among respondents was in their desire to preserve energy and the environment, indicating that environmental concerns are a key motivation for considering EVs. Overall, the findings indicate that respondents value the ecological benefits of EVs with a shared commitment to sustainability.

4.4.9 *Government Support*

Table 12 : Descriptive Statistics - Government support

Item	Statement	Frequency	%
GS1	Government's monetary incentives to support EV buyers such as tax reduction, price subsidy and free of charging encourage me to buy and use an Electric Vehicle.	4.81	1.794
GS2	Government's non-monetary incentives to support electric cars buyer such as free-parking, priority to use bus lane/parking lots encourage me to buy and use an Electric Vehicle.	4.54	1.783
GS3	I believe that the government should fund the construction of charging stations to cover the whole country.	5.60	1.630
GS4	I think that the government should have measures to exempt charging fees for Electric Vehicle users.	5.32	1.635

The results for GS indicate that respondents generally support government initiatives aimed at encouraging EV adoption. There was moderate agreement that financial incentives such as tax reductions, price subsidies, and free charging would motivate people to purchase and use EVs. However, non-monetary incentives like free parking and priority access to bus lanes were viewed somewhat less favourably.

Respondents expressed strong support for government involvement in expanding charging infrastructure, with many agreeing that the government should fund the construction of charging stations nationwide. Additionally, there was significant agreement on the need for measures that would exempt EV users from charging fees. The findings indicate that respondents believe that both financial and infrastructural government support plays a crucial role in encouraging the adoption of EVs.

4.4.10 *Behavioural Intention*

Table 13 : Descriptive Statistics - Behavioural Intention

Item	Statement	Frequency	%
BI1	I intend to purchase an Electric Vehicle in the future.	4.60	1.789
BI2	I am very likely to purchase an Electric Vehicle soon if the opportunity arises.	4.36	1.833
BI3	I intend to purchase an Electric Vehicle although they are expensive.	3.99	1.771
BI4	I would encourage my friends/family/colleagues to purchase an Electric Vehicle.	4.28	1.648

The results for BI indicated that respondents somewhat agreed that they intent to purchase an EV soon and in the future. However, their views on immediate adoption are more varied. While many expressed a general intention to buy an EV at some point, there was less enthusiasm about making an immediate purchase, indicating some hesitation or uncertainty presently.

When considering the higher cost of EVs, respondents showed even more uncertainty, with some expressing reluctance to commit to buying due to price concerns. Additionally, respondents were neutral but somewhat agreed about encouraging others, such as friends, family, or colleagues, to buy an EV, suggesting that although they are somewhat open to the idea, they are not yet fully convinced or enthusiastic enough to actively promote EV adoption. Overall, the findings show a mix of intention and uncertainty, with factors like cost and immediate availability influencing respondents’ readiness to adopt EVs.

4.5 Normality Testing

According to Hatem et al. (2022), the normality of data can be assessed through skewness and kurtosis values. In this study, the normality check was conducted using IBM SPSS v29, which calculated the skewness and kurtosis values for each variable in the research model used. Table 14 below shows the normality testing results.

Table 14 : Skewness and Kurtosis

Variables	Skewness	Kurtosis
Performance Expectancy (PE)	-0,780	0,010
Effort Expectancy (EE)	-0,822	0,815
Social Influence (SI)	-0,130	-0,795
Facilitating Conditions (FC)	-0,034	0,044
Hedonic Motivations (HM)	-0,488	-0,102
Price Value (PV)	-0,222	-0,831
Habit (HB)	-0,577	-0,120
Environmental Concerns (EC)	-0,929	0,958
Government Support (GS)	-0,952	0,342
Behavioural Intention (BI)	-0,423	2,390

According to Hair et al. (2010) acceptable thresholds for normality are defined as skewness values within the range of -2 to +2 and kurtosis values between -7 and +7. The results of the normality test showed that all variables in the study fell within these acceptable thresholds.

These findings confirmed that the dataset is suitable for advanced statistical methods, including regression analysis and Structural Equation Modelling (SEM).

4.6 Common Method Bias

Before proceeding with the measurement model for this study, the variables were tested for Common Method Bias (CMB). According to Kock et al. (2021), CMB is a significant concern in behavioural research because the same respondents provide responses for both independent and dependent variables. In this study, CMB was tested using IBM SPSS v29. A Harman’s Single Factor Test was conducted on all dependent and independent items to determine if common method variance was present. The key output of this test is the percentage of variance explained by the first factor. According to Fuller et al. (2016), if the total variance extracted by a single factor exceeds 50%, then common method bias is present.

The results of the analysis indicated that the percentage of variance explained by the first factor is 31.945%. This indicated that common method bias did not occur with the collected data. Based on these results, the dataset was deemed suitable for conducting SEM.

Boomsma (1985) proposed a minimum sample size of 100 to 200 participants for reliable SEM estimation. The sample size of 309 participants for this study exceed these guidelines for SEM. Furthermore, Nunnally & Bernstein (1967) advocated for a ratio of at least 10 cases per variable, which, in this study, translates to a requirement of 100 cases (10 variables × 10 cases per variable). This is also satisfied by the sample size of 309 participants for this. These guidelines collectively support the adequacy of the study's sample size for SEM analysis.

4.7 Measurement Model Analysis

Measurement model analysis is a key aspect of Structural Equation Modelling that focuses on the connections between latent variables and their associated indicators (Bhale, 2024). Confirmatory Factor Analysis process was followed to test whether the data fits the UTAUT2 model. This process began with the specification of the measurement model, where latent variables were defined and linked to their respective observed indicators.

Once the model was estimated, its goodness of fit was evaluated using various fit indices to assess how well the model represents the data. Reliability and validity of the measurement model were also tested to ensure that the indicators accurately reflect the latent constructs they are meant to represent.

The questionnaire for this research study had 41 statements. To measure how well these statements measure the 10 latent variables for this study, a Confirmatory Factor Analysis (CFA) was conducted. A CFA measurement model was developed and analysed using IBM SPSS AMOS v29. All constructs within the study were included in the model and covariances established between them. This step aimed to draw the measurement model and to assess both the model fit and the reliability and validity of the research model.

4.7.1 *Measurement Model Fit - Initial*

Though there are numerous measures that are used to assess how well the model fits the data, Chi-square (CMIN), Chi-square divided by degrees of freedom (CMIN/df), root mean square error of approximation (RMSEA), p-value for the test of close fit (P-CLOSE), Comparative fit index (CFI), Tucker-Lewis index (TLI) and Goodness of Fit Index (GFI) were used in this study's analysis.

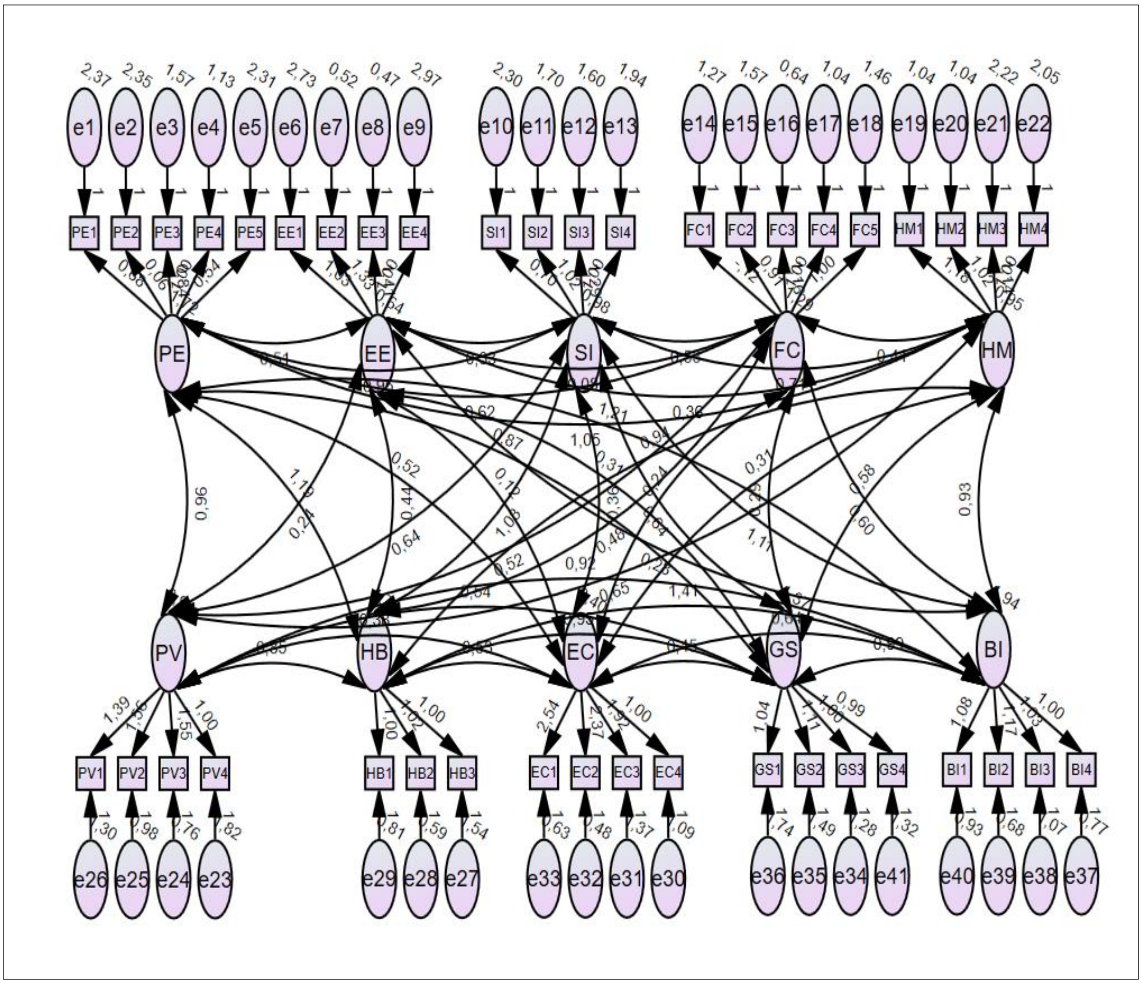
The initial results of the CFA measurement model, presented in Table 15 and Figure 5, suggested that the model required further refinement. While some indices fall within acceptable ranges, others failed to meet established thresholds, indicating areas where improvement was needed. The CMIN/DF (2.422) suggested a reasonable model fit, and the RMSEA (0.068) fell within the acceptable range, indicating adequate approximation to the observed data. However, the PCLOSE value of 0.000 indicated that the model does not exhibit a close fit to the data. Additionally, the CFI (0.841), TLI (0.842) and GFI (0.760) were below the minimum threshold of 0.90 and did not meet the minimum threshold for acceptable fit.

