

**Determinants of the use of Liquefied Petroleum Gas for South African
households**

Applied Research Project

submitted by

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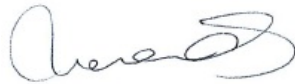
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DECLARATION

I, Bernard Muanda, declare that this research project 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 Business Administration in the Graduate School of Business Administration, University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Bernard Ngueji Muanda



Signed at ...Midrand.....

On the28..... day ofFebruary..... 2023.....

DEDICATION

This work is dedicated to my wife, Bijou Muanda, my children Bill, Belle and Blanche Muanda and my nieces Jenny and Dorcas for their patience, support and assistance during the past two years.

ACKNOWLEDGEMENTS

I thank my supervisor, Dr Bongani Munkuli, for his support, patience, dedication, commitment, and enthusiasm for discussing my report content by any available communication means.

I appreciate Wits Business School staff, particularly Thobile Sedumedi and Dr Thabang, for bringing new ideas to the school and, most notably, for listening to us.

A special thank you go to all my syndicate groups, new friends I met, and all the 2021 Saturday B class students. I learnt a lot from everyone and appreciated the contribution through our interactions.

SUPPLEMENTARY INFORMATION

Project format:	Research article
Nominated journal:	Journal of Energy in Southern Africa
Supplementary files:	Database of recorded participant responses Schedule of interview questions

Contents

DECLARATION.....	i
DEDICATION	ii
ACKNOWLEDGEMENTS	iii
SUPPLEMENTARY INFORMATION.....	iv
ABSTRACT	11
1 INTRODUCTION.....	12
1.1 Background.....	12
1.2 Problem statement.....	13
1.3 Research purpose.....	14
1.4 Research questions	14
1.5 Significance of the research.....	14
1.6 Scope and delimitation.....	15
1.7 Thesis outline.....	15
2 LITERATURE REVIEW.....	16
2.1 Introduction	16
2.2 Liquefied Petroleum Gas.....	18
2.2.1 Production, advantages and disadvantages.....	18
2.2.2 Factors driving the use of liquefied petroleum gas	19
2.2.3 LPG in South Africa	22
2.2.4 Alternative energy source.....	24
2.3 Empirical research on LPG in South Africa.....	24
2.3.1 Country outlook	24
2.3.2 Prior research into the use of LPG	25
2.4 Theory.....	27

2.4.1	Planned Behaviour	27
2.5	Hypotheses Development	29
2.5.1	Attitude	30
2.5.2	Subjective Norms	31
2.5.3	Perceived Behaviour Control	31
2.5.4	Intention.....	31
2.5.5	Research hypothesis	32
2.6	Conclusion	32
3	RESEARCH METHODOLOGY	33
3.1	Introduction	33
3.2	Research approach and design	33
3.3	Research data types and collection methods.....	34
3.3.1	Data types	34
3.3.2	Data collection and storage	35
3.4	Target population	35
3.5	Ethical considerations for collected data	37
3.6	The research model	37
3.7	Data processing	38
3.7.1	Data cleaning and coding	38
3.7.2	Descriptive statistics	39
3.7.3	Multivariate analysis	40
3.8	Analysis using PLS-SEM	42
3.8.1	Measurement model's evaluation	43
3.8.2	Structural model evaluation	45

3.9	Conclusions.....	49
4	ANALYSIS	50
4.1	Descriptive statistics.....	50
4.1.1	Survey completion rate	50
4.1.2	Demographics	50
4.2	Model validation and evaluation of path coefficients	52
4.2.1	Reflective measurement model's evaluation	52
4.2.2	Structural model evaluation	58
4.3	Path coefficients.....	59
4.3.1	Path coefficient.....	59
4.3.2	Indirect effect.....	60
4.3.3	Total effect.....	60
4.4	Relevance and significance of results	61
4.4.1	Indicator loadings validation	62
4.4.2	Structural model validation	63
4.5	Assessment for control variables	64
4.6	Conclusions.....	67
5	DISCUSSION OF FINDINGS.....	70
5.1	Overview	70
5.2	Relationships mediated by intention.....	70
	Relationship between attitude and LPG usage	70
5.2.1	Relationship between norms and LPG usage.....	71
5.2.2	Relationship between behavioural control and usage	71
5.3	Direct relationship	71
5.3.1	Relationship between intention and LPG usage	71

5.3.2	Relationship between behavioral control and LPG usage	72
6	SUMMARY AND CONCLUSIONS	73
6.1	The drivers of the use of LPG	73
6.2	Policy implications.....	73
6.3	Business implications.....	73
6.4	Conclusions.....	74
6.5	Recommendation for further research.....	74
	BIBLIOGRAPHY	75
	ANNEXURES.....	83
	Cost of electricity.....	83
	T-statistics results	84

LIST OF FIGURES

Figure 1: Ten-years electricity price Increase	21
Figure 2: Electricity vs LPG - comparison of price increase.....	23
Figure 3: Proposed model for the usage (adapted from the theory of planned behaviour).....	30
Figure 4: Measurement and structural model	44
Figure 5: Model with control variables	48
Figure 6: Indicator loadings and reliability	52
Figure 7: Model validation and indicator reliability	54
Figure 8: Results of PLS-SEM path analysis (without control variables).....	61
Figure 9: Model validation with control variable	66
Figure 10: Average electricity price 2003-2021 (Eskom, 2022)	83

LIST OF TABLES

Table 1: Coding for categorical variable's data.....	39
Table 2: Alternative interpretation of R ² values.....	47
Table 3: Respondent's progress.....	50
Table 4: Respondent demographics.....	51
Table 5: Reflective measurement indicators' reliability	53
Table 6: Construct (latent variables) reliability indexes.....	54
Table 7: Results of Fornell-Lacker criterion assessment	55
Table 8: Results of Heterotrait-Monotrait ratios	55
Table 9: Results of the cross-loading assessment	57
Table 10: Results of collinearity assessment.....	58
Table 11: Explanatory power's R-square values	58
Table 12: Effect size's F-square values.....	59
Table 13: Direct effect of the dependent variables on the use of LPG	59
Table 14: Indirect effect of the dependent variables on the use of LPG.....	60
Table 15: Total effect of the dependent variables on the use of LPG	60
Table 16: Results of T-statistics for outer loading (measurement items)	62
Table 17: T-statistics for path coefficients (direct effect) of the model	63
Table 18: T-statistics for indirect effects of the model.....	63
Table 19: T-statistics for total effects of the model	64
Table 20: Control variable effect on the output.....	65
Table 21: Effect of education on the determinants of intention and use.....	66
Table 22: Summary of hypothesis assessments	68
Table 23: Indirect effects on the use of LPG	69
Table 24: Annexure – path coefficient's bootstrap results	84
Table 25: Annexure – indirect effect's bootstrap results	84
Table 26: Annexure – specific indirect effect's t-statistics.....	84
Table 27: Annexure – bootstrapped total effect's results	84
Table 28: Annexure – outer loading's bootstrap results.....	85

ABSTRACT

Introduction – South Africa is experiencing the worst energy crisis in decades, and this is causing untold pains for many users across South Africa. At the same time, alternative energy such as liquefied petroleum gas (LPG) usage is lower than similar emerging economies. The purpose of this research is to examine empirically the determinants of LPG usage for South African households.

Design methodology – The author uses applies 118 responses to a survey to determine the drivers of LPG usage for South Africa households. To meet these objectives, the author combines the theory of planned behaviour model and partial least square structural equation modelling (PLS-SEM) to validate the hypothesis.

Findings – The study found that behavioural control and intention to use LPG are the precursors to the eventual use of LPG.

The relationship between behavioural control and LPG usage is stronger than the relationship between intention and the LPG usage. Attitude towards LPG, the perceived behavioural control and the norms, respectively in order of strength, have a positive relationship with the intention to use LPG. Finally, less educated respondents were likely to switch to LPG usage as opposed to the more educated counterparts.

Research implications – The study contributes mainly to enhancing government policy with regards concerning the increase of LPG usage by providing key factors to target for marketing and education for the end user. Key policies will contribute to increasing LPG usage, hence positive contribution to the economy. The value of this study is the first to analyse the determinants of LPG usage for South African households using the theory of planned behaviour and structural equation modelling. Hence, it contributes to the debate surrounding the adoption and increase of LPG usage.

Keywords- South Africa, Energy, Liquefied Petroleum Gas., Partial Least Squares, Structural equation modelling, Theory of planned behaviour.

1 INTRODUCTION

This research project investigates the determinants of using Liquefied Petroleum Gas for South African households. Section 1.1 provides the background to the research, followed by section 2, which contains the problem statement discussion, and then section 1.3, which lays down the research purpose.

Section 1.4 deals with the research question, and section 1.5 address the significance of the study. Finally, section 1.6 lists the research scope and delimitation, followed by section 1.7, which deals with the preface.

1.1 Background

Energy consumption is essential to economic development (Yeager et al., 2012), and the causal relationship between energy consumption and economic growth is country-specific. No causality refers to the lack of a relationship between energy consumption and economic growth, while unidirectional causality exists when economic growth affects energy consumption or vice-versa. A case of bidirectional causality implies that economic growth and energy consumption affect each other (Asghar, 2008).

A unidirectional causality characterises energy-dependent economies from economic growth to energy consumption. Similarly, non-energy-dependent economies experience a unidirectional causality from energy consumption to economic growth. Regardless of the causality, energy systems are still necessary for the economy to power production for industries and the services to the population. The primary drivers for their demands are the population, the economic activity per capita and the technology performance (Asghar, 2008; Yeager et al., 2012).

The South African Department of Mineral Resources and Energy (DMRE) states, “Energy is the lifeblood of the South African economy and is an important sector of the economy that creates jobs and value by extracting, transforming and distributing energy goods and services throughout the economy”. According to the DMRE, the energy mix in South Africa is predominantly coal at 65%, followed by Crude Oil (18%), Renewable and waste (11%), Gas (3%), Nuclear (2%) and Geothermal (1%) (Ratshomo & Nembahe, 2022).

South African electrical energy is 83% produced from coal, while the balance comes from pumped storage, gas, nuclear, hydro and solar (Ratshomo & Nembahe, 2022). The production of electricity from coal is a significant source of considerable pollution (Masekoameng et al., 2010).

Although households account only for 7% of the total energy needs in South Africa, it accounts for 11% of the total electrical energy consumption, while industrial, commercial, agricultural, traction and mining take the balance of 89% (Eskom, 2022).

The growth of electricity demand and the lack of new generation capacity has reduced reserve margins since 2007. Therefore, breakdowns at existing power stations will likely lead to blackouts on some parts of the network. This action would affect households, commerce and industries, causing an energy crisis (Pierce & Le Roux, 2022).

South Africa is currently experiencing an electrical energy crisis that profoundly affects its economy and therefore requires consideration for alternative energy and possibly a rebalancing of energy usage. The unfolding energy crisis in South Africa requires the government to seek short, medium- and long-term interventions to avert the crisis and prevent economic collapse. One way to achieve this is by reprioritising energy resources based on their availability. The government looks at various ways, including LPG (DMER, 2019).

1.2 Problem statement

The use of liquefied petroleum gas in South African households is lower than in leading and similar economies worldwide (The Global Economy, 2021). At the same time, the ongoing electricity disruptions are likely to disturb households' activity scheduling, given that the supply schedule is not available in the long term. The misalignment between household and utility electricity rationing could lead to social problems such as unplanned expenses and less disposable income.

South Africa started experiencing disruptions to its electrical energy distribution in 2007 (CSIR, 2021). Despite the inconvenience created by frequent interruptions in the electrical energy supply, the use of LPG in households remains low compared to similar economies

(The Global Economy, 2021). It is, therefore, essential to analyse and understand the drivers of using LPG in the household.

1.3 Research purpose

The research purpose is to evaluate the determinants of households' use of LPG in South Africa.

1.4 Research questions

Based on the problem statement and research objective, the following primary research question guides and shapes the research literature, data acquisition, analysis and results:

- What determines the use of LPG in South African households?

After the main question, the following sub-questions apply:

- 1) How is attitude related to the usage of LPG?
- 2) How do norms relate to the usage of LPG?
- 3) How does behavioural control relate to the use of LPG?

1.5 Significance of the research

This research will unpack the factors that determine the use of LPG in South African households. Understanding the determinants of the use of LPG is crucial in its marketing and promotion to the public. A successful campaign can lead to increased use of LPG and, by extension, reduced pressure on the electrical grid.

Understanding the determinant of the use of LPG could also assist in shaping energy policies while providing industries with sufficient intelligence needed for positioning in the market, thereby increasing the LPG usage to the benefit of the broader economy. Furthermore, these determinants could serve utilities such as municipalities in predicting the savings resulting from lower demand charges.

This study is the first to analyse the determinants of LPG usage for South African households using the theory of planned behaviour and structural equation modelling. Hence, it contributes to the debate surrounding the adoption and increase of LPG usage.

1.6 Scope and delimitation

The scope of this research is limited to finding the determinant of the use of LPG in households in South Africa and has the following limitations:

- (1) It does not investigate the reduction in electricity's peak demand and the associated correlation with LPG usage.
- (2) It does not address the long-term cost-benefit analysis comparing LPG and electrical energy use.
- (3) It does not contain the LPG energy policy design analysis.

1.7 Thesis outline

This thesis report has five chapters in total. Chapter 1 is the introduction that provides the background, problem statement, objectives, and statements based on the hypothesis. Additionally, it has provided the significance of this research, its scope delimitation and the deliverables.

Chapter 2 focuses on the literature review on LPG in the South African context. It will explore the advantages, opportunities, and challenges of LPG. Furthermore, it compares LPG to electricity from a perspective of legacy prices, trends and vulnerability to external events.

Chapter 3 addresses the research methodology that discusses instruments and strategies used to acquire, store and analyse data to find the determinant of the use of LPG.

Chapter 4 provides the application of the methodology developed in chapter 3. Finally, Chapter 5 provides the discussions and conclusions on the research and the recommendations for future research on the subject.

2 LITERATURE REVIEW

The literature review provides a background on the energy issues faced by South Africa. Furthermore, it investigates the previous research on using Liquefied Petroleum Gas (LPG). It focuses on using LPG as alternative energy for household cooking and heating. Finally, the research discusses the choice of a theory adopted for analysing the drivers of LPG usage.

2.1 Introduction

Electricity dominates the energy demand in most South African households (Ratshomo & Nembahe, 2021), for which a large part covers heating and cooking needs (Mohlakoana & Annecke, 2009).

The electrical energy supplied to these households is mainly generated by coal (Ratshomo & Nembahe, 2021). Although coal is a cheap form of energy, it raises many environmental concerns because of its considerable greenhouse emission. South Africa has abundant coal reserves, but efforts are in place to reduce its impact as much as possible by increasing the penetration of cleaner energy sources (DMER, 2019).

Despite the low cost of electrical energy, South Africa has experienced rolling load shedding since 2007. The unserved energy is growing significantly due to the existing power stations' lack of reliable generation capacity. By the winter of 2022, power rationing had reached levels never experienced in South African recent history (Pierce & Le Roux, 2022). The electricity supply rationing routine known as load shedding now applies frequently whenever the generation capacity cannot meet the demand. During this routine, businesses and households cannot access electricity from the grid for as little as an hour to four hours, once or many times daily (CSIR, 2021).

Any load interruption harms both the supplier and the consumer. For the supplier, there is a cost of unserved energy that harms the revenue. Consumers in the production industries experience lost production time, can potentially miss production targets and become less competitive. Residential consumers pay the price of inconveniences such as spoiled food, unplanned expenses and more extended periods in traffic. Hence, electricity supply interruption negatively affects the national economy (Goldberg, 2015).

Although all sectors of the economy are affected by load-shedding practices, some are affected more than others. Based on this argument, it is crucial for South Africa as a country to realign its strategy to redistribute its energy across all sectors based on their impact on economic growth (Kimemia & Annegarn, 2016). Since electricity power most of the industrial and commercial sectors that contribute significantly to the economy, it could be worthwhile to prioritize these industries by reducing the demand from the other sectors, such as the household, and this is achievable if the household adopts alternative energy sources such as LPG.