Table 15 : Initial CFA Model Fitness

Acronym	**Acceptable fit**	**Resulting fit**
CMIN		1777.954
CMIN/DF	≤ 3 (Kline, 2011)	2.422
RMSEA	≤ 0,08 (Hu & Bentler, 1999)	0.068
PCLOSE	> 0.000 (Kline, 2016)	0.000
CFI	≥ 0,90 (Fan et al., 1999)	0.841

TLI	≥ 0,9 (Brown, 2006)	0.842
GFI	≥ 0,8 (Jöreskog & Dag, 1996)	0.760

Figure 5 : Initial Measurement Model



Source: Author's own compilation

4.7.2 *Measurement Model Fit – Revised*

To improve the fit of the initial model, the standardised regression weights results were examined. In factor analysis, factor loadings represent the correlation between observed variables and their underlying latent constructs (Schuster & Yuan, 2005). Factor loadings below 0.40 are often considered weak, indicating that the variable may not effectively measure the intended factor (Hair et al., 2010).These authors also advised that those factor loadings can be removed to improve the reliability of the model. Therefore, two factor loadings, PE2 and FC1, were removed from the model.

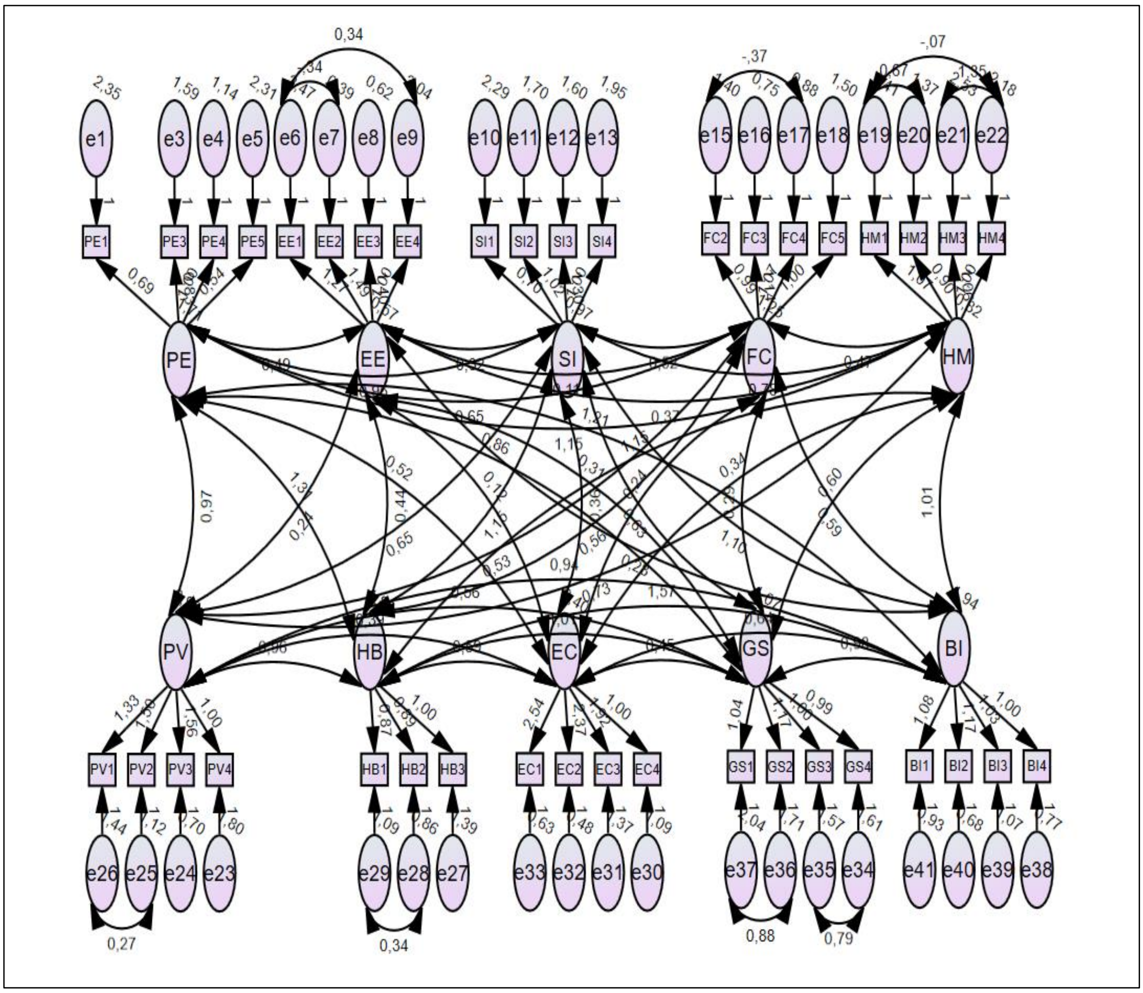
The items in Table 16 and below are an interpretation of the revised model and represent the goodness of fit indexes which were checked against CFA model fit guidelines.

The revised model's fit indices demonstrated a good overall fit. The CMIN/DF (1.847) fell below the acceptable threshold of ≤ 3, indicating a good fit. The RMSEA (0.052) met the acceptable threshold of ≤ 8. The PCLOSE of 0.191 was above the threshold of 0.00, supporting the hypothesis of a close-fitting model. The CFI (0.914) and TLI (0.902) both exceeded the threshold of 0.90, indicating acceptable and reasonable fits. Finally, GFI (0.830) also met the acceptable fit threshold of ≥ 0.8. These fit indices indicated that the model achieved acceptable to good fit across the measures.

Table 16 : Revised CFA Model Fitness

Acronym	Acceptable fit	Resulting fit
CMIN		1195.172
CMIN/DF	≤ 3 (Kline, 2011)	1.847
RMSEA	≤ 0,08 (Hu & Bentler, 1999)	0.052
PCLOSE	> 0.000 (Kline, 2016)	0.191
CFI	≥ 0,90 (Fan et al., 1999)	0.914
TLI	≥ 0,9 (Brown, 2006)	0.902
GFI	≥ 0,8 (Jöreskog & Dag, 1996)	0.830

Figure 6 : Revised Measurement Model



Source: Author's own compilation

These results suggested that the revised model adequately represents the data, supporting its use in further analysis.

4.7.3 *Reliability and Validity Analysis*

This section addresses the reliability and validity of the instruments and methods used in the study to ensure the credibility and trustworthiness of the results. In the context of this study, reliability or internal consistency looked at how well the survey statements listed to assess factors influencing EV adoption work together to reliably measure the constructs of the conceptual model. The Reliability and Validity Analysis results showing factor loadings, Cronbach's Alpha, Composite Reliability (CR) and Average Variance Extracted (AVE) are presented in Table 17.

Cronbach’s Alpha

Cronbach’s alpha (Cronbach, 1951) is among the most commonly used reliability measures in research. Therefore, the data collected for this study was tested against Cronbach’s Alpha. According to Cronbach (1951), the purpose of Cronbach’s alpha is to measure the internal consistency or reliability of a set of items in a survey to assesses how well multiple items that are supposed to measure the same construct produce consistent results.

As advised by Hair et al. (2010), factor loadings below 0.4 derived from the standardised regression weights in IBM SPSS AMOS v29 were removed from the model. Cronbach’s alpha for the remaining factor loadings was then calculated on IBM SPSS v29 using this formular below. Cronbach’s Alpha results are presented in Table 17.

Figure 7: Cronbach's Alpha Formular

$$\alpha = \frac{N}{N-1}\left(1 - \frac{\sum \sigma^2_{\text{items}}}{\sigma^2_{\text{total}}}\right)$$

The Cronbach's alpha values for the constructs ranged from 0.669 to 0.910. Pallant (2007) has stated that Cronbach’s Alpha values above 0.6 are generally considered acceptable and indicate high reliability. Morgan et al. (2004) supported this view, stating that values between 0.6 and 0.9 are deemed acceptable for determining validity and internal consistency.

Composite Reliability

Composite Reliability (CR) also measures internal consistency and reliability of the constructs included in a research model. While Cronbach’s Alpha assumes equal weight for all items, Composite Reliability accounts for the actual factor loadings of each item, providing a more precise measure (Hair et al., 2018). In this study, CR was evaluated using IBM SPSS AMOS v29. CR values of 0.7 or higher are generally considered acceptable (Hair et al., 2018).

However, CR values of between 0.6 to 0.7 are acceptable for survey analysis (Shrestha, 2021). The standardised regression weights were utilised in the James Gaskin research toolkit to compute the CR values using the formular below. Composite reliability results are presented in Table 17.

Figure 8: Composite Reliability Formular

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum \varepsilon_i}$$

The CR values for the constructs ranged between 0.648 and 0.911. The BI group had the highest reliability with a CR value of 0.911, while the HM group had the lowest reliability with a CR value of 0.648. Overall, all the composite reliability values for the constructs were between 0.6 and 0.9 demonstrating acceptable composite reliability.

Following the reliability analysis, the next step was to examine structural validity, which involved evaluating both convergent validity and discriminant validity.

Convergent Validity: AVE

Convergent validity assesses whether the indicators of a construct are highly correlated, ensuring that they measure the same underlying concept (Lim, 2024). According to Ab Hamid et al. (2017), to assess convergent validity, researchers need to evaluate the factor loading of each indicator, composite reliability (CR), and the average variance extracted (AVE).

Composite reliability was evaluated in the previous step and found to have acceptable reliability. To determine the AVE values, IBM SPSS AMOS v29 was used and the AVE calculated using the formular below. AVE results are presented in Table 17.

Figure 9: AVE Formular

$$AVE = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum_i \operatorname{var}(\varepsilon_i)}$$

The CFA measurement model was first run to show the factor loadings which are necessary for calculating the AVE and the standardised factor loadings for each measurement item associated with a construct were extracted. According to Fornell & Larcker (1981), an AVE value of 0.5 or higher is generally recommended. However, they also noted that AVE values below 0.5 are acceptable if the CR exceeds 0.6.

Four constructs had AVE values that were below 0.5 (PE, EE, HM, and GS). However, these constructs had CR values that were above 0.6. Therefore, all constructs demonstrated acceptable convergent validity. The lower AVE values could suggest issues in the measurement of the construct, but their CR values provided some support for their inclusion in the model.

Table 17: Reliability and Validity Analysis

Variable	Item	Factor Loading	Cronbach's Alpha	Composite Reliability	AVE
Performance Expectancy	PE1	0.505	0.678	0.686	0.365
	PE2	eliminated			
	PE3	0.653			
	PE4	0.774			
	PE5	0.423			
Effort Expectancy	EE1	0.521	0.693	0.758	0.460
	EE2	0.875			
	EE3	0.803			
	EE4	0.399			
Social Influence	SI1	0.416	0.669	0.672	0.346
	SI2	0.611			
	SI3	0.71			
	SI4	0.577			
Facilitating Conditions	FC1	eliminated	0.812	0.833	0.557
	FC2	0.684			
	FC3	0.827			
	FC4	0.787			
	FC5	0.675			
	HM1	0.633	0.748	0.648	0.317

Hedonic Motivations	HM2	0.57			
	HM3	0.518			
	HM4	0.523			
Price Value	PV1	0.728	0.842	0.839	0.570
	PV2	0.806			
	PV3	0.874			
	PV4	0.581			
Habit	HB1	0.751	0.833	0.812	0.590
	HB2	0.796			
	HB3	0.757			
Environmental Concerns	EC1	0.897	0.845	0.855	0.606
	EC2	0.909			
	EC3	0.722			
	EC4	0.521			
Government Support	GS1	0.603	0.800	0.733	0.407
	GS2	0.679			
	GS3	0.637			
	GS4	0.63			
Behavioural Intention	BI1	0.841	0.910	0.911	0.720
	BI2	0.893			
	BI3	0.811			
	BI4	0.846			

Discriminant Validity: HTMT2

Discriminant validity measures the extent to which a construct or variable is distinct and independent from other constructs or variables in a model (Roemer et al., 2021). Heterotrait-Monotrait Ratio (HTMT2) was used to test discriminant validity of the variables in the research model. While the Fornell-Larcker criterion, which examines shared variance, was once widely used, the HTMT method proposed by Henseler et al. (2015) provides a more reliable and contemporary measure for establishing discriminant validity. Heterotrait-Monotrait Ratio (HTMT2) results are presented in Table 18*.*

According to Ab Hamid et al. (2017), HTMT2 offers a more consistent measure than the traditional HTMT. Implied correlations from the model were extracted from IBM SPSS AMOS v29 and used in HTMT calculator provided at *https://www.henseler.com/htmt.html* to compute the HTMT2 values. According to established guidelines, an HTMT value below 0.90 indicates that discriminant validity has been achieved between the reflective constructs (Roemer et al., 2021). All the values were below 0.90 indicating that there is no construct-overlap, and the measurement scales capture unique aspects of the constructs they intend to measure.

Table 18 : Discriminant Validity HTMT2

GS										
BI	0,554									
EC	0,546	0,718								
HB	0,560	0,788	0,650							
PV	0,471	0,681	0,633	0,698						
HM	0,428	0,605	0,428	0,665	0,550					
FC	0,137	0,387	0,348	0,354	0,469	0,219				
SI	0,519	0,813	0,605	0,817	0,675	0,644	0,466			
EE	0,295	0,191	0,185	0,359	0,284	0,441	0,066	0,356		
PE	0,496	0,679	0,644	0,714	0,755	0,734	0,449	0,726	0,378	
	GS	BI	EC	HB	PV	HM	FC	SI	EE	PE

4.8 Structural Model Analysis

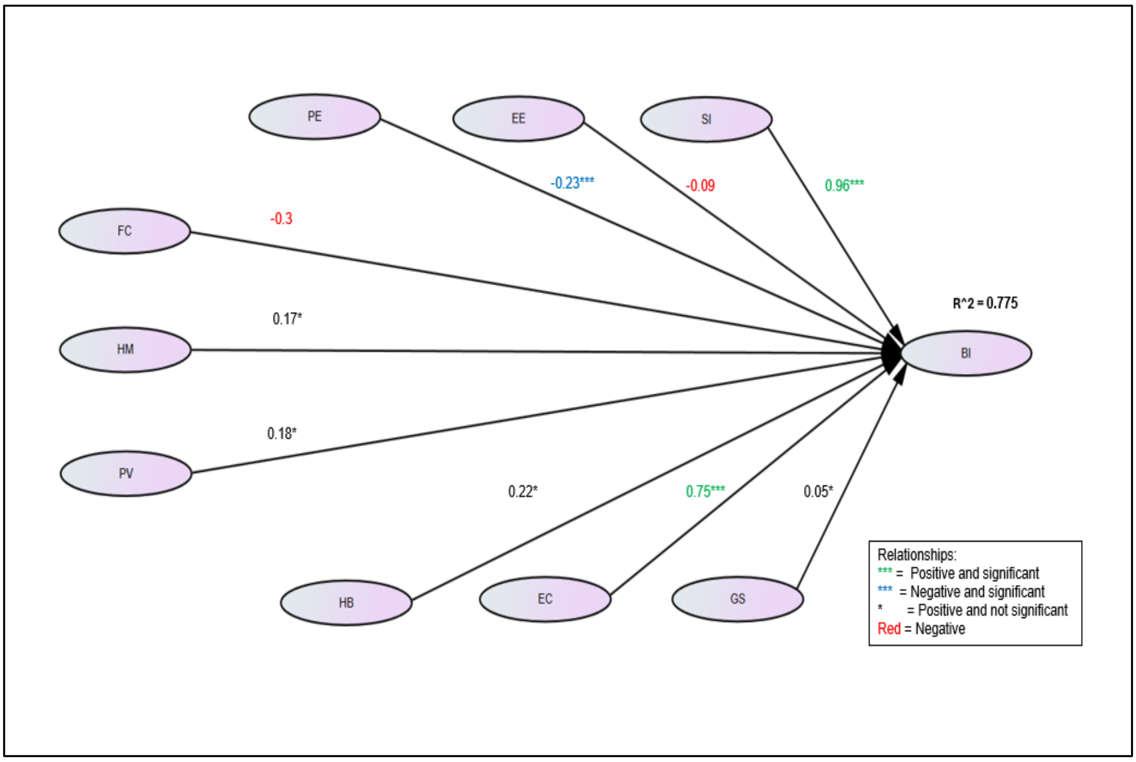
Structural model analysis analyses the complex relationships among constructs and indicators (Hair et al., 2021b). Structural model analysis in this study was performed using IBM SPSS AMOS v29 to evaluate the relationships between latent constructs. The analysis focused on the overall fit of the model and how well it explained the observed data to assess the relationships between the latent variables. A structural model was drawn to assess the relationships between the constructs, show the standardised path coefficients and to determine the model fit indices.

The structural model fit indices demonstrated acceptable values, confirming a good fit for the model. The Chi-square (CMIN) value was 1190.933, with a CMIN/DF of 1.855, which is within the threshold of ≤ 3, indicating an acceptable fit. The RMSEA was 0.053, which is classified as acceptable because it was below 0.08. The PCLOSE value of 0.169 further substantiated the close fit of the model, as it exceeded the threshold of > 0.000. The CFI achieved a value of 0.914, surpassing the acceptable benchmark of ≥ 0.90. The TLI was recorded at 0.901, indicating a good fit, while the GFI yielded a value of 0.831, meeting the criteria for an acceptable fit (≥ 0.8).

Table 19 : Structural Model Fitness

Acronym	Acceptable fit	Resulting fit
CMIN		1190.933
CMIN/DF	≤ 3 (Kline, 2011)	1.855
RMSEA	≤ 0,08 (Hu & Bentler, 1999)	0.053
PCLOSE	> 0.000 (Kline, 2016)	0.169
CFI	≥ 0,90 (Fan et al., 1999)	0.914
TLI	≥ 0,9 (Brown, 2006)	0.901
GFI	≥ 0,8 (Jöreskog & Dag, 1996)	0.831

Figure 10: Structural Model Presentation



Source: Author's own compilation

4.9 Hypothesis Testing

To examine the relationship between the 9 independent variable and behavioural intention the dependent variable, structural equation modelling was used. The results of the hypothesis testing, conducted using IBM SPSS AMOS v29, are summarized in Table 20 below.

Hypothesis Table

Table 20 : Hypothesis Testing Results

Hypothesis	Relationship	t-value	p-value	Result
H1	PE → BI	-0.954	0.34	Not supported
H2	EE → BI	-2.124	0.034	Supported
H3	SI → BI	2.708	0.007	Supported
H4	FC → BI	-0.496	0.62	Not supported

H5	HM → BI	1.181	0.238	Not supported
H6	PV → BI	1.244	0.213	Not supported
H7	HB → BI	1.304	0.192	Not supported
H8	EC → BI	4.12	***	Supported
H9	GS → BI	0.773	0.439	Not supported

In hypothesis testing, statistical significance was evaluated using p-values and t-values. A p-value below the threshold of 0.05 indicates statistical significance. Hypotheses that fail to meet these criteria are generally not considered statistically significant and are thus not supported.

Interpretation of the Hypotheses

H1: PE → BI

The results revealed that the effect of performance expectancy on behavioural intention to adopt EVs is negative and not statistically significant ($t = -0.954$, $p = 0.34$). This lack of significance indicates that PE did not have a meaningful influence on BI in this context. As a result, H1 is not supported.

H2: EE → BI

The effect of effort expectancy on behavioural intention was statistically significant, although negative ($t = -2.124$, $p = 0.034$). This indicated that EE has a significant influence on BI, supporting H2.

H3: SI → BI

The results indicated a positive and statistically significant relationship between social influence and behavioural intention ($t = 2.708$, $p = 0.007$). Therefore, H3 is supported.

H4: FC → BI

The effect of facilitating conditions on behavioural intention was negative and not statistically significant ($t = -0.496$, $p = 0.62$). This implied that FC does not have a meaningful impact on BI in this context. As a result, H4 is not supported.

H5: HM → BI

The analysis indicated that the relationship between hedonic motivation and behavioural intention is positive but not statistically significant ($t = 1.181$, $p = 0.238$). Therefore, HM did not significantly affect BI. Thus, H5 is not supported.

H6: PV → BI

The relationship between price value and behavioural intention was positive but not statistically significant ($t = 1.244$, $p = 0.213$). This indicated that PV does not have a meaningful influence on BI. Therefore, H6 is not supported.

H7: HB → BI

The results indicate that the effect of habit on behavioural intention is positive but not statistically significant ($t = 1.304$, $p = 0.192$). This indicates that HB does not significantly influence BI in this context. As a result, H7 is not supported.

H8: EC → BI

The relationship between environmental concern and behavioural intention was found to be positive and statistically significant ($t = 4.12$, $p < 0.001$). This indicated that EC has a strong and significant positive influence on BI. Therefore, H8 is supported.