LPG is billed as clean cooking energy, and many countries have embarked on a drive to increase its use and reduce the dependency on solid fuels such as wood, charcoal, and paraffin (Asante et al., 2018, 2018; Chindarkar et al., 2021; Chiumia et al., 2022). LPG was also seen in the same light in South Africa, although much research to this effect was focused on the rural community (EDRC, 2003; Mohlakoana & Annecke, 2009).

Switching from electricity to LPG positively impacts the electricity network and provides an opportunity for a clean and sustainable cooking alternative. Increased usage of LPG could assist with energy challenges while reducing carbon emissions. However, its success and sustainability depend on effective policies that address the supply chain to make LPG affordable and accessible (EDRC, 2003).

To date, the government of South Africa has embarked on multiple pilot projects. Understandably, these focused on low-income households as they are likely to be affected the most by the energy crisis and the price. In one of the schemes employed by the government, the strategy consisted of distributing LPG kits comprising a stove and cylinder to the households, sometimes in exchange for the electrical stove (EDRC, 2003). This approach eliminated the cost of switching from electricity to LPG since the user's remaining task was to refill the bottle once the initial LPG was exhausted.

Furthermore, the government has implemented policies for subsidies to the free basic alternative Energy schemes like free basic electricity, in which LPG was considered for low-income households. The scheme has been effective since 2003 (Kimemia & Annegarn, 2016).

The government introduced regulations in 2010 to control the cost of LPG supplied to residential consumers so that it remained affordable for households. In doing so, the government expected an improvement in the uptake of LPG for cooking and heating, but the shortage of LPG impeded the program during winter periods (Kimemia & Annegarn, 2016). These shortages can only make it difficult for consumers to switch permanently to LPG.

Considering the recent electrical energy challenges, the government has revised its strategy and looks determined to improve the uptake of LPG in households (DMER, 2021a). These interventions will not only reduce the usage of coal, paraffin and biomass. However, they will also contribute to the reduction of the demand on the electricity grid and contribute to reducing the carbon footprint.

2.2 Liquefied Petroleum Gas

2.2.1 Production, advantages and disadvantages

Liquefied Petroleum Gas (LPG) is a by-product of crude oil extraction. Its vital ingredient includes propane and butane, of which the weighing varies depending on the use and the country's specific regulations (Finlayson-Pitts & Pitts, 2000; Nolan, 2019). It has a high calorific value and can be used for applications requiring heat, such as cooking and heating (Baumgartner et al., 2019).

LPG has a negligible environmental footprint compared to other biomass used for cooking and heating. Furthermore, there is a surplus of LPG at the global level, and some are flared or vented at production sites. Despite the availability, affordability and accessibility to LPG are cited as the barriers to its use in most low-income countries (Van Leeuwen et al., 2017).

LPG closely competes with Compressed Natural Gas (CNG) and Liquefied Natural Gas (LNG) in the gas range used for heating applications. However, LPG has advantages over CNG and LNG: it is easy to store and transport (Sinor, 1992). In cooking and heating application, LPG emits less greenhouse gas than other petroleum and biomass (Turedi & Turedi, 2021; Weyant et al., 2019). LPG's disadvantage is that it is heavier than air; when leaked, it does not evaporate as fast as the other gases. Thus it makes LPG leakage

detection difficult. For this reason, LPG is considered more hazardous than CNG and LNG, hence the safety concerns associated (Paliwal et al., 2014; Tauseef et al., 2010).

2.2.2 Factors driving the use of liquefied petroleum gas

Global outlook

According to research, most developed and developing countries, including Brazil, Russia, India, China, and South Africa (BRICS), have higher LPG usage (The Global Economy, 2021). However, for underdeveloped countries in which the population relies on biomass for cooking, researches cite the emission performance as one of the main reasons for many governments' efforts to promote the increase of LPG usage in households (Asante et al., 2018; Kimemia & Annegarn, 2016; Pantangi et al., 2011; Pope et al., 2018). Although South Africa's use of biomass is not widespread and is confined to rural areas, the overreliance on electrical energy for cooking and heating could become a concern for households when considering the ongoing crisis with the electrical energy supply. Therefore, using LPG as alternative energy cannot be considered in isolation without addressing the current electricity crisis besieging the South African economy.

Energy crisis in South Africa

Over the last two decades, the South African electricity generation capacity has significantly decreased, while new generation capacity has not been commissioned as planned. Since 2007, South Africa had experienced many instances when the electricity demand outstripped the same generation capacity (CSIR, 2021). One frequent cause in 2022 is the loss of generating units at one or more power stations (SA News, 2022). Under these conditions, an electrical load-rationing (load shedding) program is rolled out whenever the reserve margin is low for the national grid to maintain stability and avoid a blackout (Hong & Hsiao, 2021).

Although a necessary step to stabilize the electrical network, rationing of the electrical load hurts the economy. It should be avoided through various measures to ensure that electricity generation is always lower than the demand at any given time (Yeager et al., 2012). This condition can be achieved by building a new power generation plant,

implementing demand-side energy management (DSM) to reduce the load, and using alternative energy such as LPG.

The penetration of RES in South Africa has been slower than anticipated in various Integrated Resource Plans (IRP) released over the past decade by the government (DMER, 2019; Ratshomo & Nembahe, 2021). Therefore, fast-tracking them is unlikely to change South Africa's fortunes in the short term.

Bulk power generation plants (regardless of the primary energy) require significant capital and long lead time to the point that the impact cannot be immediate but only upon construction completion. In the meantime, continuous load shedding will damage the economy and could lead to major socio-economic problems. It is, therefore, essential to consider the penetration of alternative energy.

The South African population has grown less than 2% annually for the past decade. Over this period, the number of households and access to electricity has increased (STATS SA, 2019). The additional load brought by new households' connections to the grid can only contribute to the pressure on the electrical grid if there is no additional generation capacity.

Electrical energy supply disruptions affect households, students, workers, industries and all sectors of society. In the competitive global economy, disruptions to electrical supply could render the local industries less competitive in the global market. A scenario such as this could increase unemployment and create challenges for socio-economic development (Lenoke, 2017). Therefore, seeking and promoting to shift away from complete reliance on electrical energy is crucial.

The historical cost of electricity

South African electricity remains the cheapest in the BRICS block and one of the lowest in developing countries due to the over-investment in the electrical grid in the 1990s. The socio-political pressure and the need to increase access to electricity, especially in rural areas, are cited as the main reason for the everyday use of LPG in South Africa (Bohlmann & Inglesi-Lotz, n.d.). However, the cost of electrical energy has increased

steadily for the last decade, during which domestic consumer tariff increases second only to agricultural consumers (Eskom, 2022).

The analysis of historical data obtained from the public domain (Eskom, 2022) shows that the cost of electricity has been, in most cases, higher than year-on-year inflation from 2004 to 2021, as presented in Figure 1. Over this period, the cumulative electricity increase was 211% against 90% for the Consumer Price Index (CPI), highlighted by a maximum 31% hike in 2010 against 7.1% CPI. The calculated average electrical energy price increase was 12% against a 5% average CPI per annum over the same period.

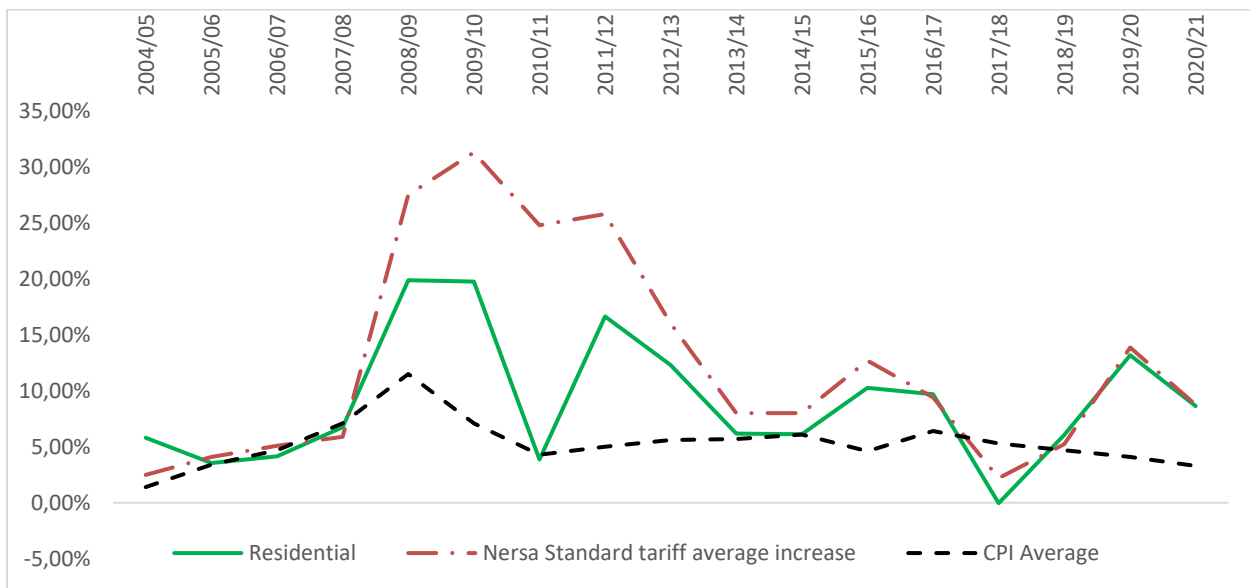


Figure 1: Ten-years electricity price Increase¹

Considering the massive debts, ageing power stations, and lack of sufficient capacity, it is likely that Eskom will continue to apply for more tariff increases for electricity consumption, such as the most recent 20% hike for 2023, followed by 13% in 2024 as approved by National Energy Regulator of South Africa (NERSA, 2022). Eskom has argued that these increases are necessary to ensure that it can meet its debt obligations and attract more capital needed to fund its electricity generation expansion programs. If Eskom secures funding for new generation plants, economics dictate that consumers will bear the cost through tariff increases, as has been the case for the past decade. Its

¹ Source: (Eskom, 2022), STATSA and own calculations

massive debt implies that a tariff increase is inevitable and will lead only to higher electrical energy costs for the household, hence the need to look for alternative energy such as LPG.

2.2.3 LPG in South Africa

Production

South Africa has six petrol refineries, but only five produce LPG, accounting for 80% of the consumption in South Africa, while the remaining is imported (Ratshomo & Nembahe, 2022; SAPIA, 2014). These refineries give South Africa a unique position compared to most of its African peers due to the local experience. It makes it possible for South Africa to ramp up the production of LPG because of the experience, the legal framework and the infrastructure that makes production and distribution a lot easier.

Despite South Africa's competitive advantage that it has refineries, a report commissioned by the competition commission of South Africa in 2014 observed that LPG production in South Africa is declining, and imports fill the gap. The decline in LPG production is driven first by the stringent government LPG price regulations and second by opportunities offered by other products that use the same petroleum ingredients (Mncube et al., 2017). Furthermore, the closing of Engen Refinery (ENREF) following an explosion in 2020 and the inefficiency and high cost of running the existing but aged refineries exasperate the availability of LPG on the local market.

Industry experts believe that the issue of LPG shortage can be solved if the government intervene in various policies and leverages the existing infrastructure to encourage import while protecting the local industry. To this effect, Engen has announced the creation of a terminal for imported refined products. At the same time, the South African government is pursuing the development of a new refinery financed by Saudi Arabia (Fitch Solutions, 2022).

On the regulatory side, the government of South Africa has recognised the role that LPG can play in the economy, particularly on the demand side management, to reduce the pressure on the electricity demand and delay investment in new power plants. It has since been the developed option for LPG market expansion, with various interventions to

address the market structure, infrastructure, pricing framework, cylinder network, negative perception, compliance, monitoring and enforcement (DMER, 2021a, 2021b).

The historical cost of LPG

To get a perspective on the prices of LPG, historical costs of LPG are analysed in Figure 2 from data available from the public domain. The analysis shows that the price of LPG remained mostly below inflation between 2013 and 2021. The LPG price increased by 3% yearly, while the average inflation over the same period was 5% (SAPIA, 2022; STATS SA, 2019). The average yearly price increase was less than the inflation for most years. Records also show a price decrease in 2015/16, indicating that the price change can increase or decrease. In contrast to this trend, the price of electricity is less likely to decrease given the current context.

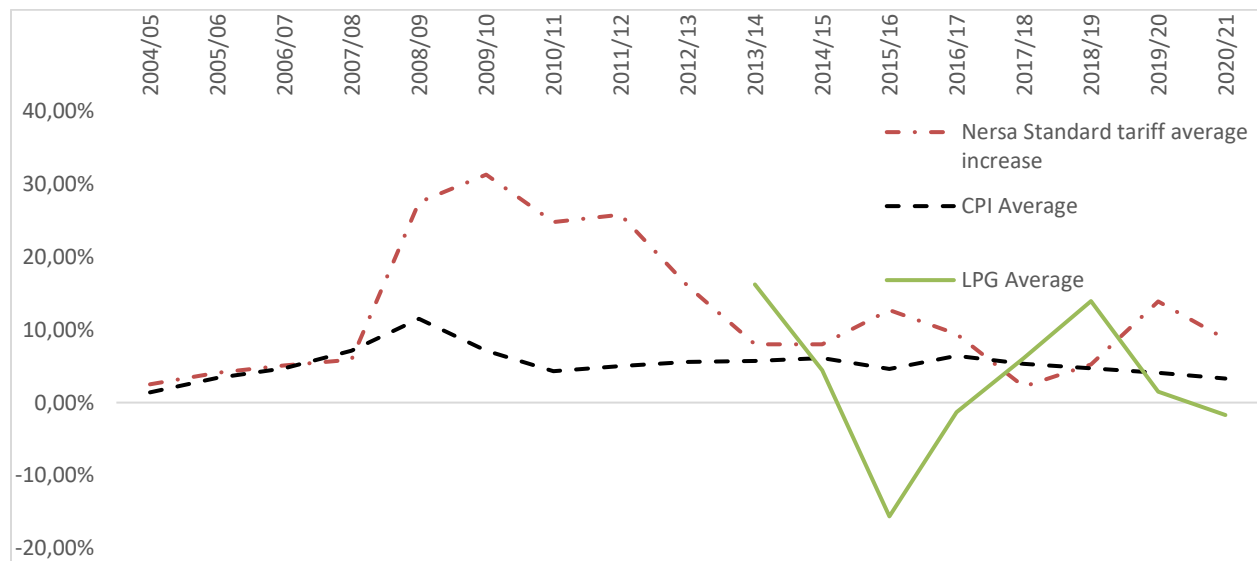


Figure 2: Electricity vs LPG - comparison of price increase²

Historic LPG price changes in Figure 2 do not follow a specific pattern. However, history shows that some world events have affected the cost of crude oil in recent years. Since LPG is a by-product derived from crude petroleum extraction and South Africa is a net importer, LPG is equally sensitive to world shock on petrol prices (Huntington, 2018).

² Source: (Eskom, 2022), (SAPIA, 2022) and own work

Since South Africa imports most crude oil (Ratshomo & Nembahe, 2021), LPG prices are sensitive to global markets and events.

In South Africa, one advantage of using LPG is the price regulation by the government. However, the price sensitivity is still more than electricity, for which the price cannot change on the spot but instead follows a rigorous process and is fixed for one or more years.

2.2.4 Alternative energy source

As the electricity cost keeps increasing, it will likely become unaffordable for many households at some stage. Combining this scenario with frequent interruptions of the electrical supply could provide a strong motivation for more households to switch from using electrical energy to LPG.

Replacing electrical energy with gas for cooking and heating by households could reduce the pressure on the demand for electrical energy and contribute to reducing greenhouse emissions by displacing the demand from coal power stations.

2.3 Empirical research on LPG in South Africa

2.3.1 Country outlook

Currently, all gases combined represent less than 3% of the energy mix in South Africa (Ratshomo & Nembahe, 2021). Currently, the choice of LPG is mainly individual (Coetzee, 2021), but plans at the government level are conveyed in the country's integrated resource planning, the gas master plan. The LPG rollout strategy paper indicates that the LPG share of the energy mix will increase according to (DMER, 2019, 2021a, 2021b).