H9: GS → BI

The analysis shows that the effect of government support on behavioural intention was positive but not statistically significant ($t = 0.773$, $p = 0.439$). This indicated that GS did not significantly influence BI. Therefore, H9 is not supported.

4.10 Coefficient of Determination

The coefficient of determination explains the proportion of variance in a dependent variable that is accounted for by the independent variables in a regression or structural model (Hair et al., 2018) The r-squared value ranges from 0 to 1, where higher values indicate stronger explanatory power of the model.

Table 21 : Coefficients of Determination

Dependent Variable		R-squared Value
Behavioural Intention	0.775	

The R-squared value for the structural model was 0.775, indicating that the independent variables collectively explained 77.5% of the variance in behavioural intention to adopt EVs. This indicated strong model fit, as a higher R-squared value suggested a greater proportion of variance in the dependent variable was accounted for by the predictors.

This meant that the model supported the relevance of the included factors in understanding behavioural intention toward EV adoption. However, although the R-squared value supported the model's effectiveness, 22.5% remained unexplained. Future research using moderating and mediating factors could explore additional variables to enhance the model's predictive accuracy.

4.11 Text Analysis

This text analysis section focused on the data derived from Section C of the online survey conducted via Qualtrics. This section included two non-mandatory open-ended questions designed to gather insights into participants' perceptions and opinions EV adoption in South Africa that might not have been answered by the Likert-scale questions based on the UTAUT2 conceptual model for this study. Of the 309 valid responses used for data analysis, an average of 277 respondents chose to answer these two open-ended questions, demonstrating a significant level of engagement with this part of the survey.

The following questions were asked:

> *Q1: What do you think are the biggest challenges or barriers to adopting electric vehicles in South Africa?*
>
> *Q2: In your opinion, what could be done to encourage more people to switch to electric vehicles in South Africa?*

4.11.1 *Word Cloud Generation*

The word cloud generation process for the open-ended survey responses was conducted using Python and the Scikit-learn library. The data was first loaded from an Excel file and pre-processed by removing null values to eliminate incomplete responses and to resolve data type inconsistencies for compatibility with text analysis tools. Additional cleansing steps included removing irrelevant characters, symbols, and extraneous spaces, as well as standardising text by converting all responses to lowercase.

The cleaned data was then processed using Scikit-learn to generate a word cloud, with measures such as the iterative introduction of stop-words such as "and" "the" and "of" and the application of a 50-word limit to focus on the most significant terms.

The process involved multiple runs to refine the stop-word list to exclude irrelevant terms. This iterative approach ensured that the final word cloud highlighted key terms in the dataset, providing a foundation for the subsequent thematic analysis of the responses.

Figure 11: Barriers to EV Adoption Word Cloud

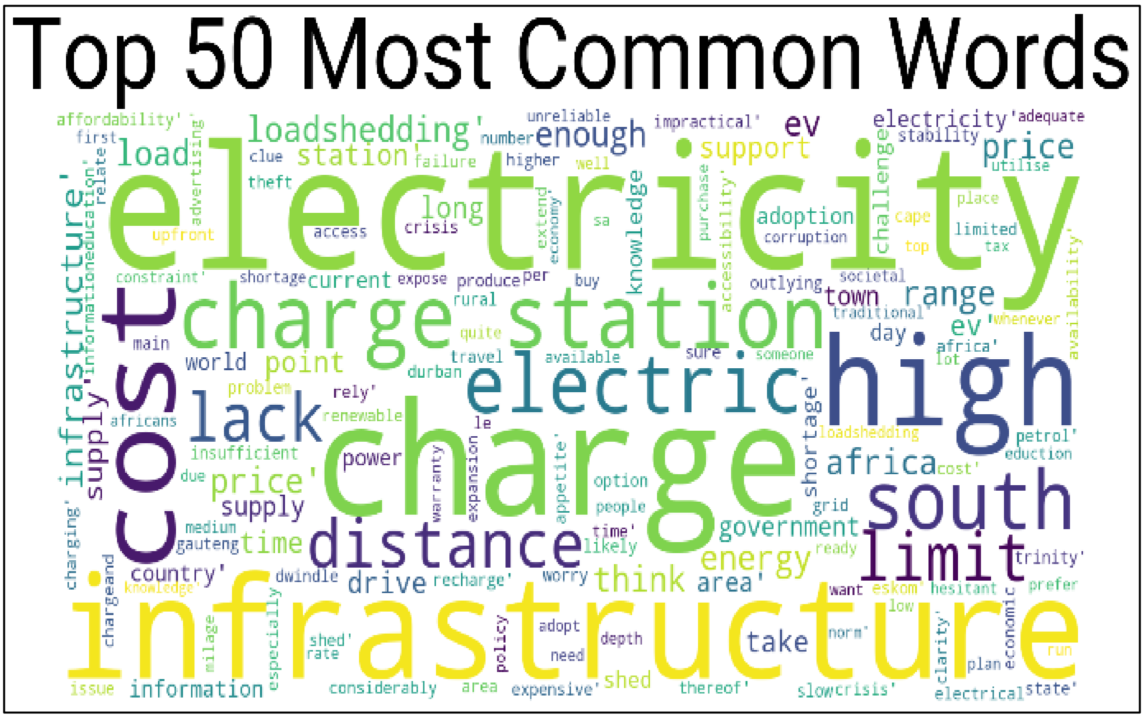
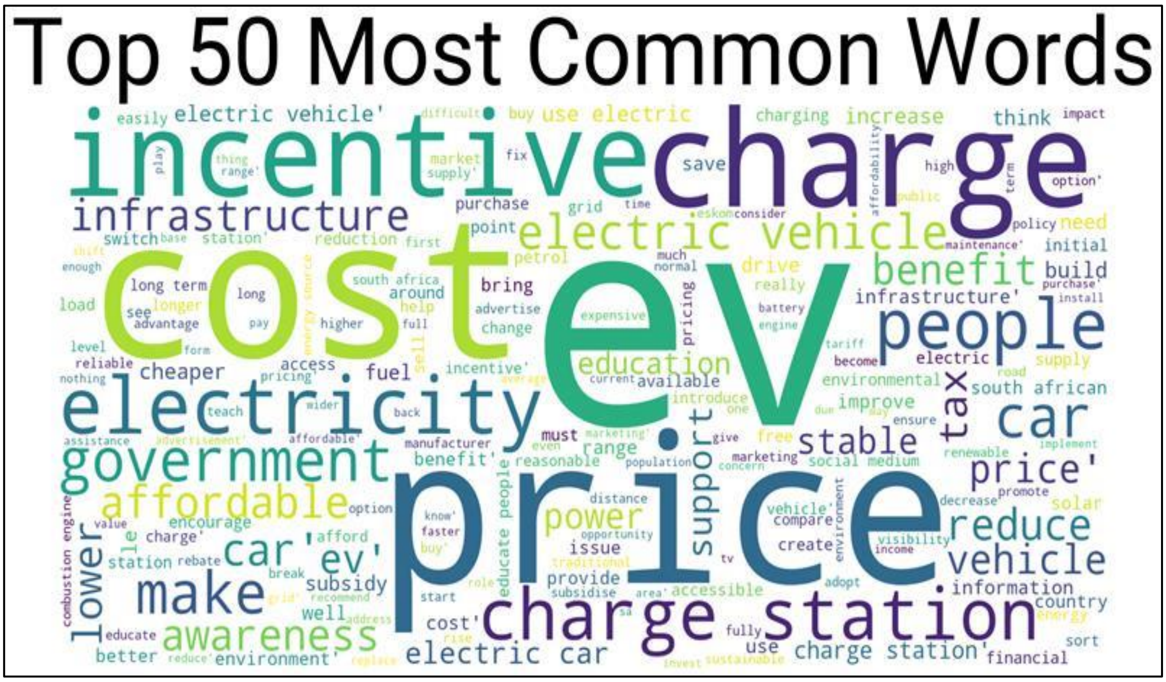


Figure 12: Enablers of EV Adoption Word Cloud



4.11.2 *Themes*

Building on the insights from the word clouds, a more detailed analysis was conducted by searching for frequently occurring keywords in the responses. These keywords were then used to group the responses into themes. This process involved close reading and categorisation of the data, ensuring that the themes accurately reflected the content of the responses. The tables below were generated to summarise the frequency of keywords and themes, providing a clear and structured representation of the findings.

Table 22 : Themes - Barriers to EV Adoption in South Africa

Themes	Frequency
Charging Infrastructure	117
Electricity Supply Issues	113
Cost of EVs	96
Range and Battery Issues	45
Public Awareness/Education	39
Government Support & Incentives	25

Table 23 : Themes - Enablers of EV Adoption in South Africa

Themes	Frequency
Infrastructure and Electricity Stability	120
Affordability	83
Government Support & Incentives	75
Education and Awareness	74
Longer Driving Range	10
Social and Cultural Considerations	9

The qualitative text analysis, derived from the open-ended survey responses, provided deeper insights into the barriers and enablers of EV adoption in South Africa. Key barriers included inadequate charging infrastructure, electricity supply issues, and the high cost of EVs. Conversely, the main enablers identified were improvements in infrastructure and electricity stability, making EVs more affordable, affordability, increased government support and incentives as well as education and awareness about EVs.

4.12 Summary of Results

The hypothesis testing results from the SEM analysis revealed that three independent variables, social influence, environmental concerns, and effort expectancy have a statistically significant influence on the behavioural intention to adopt EVs in South Africa. Conversely, performance expectancy, facilitating conditions, hedonic motivation, price value, habit, and government support did not show a statistically significant impact on BI. The R-squared value of 0.775 indicated that 77.5% of the variance in BI was explained by independent variables, demonstrating a strong model fit. However, the remaining 22% indicated that other factors, such as moderating or mediating variables, could further enhance the model’s predictive accuracy.

The qualitative text-analysis of the survey responses provided deeper insights into the barriers to and facilitators of EV adoption in South Africa. The responses indicated that barriers to and facilitators of EV adoption in the country are multifaceted and influenced by political, economic, social, and technological factors.

CHAPTER 5. DISCUSSION OF RESULTS

5.1 Introduction

This chapter discusses the study's hypotheses that helped to analyse and assess the factors influencing EV adoption in South Africa. It examines how the independent variables of the proposed conceptual UTAUT2 model for this study impact behavioural intention, aligning with the research objectives. The research objectives are discussed in this chapter. The findings are interpreted within the South African context, drawing on prior research on UTAUT2, technology adoption models, and EV adoption. Empirical results from the previous chapters are explained to provide insights into observed outcomes.