In comparison to its BRICS³ peers, South Africa consumes 2.6% of gas energy per capita compared to 10% for Brazil, 6.7% for India and 8.2% for China but globally, this figure stands at less than 25% with the United States of America and European countries that lead the charts (Ritchie et al., 2020). The integrated resource plan (IRP) of 2019 shows

³ At the time of this writing, the data for Russia was not available.

that South Africa intends to use gas as alternative energy by increasing its usage to 15.7% of the energy mix by 2030. Amongst these gases features LPG, which the government mainly promotes for households (DMER, 2019).

In its rollout strategy for LPG, the government acknowledged that the increase in its use is possible only if it overcomes the challenges related to the market structure, infrastructure, price structures, cylinder management, negative perception, and compliance enforcement. For this reason, the government must review and update most of its policies if LPG must play a crucial role in resolving the energy crisis (DMER, 2021a).

From the challenges acknowledged by the government, it is evident that the success of its promotion of the use of LPG depends on factors such as price, incentives, perception of safety and availability, as experienced by the end user. Available literature has analysed the determinants of LPG use (Pope et al., 2018), challenges, and opportunities (Matthews, 2014). Other researchers explored scaling up LPG usage by improving awareness and the infrastructure (Asante et al., 2018), but none addressed the main drivers for the urban population.

2.3.2 Prior research into the use of LPG

Previous research aimed at finding the social determinants of energy observed multiple fuel use, monitored fuel substitution, analysed the decision-making process and investigated the fuel and appliance–user interaction used in low-income households in the Western Cape. The research found that accessibility, affordability and perceived safety were the significant determinants of household energy use (Mehlwana & Qase, 1996).

The Energy and Development Research Centre at the University of Cape Town evaluated the potential increase in the use of LPG for cooking among rural households because of poor safety related to the use of wood and paraffin. They focused on the supply, distribution, and pricing in remote rural areas and found that increased use of LPG could displace other forms of energy. However, they also found that the LPG roll out success was impeded by the electrification rollout that made cooking from electricity cheaper than LPG and also due to poor accessibility (EDRC, 2003).

Mohlakoana and Annecke conducted a longitudinal study in Khayelitsha informal settlement to analyse the impact of the LPG exchange program on low-income households. They found that rolling out LPG to low-income households in Cape Town lowered the electricity demand at peak times, as most respondents indicated that they cook in the late evening. Furthermore, the majority of the respondent that participated in the program remain long-term users of LPG (Mohlakoana & Annecke, 2009).

A study on the LPG intervention in households in Atteridgeville township near Pretoria interviewed 200 households to assess the long-term success of the government's pilot LPG project. They found that 70% of those that switched from electricity to LPG continued to use it and reported that its usage had improved their welfare. However, they observed that the permanent use of LPG could have been higher if there was no provision for Free Basic Electricity (FBE) subsidy (Kimemia & Annegarn, 2016).

Research on the supply of clean energy services to the urban and peri-urban poor acknowledged the benefits of national electrification but once again found that poor households could not afford electricity and LPG because of higher prices than paraffin. In particular, LPG inaccessibility is because of the poor network, the distance to distribution outlets and the high cost of appliances (Visagie, 2008).

The above pilot project provides sufficient evidence that the use of LPG can reduce the demand for electricity on the network. However, most of the studies and pilot projects carried out focusses on low-income and rural areas of South Africa and found affordability and accessibility to be the main barrier to accessing LPG. They also found that free basic electricity granted by the government to poor households worked against the adoption of LPG in households. However, these studies occurred when South Africa had sufficient generation capacity to meet the demand. Thus, urban households with higher affordability and accessibility had no incentive to switch to LPG since they most likely have access to electricity at a low cost compared to LPG. Furthermore, it does not consider or determine the drivers of the use of LPG, let alone for urban consumers. In this context, the present research seeks to determine the factors affecting urban households' use of LPG for cooking and heating.

On the back of recurring load shedding since 2007, the South African government realized that electricity is becoming a challenge. They have made various interventions to increase the usage of LPG among households. These interventions include the LPG price regulation and the recently published draft regulation on the LPG rollout strategy (DMER, 2021a). If well managed, it is possible to roll out LPG to urban areas with a significant middle-income population consuming more electricity while having the infrastructure that can deliver LPG.

Knowing the drivers of LPG use is essential for programs encouraging more households to switch from electricity to LPG. In this context, this research uses the theory of planned behaviour to find the determinant of the use of LPG, as discussed in the following section.

2.4 Theory

2.4.1 Planned Behaviour

The theory of planned behaviour extends the theory of reasoned action based on the premise that attitude and subjective norms influence intention. It posits that attitude and subjective norms are the key components that predict an individual's intention and behaviour. The theory of planned behaviour extends the theory of reasoned action by adding Perceived Behavioural Control as the third component that influences both the intention and the actual behavioural. Both theories imply that the main predictor of an individual's to perform a behaviour is their intention to perform that behaviour. Therefore, an individual's intention becomes a precursor to their behaviour (Ajzen et al., 2009, 2014).

The theory of planned behaviour has three constructs. Attitude evaluates a particular behaviour as favourable or unfavourable (Ajzen, 1985). Belief and evaluation determine the attitude, the motivational factor influencing behaviour (Ajzen, 1991). It is, therefore, internal to the individual.

Subjective norms are related to the acceptance of the individual in social circles. They are also described as "social pressure to perform or not to perform a given behaviour" and are a combination of normative belief and motivation to comply (Asare, 2015). Normative beliefs emanate from external pressure to comply or not comply with a particular behaviour.

Subjective norms are actions an individual takes to fit in with the society around them. It results from pressures from immediate social networks such as friends, family, and peers, and their total sum shapes the subject's norms. Therefore, subjective norms are external influences on the individual's intention to behave in a particular manner.

Perceived behavioural control relates to the individual's perception or belief of "the ease or difficulty of performing the behaviour of interest". It indicates a high propensity to behave when the subjects perceive the act as more manageable (Barbera & Ajzen, 2020). Control beliefs shape perceived control behaviour. The ease of performing a behaviour could depend on other factors such as infrastructure, affordability, government incentives, supply chain and even payment systems that all facilitate the ease of assembling the necessary conditions to make it easy for the individual to perform a given behaviour (Bosnjak et al., 2020).

The literature reveals extensive use of the theory of planned behaviour in applications related to renewable energy sources. For instance, to link environmental concerns, knowledge, and beliefs about salient consequences of using renewable energy to predict the consumer willingness to pay a premium for renewable energy (Bang et al., 2000).

The theory of planned behaviour was applied in Iran and used to find that "moral norms, attitudes and perceived behavioural control" were, more significantly, the main factors that influenced the willingness to use and the public acceptance of renewable energy. In contrast, subjective norms played no role (Yazdanpanah & Forouzani, 2015).

Further use of the theory of planned behaviour includes investigating factors that influence consumers' willingness to pay for renewable energy in Pakistan and found a moderate relationship between the attitude, subjective norms and behavioural control and the willingness to pay for renewable energy. However, the research also found that the belief about renewable energy costs reduced the willingness to pay and that environmental concerns had no significant effect (Irfan et al., 2020).

Research in Lithuania used the theory of planned behaviour and found that subjective norms positively influenced the intention to use renewable energy while the attitude had little effect (Liobikienė et al., 2021).

Elahi extended the use of the theory of planned behaviour beyond the willingness to pay for renewable energy to investigate farmers' willingness to install renewable energy technology. The study found that the perception of the high cost of photovoltaic systems price reduced the farmers' intention to adopt solar technology. However, farmers were willing to pay for green energy (Elahi et al., 2022).

In South Africa, there is no evidence of a study on the intention to use LPG based on the theory of planned behaviour. Given that the intention to use LPG as an alternative energy source to electricity for cooking and heating applications is crucial for its adoption and increased usage. Therefore, the present research applies the theory of planned behaviour to determine the consumer's drivers for using LPG.

2.5 Hypotheses Development

Most LPG researches in South Africa were quantitative and focused mainly on the opportunities and challenges of using LPG for low-income households or rural communities (EDRC, 2003; Kimemia & Annegarn, 2016) but the research that investigated the user intention or willingness to pay or use a particular energy type focus mainly on the renewable energy. Furthermore, they applied to countries other than South Africa (Irfan et al., 2020; Oerlemans et al., 2016; Wojuola & Alant, 2017). Some of these researches used planned behaviour (Bosnjak et al., 2020; Liobikienė et al., 2021; Yazdanpanah & Forouzani, 2015).

The model given in Figure 3 provides the application of the theory of planned behaviour in the context of this research. According to the theory, its primary constructs remain attitude, subjective norms and perceived behavioural control that determine the intention that leads to the actual behaviour.

In the context of South Africa and amid the energy crisis, the theory of planned behaviour uses the three constructs to predict the intention and, ultimately, the use of LPG.

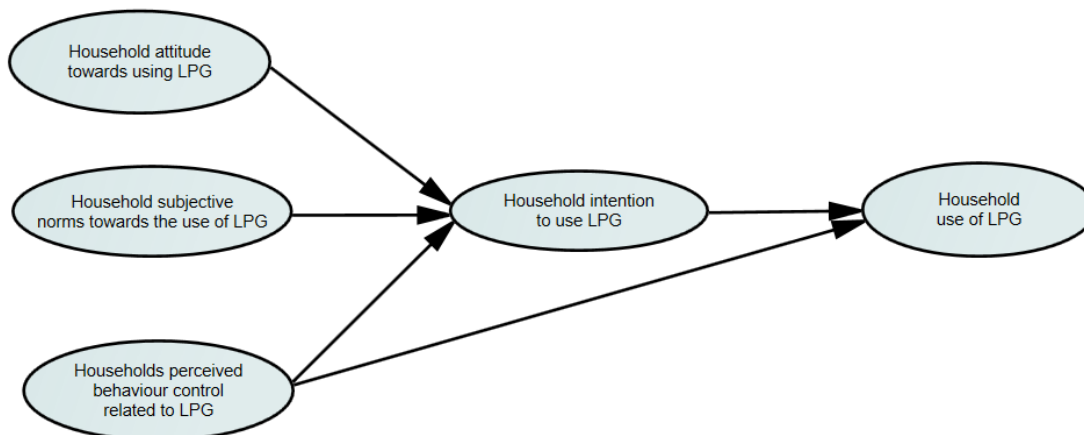


Figure 3: Proposed model for the usage (adapted from the theory of planned behaviour)

2.5.1 Attitude

Research shows that attitude is the motivational factor influencing behaviour (Ajzen, 1991). Furthermore, behavioural beliefs shape attitude; attitude becomes an internal force or influence (Bosnjak et al., 2020). Research shows that factors that can influence the attitude concerning the use of energy include environmental concerns (Irfan et al., 2020; Liobikienė et al., 2021), safety concerns about the use of LPG (Ozoh et al., 2018; Paliwal et al., 2014) and the belief about the cost and benefits of LPG as a source of energy (Ozoh et al., 2018).

The concern about the environment contributes towards the attitude since it encourages the subject toward behaviours that preserve the environment (Van Leeuwen et al., 2017). Conversely, safety concerns, along with the high cost of LPG, contribute negatively to the attitude towards the use of LPG. The concern about the explosive nature of LPG creates a negative perception and a poor attitude among potential users (DMER, 2021a; Ozoh et al., 2018; Paliwal et al., 2014).

Previous research reported that the low cost of electricity is one of the factors slowing down the adoption of LPG in households. Therefore, the cost can somewhat influence the attitude towards using LPG or electricity (Kimemia & Annegarn, 2016).

The relationship between attitude and intention was found to be positive in energy research (Halder et al., 2016; Irfan et al., 2020), environmental studies (Budovska et

al., 2020) and even in health science (Asare, 2015). These findings lead to the hypothesis that attitude positively correlates to the usage of LPG.

2.5.2 Subjective Norms

Subjective norms originate from external pressure, for example, from peers and family. To this effect, the model considers normative beliefs from family, friends and colleagues. It assesses the likelihood for an individual to have an intention that could lead to the use of LPG if the peers and family are engaging in the same behaviour.

Social circles represent one of the most important fabrics of societies. Therefore a human can copy other humans or behave in a particular way to fit in or by conviction because of the peers' behaviour. Subjective norms had a positive relationship with intention in pro-environmental studies (Budovska et al., 2020), in research for the use of bioenergy (Halder et al., 2016), and the research into the willingness to pay for renewable energy (Irfan et al., 2020). For this reason, it is hypothesised that society, family, colleagues and friends can influence the user to use LPG by driving his intention through social pressure.

2.5.3 Perceived Behaviour Control

Control behaviour is associated with the easiness of performing specific actions that could define a given outcome. The beliefs shape the perceived behavioural control. According to the expended theory of planned behaviour (Bosnjak et al., 2020), perceived behavioural control can moderate the impact of attitude and subjective norms. It could amplify or attenuate the overall behaviour.

Concerning LPG, previous studies have considered knowledge, ability, resources, control, distribution network development, and government interventions as factors affecting perceived behavioural control (Maes & Verbist, 2012; Tei Mensah, 2014). Similarly, perceived behavioural control can play a significant role in the household intention or use of LPG.

2.5.4 Intention

The intention to use LPG is a precursor to the actual usage that defines the behaviour. Research in energy saving (Canova & Manganelli, 2020), health science (Asare, 2015) and the hospitality industry (Budovska et al., 2020), to mention a few, have all

demonstrated a positive relationship between intention and actual behaviour. Based on this theory, it is hypothesised that the intention to use LPG will have a positive relationship with the actual usage.

2.5.5 Research hypothesis

Based on the theory and previous research on the use of LPG, the following are the research hypothesis:

- **H1:** Attitude is positively related to the intention to use LPG.
- **H2:** Norms are positively associated with the intention to use LPG.
- **H3:** Behavioural control is positively linked to the intention to use LPG.
- **H4:** Intention is positively related to the use of LPG.
- **H5:** Behavioural control is positively related to the use of LPG.

2.6 Conclusion

The electrical energy crisis in South Africa requires relooking at the energy sector by compensating for the deficit with other forms of energy. LPG is a popular alternative energy cleaner than other petroleum products for household cooking and heating. Whereas electricity cost has increased mainly above the inflation levels, LPG cost increases have remained below inflation.

Increased use of LPG could reduce the pressure on the electrical network and reduce the magnitude and frequency of load shedding on businesses and industries. By reducing the pressure on the electrical network, LPG will contribute to the socioeconomic growth of South Africa while also reducing the emission of gas because of high electricity generation to satisfy the demand.

Increasing the usage of LPG is possible only if the end consumer intends to use it and is willing to switch (and pay) for it. Therefore, the extensive adoption of LPG depends much on household intention to switch and the actual use. Finding the determinant through the prediction of intention and the eventual use becomes vital in determining the course of actions and interventions from the policymakers to reduce the pressure on the electrical network in the short and medium term.

3 RESEARCH METHODOLOGY

3.1 Introduction

The section provides the methodology for researching the determinants of the use of LPG in South African households amid the ongoing electrical energy supply disruptions. It provides plans and procedures used in this research. It includes broad assumptions and covers data collection methods, analysis, and results interpretation. In line with guidelines, this section provides a framework that facilitates the selection of subjects, sites and data collection procedures necessary for answering the research questions (Bordens & Abbott, 2018).

3.2 Research approach and design

A research approach depends on resolving the problem, but the most common are quantitative, qualitative and mixed analysis. These approaches are not necessarily opposite or completely standalone, but often research tends to use one more than the others (J. W. Creswell & David Creswell, 2018).

The quantitative method relies on one or more variables and uses numbers and statistics to derive its findings. Therefore, it relies on mathematics and statistical analysis to examine the subject. Its form of expression is primarily numbers, graphs and tables, and in most cases, it requires a large data sample. Furthermore, quantitative analysis often uses closed or multiple-choice questions, while its primary data collection method is measurement aimed at maintaining objectivity and replicability (J. W. Creswell & David Creswell, 2018).