5.2 Summary of the Study

The study employed a quantitative approach through an online survey, collecting 309 valid responses. The research objectives focused on identifying the factors influencing EV adoption through the application of the UTAUT2 framework. The key research objectives are:

- To assess the degree of influence that UTAUT2 constructs have on the intention to adopt EVs in South Africa.
- To assess the degree of influence of that environmental concerns and government support have on the intention to adopt EVs in South Africa.
- To identify the barriers and enablers of EV adoption among South African consumers.

5.3 The Influence of UTAUT2 Constructs

This section presents the findings related to RO1 which aimed to assess the extent to which UTAUT2 constructs influence South Africans' behavioural intention to adopt EVs. Seven hypotheses were formulated based on the UTAUT2 framework. However, the results indicated that with regards to the UTAUT2 model, only effort expectancy and social influence have a statistically significant impact on the behavioural intention to adopt EVs in South Africa. A detailed analysis of these findings will be provided in this section.

5.3.1 *Social Influence*

Social influence (SI) was identified as the strongest predictor of the behavioural intention to adopt EVs in South Africa, supporting (H3). The positive and statistically significant effect of SI ($\beta = 2.708$, $p = 0.007$) is consistent with growing research highlighting the importance of social influence in technology adoption and EV adoption. For instance, Ajao et al. (2025) emphasised SI as a key driver of EV adoption in Sub-Saharan Africa, while Nordhoff et al. (2020) also found SI to be a positive predictor in their European study on autonomous vehicles.

South Africa is deeply rooted in the culture of Ubuntu, which is characterised by interconnectedness and a sense of shared community. Adeola (2024) found that because of their Ubuntu values, South Africans can be influenced by social norms and culture when making decisions. Irene et al. (2024) further noted that group norms in South Africa predict pro-environmental behaviour and social identity significantly shape individual actions related to environmental concerns, such as EV adoption. Scholtz et al. (2023) also mentioned the role of peer influence in the EV market in South Africa. These authors stated that the ownership of EVs by family and friends influences the likelihood of individual adoption. This underscores the relevance of SI in this context. Manutworakit (2021), also supported these findings by stating that social influence was a significant factor in remoulding human behaviors and intentions toward adopting EV technology, especially in developing countries.

However, while South Africans tend to look to peers, families, and communities when making decisions, descriptive statistics from this study (mean = 3.36, SD = 1.668) reveal that EV ownership is not yet widely perceived as a prominent social trend. This reflects the current state of EV adoption in South Africa, where interest is increasing but broader social acceptance remains on the horizon, hindered by factors such as high EV costs and limited charging infrastructure.

5.3.2 *Effort Expectancy*

The effect of EE on the behavioural intention to adopt EVs was found to be statistically significant but unexpectedly negative. (β = -2.124, p = 0.034). The statistical significance of effort expectancy on behavioural intention to adopt EVs is consistent with Gunawardane & Thilina (2019) study on EV adoption in Indonesia. Similarly, Abbasi et al. (2021) also identified effort expectancy as significant in EV adoption, although they noted that people are more likely to adopt EVs if they perceive them as requiring less effort than internal combustion engine vehicles.

To support the negative t-value, which introduces nuances to the findings, Winata & Tjokrosaputro (2022) found that effort expectancy may not positively impact adoption if users anticipate other challenges when using a new technology. In this case, the negative relationship indicates that although respondents perceive EVs as easy to use, they may also anticipate other barriers that make adoption less likely, such as insufficient charging infrastructure or financial constraints. Thus, despite the perceived ease of use, concerns about these barriers may override the desire to adopt EVs.

The study's descriptive statistics support this interpretation. While respondents indicated that EVs would be easy to learn to use and that they could become skilful at using them, concerns arose regarding the availability of necessary resources. Abdul Qadir et al. (2024) emphasised the importance of resources such as charging infrastructure, financial incentives, and education campaigns in facilitating EV adoption. These resources are still considered barriers in South Africa, according to the survey responses. This limits the effectiveness of the perceived ease of use of EVs.

Therefore, although the user-friendliness of EVs may influence their adoption, the perceived lack of resources and other external factors appear to reduce the overall impact of effort expectancy as a predictor of behavioural intention to adopt EVs in South Africa.

5.3.3 *Performance Expectancy*

In this study, the effect of PE on the behavioural intention to adopt EVs in South Africa shows an insignificant relationship (β = -0.496, p = 0.62), which contrasts with some studies of China (Zhang, 2024) and Germany (Chau, 2023) reviewed for this study. Due to low factor loadings, PE2 was eliminated, but the overall construct remained statistically insignificant. This result aligns with the findings of Handopo and Elfindah (2024) who examined consumer willingness to adopt EVs in Indonesia and found PE to be a negative and insignificant factor.

Similarly, Abbasi et al. (2021) reported no significant relationship between PE and EV adoption intentions among Malaysian consumers. Handopo and Elfindah (2024) further stated that PE does not directly motivate people to use EVs; however, a positive attitude towards EVs plays a major role in the final decision to use an EV. These authors posited that PE has less influence, where other factors, such as price value and environmental factors are perceived to be more important than just performance.

In South Africa, market penetration is below 1% (Scholtz et al., 2023), whereas it is 25% in China (Hove, 2024). This low penetration is supported by the frequency analysis in which none of the respondents owned an EV. This indicated limited awareness of and experience with EV benefits. According to Rogers' Diffusion of Innovation theory (1962), lack of awareness can hinder adoption. Descriptive statistics on PE suggested that despite seeing EVs as beneficial, users may not adopt them if factors like driving range, charging infrastructure, and charging times matter more to them. These results align with García de Blanes Sebastián et al. (2023) in Spain, who found that charging concerns can outweigh positive EV performance expectations. These findings indicate that, for South Africa, addressing infrastructure and practical concerns could be more influential than merely improving perceptions of the usefulness and benefits of EVs.

5.3.4 *Facilitating Conditions*

The effect of facilitating conditions (FC) on the behavioural intention (BI) to adopt EVs was found to be negative and statistically insignificant (β = -0.496, p = 0.62).

These results indicate that facilitating conditions do not have a meaningful influence on behavioural intention to adopt EVs in South Africa. The result was unexpected, given that facilitating conditions are generally believed to encourage technology adoption (Venkatesh et al., 2003). However, other studies have supported these findings. Fadzil (2017) found that FC had a negative and insignificant effect on mobile app adoption, indicating that consumers without the necessary resources and support are unlikely to adopt new technologies. Pamidimukkala et al. (2024) also reported findings that note that barriers related to technology and infrastructure can discourage adoption.

However, these results are consistent with the descriptive statistics of the FC measurement items. Participants had the most agreeability out of all measurement items on the importance of charging stations and service centres for EV adoption (mean = 6.44, SD = 1.137), while the scores (mean = 2.61, SD = 1.623) for charging infrastructure sufficiency were extremely low. This indicates widespread dissatisfaction and limited trust in the existing infrastructure to support EV adoption. Participants also disagreed that they had access to reliable maintenance and repair services as well as to help from others when experiencing difficulties while using an EV.

These findings indicate that South Africa’s inadequate EV infrastructure negatively affects the adoption of such vehicles. Furthermore, the negative relationship between FC and BI may indicate that, despite the presence of some facilitating conditions, respondents perceive EV adoption as unfeasible due to other overriding factors. This highlights the need for significant improvements in charging infrastructure and support services to enhance EV adoption in South Africa.

5.3.5 *Hedonic Motivations*

The effect of hedonic motivations on the behavioural intention (BI) to adopt EVs was found to be positive but statistically insignificant ($\beta = 1.181$, $p = 0.238$). While studies such as Higueras-Castillo et al. (2023) in Spain find hedonic motivations such as driving enjoyment to improve EV adoptions, other studies such as Irfanto

& Aprilianty (2022) found HM to have an insignificant influence on EV adoption in Indonesia. Their findings are consistent with findings from this study.

The descriptive statistics of this study support these findings because while participants found EVs enjoyable and interesting due to smoothness and advanced technology, their perceptions of satisfaction with the EV range and distances they could travel with an EV were negative. This means that in markets such as South Africa, where infrastructure for EVs is still developing, consumers may prioritise functional attributes over hedonic ones, making HM less influential on BI.

5.3.6 *Price Value*

The effect of PV on the behavioural intention to adopt EVs was found to be positive but statistically insignificant ($\beta = 1.244$, $p = 0.213$). According to Venkatesh et al. (2012), when users perceive the benefits of technology as more valuable than the monetary costs, they are more likely to adopt that technology. However, Irfanto & Aprilianty (2022) found that in developing countries like Indonesia, consumers focus more on the high cost of EVs than on their long-term benefits. Similarly, Manutworakit (2021) found price value insignificant in Thailand, because the prices of EVs are higher than those of ICEVs. High cost of EVs is one of the most cited barriers to EV adoption for South Africa in this study. Observations from the descriptive statistics of this study also support these findings and support the rejection of H6.

Although the findings on statements asking respondents whether they recognise the potential long-term financial and value benefits of EVs were agreeable, most respondents did not perceive EVs as being reasonably priced. This discrepancy indicates that despite acknowledging the benefits of EVs, South African consumers may not be willing or able to invest in EVs due to their high initial costs. This indicates that in developing EV markets, consumers may prioritise immediate factors, like charging infrastructure, and cost factors over perceived benefits like long-term cost savings.

5.3.7 *Habit*

The influence of HB on the behavioural intention to adopt EVs was found to be positive but statistically insignificant ($\beta = 1.304$, $p = 0.192$). The rejection of H7 is consistent with findings from prior studies. For instance, Singh et al. (2023)'s investigation of factors influencing EV found that habit does not significantly impact adoption in the Himalayan region. They attributed this to the similarities between EV and ICEV driving habits, which would allow users to transition seamlessly to EVs without disrupting their usual driving behaviours.

A study by Wang et al. (2020) also support the findings as these authors found that habit does not significantly influence green purchasing intention**.** This indicates that individuals do not automatically engage in green purchasing based on habit. Instead, their decisions to buy green products (such as EVs) is more intentional, driven by factors like attitude, social influence, and environmental concern.

5.4 The Influence of Environmental Concerns and Government Support

According to the literature review of this study, environmental awareness has become a key driver of EV adoption globally, while government policies and incentives play a crucial role in encouraging EV adoption in many countries. Therefore, incorporating environmental concerns (EC) and government support (GS) as additional constructs to the theoretical UTAUT2 model is essential for understanding the adoption of EVs in South Africa. This section examines how EC and GS influence South Africans' behavioural intention to adopt EVs.

5.4.1 *Environmental Concerns*

The results for this study indicate that environmental concerns are the second strongest indicator of the intention to adopt EVs in South Africa. The influence of EC on the behavioural intention to adopt EVs was found to be positive and statistically significant ($\beta = 4.12$, $p < 0.001$). The primary motivation for countries to prioritise and transition to electric vehicles is the need to reduce greenhouse gas emissions from the transportation sector. In the descriptive statistics, respondents expressed strong agreement with statements highlighting that the use of EVs can address environmental issues, protect the environment for future generations, and reduce pollution. These findings further support the results of the hypothesis.

Although EC is not included among the constructs of UTAUT2, other studies on EV adoption, such as Cui et al. (2021), which investigated the purchase motivation for EVs in China, identified EC as the most significant predictor of adoption. Chau (2023) conducted a German study that considered environmental concerns and found that EC positively impacted EV adoption.

Kim and Lee (2023) also highlighted that individuals with greater environmental consciousness are more inclined to prioritise sustainable and eco-friendly technologies like EVs. Supporting this, a South African study by Maduku (2024) stated that heightened environmental awareness fosters a sense of responsibility among consumers, which positively impacts their adoption behaviour. Collectively, these findings underscore the critical role of EC in shaping EV adoption intentions.

5.4.2 *Government Support*

The influence of GS on the behavioural intention to adopt EVs was positive but statistically insignificant ($\beta = 0.773$, $p = 0.439$). This result is in contrast with prior studies, such as Chau (2023), in Germany, which found that supportive government policies and measures positively influence the intention to adopt EVs. Similarly, research by Hasudungan et al. (2024) in Indonesia highlighted the significant effect of EV subsidies and tax reductions on adoption.

However, other studies have reported findings similar to those of the present study. Correia Sinézio Martins et al. (2024) found that the impact of policies on EV adoption varies across countries. These variations depend on factors such as GDP and renewable energy consumption. These authors stated that countries with higher GDPs tend to have more resources, better infrastructure, and the financial capacity to respond effectively to policies. Additionally, nations already relying on renewable energy may experience different effects from policies than those that depend more on fossil fuels. In a study conducted in Vietnam, Cuong et al. (2024) also found that government support had little impact on EV adoption, attributing this to the lack of robust policies from the Vietnamese government compared to more developed nations.

The descriptive statistics of this study reveal that although participants acknowledge that both monetary and non-monetary incentives could drive EV adoption, their perceptions do not directly translate into a stronger behavioural intention to adopt EVs in South Africa. According to South Africa's EV white paper (2023), although the government is planning to introduce incentives, it is yet to implement widespread government support for EV buyers.

5.5 Barriers and enablers of EV adoption

This purpose of this research objective was to provide survey participants with an opportunity to elaborate on the challenges and barriers they perceive as hindering EV adoption, as well as to suggest potential enablers for promoting EV uptake in South Africa.

5.5.1 *Technological Factors*

Technology factors, such as charging infrastructure, range and battery issues, and electricity supply issues, were the most mentioned barriers to EV adoption in South Africa. At the same time, most respondents highlighted that improving the availability and accessibility of charging stations, along with ensuring a sustainable and affordable electricity supply, would encourage EV adoption. This aligns with prior studies by Pamidimukkala et al. (2024), which found that a lack of charging infrastructure and a limited driving range were the most frequently cited barriers in a global review of EV adoption. Madaram et al. (2024) supported this by recommending that technical issues must be addressed to promote EV adoption and innovation.

Additionally, South Africa has faced persistent power supply issues, particularly loadshedding. According to Tongwane & Moeletsi (2021), charging EVs in South

Africa is currently more carbon intensive than using ICEVs. These authors also stated that the country's power supply constraints are not conducive for rapid EV adoption. Their findings suggest that expanding national power generation through renewable energy sources would be valuable for EV adoption, reenforcing the survey participants' emphasis on improving electricity supply as a key enabler.

5.5.2 *Economic Factors*

Economic factors, such as the high upfront cost of EVs were also listed as another significant barrier. Participants believe that making EVs affordable and introducing more entry-level options would make them affordable for middle- and lower-income consumers. The average price of EVs is currently higher than the average price of a new ICEVs (Krishna, 2021). In a study of socio-economic barriers to EV adoption in South Africa, Moeletsi (2021) highlighted the high purchase prices and high battery prices as barriers to adoption.

Even with the promise of long-term cost savings, the high upfront cost creates a challenge for adoption (George et al., 2024). To overcome cost barriers, Li & Wang (2023) found that governments can offer purchase incentives and subsidy programs to alleviate consumers' financial burden. However, South Africa currently lacks similar initiatives, which further hinders potential buyers' ability to embrace EVs.

5.5.3 *Political Factors*

Government support and incentives or lack thereof have been mentioned as barriers and enablers of EV adoption by the survey participants. Abdul Qadir et al. (2024), did a comprehensive study of government strategies, policies and incentives and found them to be essential in overcoming challenges with EV adoption. These authors found that both non-fiscal and fiscal incentives can encourage mass conversion to EVs.

In the survey responses, most people believe that the issue of charging infrastructure is one that can be solved with government intervention. In their study that explored potential models for developing infrastructure, Kumar et al. (2021) found that models where government invests in infrastructure and provides subsidies to consumers are more effective at generating EV demand and market share than models where car manufacturers are expected to invest in infrastructure. This underscores the significant role that governmental involvement could play in shaping the future of EV adoption in South Africa.

5.5.4 *Social Factors*

Lack of information, education, and knowledge about EVs and their benefits were identified as barriers to EV adoption. Participants recommended leveraging advertising, social media, and success stories to highlight the environmental and financial benefits of EV ownership. Furthermore, some participants highlighted the importance of social and cultural considerations, emphasising the need to normalise EVs and shift societal attitudes.

English (2024) stated that raising public awareness of EVs can increase sales. Their study recommended that EV business owners should use social media to share information about EVs, such as EV development opportunities, charging convenience, and environmental benefits, to drive positive social change about EVs.

5.6 Conclusion

In this study, social influence and environmental concerns emerged as the strongest predictors of the behavioural intention to adopt EVs in South Africa. With a path coefficient of 0.96, the results indicate that as social influence increases, the likelihood of individual intention to adopt an EV increases significantly. This highlights the importance of community and peer perceptions in driving adoption, especially in South Africa. The path coefficient of 0.75 for EC indicates a strong positive relationship between environmental awareness and the intention to adopt EVs, highlighting the importance of sustainability concerns in shaping adoption intentions.

Effort expectancy also had a statistically significant influence on EV adoption. However, the negative relationship observed for this construct indicates that concerns surrounding infrastructure and other barriers tend to outweigh the perceived ease of use. This implies that in South Africa, factors such as EV infrastructure, EV benefits, and EV costs are more influential than ease of use.

Furthermore, other factors such as performance expectancy, facilitating conditions, hedonic motivations, price value, and habit were found to have no significant impact on adoption intentions. Addressing issues that cause their insignificant influence should be prioritised to enhance EV adoption in South Africa. Government support showed a statistically insignificant effect on BI, suggesting that the current level of government incentives and policies in South Africa are not yet sufficient to significantly influence adoption.

Overall, for South Africa to achieve widespread EV adoption, a multi-faceted approach that not only builds on strong social and environmental drivers but also mitigates key barriers related to performance, charging infrastructure, lack of government incentives, and high EV costs is needed.

CHAPTER 6. CONCLUSIONS & RECOMMENDATIONS

6.1 Introduction

This chapter presents the conclusions and recommendations for this study. It highlights the contribution of this research to the expanding body of knowledge on consumer behavioural intentions in emerging markets, particularly focusing on the adoption of EVs. By applying the UTAUT2 framework to EV adoption, a relatively underexplored area, this section offers recommendations for policymakers and industry stakeholders, to address barriers and to accelerate the country's transition to EVs. Finally, this chapter also acknowledges the study's limitations and proposes avenues for future research to further deepen the understanding of technology and EV adoption in South Africa.

6.2 Research Summary

The urgent need to curb greenhouse gas emissions and combat climate change has propelled the global automotive industry towards the adoption of EVs. In South Africa, however, the adoption of EVs remains very low, hindered by high costs, lack of charging infrastructure, and technical and organisational support challenges. As the country navigates this crucial transition, regulators, manufacturers, and consumers play a pivotal role in determining the success of EV adoption, which is an essential step towards achieving South Africa's environmental and economic goals.

EVs are a disruptive technologies to South Africa; therefore, the main objectives of this study were to evaluate how South Africans are adopting this new technology by employing the well-established UTAUT2 model and to uncover the barriers and enablers of EV adoption that are specific to South Africa. Through the UTAUT2 model, this study hypothesised that constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, environmental concern, and government support shape consumer behavioural intention to adopt EVs.

Although these independent variables explained 78% of the variance in behavioural intention, only effort expectancy, social influence, and environmental concerns were found to have a statistically significant influence on behavioural intention. Social influence and environmental concerns were found to be the strongest predictors of EV adoption in South Africa.

EVs are a productivity-focused technology, with their adoption largely driven by government incentives and the potential for lower overall ownership costs. Therefore, it is noteworthy that in this study, factors such as performance expectancy, facilitating conditions, price value, and government support were found to have no significant impact on the intention to adopt EVs. These results differ from those of studies conducted in countries with more advanced EV adoption. However, a deeper analysis of the barriers and enablers of EV adoption in South Africa supported these divergent findings. Insufficient infrastructure, the issues of unstable electricity supply, lack of government incentives, and high EV costs affect consumer perceptions, attitudes, and trust that EVs can be a viable mobility solution in South Africa.

While highlighting and leveraging the key enablers that positively influence EV adoption is essential, it is equally important to address the variables that show little impact on behavioural intention

6.3 Theoretical Contributions

This study applied the UTAUT2 technology adoption model to examine the factors influencing EV adoption in South Africa. This study also introduced two additional constructs, environmental concerns and government support, to enhance the UTAUT2 model's applicability in the context of electric vehicles. Although numerous international studies have explored EV adoption, no study has specifically used UTAUT2 to assess EV adoption in South Africa. Although it is widely recognised that government policies and environmental sustainability drive EV adoption, these factors are not typically integrated into the UTAUT2 framework when analysing behavioural intentions. By incorporating government support and environmental concerns, this study extends the theoretical foundation of UTAUT2, providing a more comprehensive understanding of the determinants of EV adoption in a developing market context. This study also contributes to the growing body of literature on the barriers and enablers of EV adoption in South Africa. While extensive research has been conducted globally, surveying South African consumers has provided new insights into the country’s unique challenges in adopting EVs.