Qualitative research generates ideas to develop a theory or hypothesis, whereas analysis focuses on summaries, classifications, and data analysis. It aims to explain and provide answers to theories to draw a conclusion based on findings (J. Creswell & Poth, 2018).

The mixed research method combines quantitative and qualitative methods. For instance, one of its applications is using qualitative methods to explain quantitative findings. Inversely, the quantitative method allows for generalising the qualitative findings to a larger population (J. W. Creswell & David Creswell, 2018).

Although there are many research design types, the most common generic designs currently used are cross-sectional and longitudinal (Creswell & David Creswell, 2018). In cross-sectional research, data is collected from different observations simultaneously but does not necessarily use control variables. In contrast, longitudinal research studies observe the same variables consistently over a defined period (Bordens & Abbott, 2018). Research based on the theory of planned behaviour has been carried out to predict human behaviour related to renewable energy (Irfan et al., 2020; Liobikienė et al., 2021), health (Asare, 2015) and environment (Hartmann & Apaolaza-Ibáñez, 2012). In each case, there is evidence of the successful use of the quantitative research approach applied to cross-sectional data.

The theory of planned behaviour was assessed using a quantitative analysis approach applied to cross-sectional data to determine the influence of consumers' intention factors on willingness to pay for renewable energy. The research relied on multiple variables and constructs based on Likert scale measurement, and the measurements for each observation were taken simultaneously and not repeated. The analysis relied on statistics, including structural equation modelling, to evaluate the relationship between multiple constructs.

Considering that this research objective is to identify the determinants of using LPG, the study involves multiple variables and observations but does not investigate how these observations change with time. It is confirmatory and seeks to deduce relationships between latent variables. For this reason, the methodology adopted for this research uses a quantitative method and cross-sectional research design.

3.3 Research data types and collection methods

3.3.1 Data types

The research first collects the demographic data to be used in descriptive statistics to understand the sample population that has taken the interview. Secondly, this research objective requires a quantitative analysis approach and the time constraints limit it to a cross-sectional research design. Therefore, the schedule of measurements requires results that are as close as possible to numerical values to allow the use of quantitative

analysis on the primary constructs data. For this reason, the remaining questions follow a Likert scale response model to provide ordinal meaning for quantitative analysis.

The choice of ordinal data is also justified by similar research that used the theory of planned behaviour and relied on interviews based on fully structured questions to measure the variables for each observation using a five-point Likert scale (Irfan et al., 2020; Liobikienė et al., 2021). Using a similar approach, the survey instrument for this research uses five-point Likert scale questionnaires adapted from similar studies.

3.3.2 Data collection and storage

Data collection instruments used for measurement can be face-to-face or telephone interviews, online or email questionnaires or a mix of one or more. The ultimate collection depends on the nature of the research and the available resources for data collection. This research used the online Qualtrics tool to capture the questionnaires, distribute the link and collect answers for further analysis. Hence, the data used in the research is from a primary source.

Qualtrics and Google Form survey tools are available to its Business School students, but the former has better resources and rendering, hence the choice for running the survey from Qualtrics.

Qualtrics cloud server provided password-protected partitions for each respondent to store the information collected without the possibility of the respondent seeing the answers from others. Similarly, a password-protected laptop provided a repository for all copies of the survey.

3.4 Target population

Residents of South Africa experience frequent power interruptions due to rationing by the power utility company. They are equally affected financially and inconvenienced by the discomfort of having the primary energy source interrupted. For this reason, they form the target population for this research.

This research intends to find the determinants of using LPG for cooking and heating in South Africa. It, therefore, addresses the broader South African society, hence, anyone that makes household decisions. Hence, the participants are the working population

based on a random sample, and their choice remains on the premise that each makes energy-related decisions to some extent. Therefore, the survey questionnaire expected respondents of all ages, gender and socioeconomic backgrounds.

The population sampling for this research consisted of a random sample wherein every subject had an equal probability of being selected to respond to the questionnaire.

Similar studies on the factors influencing the adoption of photovoltaic systems in the rural areas of Poland used a sample of 521 (Angowski et al., 2021). An investigation into energy-saving behaviour in the workplace using the theory of planned behaviour used a sample of 295 participants (Canova & Manganelli, 2020), while a study to determine the renewable energy usage intention using the theory of planned behaviour based on 1005 observations (Liobikienė et al., 2021). Finally, the factors influencing the user's willingness to pay for renewable energy were determined using the theory of planned behaviour applied to 349 samples (Irfan et al., 2020). From these researches, the sample population has varied between 295 and 1005.

Penman suggests quantitative studies have more observations than variables and that analysis based on regression should have a sample size greater than forty observations. As a guideline, he proposed that every variable should have at least five observations (Penman, 2021). Applying this technique to the forty-four variables used in the questionnaires implies at least 220 observations.

Other ways of determining the sampling size require a priori significance, effect size and significant levels. Since data accuracy is critical for research, it should provide confidence and remain as close to reality as possible to resolve the research problem. A priori significance power of .8 or an effect size of .2 at a significance level of .05 or 95% confidence level requires at least 300 observations.

Generally, quantitative research methods require many observations of samples to get the best significance while reducing the sampling error, such as generalising the results to a larger population as accurately as possible (J. W. Creswell & David Creswell, 2018). Based on similar researches' sample discussed and the calculation based on a priori significance power and the effect size, a sample size of 300 respondents was considered adequate for this research.

3.5 Ethical considerations for collected data

Ethics in research consists in promoting the aim of the research to seek knowledge and truth while avoiding errors. Ethics promotes trust, accountability, mutual respect, and fairness while ensuring that researchers are accountable. These values build public support for the research and guarantee social values, human rights, animal welfare, public health, and safety (David B. & Resnik J.D., 2020).

To comply with ethics requirements, the first page of the questionnaire carried a consent form that constitutes a written commitment that the research data will be used only for the research as intended. Furthermore, the consent provided the author's undertaking that the collected data use is strictly for academic research.

Further steps taken to protect the identity of each respondent included the non-activation of the option that records each respondent's personal information, such as location. To this effect and in line with the POPIA Act, no identification data (name, email address, telephone number, social media handles, identity, or passport number) was requested or collected from the respondents. Finally, an ethics application was successfully lodged with Wits Business School's ethics clearance committee to ensure that the university's code of ethics bound the research.

3.6 The research model

The research methodology uses a deductive or waterfall approach using the Theory of Planned Behaviour. The theory explains the three primary constructs of human behaviour: attitude, subjective norms and perceived behavioural control. Applying the theory of planned behaviour to the use of LPG hypothesises that attitude has a positive relationship with LPG usage, norms are positively associated with the use of LPG, and behavioural control has a positive association with the use of LPG, all through the intention except for the control behaviour. A unique path consists of the positive relationship between behavioural control and usage.

The structural model of Figure 3 encapsulates these hypotheses, where the theory posits that the causes of a positive intention are the combined effect of attitude, subjective norms and perceived behavioural control. The model further implies unidirectional causality

between the constructs. Hence, the following equations, in which the left side represents the dependent variable and the right side represents the sum of the weighted dependent variable, represent the econometric model in which α values are the factor loadings between the exogenous variables (ATT, SBN and PBC) and the endogenous variable (INT). Similarly, β values are the factor loadings between the exogenous variable (PBC), endogenous variable (INT) and the last endogenous variable (USE).

$$INT = \alpha_0 + \alpha_1ATT + \alpha_2SBN + \alpha_3PBC + \varepsilon \dots \dots \dots \text{Equation 1}$$

$$USE = \beta_0 + \beta_1INT + \beta_2PBC + \varepsilon \dots \dots \dots \text{Equation 2}$$

The first equation posits some constant intention (α_0) towards using LPG, but it is further complemented by attitude, subjective norms and perceived behavioural control. Similarly, the second equation implies a constant level of LPG use (β_0) that is complemented by the perceived behavioural control and the attitude.

In both equations, the effect of the other unexplained variance is captured by the error (ε). Lastly, the variable intention (INT) is the common factor in both equations. Thus, it is a mediation factor between the independent variables and highlights their indirect effects on the use of LPG.

3.7 Data processing

The procedure adopted for data analysis is adapted from similar research (Irfan et al., 2020), (Batley et al., 2000; Oerlemans et al., 2016) and leading practices in the following steps (Hair et al., 2019; Raykov & Marcoulides, 2012; Thakkar, 2020):

- Data cleaning.
- The second step is concerned with sample adequacy and data reliability testing.
- Descriptive statistics.
- Multivariate analysis and deductions.

3.7.1 Data cleaning and coding

The first data assessment consists of analysing the data to identify incomplete surveys, erroneous data and outliers. The assessment consists of replacing the missing data and outliers with average values in case the sample size of the respondent is small. In the

case of an extensive sample returned from the survey, the data cleaning process will dismiss all incomplete and outliers from the final data set. Replacing missing values will not exceed 5% of the data collected for reliability reasons.

Information coding is the next step following data cleaning for errors, missing values and outliers. Coding is necessary to ensure the data's usability in subsequent analysis. For instance, the categorical data recorded in the demographic information are helpful variables for moderation, mediation or control of relationships within the analysis. For instance, they provide information on gender, education and other variables that make group analysis possible.

Table 1: Coding for categorical variable's data

AGE_GROUP	CODE	PROVINCE	CODE	GENDER	CODE
18-24	1	Free state	1	Male	0
25-34	2	Gauteng	2	Female	1
35-44	3	Kwazulu Natal	3	Other	2
45-59	4	Mpumalanga	4		
60 or older	5	North-West	5		
Under 18	6	Western Cape	6		
		Limpopo	7		
		Northern Cape	8		
		Eastern Cape	9		
EDUCATION	CODE	LPG_USER	CODE	AREA_TYPE	CODE
Post-Matric certificate	0	No	0	Other	3
Secondary School	1	Yes	1	Suburbs	1
University Degree	2			Township	0
Others	3				

Information coding applies to categorical variables used mainly to acquire demographic data. Table 1 provides information on the applicable codes for each categorical variable used in the research.

3.7.2 Descriptive statistics

Decisions, behaviours and attitudes are likely to differ across demographics. This research will use descriptive statistics to understand the respondents' characteristics and determine the data centrality and the spread of the information collected.

3.7.3 Multivariate analysis

Although the correlation provides information on the relationship between constructs, it does not provide the causality relationship between them. Causality analysis is achievable using regression analysis to explain or predict a dependency of one variable on one or more independent variables (Thakkar, 2020).

Modern techniques provide various multivariate methods that analyse causality relationship problems. Selecting a multivariate technique requires understanding the relationship between the variables under examination and consideration for the measurement scale of the dependent variable and that of the predictor (independent) variable (Hair et al., 2019).

The present research aims to find the determinant of the use of LPG based on the theory of planned behaviour implies analysing the causality between constructs. However, the constructs in this research are all latent variables and, therefore, are not directly measurable. Instead, they are measured indirectly via manifest variables (Hair et al., 2021).

The manifest variables are the responses collected from the questionnaires designed for each construct. Using more items per construct reduces the measurement error and increases the reliability, but too many can lead to collinearity issues (Hair et al., 2021).

From the model in Figure 4, the strength of the measurement model comprises attitude, norms and behavioural control). Furthermore, the structural model comprising the intention and use requires multiple regressions to determine the causality. However, their relationship comprises multiple inputs – multiple outputs.

Determining the causality between the dependent and independent variables requires applying multivariate analysis techniques. These include but are not limited to regression, discriminant and structural equation modelling (SEM). However, the application of these analysis techniques varies; therefore, the suitability must be adapted accordingly (Denis, 2020; Loehlin & Beaujean, 2017).

Although determining the causality relationship between one or more dependent variables and a single independent variable requires multiple regressions, their use in determining

the outcome in multiple dependent and multiple independent variables is limited due to the cumulative error introduced by partial analysis. Furthermore, multiple regression analysis is unsuitable for relationships involving latent variables, and this function is better suited to structural equation modelling techniques (Hair et al., 2019).

On the backdrop of the data type and the theory hypothesised herein, the relationship between the multiple dependent and multiple independent variables, the potential moderation effect and the use of latent variables, there is a potential for multiple relationships between variables. Given the number of variables, constructs, and the complex nature involving moderation of the intention and use of LPG constructs, structural equation modelling (SEM) fits well as the most suitable multivariate technique to apply for the research herein.

A structural equation model (SEM) combines measurement and a structural model. The former provides a means to measure the latent variable through the indicators, while the last specify relations among latent (Şimşek & Noyan, 2012). SEM is emerging as the most robust analysis technique because of its ability to perform the analysis simultaneously. Unlike other techniques, it has since developed into many variants to meet various needs and applications across multiple disciplines (Fan et al., 2016).

SEM can analyse the simultaneous relationship between constructs indirectly measured by manifest variables. Therefore, the model incorporates latent and observed variables (Thakkar, 2020). Some analysis results are sensitive to the direction of causality between the latent and the indicators, hence the concept of reflective and formative constructs. A reflective construct denotes the causality relationship from the construct to the indicator. Similarly, a formative construct implies causality from the measured variable to the construct (Wong, 2013). The type of constructs and the underlying data are necessary to determine the most appropriate choice of SEM variant for the analysis.

SEM has two broad types to solve the multiple regression equations: covariance-based and partial least square. Covariance-based structural equation modelling (CB-SEM) has been used for several decades in social science and is still the preferred method. It helps confirm or reject theories by testing hypotheses. However, it is suitable when the

population sample is large, the data exhibits normal distribution, and the model specification correctly links the variables (Becker et al., 2013; Hair et al., 2011).

In contrast to CB-SEM, partial least square structural equation modelling (PLS-SEM) does not have restrictions on the data distribution. It is, therefore, practical when the sample size is small, applications have little available theory, predictive accuracy is paramount and correct model specification is uninsured” (Wong, 2013).

The research herein is concerned with applying a theoretical framework from the theory of planned behaviour from a prediction perspective. It has five constructs, but the endogenous constructs that form the central part of the theory are all reflective. On this basis of a model of mixed formative and reflective construct, Partial Least Square SEM is advised (Dash & Paul, 2021; Hair et al., 2019). Furthermore, the choice of PLS-SEM for this research results from the fact that this research is exploratory, with the potential to extend the existing theory and identify drivers. (Hair et al., 2011)

SEM involves complex mathematics (Loehlin & Beaujean, 2017; Raykov & Marcoulides, 2012), but no software provides all variants in a single package. SPSS AMOS is oriented toward reflective construct and therefore uses covariance-based SEM. In contrast, the SmartPLS design is to analyse reflective and formative construct-based SEM using the Partial Least Square method (Dash & Paul, 2021).

This research's underlying SEM model relies on hypotheses using reflective constructs. Furthermore, the sample size is smaller than 200 due to time constraints and a limited audience. For this reason, Smart-PLS was the most suitable software for the analysis due to the advantages of its partial least square algorithm.

3.8 Analysis using PLS-SEM

Following a successful cleaning of raw data, the structural equation modelling requires validation along with the structural models. The validation includes a quality check consisting of reliability and validity checks followed by the model fit.

As the primary literature indicates, SEM combines measurement and structural models. For this reason, SEM evaluation requires evaluating both models. The measurement model may comprise formative or reflective, or both construct groups. Therefore, the

analysis applied to each model is not necessarily the same but follows the construct's model type. The model used for this research is derived from the theory encapsulated in Figure 3 and expanded for measurement and analysis as presented in Figure 4. Since all the constructs are reflective, the discussions on the model evaluations do not consider steps that apply to formative constructs.

3.8.1 Measurement model's evaluation

The research model's measurement constructs for attitude, norms and control behaviour are reflective. Therefore only reflective measurement assessment applies in the following sections.

Factor analysis

Indicators are essential to the SEM, allowing for measuring latent constructs. Evaluating indicators provide a means of assessing how well they represent or explain their parent constructs.

A reflective measure's indicator reliability uses bivariate correlation with its parent construct. Indicator loading of more than 0.708 is considered acceptable, those below should be treated based on the research context, but generally, it is advisable to remove values that are less than 0.4 (Hair et al., 2021).