6.4 Practical Contributions

The findings of this provide critical insights for policymakers, automakers, and stakeholders in the transportation sector. Social influence, environmental concerns and effort expectancy were found to have statistically significant influence on the behavioural intention to adopt EVs in South Africa. Therefore, stakeholders must focus leveraging public opinion and endorsements, environmental benefits, and the perceived ease of use of electric vehicles to drive adoption.

Performance expectancy, facilitating conditions, price value, hedonic motivations, habit, and government support did not have a statistically significant influence on behavioural intention to adopt EVs. Despite their theoretical importance, these constructs did not demonstrate a direct influence in the context of EV adoption in South Africa. However, these factors are still very relevant. There is a need for more nuanced exploration into the underlying conditions that diminish their significance.

To promote greater EV adoption, efforts should also focus on addressing the contextual or perceptual barriers that render these factors ineffective. Understanding the reasons for the limited effects of these variables is crucial for designing targeted interventions that can effectively encourage the widespread adoption of EVs.

6.5 Recommendations

In the context of South Africa’s transition to EVs, the recommendations of this study are multi-faceted and extend to various stakeholders, including the government and the automotive industry.

6.5.1 *Recommendations for Policymakers*

The growing concerns surrounding climate change, coupled with the increasing societal acceptance of green technologies, present policymakers with an opportunity to develop policies that align with these motivations. Policymakers can harness the positive influence of social influence and environmental concerns on South Africans' behavioural intentions to adopt EVs. Given that environmental concerns have been identified as a key motivator for EV adoption in South Africa, the government must take steps to raise public awareness regarding the country’s emission reduction targets and its EV sales goals, which will eventually restrict the sale of new ICEVs. Through government-led educational campaigns, policymakers can shift public perception, increase consumer confidence, and ultimately drive demand for more sustainable modes of transport.

Policymakers can also leverage the strong impact of social influence on behavioural intention to adopt EVs through peer and corporate influence through strategic initiatives. For example, policymakers can promote EV adoption via social media campaigns, community-driven programs, and government-led events such as EV expos and test drives. In addition, incentives for early adopters and the appointment of celebrity ambassadors as role models can further encourage adoption. Corporate social responsibility policies could also play a crucial role in encouraging government agencies, Bus Rapid Transit (BRT) systems, and private companies to transition to EVs, thereby enhancing public exposure and fostering acceptance.

While research conducted in various countries underscores the pivotal role that governments have played in promoting EV adoption, this study reveals that government support does not have a statistically significant impact on EV adoption in South Africa. This finding can be attributed to the limited or lack of policies that actively support EV adoption. Consequently, policymakers in South Africa should adopt a comprehensive approach to promoting this transition.

In 2025, the South African government approved a 150% tax deduction to encourage local manufacturing of battery electric vehicles (BEVs) and hybrid electric vehicles (HEVs). Although this is a significant step forward, broader financial incentives for consumers are essential to enhance EV adoption. In addition to supporting domestic production, policymakers should consider reducing the 25% import duty on EVs, introducing purchase subsidies, and implementing tax rebates. These measures can help bridge the price gap between EVs and ICEVs, making EVs more accessible and affordable for consumers, thus strengthening the impact of price value on behavioural intention.

EV charging infrastructure plays a direct role in shaping the impact of facilitating conditions on behavioural intention. However, this study, along with previous research, highlights that inadequate or insufficient charging infrastructure can negatively influence consumer perceptions of key factors associated with EV adoption, such as performance expectancy, effort expectancy, price value, and hedonic motivation. To address this need, policymakers must prioritise the expansion of reliable public and private charging networks by incentivizing infrastructure development, supporting private charger installations, and fostering partnerships with businesses to enhance the accessibility of EV chargers.

Improving charging infrastructure alone will not be sufficient if South Africa's unstable electricity grid remains unresolved. Load shedding poses a significant barrier to EV adoption, as consumers are deterred by concerns over unreliable access to charging. Therefore, policymakers must focus not only on expanding charging networks but also on improving energy stability through increased renewable energy generation and grid resilience. Integrating solar, wind, and other renewable energy sources into EV charging infrastructure will be key to ensuring a sustainable and reliable transition.

6.5.2 *Recommendations for Car Manufacturers*

Growing environmental concerns and increasing social awareness provide a strong foundation for promoting EV adoption in South Africa. These factors create an opportunity for automotive manufacturers and sellers to align their strategies with consumer values. By leveraging digital, customer-centric approaches, such as intuitive websites, apps, and online platforms, stakeholders in the automotive industry can effectively engage consumers, providing them with the information needed to make informed decisions about EVs. In addition, social media influencers, brand ambassadors, and targeted social media marketing campaigns can significantly increase public awareness and foster consumer engagement.

Moreover, South Africa's push towards developing smart cities presents further opportunities for collaboration between the automotive industry and local governments. By integrating EVs into urban mobility strategies, such as public transportation and car-sharing services, industry stakeholders can support the adoption of EVs in urban environments. These strategies will not only contribute to increasing the adoption of EVs but also help shape public perceptions of the benefits of using EVs, particularly the hedonic motivations, which have been found to have limited influence on adoption in South Africa.

Despite South Africans' growing interest in EVs, the present study found that factors such as performance expectancy, price value, and facilitating conditions did not significantly influence South Africans' behavioural intention to adopt an EV. While government incentives can help reduce the cost of EV production and improve charging infrastructure, manufacturers must focus on the design, performance, and pricing of EVs to meet local needs. South Africans often travel long distances between provinces, leading to concerns about the suitability of EVs for such journeys. However, research indicates that advancements in battery technology, charging times, and driving range are addressing these concerns. Manufacturers should therefore invest in high-quality battery technology and continue to improve it through research and development to ensure that EVs become a viable option for long-distance travel.

Education and communication about these technological advancements will also play a key role in shifting consumer perceptions, addressing misconceptions, and encouraging a more widespread adoption of EVs.

South African consumers are particularly concerned about service accessibility, reliability, and maintenance when adopting new technologies like EVs. Although facilitating conditions, such as service and maintenance networks did not significantly influence the intention to adopt EVs in this study, they are essential for long-term adoption. Automakers must prioritise the development of an extensive and visible network of service centres dedicated to EVs, ensuring that consumers have easy access to support and maintenance. Additionally, partnerships with academic institutions to train technicians and service personnel will be critical to maintaining these centres and ensuring they are well-equipped to handle the unique needs of EVs. Offering extended warranties and service plans can further enhance consumer confidence, assuring potential buyers that any maintenance or support needs will be met with minimal cost and effort.

Price sensitivity is another significant barrier to EV adoption in South Africa. While long-term savings on the total cost of ownership are important, the high upfront cost of EVs remains a significant challenge for many consumers. To address this, manufacturers must focus on introducing more affordable EV models and exploring innovative business models, such as subscription services. These services, which allow consumers to lease EVs without long-term commitment, could make electric vehicles more accessible to a wider range of South Africans, particularly those hesitant about the initial investment.

6.6 Study Limitations

This study has several limitations that must be considered when interpreting the findings. First, the sample size of 309 participants may not be fully representative of the broader South African population, which could affect the generalisability of the results. Additionally, as the South African EV market is still in its early stages of development, the factors influencing its adoption are likely to evolve. This suggests that future research should explore longitudinal studies to track shifts in consumer behaviour and industry developments.

A further limitation is that none of the participants owned an electric vehicle, which raises questions about the accuracy of their responses regarding their intentions and understanding of EVs. The absence of direct experience with EVs could influence the reliability of their adoption and usage patterns.

Moreover, some Average Variance Extracted (AVE) values were found to be below 0.5; however, they were accepted due to the Composite Reliability (CR) being above 0.6. Future studies may benefit from refining the measurement items for these constructs to improve their AVE values.

Another area not explored in this research was the moderating effects of variables such as age, gender, and experience. These factors could provide valuable insights into how demographic groups perceive and adopt EVs. The study also did not incorporate mediating variables, thus overlooking potential interactions between different constructs that could influence adoption decisions.

Finally, this study focused on behavioural intention rather than actual usage behaviour, which may not fully capture the complexities of real-world adoption and the factors driving the use of EVs in practice.

6.7 Future Research Directions

This study provides a new direction for future research on EV adoption. Future research on EV adoption in South Africa could benefit from a larger, more diverse sample that better represents the broader population, ensuring the generalisability of findings, especially by including participants with firsthand experience of owning and using EVs. Longitudinal studies should also be conducted to track shifts in consumer behaviour and industry developments over time, providing insights into evolving factors influencing EV adoption.

Additionally, future research should explore the moderating effects of variables such as age, gender, and experience, as these may significantly influence the adoption process for the different groups. Further studies should also examine the role of mediating factors such as trust, risk perceptions and attitude towards EVs to investigate how these factors might change the influence of certain constructs on BI.

Furthermore, to gain a more accurate understanding of real-world EV adoption, future research should incorporate studying the effect of BI and other UTAUT2's constructs on actual use behaviour.

6.8 Conclusion

South Africa's automotive industry is a cornerstone of the nation's economy, contributing significantly to GDP and positioning the country as a key global supplier of vehicles and components. However, as international markets tighten emissions regulations, demand for locally produced ICEVs is expected to decline. To remain competitive, South Africa must transition towards EV production and adoption. This shift requires not only supportive government policies but also industry-driven strategies that foster local manufacturing and consumer confidence in EVs.

This study examined the factors influencing EV adoption in South Africa using an adapted UTAUT2 model, incorporating environmental concerns and government support as additional variables. While global research emphasises performance expectancy, price value, and government incentives, this study found that in South Africa, only social influence, environmental concerns, and effort expectancy had the most significant impact on consumers' behavioural intention to adopt EVs. The findings highlight critical barriers, including high costs, inadequate infrastructure, unreliable electricity supply, and a lack of government incentives as factors that hinder adoption drivers seen in more mature EV markets.

For automakers and industry stakeholders, the growing emphasis on environmental consciousness and social influence presents an opportunity to align with consumer values. Other priorities should include advancing battery technology, expanding service networks, developing local expertise, and introducing more affordable EV models. Additionally, innovative business models such as subscription-based ownership and flexible financing can help mitigate affordability concerns. Enhancing the overall user experience through real-time technological support, accessible maintenance, and convenience-driven solutions will further drive adoption.

Ultimately, South Africa’s ability to transition to electric mobility will depend on strategic collaboration between government, industry, and consumers. By addressing key barriers and capitalising on market opportunities, the country could position itself as a leader in sustainable transportation while safeguarding the future of its automotive sector.