Internal consistency reliability

Internal consistency reliability consists of assessing the fitness of multi-item variables to form a single construct using Cronbach's alpha method for each group of an item forming a construct. Although the interpretation of Cronbach alpha reliability results is research-dependent, many researchers advise that values between 0.5 and 0.7 are acceptable, while those greater than 0.70 are considered excellent (Hair et al., 2019).

An alternative measure of consistency reliabilities is ρ_c (Rho_c) is the composite reliability that provides values higher than the traditional Cronbach's alpha. This indicator is considered liberal; therefore, the reliability lies between the two values and is referred to as ρ_A (Rho_a) (Hair et al., 2021).

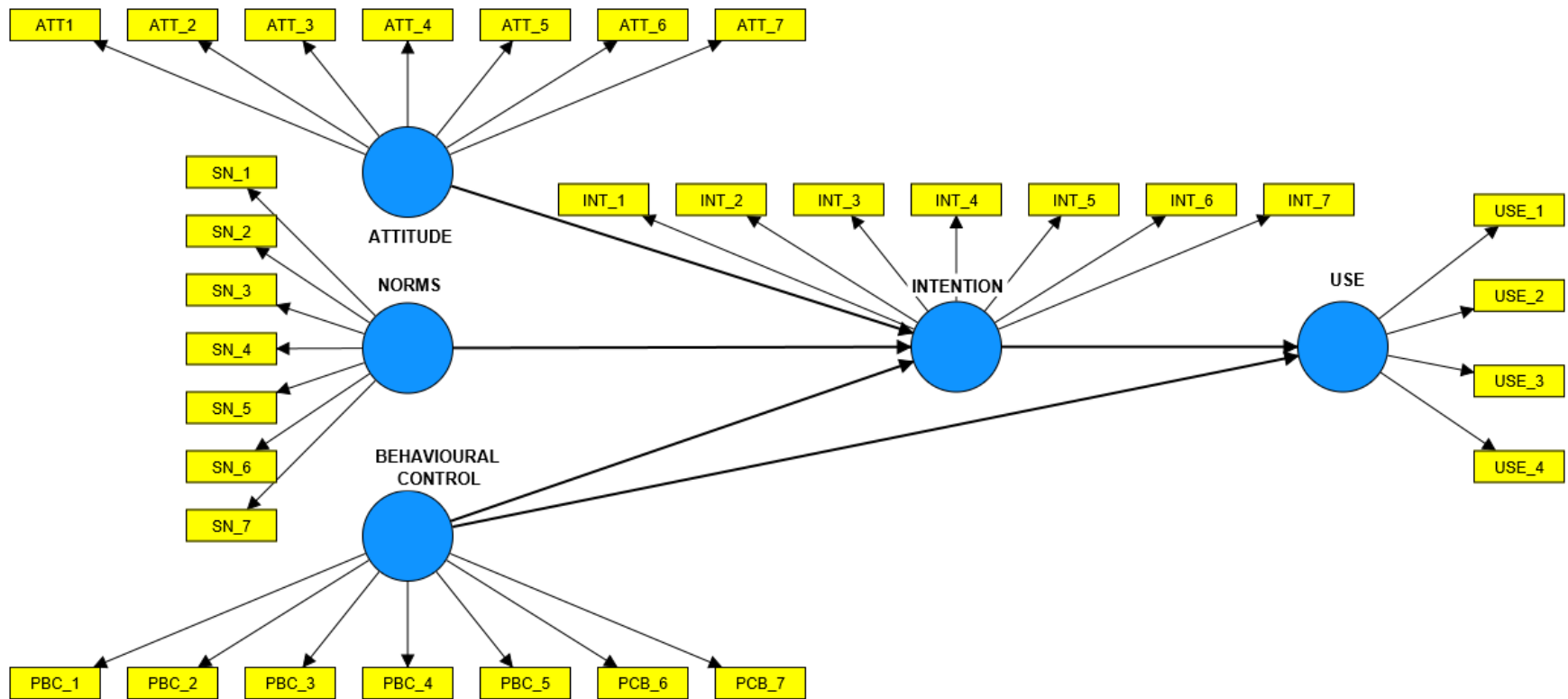


Figure 4: Measurement and structural model⁴

⁴ Rectangles represent measurement items
 Circles represent latent variables
 Arrows indicate the relationship direction

Convergent validity

Convergent validity helps assess if the items in a given measure represent well their associated construct. It is determined by computing the Average variance extracted (AVE) and is acceptable when its value is more significant than 0.5 (Hair et al., 2011).

Discriminant validity

Discriminant validity is essential in testing the uniqueness of constructs in a particular experiment. A given measurement of discriminant validity indicates the extent to which the construct carries unique information that differs from the other construct in the same study. The verification of discriminant validity uses a series of one or more of the following test methods:

- The Fornell and Lacker criterion states that discriminant validity is satisfactory when the square root of the construct's AVE is higher than its correlation with other constructs (Hair et al., 2011).
- Discriminant validity is successful when the cross-loadings of a particular item are lower on null on other items' parent construct while remaining dominant on its parent construct. For each item, the item's loading differences between constructs should remain higher than .10 for an acceptable discriminant validity (Hair et al., 2011).
- Heterotrait-Monotrait (HTMT) Ratio is an assessment based on measuring the average correlation of the indicators across constructs. For a distinction between constructs, a value less than 0.85 is suggested for distinct constructs and less than 0.90 for structurally similar constructs (Henseler et al., 2015).

3.8.2 Structural model evaluation

The structural equation assessment will comprise a series of tests designed to ensure that the model is not biased and represents well the theoretical framework.

Collinearity assessment

By design, formative indicators should reflect little correlation (collinearity) between them, as they are not necessarily interchangeable. A strong correlation between formative

indicators is undesirable as it could impact their weights and significance (Hair et al., 2021).

This research uses reflective indicators for the structural model's endogenous constructs (intention and usage). Reflective indicator items can be interchangeable; hence the expectation for a considerable correlation between them, although not desired as with formative indicators.

One way to assess the collinearity level is to use the Variance Inflation Factor (VIF) method. The available theory does not provide a valid range of results but suggests that values higher than 5 indicate a potentially high correlation among indicators (Hair et al., 2021). Therefore, a good measurement should result in VIF lower than 5.

Path coefficients

Path loading or weight conveys the relationship between the structural model's components. A path coefficient conveys the strength of a relationship between two variables, whereas the weight between different paths provides a means to rank their relative statistical importance (Raykov & Marcoulides, 2012; Wong, 2013).

Path coefficients and weight serve to determine the direct effect of one variable on another. Furthermore, there are also used to assess the indirect effects of one variable on the other via an intermediate. They represent a solution to simultaneous regressions carried out in SEM to provide causality between the dependent and independent variables (Thakkar, 2020).

Significance and relevance

The path coefficient significance and relevance results come from the bootstrapping technique in which the number of cases used is higher than the number of observations from the survey sample. The recommended sample in bootstrapping is 5000. The evaluation criteria use t-values for two-tailed tests: 1.65 (significance level of .1), 1.96 (significance level of .05) and 2.58 (significance level of .01) (Hair et al., 2021). In the present context, an a priori significance of 1.96 at a .05 significance level is sufficient for use throughout this research.

Explanatory power

The structural model used for the research relies on R-square (R^2) and F-square (F^2) statistics techniques. R^2 is a statistic that explains the variance in each endogenous variable. The R^2 , also known as the coefficient of determination, assesses the model's explanatory power. Its value ranges from 0 to 1, with a higher value providing a better explanatory power (Hair et al., 2021).

The measure of R^2 is subjective and research dependent; therefore, its interpretation depends on the research context. However, the literature provides some standards for guidelines. For instance, Table 2 provides some interpretations of R^2 for endogenous latent variables.

Table 2: Alternative interpretation of R^2 values

Substantial	Moderate	Weak	Authors
0.26	0.13	0.02	(Cohen, 1988)
0.75	0.50	0.25	(Hair et al., 2011)

An additional test of explanatory power that assesses the effect of removing a selected predictor's construct on the endogenous R^2 value is F^2 , also known as the effect size (Hair et al., 2021). An effect size is small for values greater than or equal to 0.02, medium for F^2 values greater than or equal to 0.15 and significant for F^2 values greater than or equal to 0.35 (Cohen, 1988).

Control variables

Although path coefficients provide a causal relationship, it is advisable to identify other variables that can influence any of the outcomes (intention and use of LP) and render the result biased. In this context, the gender, age group, location, area type and whether the respondent is currently using LPG are all potential control. Thus, the analysis considers the impact of each on the outcome per Figure 5.

The effect of each control on the endogenous variables (intention and use of LPG) consists in analysing the path analysis and t-statistics obtained from the bootstrapping method. The next step is comparing the results to those from a case without control variables. A control variable is significant only if its t-value is higher than 1.65 with a corresponding p-value of less than .05. Each variable that shows significance becomes the control variable to use for accounting for potential bias.

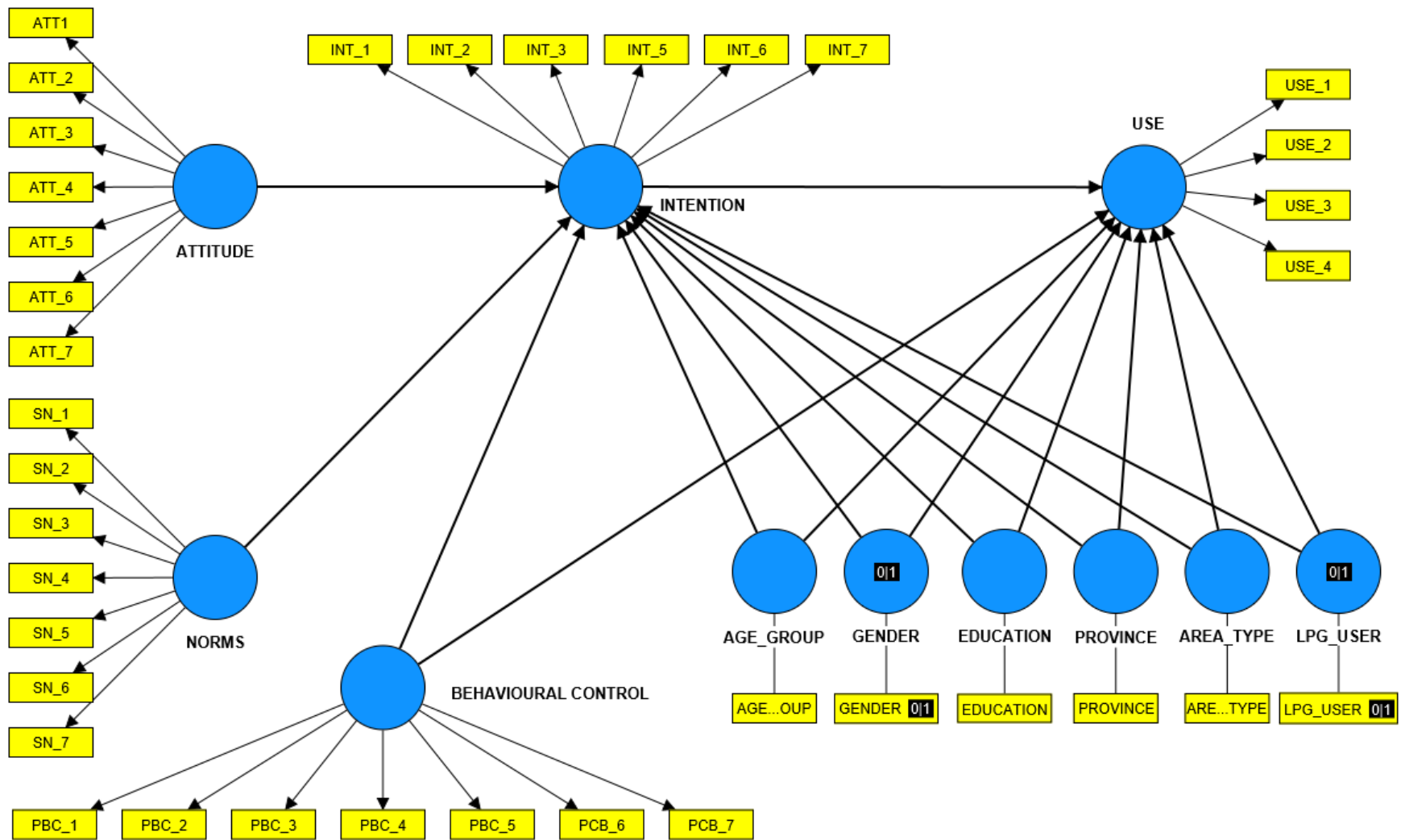


Figure 5: Model with control variables

3.9 Conclusions

The research methodology adopted allows the identification of a target population, the collection of data and the building of a model based on the theory of planned behaviour to find the determinants of the use of LPG. For the model to be credible, it is vital to evaluate its measurement and structural models and to check other factors that could bias the final results.

Model validation will determine the model readiness and be suitable for estimating the strength of relationships between constructs in the structural model. Further analysis will determine the possible control variables, and those identified as significant become part of the final model.

The ultimate results consider SEM results with and without the control variables to assess the magnitude and extent of the control variable effect on the predicted variables. This implies using a model with and without a control variable.

The derived path coefficients, magnitude and significant levels will represent the strength of the relationship between the predictors and the predicted (intention and the use of LPG) variables. Thus revealing the strength and the significance of the causal relationship and basis to validate or reject the hypothesis concerning the drivers of the use of LPG.

4 ANALYSIS

The research uses the theory of planned behaviour to establish the determinants of the use of LPG for households in South Africa. This chapter provides the application of the methodology from the previous section, and it contains the results obtained from applying the PLS-SEM to the theoretical model using SmartPLS software.

4.1 Descriptive statistics

4.1.1 Survey completion rate

The survey targeted respondents using an anonymous link to personal and professional networks and social and academic groups. As given in Table 3, 155 respondents attempted to provide answers, but only 118 (76%) completed the survey.

Table 3: Respondent's progress

Number of respondents	% of respondents	Progress on closing date (%)
6	4%	6
2	1%	19
2	1%	25
1	1%	38
13	8%	50
7	5%	56
2	1%	63
2	1%	69
1	1%	81
1	1%	88
118	76%	100

Considering only the completed questionnaires, the correct sample size had only 118 responses. Given that the PLS-SEM is suitable for application with low samples, there was no need to replace the missing or incomplete values.

4.1.2 Demographics

The demographic information in Table 4 indicates the type of respondents that participated in the survey. Of the 118 respondents, most were male (66.9%). Adults groups (25-59 years) represented 94.9% of the respondents. 71% of respondents with university degrees dominated the respondent's educational background. Respondents

live in Gauteng (64%), Kwazulu Natal (24.6%), the Western Cape (7.6%), Mpumalanga (1.7%), North-West and Free state (0.8% each). There were no respondents from the Eastern Cape, Northern Cape and Limpopo.

Table 4: Respondent demographics

Demographic Features	Possible Options	Number of Responses	Percentage
Age	Under 18	2	1,7%
	18-24	3	2,5%
	25-34	26	22,0%
	35-44	48	40,7%
	45-59	38	32,2%
	60 or older	1	0,8%
Gender	Female	39	33,1%
	Male	79	66,9%
Education	University Degree	84	71,2%
	Post-Matric certificate	9	7,6%
	Secondary School	9	7,6%
	Others	16	13,6%
Province	Free state	1	0,8%
	Gauteng	76	64,4%
	Kwazulu Natal	29	24,6%
	Mpumalanga	2	1,7%
	North-West	1	0,8%
	Western Cape	9	7,6%
Area	Suburbs	105	89,0%
	Township	9	7,6%
	Other	4	3,4%
Exiting LPG User	No	55	46,6%
	Yes	63	53,4%

The majority of the respondents identified their household location as suburbs (89%), township (7.6%) and other types of areas (3.4%). Finally, 53% of the respondents indicated they are currently using LPG.

4.2 Model validation and evaluation of path coefficients

The following analysis relies on the measurement and structural models composed of attitude (ATT), intention (INT), subjective norms or norms (SN), perceived behavioural control (PBC) and usage (USE), as presented in Figure 4.

4.2.1 Reflective measurement model's evaluation

Indicators' reliability

The first reliability analysis applied to the resulted in lower values provided where the indicator loadings for indicators INT_1, INT_4 for the intention construct, PBB_6 and PBC_7 for perceived behavioural control, and USE_1 for usage were below the acceptable limit (0.708). However, all remained higher than 0.4, considered a poor loading that should be removed from the analysis.

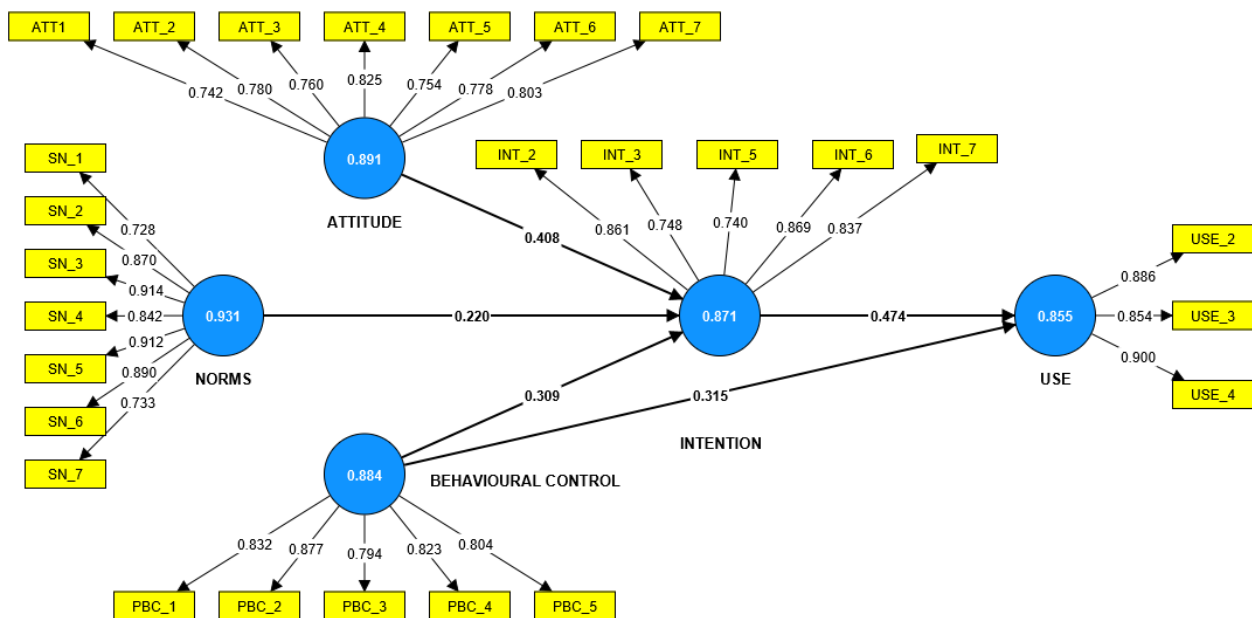


Figure 6: Indicator loadings and reliability⁵

After observing that their deletion improved the model, these indicators were permanently removed. This action resulted in items' loadings higher than 0.708 for the remaining items (see Table 5 and Figure 6). The loading magnitudes of the remaining items indicate that

⁵ Values in blue circles indicate Cronbach Alpha reliability. Values pointing to yellow rectangles are items loadings. Values between blue circles are path coefficients.

each model construct explains more than 50% of the indicator variance. Thus, these results prove the indicators' excellent reliability (Hair et al., 2021).

Table 5: Reflective measurement indicators' reliability

INDICATOR	ATTITUDE (ATT)	INTENTION (INT)	PERCEIVED BEHAVIOURAL CONTROL (PBC)	SUBJECTIVE NORMS (SN)	USE
ATT_1	0.742				
ATT_2	0.780				
ATT_3	0.760				
ATT_4	0.825				
ATT_5	0.754				
ATT_6	0.778				
ATT_7	0.803				
INT_2		0.861			
INT_3		0.748			
INT_5		0.740			
INT_6		0.869			
INT_7		0.837			
PBC_1			0.832		
PBC_2			0.877		
PBC_3			0.794		
PBC_4			0.823		
PBC_5			0.804		
SN_1				0.728	
SN_2				0.870	
SN_3				0.914	
SN_4				0.842	
SN_5				0.912	
SN_6				0.890	
SN_7				0.733	
USE_2					0.886
USE_3					0.854
USE_4					0.900

Internal consistency reliability and Convergent validity

Assessing the internal consistency reliability provided using Cronbach's alpha, Rho_b, and Rho_c reliability index provided the results of Table 6. All three indicators provided values higher than 0.70 and thus indicated excellent reliability (Hair et al., 2011).

Table 6: Construct (latent variables) reliability indexes

Variable	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ATT	0.891	0.894	0.915	0.605
INT	0.871	0.882	0.906	0.661
PBC	0.884	0.891	0.915	0.683
SN	0.931	0.933	0.945	0.713
USE	0.855	0.858	0.912	0.775

The computed AVE is higher than the acceptable value of 0.5 for each construct. Since each item has a high convergence validity score of more than 0.5, they all accurately measure their parent constructs (Hair et al., 2011).

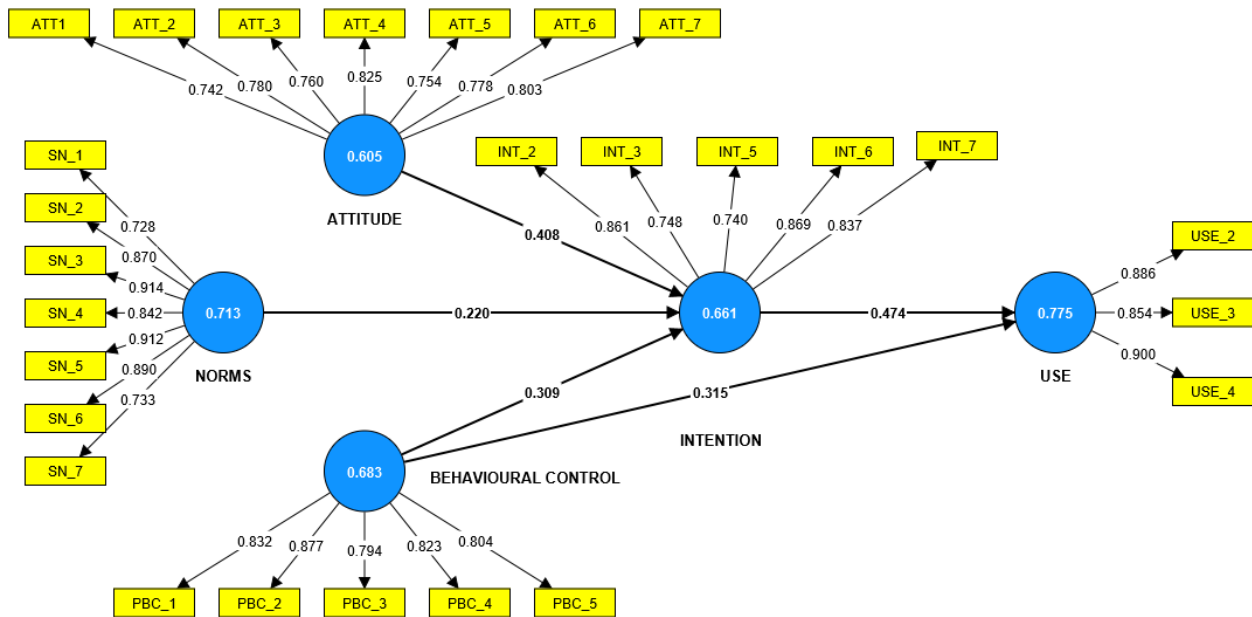


Figure 7: Model validation and indicator reliability⁶

⁶ Values in blue circles indicate the average variance extracted (AVE). Values pointing to yellow rectangles are items loadings. Values between blue circles are path coefficients.

Discriminant validity

This section assesses each construct's uniqueness by applying all three discriminant validity testing approaches consisting of Fornell-Lacker, cross-loading and Heterotrait-Monotrait ratios.

Table 7: Results of Fornell-Lacker criterion assessment

Construct	ATT	INT	PBC	SN	USE
ATT	[0.778] ⁷				
INT	0.752	[0.813]			
PBC	0.636	0.693	[0.826]		
SN	0.669	0.667	0.564	[0.845]	
USE	0.624	0.692	0.643	0.573	[0.881]

Firstly, the Fornell-Lacker criterion application onto the indicators leads to the values in Table 7. The subsequent analysis of Table 7 values showed that each construct's square root of AVE was higher than the corresponding correlation with other constructs. Thus, the measurement model satisfied the Fornell-Lacker criterion (Hair et al., 2011).

The second assessment of validity consisted of calculating the Heterotrait-Monotrait ratios provided. Analysis of the HTMT ratio results showed that all the ratios were lower than 0.85, thus indicating that each construct is distinct from the others (Henseler et al., 2015).

Table 8: Results of Heterotrait-Monotrait ratios

Construct	ATT	INT	PBC	SN
ATT				
INT	0.844			
PBC	0.706	0.773		
SN	0.729	0.731	0.609	
USE	0.706	0.789	0.727	0.634

All three discriminant validity tests contributed to the conclusion that each of the five constructs forming the model carries unique information.

Finally, the test of discriminant validity assessment consists of verifying each item's cross-loading on other items' parent constructs. The left side of Table 9 provides the loading of

⁷ Value in [] indicates the square root of AVE

each item on its parent and other constructs. The assessment consists of analysing the difference between each item's loading on its parent construct and its loading on each of the other constructs, provided on the right side of Table 9.

In line with the criteria of considering differences higher than 0.1 acceptable (Hair et al., 2011), the cross-loading differences in Table 9 show that all differences are acceptable. Therefore, each construct of the model passed the cross-loading assessment.

In conclusion, the measurement model of all five constructs passed the reliability and validity tests, hence showing that they were suitable for inclusion in the model. Therefore the model was declared reliable and valid in representing the items and their associated constructs, paving the way to the structural model evaluation.

Table 9: Results of the cross-loading assessment

Indicators' loading for constructs indicators						Indicators' cross-loading across constructs					
Construct	ATT	INT	PBC	SN	USE	Construct	ATT	INT	PBC	SN	USE
ATT_1	0,742	0,550	0,435	0,505	0,491	ATT_1		0,192	0,307	0,237	0,251
ATT_2	0,780	0,529	0,452	0,517	0,460	ATT_2		0,251	0,328	0,263	0,320
ATT_3	0,760	0,520	0,558	0,414	0,475	ATT_3		0,240	0,202	0,346	0,285
ATT_4	0,825	0,653	0,620	0,485	0,476	ATT_4		0,172	0,205	0,340	0,349
ATT_5	0,754	0,589	0,372	0,514	0,512	ATT_5		0,165	0,382	0,240	0,242
ATT_6	0,778	0,604	0,465	0,584	0,517	ATT_6		0,174	0,313	0,194	0,261
ATT_7	0,803	0,628	0,547	0,613	0,470	ATT_7		0,175	0,256	0,190	0,333
INT_2	0,706	0,861	0,680	0,625	0,688	INT_2	0,155		0,181	0,236	0,173
INT_3	0,545	0,748	0,500	0,425	0,518	INT_3	0,203		0,248	0,323	0,230
INT_5	0,556	0,740	0,513	0,487	0,493	INT_5	0,184		0,227	0,253	0,247
INT_6	0,658	0,869	0,610	0,607	0,543	INT_6	0,211		0,259	0,262	0,326
INT_7	0,567	0,837	0,481	0,542	0,544	INT_7	0,270		0,356	0,295	0,293
PBC_1	0,615	0,604	0,832	0,546	0,621	PBC_1	0,217	0,228		0,286	0,211
PBC_2	0,554	0,559	0,877	0,423	0,608	PBC_2	0,323	0,318		0,454	0,269
PBC_3	0,454	0,465	0,794	0,354	0,447	PBC_3	0,340	0,329		0,440	0,347
PBC_4	0,463	0,516	0,823	0,456	0,466	PBC_4	0,360	0,307		0,367	0,357
PBC_5	0,515	0,686	0,804	0,523	0,485	PBC_5	0,289	0,118		0,281	0,319
SN_1	0,565	0,581	0,488	0,728	0,550	SN_1	0,163	0,147	0,240		0,178
SN_2	0,608	0,629	0,563	0,870	0,499	SN_2	0,262	0,241	0,307		0,371
SN_3	0,595	0,574	0,462	0,914	0,444	SN_3	0,319	0,340	0,452		0,470
SN_4	0,523	0,497	0,373	0,842	0,438	SN_4	0,319	0,345	0,469		0,404
SN_5	0,527	0,531	0,465	0,912	0,467	SN_5	0,385	0,381	0,447		0,445
SN_6	0,533	0,543	0,461	0,890	0,489	SN_6	0,357	0,347	0,429		0,401
SN_7	0,576	0,555	0,484	0,733	0,474	SN_7	0,157	0,178	0,249		0,259
USE_2	0,511	0,593	0,579	0,511	0,886	USE_2	0,375	0,293	0,307	0,375	
USE_3	0,660	0,669	0,593	0,556	0,854	USE_3	0,194	0,185	0,261	0,298	
USE_4	0,457	0,551	0,517	0,432	0,900	USE_4	0,443	0,349	0,383	0,468	

4.2.2 Structural model evaluation

Collinearity assessment

The structural model's assessment for collinearity uses Variance Inflation Factors (VIF) between dependent and independent constructs where the dependent variables are predictors, and the independent variables are the predicted quantities except for intention (INT), which is both dependent and independent variable.

As per the results in Table 10, all VIF values are below the threshold of 5, thus indicating no collinearity issues between the constructs (Hair et al., 2021).

Table 10: Results of collinearity assessment

Construct	INT	USE
ATT	2.201	
INT		1.922
PBC	1.782	1.922
SN	1.923	

Explanatory power

Considering the two endogenous variables from the model (intention and use), the calculated R^2 values given in Table 11 indicated moderate to substantial explanatory power based on the evaluation criteria suggested (Hair et al., 2011).

The coefficient of determination R^2 values of 0.668 for intention (INT) indicates that the attitude (ATT), norms (SN) and behavioural control (PBC) moderately explain 66.8% of its variance. Similarly, R^2 value of 0.530 indicates that behavioural control (PBC) and intention (INT) moderately explain 53% of the variance in use.

Table 11: Explanatory power's R-square values

Construct	R-square	R-square adjusted
INT	0.668	0.659
USE	0.530	0.522

The F^2 values computed in Table 12 indicate the effect size of removing one construct from the model. Analysing using prior research's values suggested by (Cohen, 1988), a medium effect size was found for attitude on intention (0.228), intention on usage (0.248) and perceived behavioural control on intention (0.161). Similarly, there was a small effect

size for perceived behavioural control on usage (0.110). Finally, subjective norm (SN) on intention (INT) resulted in the least significant effect (0.076).

Table 12: Effect size's F-square values

Construct	INT	USE
ATT	0.228	
INT		0.248
PBC	0.161	0.110
SN	0.076	

4.3 Path coefficients

Finally, path coefficients provide the strength of the relationship between predictors (independent variables) and predicted values (dependent variables) linked by Equation 1 and 2. Although the coefficient shown in Figure 6 is for direct effect, indirect effects (for example, ATT → INT → USE) is relevant in this research, wherein the purpose is to establish a relationship between the independent variables and the use of the LPG.

4.3.1 Path coefficient

Path coefficients provide the direct relationship between variables. The results of Table 13 provide evidence of the causal relationship from the independent to a dependent variable, not the significance.

Table 13: Direct effect of the dependent variables on the use of LPG

Path	Path coefficients
ATT → INT	0.408
PBC → INT	0.309
SN → INT	0.220
PBC → USE	0.315
INT → USE	0.474

Analysis of the results for intention to use LPG (INT) shows that attitude (ATT) has the most effect, followed by behavioural control (PBC) and then lastly by norms (SN).