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APPENDIX A – Participant Information Sheet

Dear Sir / Madam,

My name is Puleng Morota. I am a Master of Management in Digital Business (MMDB) candidate at Wits Business School. My supervisor is Dr Tebogo Sethibe.

The title of my study is **"Factors Influencing Electric Vehicle Adoption in South Africa"**. The purpose of this study is to identify and analyze the factors that influence potential consumers' intentions to transition to Electric Vehicles (EVs) in South Africa.

I am inviting you to take part in answering an online questionnaire to assist me with my research. The questionnaire should take **less than 15 minutes to complete**.

Your participation is completely **voluntary**, and you will not be advantaged or disadvantaged in any way, whether you choose to complete the survey or not. Taking part in the research study **will not cost you anything**. You will also **not be paid** for participating in this research study. If you access the survey, you can choose to stop answering the survey at any point before submitting. Submission of the completed survey will be regarded as **consent** to participate in the study.

Your responses will remain strictly **confidential**, and your **anonymity** is guaranteed as no individually identifying information (such as your name or identity number) will be recorded in the dataset.

This research study will be written up as a research report and will be available on the university library website. If you would like to receive a summary of this report, I will be happy to send it to you.

If you have any questions during or afterwards about this research study, feel free to contact me or my supervisor on the details listed below.

If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za.

Yours sincerely,

Puleng Morota

Researcher:

Puleng Morota

942940@students.wits.ac.za

0658622754

Supervisor:

Dr Tebogo Sethibe

Tebogo.sethibe@wits.ac.za

0124279727

APPENDIX B – Research Instrument

Research Title: Factors Influencing Electric Vehicle Adoption in South Africa

Researcher: Puleng Morota

This research focuses on the intention to adopt electric vehicles (EVs). It is not limited to people who already own or have experience with EVs. The study is interested in understanding what factors influence a person's willingness or intention to consider using an EV in the future, regardless of whether they've used or owned one before. This means anyone can participate, as the survey is about exploring attitudes, beliefs, or potential barriers and motivators toward EV adoption, rather than experiences with current ownership or usage.

In the context of this research, EVs refers to all forms of vehicles that are powered by one or more electric motors. It does not specify or differentiate between various types of electric vehicles.

Please read each statement carefully and pick only one box that most closely aligns with your perspective.

SECTION A: DEMOGRAPHIC INFORMATION In this section, we aim to collect essential demographic details to understand the diversity of participants and to identify trends and patterns in the research findings.

SECTION A: DEMOGRAPHIC INFORMATION

1. **Age:**
   ☐ Under 18
   ☐ 18-24
   ☐ 25-34
   ☐ 35-44
   ☐ 45-54
   ☐ 55-64
   ☐ 65 and over
2. **Gender:**
   ☐ Male
   ☐ Female
   ☐ non-binary
   ☐ Prefer not to say
3. **Highest Level of Education:**
   ☐ No formal education
   ☐ Primary education
   ☐ Secondary education
   ☐ Tertiary education (Diploma, bachelor's degree)
   ☐ Postgraduate education (master's degree, Ph.D.)
4. **Employment Status:**
   ☐ Employed full-time
   ☐ Employed part-time
   ☐ Self-employed
   ☐ Unemployed
   ☐ Student
   ☐ Retired
5. **Monthly Household Income:**
   ☐ Less than R10,000
   ☐ R10,000 - R19,999
   ☐ R20,000 - R29,999
   ☐ R30,000 - R39,999
   ☐ R40,000 - R49,999
   ☐ R50,000 and above
6. **Car Ownership:**
   ☐ Yes, I own a car
   ☐ No, I do not own a car

SECTION B:

SECTION B1: PERFORMANCE EXPECTANCY Performance expectancy in the context of Electric Vehicles (EV) refers to the belief that using an EV will significantly enhance the user's performance and efficiency in transportation tasks.							
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Some what agree (5)	Agre e (6)	Stron gly agree (7)

I am satisfied with current average driving range of Electric Vehicles (around 350km per full charge). (1)							
I think the current charging time of Electric Vehicles needs to be improved. (2)							
With the fuel price increasing significantly, I think using an Electric Vehicle could lower my fuel expense. (3)							
With the current performance of electric vehicles like driving range, charging time, and saving of fuel cost, I think that an Electric Vehicle could enhance my driving experience. (4)							
I think that the distance that an Electric Vehicle can be run is enough to meet the needs of everyday use. (5)							
SECTION B2: EFFORT EXPECTANCY Effort expectancy in the context of Electric Vehicles (EVs) refers to the perceived ease of use associated with operating and maintaining an EV. It encompasses the belief that users will find driving an EV to be straightforward and manageable, with minimal effort required for tasks such as charging, navigation, and general upkeep.							
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Using an Electric Vehicle would be easy for me, as there is no big difference between using Electric Vehicles and using traditional vehicles. (1)							
I think it would be easy for me to learn how to use an Electric Vehicle. (2)							
I think it would be easy for me to become skillful at using an Electric Vehicle. (3)							
I think I have the necessary resources to use an Electric Vehicle. (4)							
SECTION B3: SOCIAL INFLUENCE Social influence in the context of Electric Vehicles (EVs) refers to how societal norms, peer pressure, and the opinions of others affect an individual's decision to adopt and use EVs.							
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Buying and using an Electric Vehicle is a social trend in South Africa. (1)							
People around me will support my decision if I choose to buy an Electric Vehicle. (2)							
If people around me buy and use Electric Vehicle, I would also consider buying one. (3)							
Other people will be impressed if I purchase an Electric Vehicle. (4)							
SECTION B4: FACILITATING CONDITIONS Facilitating conditions refer to the resources, infrastructure, and support systems available to individuals that enable or hinder the adoption and effective use of Electric Vehicles (EVs). These conditions can significantly influence the perceived feasibility and convenience of owning and operating an EV.							
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I think charging stations and service centres are important for Electric Vehicle buyers. (1)							
In South Africa, there is currently 350 charging stations. I think the charging infrastructure in SA is sufficient for Electric Vehicle users. (2)							
I think it is easy to charge and find support for an Electric Vehicle when it has issues. (3)							
I have access to reliable maintenance and repair services for Electric Vehicles. (4)							
I believe I can get help from others when I have difficulties using an Electric Vehicle. (5)							
SECTION B5: HEDONIC MOTIVATIONS Hedonic motivations refer to the pleasure and personal satisfaction people gain from using Electric Vehicles (EVs).							
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I think that I would find driving an Electric Vehicle to be an enjoyable experience. (1)							
I think driving an Electric Vehicle is interesting due to its smoothness, high acceleration, and high technology. (2)							
I believe that I would feel free to travel with an Electric Vehicle even if it runs for a limited distance. (3)							
I believe I would be satisfied with the distance travelled using an Electric Vehicle. (4)							
SECTION B6: PRICE VALUE Price-value refers to the perceived balance between the cost of an Electric Vehicle (EV) and the benefits it provides.							
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I believe the long-term savings on fuel and maintenance justify the higher initial cost of Electric Vehicles. (1)							
I would be willing to pay more upfront for an Electric Vehicle because of the future cost savings. (2)							

I believe the overall value I would get from buying an Electric Vehicle is worth the investment. (3)							
I think that Electric Vehicles are reasonably priced. (4)							
SECTION B7: HABIT Habit refers to the extent to which individuals consistently choose Electric Vehicles (EVs) based on routine rather than deliberate decision-making.							
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Some what agree (5)	Agre e (6)	Stron gly agree (7)
The use of Electric Vehicles can become a habit for me. (1)							
I believe that using Electric Vehicles can become natural for me. (2)							
I believe I could get addicted to using an Electric Vehicle. (3)							
SECTION B8: ENVIRONMENTAL CONCERNS Environmental concerns in the context of Electric Vehicles (EVs) refer to the awareness and importance individuals place on the environmental impact of their transportation choices.							
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Some what agree (5)	Agre e (6)	Stron gly agree (7)
I think I would prefer to buy and use an Electric Vehicle as it helps with environmental issues such as reducing air pollution and saving natural energy. (1)							
By buying and using Electric Vehicles, I believe I can help save the environment for the next generation. (2)							
Electric Vehicles cause less pollution. (3)							
I want to preserve energy and the environment. (4)							
SECTION B9: GOVERNMENT SUPPORT Government support refers to the policies, incentives, and infrastructure investments provided to encourage Electric Vehicle (EV) adoption.							
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Some what agree (5)	Agre e (6)	Stron gly agree (7)
Government's monetary incentives to support EV buyers such as tax reduction, price subsidy and free of charging encourage me to buy and use an Electric Vehicle. (1)							
Government's non-monetary incentives to support electric cars buyer such as free-parking, priority to use bus lane/parking lots encourage me to buy and use an Electric Vehicle. (2)							
I believe that the government should fund the construction of charging stations to cover the whole country. (3)							
I think that the government should have measures to exempt charging fees for Electric Vehicle users. (4)							
SECTION B10: BEHAVIOURAL INTENTION Behavioral intention captures an individual's level of motivation to perform a behavior. In the context of Electric Vehicles, behavioral intention refers to an individual's readiness or willingness to adopt and use Electric Vehicles (EVs)							
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Some what agree (5)	Agre e (6)	Stron gly agree (7)
I intend to purchase an Electric Vehicle in the future. (1)							
I am very likely to purchase an Electric Vehicle soon if the opportunity arises. (2)							
I intend to purchase an Electric Vehicle although they are expensive. (3)							
I would encourage my friends/family/colleagues to purchase an Electric Vehicle. (4)							

SECTION C: OPEN-ENDED QUESTIONS

1. What do you think are the biggest challenges or barriers to adopting electric vehicles in South Africa?
2. In your opinion, what could be done to encourage more people to switch to electric vehicles in South Africa?

APPENDIX C – Ethics Clearance Certificate

•• PROTECTED 関係者外秘

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Busir Schoo

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/DB942940/966

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

This certificate is only valid if accompanied by formal permission from the relevant stakeholder(s).

Project title	Factors influencing electric vehicle adoption in South Africa
Investigator / Researcher	Miss Puleng Theodorah Morota
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed confidentialty.
Issue Date of Certificate	31/01/2025
Expiry date	Date of submission of the project / research report
Chairperson	Dr Ayanda Magida ☎ +27 11 717 3953 ayanda.magida@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Eti Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research a guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature   06/02/2025
                                                           Date:

APPENDIX D – Originality Report Summary

Research Report - MMDB - Puleng Morota - Final-1.pdf

ORIGINALITY REPORT

6%	8%	6%	%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

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