For usage of LPG (USE), intention (INT) is the most significant, followed by behavioural control (PBC).

4.3.2 Indirect effect

The usage of LPG represented by USE is the ultimate variable of interest. Its relationship with the determinants is through the intention variable (INT) mediation, as indicated by the paths in Table 14.

Table 14: Indirect effect of the dependent variables on the use of LPG

Path	Indirect effects
ATT -> INT -> USE	0.193
PBC -> INT -> USE	0.146
SN -> INT -> USE	0.104

According to the results, attitude (ATT) has the most indirect effect on the usage of LPG and is followed by behavioural control (PBC). Lastly, the results show that norms (SN) have a minor effect on the use of LPG.

4.3.3 Total effect

The combined effects of the dependent variables on the independent variables are crucial to establishing the drivers of LPG usage and their associated ranks. Table 15 combines Table 13 and Table 14 values to provide the overall effects.

Table 15: Total effect of the dependent variables on the use of LPG

Path	Total effects
ATT -> INT	0.408
PBC -> INT	0.309
SN -> INT	0.220
ATT -> USE	0.193
PBC -> USE	0.461
INT -> USE	0.474
SN -> USE	0.104

Analysing the drivers of intention (INT), Table 15 show consistency with the direct and indirect ones discussed in the previous sections. Its results show that attitude (ATT) remains the most significant driver, followed by behavioural control (PBC) and then norms (SN).

LPG usage relationship is most substantial with intention (INT) followed by behavioural control (PBC), attitude (ATT) and lastly, norms (SN). However, it is worth recalling that all three independent variables (ATT, SN and PBC) contribute to the intention (INT) to use LPG. Thus, it is perhaps fair to compare INT to PBC and use the indirect effect to rank the effect from the dependent variables. In that respect, intention (INT) has the most effect, then behavioural control (PBC) and then the norms (SN). Similarly, comparing the direct effect on LPG usage show that intention (INT) is a more potent driver than behavioural control (PBC).

An important observation from the direct, indirect and total effects is that all relationships are positive, implying that higher indicators will drive the desired output of higher usage.

4.4 Relevance and significance of results

The relevance and significance of loadings in the measurement model and path coefficients for the structural model are assessed using bootstrapping at a prior significance level of 0.05. At this confidence level, the expected estimates from the bootstrapping should exceed 1.96 for the t-value to be valid.

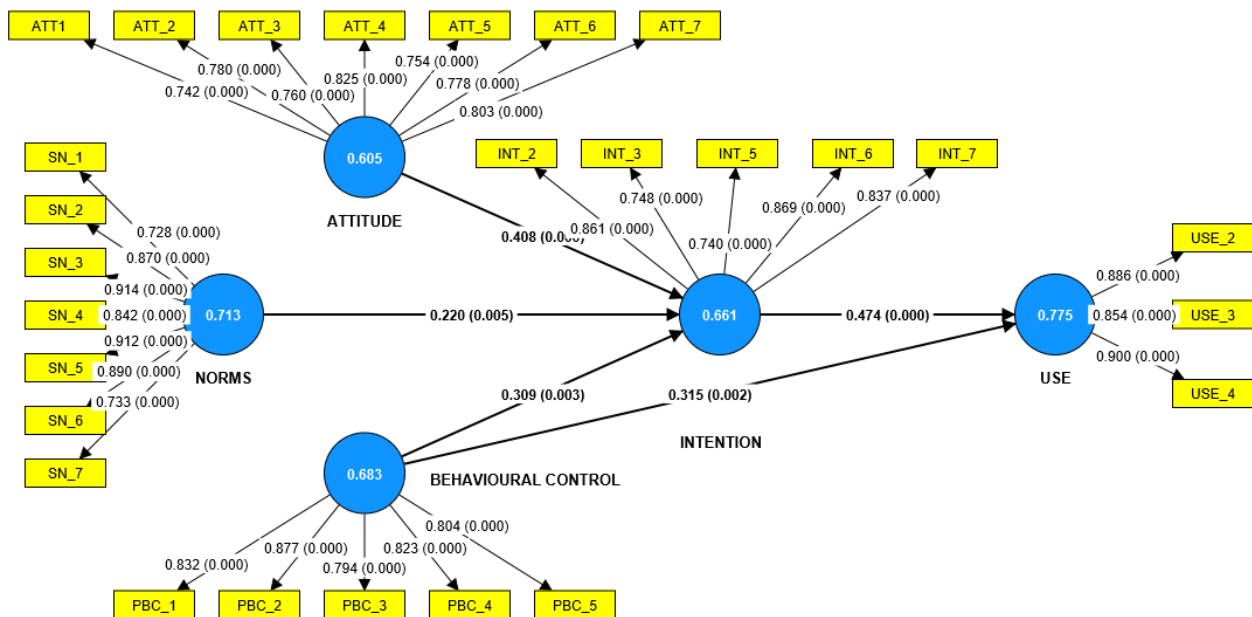


Figure 8: Results of PLS-SEM path analysis (without control variables)⁸

⁸ Arrows from blue circle to yellow rectangles represent item loadings and p-value (in bracket)

The model validation for relevance and significance of the indicator loadings and the path coefficient is based on bootstrapping results shown in Figure 8. It covers indicators loading and path coefficients provided in the analysis laid in the following sections.

4.4.1 Indicator loadings validation

Table 16 show t-values greater than 1.96 and p-values lower than 0.05 for all indicators' loadings, implying their relevance and significance. Hence, a confirmation that each measurement correctly represents the associated constructs.

Table 16: Results of T-statistics for outer loading (measurement items)

Path	Outer loadings	T values	P values
ATT_1 <- ATT	0.742	9.058	0.000
ATT_2 <- ATT	0.780	11.758	0.000
ATT_3 <- ATT	0.760	11.388	0.000
ATT_4 <- ATT	0.825	22.468	0.000
ATT_5 <- ATT	0.754	13.602	0.000
ATT_6 <- ATT	0.778	15.081	0.000
ATT_7 <- ATT	0.803	18.374	0.000
INT_2 <- INT	0.861	31.696	0.000
INT_3 <- INT	0.748	11.838	0.000
INT_5 <- INT	0.740	13.982	0.000
INT_6 <- INT	0.869	33.777	0.000
INT_7 <- INT	0.837	22.987	0.000
PBC_1 <- PBC	0.832	20.450	0.000
PBC_2 <- PBC	0.877	28.433	0.000
PBC_3 <- PBC	0.794	14.517	0.000
PBC_4 <- PBC	0.823	19.201	0.000
PBC_5 <- PBC	0.804	19.741	0.000
SN_1 <- SN	0.728	13.277	0.000
SN_2 <- SN	0.870	31.418	0.000
SN_3 <- SN	0.914	48.265	0.000
SN_4 <- SN	0.842	18.233	0.000
SN_5 <- SN	0.912	47.008	0.000
SN_6 <- SN	0.890	30.578	0.000
SN_7 <- SN	0.733	12.806	0.000
USE_2 <- USE	0.886	20.419	0.000
USE_3 <- USE	0.854	28.097	0.000
USE_4 <- USE	0.900	23.851	0.000

Arrows between blue circles represent path coefficients and p-values (in bracket)
Constructs (values within blue circle): Average Variance Extracted (AVE)

4.4.2 Structural model validation

The successful validation of the measurement and structural models allows for further analysis to be carried out on the model to validate the determinants of the use of LPG. This section refers to Figure 8 for SEM results concerning path coefficients from direct effects, indirect effects, total effects between pairs of constructs, and the outer loading of each construct's indicators.

Path coefficient

The structural model results (t-values and p-values) in Table 17 confirm that In terms of significance, the intention is driven mainly by attitude, followed by behavioural control and norms regarding relevance and significance. All three drivers are relevant with t-values greater than 1.96 and significant with p-value less than 0.05.

Table 17: T-statistics for path coefficients (direct effect) of the model

Path	Path Coefficients	T-values	P-values
ATT → INT	0.408	3.671	0.000
SN → INT	0.220	2.809	0.005
PBC → INT	0.309	2.955	0.003
INT → USE	0.474	5.879	0.000
PBC → USE	0.315	3.038	0.002

Table 17's results also show that the attitude and norms affect LPG usage since they are relevant (t-value greater than 1.96) and significant (p-value lower than 0.05).

Indirect effect

The results in Table 18 confirmed that attitude (ATT), norms (SN) and behavioural control (PBC) are all relevant and significant drivers indirectly associated with LPG usage.

Table 18: T-statistics for indirect effects of the model

Path	Path Coefficients	T-values	P-values
ATT → INT → USE	0.193	3.134	0.002
SN → INT → USE	0.104	2.563	0.010
PBC → INT → USE	0.146	2.498	0.013

Total effects

The total effects combine the path coefficients and the indirect effects of the drivers of intention and usage. From simple arithmetic, the total effect of each driver on intention and usage is in Table 19, alongside the t-values and p-values.

Table 19: T-statistics for total effects of the model

Path	Path Coefficients	T-values	P-values
ATT → INT	0.408	3.671	0.000
SN → INT	0.220	2.809	0.005
PBC → INT	0.309	2.955	0.003
ATT → USE	0.193	3.134	0.002
INT → USE	0.474	5.879	0.000
SN → USE	0.104	2.563	0.010
PBC → USE	0.461	4.859	0.000

The results show that all relationships are relevant, albeit with different relevance and significance levels. The path coefficients are valid and significant from the validation of the total effects of independent dependent variables as analysed in the model evaluation (section 4.2).

4.5 Assessment for control variables

Although the analysis in the previous sections shows the drivers of LPG usage, its validation requires verification that no other variable affect the output. To ensure the model verification for bias, age group, gender, education, location, province, area type and status of LPG use were all considered initially as control variables in the model presented in Figure 5.

The initial model intends to assess how much they affect the results discussed in the previous sections. The assessment consisted of the use of bootstrapping routine with 5000 samples.

The initial analysis of the bootstrap results in Table 20 consisted of analysing for relevance and significance of each control variable on the dependent variables (intention and usage).

Analysing the results in Table 20 showed that age, area of living and current status as an LPG user had no significant effect on LPG's intention (INT) and usage (USE). Although

some of the t-values are substantial (higher than 1.96), the corresponding significance was lower than the required p-value of .05.

Table 20: Control variable effect on the output

Relationship	Coefficient	Standard deviation	T -values	P values
AGE_GROUP -> INT	0.071	0.049	1.457	0.145
AGE_GROUP -> USE	-0.097	0.084	1.154	0.249
AREA_TYPE -> INT	-0.097	0.057	1.698	0.090
AREA_TYPE -> USE	0.017	0.107	0.161	0.872
ATTITUDE -> INT	0.404	0.101	3.988	0.000
ATTITUDE -> USE	0.205	0.059	3.478	0.001
PBC -> INT	0.375	0.104	3.616	0.000
PBC -> USE	0.474	0.109	4.345	0.000
EDUCATION -> INT	-0.159	0.069	2.294	0.022
EDUCATION -> USE	-0.077	0.072	1.067	0.286
GENDER -> INT	0.013	0.133	0.096	0.924
GENDER -> USE	-0.055	0.169	0.322	0.747
INT -> USE	0.506	0.086	5.902	0.000
LPG_USER -> INT	-0.197	0.104	1.888	0.059
LPG_USER -> USE	-0.136	0.135	1.003	0.316
NORMS -> INT	0.209	0.075	2.787	0.005
NORMS -> USE	0.106	0.043	2.461	0.014
PROVINCE -> INT	0.015	0.062	0.242	0.809
PROVINCE -> USE	-0.091	0.078	1.164	0.245

Instead, these results demonstrated a significant bias of Education on the intention to use LPG. For this reason, the subsequent analysis considers education as the only control variable in the model, and the relationship applies only to the intention variable shown in Figure 9 model.

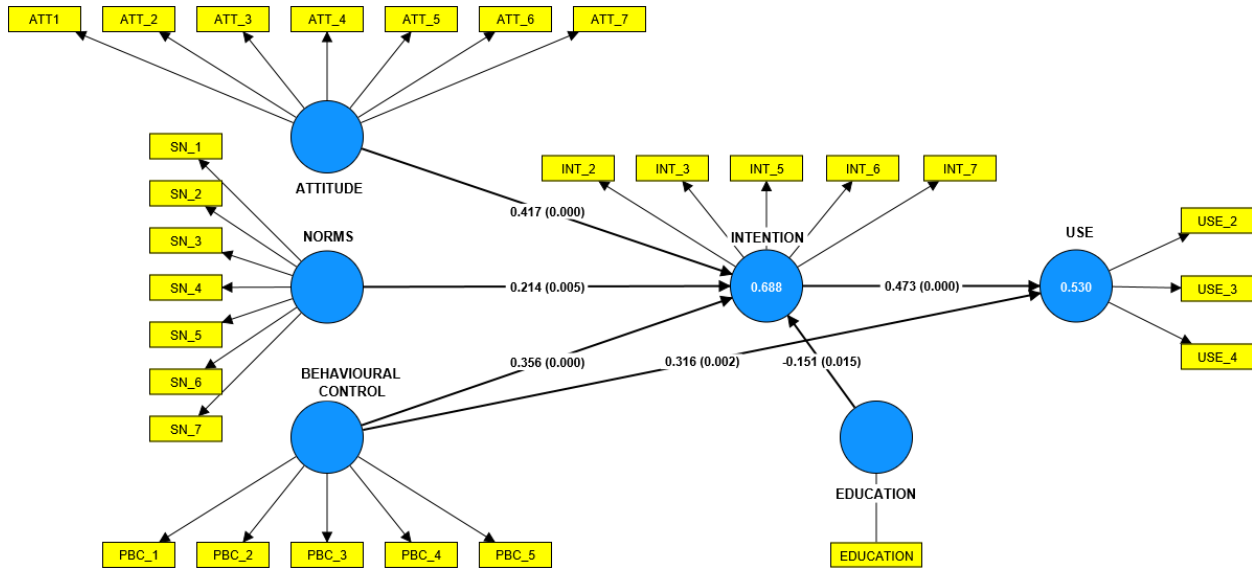


Figure 9: Model validation with control variable

Applying bootstrapping on the model above allows drawing new path coefficients necessary for assessing the control variable’s effect on the model. Comparing the results between the two models, one with no control variable (Figure 8) and the other with a control variable (Figure 9), the resulting values in Table 21 provide the effect of education on the path coefficients and, therefore, on the relationship between variables.

Table 21: Effect of education on the determinants of intention and use

Relationship	No control variable	Controlled by education on the intention			
	Path Coefficients	Path Coefficients	Standard deviation	T-value	P-values
ATT -> INT	0.408	0.417	0.102	4.068	0.000
PBC -> INT	0.309	0.356	0.097	3.658	0.000
SN -> INT	0.220	0.214	0.076	2.800	0.005
ATT -> USE	0.193	0.197	0.058	3.414	0.001
PBC -> USE	0.461	0.484	0.091	5.328	0.000
EDU -> INT		-0.151	0.062	2.432	0.015
EDU -> USE		-0.072	0.034	2.136	0.033
INT -> USE	0.474	0.473	0.080	5.881	0.000
SN -> USE	0.104	0.101	0.040	2.549	0.011

The model comparison observed that all the relationships between education (EDU) and the dependent variables were statistically significant after adding education as the control

variable on the intention to use LPG. Secondly, the relationship between attitude and intention (ATT → INT), behavioural control and intention (PBC → INT), attitude and use (ATT → USE), and behavioural control and usage (PBC → USE) improved. Furthermore, the model's comparison showed that the relationship between norms and intention (SN → INT), intention and usage (INT → USE) and norms and usage (SN → USE) deteriorated.

Considering the results while accounting for the control variable, the determinant of the use of LPG in order of effect is the behavioural control (0.484), the attitude (0.197) and the norms (0.101). However, when considering the cumulative indirect effects, the most significant determinants are attitude (0.417), behavioural control (0.356) and the norms (0.214). The combined effect of these values defines the intention (0.473), which is a more significant determinant than behavioural control (0.484).

Finally, looking at the influence of the control variable and the associated coding provided in Table 1 (0 for least educated, 2 for most educated and 3 for others), the path coefficient provides insight into the direction of the influence of the control variable (education). For instance, the path coefficient of -0.151 for EDU → INT between education (EDU) and intention (INT) implies a negative relationship between education and intention whereby the least educated have a stronger intention to use LPG. Furthermore, the path coefficient EDU → USE between education (EDU) and usage (USE) of -0.072, although small, represents the indirect effect of education on the use of LPG. Once more, it carries the message that the less educated are more likely to use LPG than their most educated counterparts.

4.6 Conclusions

One hundred fifty-five respondents took the survey, but only 118 (76%) completed it. From the complete response, most respondents are residents of major metropolitan areas and live in the suburbs, but males dominated (67%). Furthermore, the majority of respondents are university-educated adults (71%).

Factor analysis and structure analysis applied to the test resulted in satisfactory results for the measurement and the structural models. All factor loadings and path coefficients were statistically significant with and without a control variable. However, the further

analysis applied with the control variable showed that the education variable had the most significant impact on the intention to use LPG.

After introducing education (EDU) as the control variable, the overall analysis still provided relevant and significant results for the structural model's path coefficients, thus confirming that attitude, behavioural control and norms are significant determinants of using LPG for South African households.

Considering the path coefficient values, the relevance and significance of the structural equation results provides responses to the hypothesis as summarised in **Error! Reference source not found.** This summary indicates that all hypotheses are supported, although the relevance and significance are not the same, thus implying that some drivers of the LPG usage have more influence than others.

Table 22: Summary of hypothesis assessments

Hypothesis	Hypothesize path	Path Coefficient (<i>T-value</i>)	p-value	Outcome
H1: Attitude is positively related to the intention to use LPG.	ATT → INT	0.417 (4.068)	0.000	Supported
H2: Norms are positively associated with the intention to use LPG	SN → INT	0.214 (2.800)	0.005	Supported
H3: Behavioral control is positively linked to the intention to use LPG	PBC → INT	0.356 (3.658)	0.000	Supported
H4: Intention is positively related to the use of LPG	INT → USE	0.473 (5.881)	0.000	Supported
H5: Behavioral control is positively related to the use of LPG.	PBC → USE	0.484 (5.328)	0.000	Supported

These results indicated that attitude has the strongest relationship with intention and is followed by the behavioural control. Subjective norms has the least effect on the intention for a household to use LPG.

Although the previous section provided the drivers, the further analysis looks at the indirect or mediated path for the determinants of the usage of LPG provided in summary. The conclusion provided in **Error! Reference source not found.** shows that attitude has the strongest effect followed by behavioural control and the norms.

Table 23: Indirect effects on the use of LPG

Path	Path Coefficient (<i>T-value</i>)	p-value
ATT → INT → USE	0.197 (3.414)	0.001
SN → INT → USE	0.101 (2.549)	0.011
PBC → INT → USE	0.169 (2.875)	0.000

Finally, applying variable control shows that education play a vital role in the adoption and usage of LPG. In this aspect, the results shows that less educated people are more likely to start using LPG than those well educated.

5 DISCUSSION OF FINDINGS

This research objective was to evaluate the determinants of households' use of LPG in South Africa. It was built around the need to find how attitude is related to the usage of LPG, how perceived norms influence the use of LPG and how behavioural control affects the use of LPG, all in the context of South African households.

It was further hypothesized that attitude is positively related to the intention to use LPG, norms are positively associated with the intention to use LPG, intention is positively related to the use of LPG and that behavioural control is positively related to the use of LPG.

5.1 Overview

The theory of planned behaviour posits that attitude, subjective norms, and perceived control behaviour drive the intention to engage in a particular behaviour (Ajzen, 1991). The relationship between this theory's constructs and the eventual LPG usage are classified into two categories. The first category is concerned with the relationship between the constructs and the LPG usage using the intention as a mediator. The second category deals with direct relationship between the the construct and the LPG usage. Both categories' findings were found significant, hence the following discussions.

5.2 Relationships mediated by intention

These relationships intend to provide an explanation for the individual relationship between attitude, norms and behavioural control against the LPG usage with the aim of validating the hypothesis one to three.

Relationship between attitude and LPG usage

In the relationship mediated by the intention, attitude was the most significant driver of LPG usage. Its strongest indicator loadings show that increasing the LPG usage can be achieved by focusing on the users' concerns for LPG safety, its environmental and financial benefits. Furthermore, the indicator loadings insights show that most users would care about the positive effect on LPG usage on their society. Chiefly, the

environmental benefit related to pollution is one of the strongest factors leading the attitude towards the LPG usage.

5.2.1 Relationship between norms and LPG usage

Although norms' loadings are high and range between, their total effect on the usage of LPG is the weakest of all drivers but still provide evidence of strong relationship with the LPG usage. The analysis reveals that society effort has little contribution in influencing the norms but at the same time, the influence of colleagues is the strongest.

Since both items' measures were significant, it could point to the respondent's individualistic behaviour, contrasting the collective effort aimed, for instance, at a common cause. These results also suggest that the decision to use LPG is primarily individual, but the influence of society on the user of LPG cannot be neglected.

5.2.2 Relationship between behavioural control and usage

The analysis show that behavioral control's relationship with LPG usage was substantial and second only to attitude. Its construct loadings were all significant with the knowledge about using gas standing as the leading indicator while having the resources to use gas was the least significant indicator.

Both indicators imply that resources alone are not sufficient. Education the existing and potential users on the LPG usage is more important than having the tools and resources to use LPG.

5.3 Direct relationship

These relationships intend to provide an explanation for the individual relationship between attitude, norms and behavioural control against the LPG usage with the aim of validating the hypothesis four to five.

5.3.1 Relationship between intention and LPG usage

The theory of planned behaviour posits that intention is a precursor to the behaviour (Ajzen, 1991). In this analysis, considering the total effect of the mediator (intention) shows that attitude is the biggest driver of the usage of LPG, followed by behavioural control. Considering that intention is a result of attitude, norms and behavioural control,

improving each of these construct's indicators is critical in driving the use of LPG is the overall results is stronger than the individual relationships.

From the analysis, all three drivers of LPG usage provide a combined relationship with LPG usage through intention. However, the combined relationship through intention remain lower than that provided by the behavioural control.

5.3.2 Relationship between behavioral control and LPG usage

Valid loadings for behavioural control are strong and significant. The biggest contributors are resources availability and the knowledge to use LPG.

Behavioural control also has the strongest influence on LPG usage that the combined attitude, norms and behavioural control. This implies that the behavioural control alone can contribute to change the LPG usage patterns. This finding is in agreement with longitudinal research that demonstrated that a program providing LPG resources to the township community resulted in many participants maintaining the LPG (Kimemia & Annegarn, 2016).

6 SUMMARY AND CONCLUSIONS

6.1 The drivers of the use of LPG

From the analysis of the indicators and the latent variables of the structural model, attitude, norms and behavioural control all have a positive relationship with the intention to use LPG. Attitude and behavioural control alone are the most vital and significant drivers of the usage of LPG, while the effect of community norms is also significant.

The intention of using LPG emanates from the attitude toward LPG, the behavioural control and the norms the user adopts. Combining all three drivers provide a firm intention that is a powerful virtual driver of LPG usage in households. However, behavioural control alone has proved sufficient to determine household LPG usage.

6.2 Policy implications

To improve the attitude towards the use of LPG, policies on the adoption and sustained use of LPG should focus on improving the attitude through education with a focus on the environmental benefits and safety could improve the attitude of the household.

For subjective norms to have an effect, education on the use of LPG could take advantage of social events where attendees are likely to come in social groups, reinforcing the notion of collective thinking toward achieving a common goal and, for instance, overcoming environmental challenges.

Improve behavioural control measures could include subsidies for LPG stoves and cylinders, as this has been proven successful on pilot projects in Atteridgeville (Kimemia & Annegarn, 2016) and Khayelitsha (Mohlakoana & Annecke, 2009).

6.3 Business implications

By adopting policies geared toward a higher usage of LPG, the direct beneficiaries are businesses mostly in the LPG supply chain. As more and more people adopt LPG, the overall demand will increase and will provide incentives for more investment in the supply chain. Such investment will also create some indirect creates other business opportunities that benefits the economy as a whole.

6.4 Conclusions

Attitude, norms and behavioural control are all the drivers of the usage of LPG in the household. When individually mediated by intention, attitude is the most significant determinant of LPG usage, and Behavioral control is the other way that alone drives the determinant of LPG usage.

Finally, combining attitude, norms and behavioural control is the best way to increase the LPG usage in South African household.

Since attitude and behavioral control are the most significant, they can be improved by policies that addresses existing and potential users pain points. This action will lead more users from intention to LPG usage and by extension more usage and benefits for the South African LPG market and economy.

6.5 Recommendation for further research

Based on the findings and the discussions, further studies could focus on:

- (1) How to improve the attitude towards the usage of LPG;
- (2) How to improve the behavioural control of existing and potential LPG users;
- (3) The difference between respondents using LPG and those that do not at present and;
- (4) The overall impact of more LPG usage on its supply chain and the South African economy.

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ANNEXURES

Cost of electricity

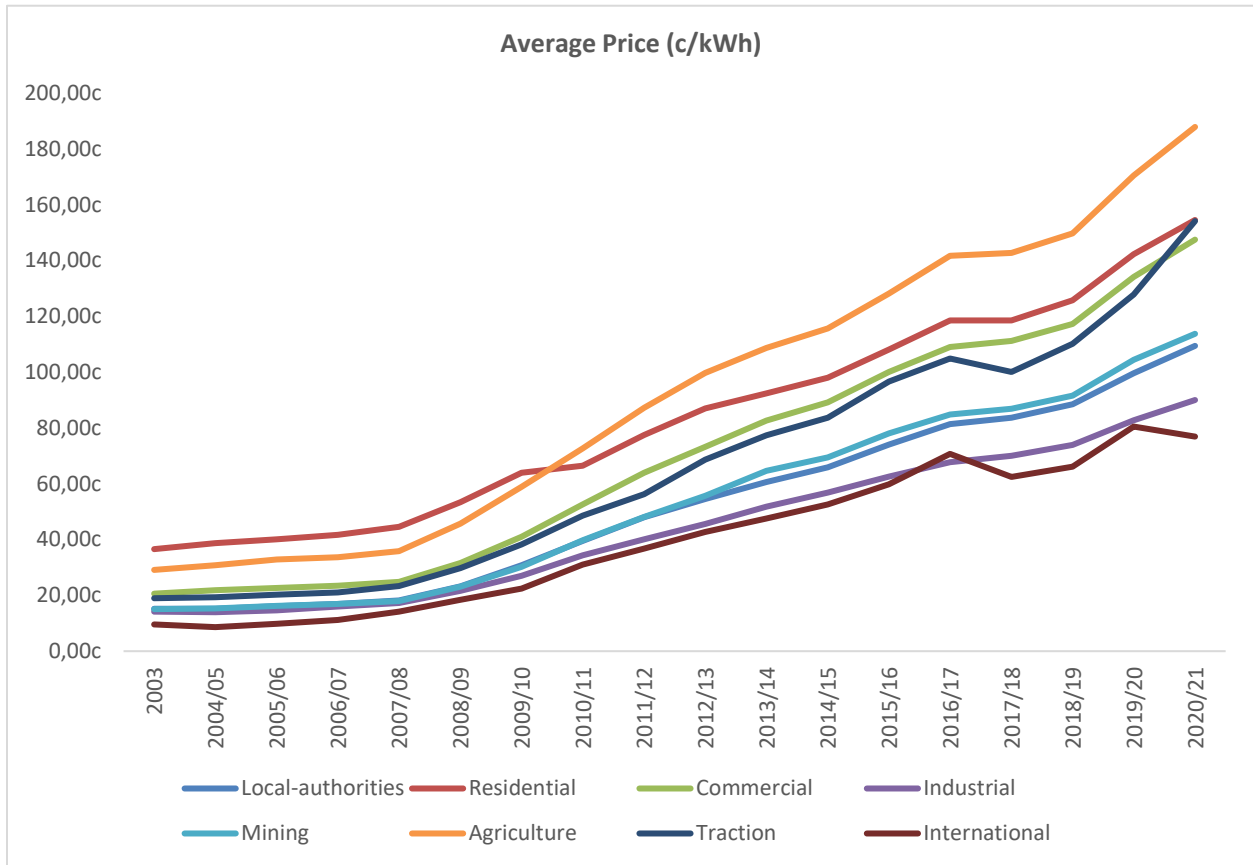


Figure 10: Average electricity price 2003-2021 (Eskom, 2022)

T-statistics results*Table 24: Annexure – path coefficient's bootstrap results*

Path	Original sample (O)	Sample mean (M)	Standard deviation	T values	P values
ATT -> INT	0.408	0.414	0.111	3.671	0.000
INT -> USE	0.474	0.473	0.081	5.879	0.000
PBC -> INT	0.309	0.304	0.105	2.955	0.003
PBC -> USE	0.315	0.312	0.104	3.038	0.002
SN -> INT	0.220	0.222	0.078	2.809	0.005

Table 25: Annexure – indirect effect's bootstrap results

Path	Original sample (O)	Sample mean (M)	Standard deviation	T values	P values
ATT -> USE	0.193	0.196	0.062	3.134	0.002
PBC -> USE	0.146	0.145	0.059	2.498	0.013
SN -> USE	0.104	0.105	0.041	2.563	0.010

Table 26: Annexure – specific indirect effect's t-statistics

	Original sample (O)	Sample mean (M)	Standard deviation	T values	P values
SN -> INT -> USE	0.104	0.105	0.041	2.563	0.010
ATT -> INT -> USE	0.193	0.196	0.062	3.134	0.002
PBC -> INT -> USE	0.146	0.145	0.059	2.498	0.013

Table 27: Annexure – bootstrapped total effect's results

Path	Original sample (O)	Sample mean (M)	Standard deviation	T values	P values
ATT -> INT	0.408	0.414	0.111	3.671	0.000
ATT -> USE	0.193	0.196	0.062	3.134	0.002
INT -> USE	0.474	0.473	0.081	5.879	0.000
PBC -> INT	0.309	0.304	0.105	2.955	0.003
PBC -> USE	0.461	0.457	0.095	4.859	0.000
SN -> INT	0.220	0.222	0.078	2.809	0.005
SN -> USE	0.104	0.105	0.041	2.563	0.010

Table 28: Annexure – outer loading's bootstrap results

Path	Original sample (O)	Sample mean (M)	Standard deviation	T values	P values
ATT_1 <- ATT	0.742	0.738	0.082	9.058	0.000
ATT_2 <- ATT	0.780	0.774	0.066	11.758	0.000
ATT_3 <- ATT	0.760	0.756	0.067	11.388	0.000
ATT_4 <- ATT	0.825	0.826	0.037	22.468	0.000
ATT_5 <- ATT	0.754	0.751	0.055	13.602	0.000
ATT_6 <- ATT	0.778	0.775	0.052	15.081	0.000
ATT_7 <- ATT	0.803	0.802	0.044	18.374	0.000
INT_2 <- INT	0.861	0.859	0.027	31.696	0.000
INT_3 <- INT	0.748	0.741	0.063	11.838	0.000
INT_5 <- INT	0.740	0.739	0.053	13.982	0.000
INT_6 <- INT	0.869	0.870	0.026	33.777	0.000
INT_7 <- INT	0.837	0.835	0.036	22.987	0.000
PBC_1 <- PBC	0.832	0.831	0.041	20.450	0.000
PBC_2 <- PBC	0.877	0.875	0.031	28.433	0.000
PBC_3 <- PBC	0.794	0.789	0.055	14.517	0.000
PBC_4 <- PBC	0.823	0.819	0.043	19.201	0.000
PBC_5 <- PBC	0.804	0.805	0.041	19.741	0.000
SN_1 <- SN	0.728	0.725	0.055	13.277	0.000
SN_2 <- SN	0.870	0.870	0.028	31.418	0.000
SN_3 <- SN	0.914	0.913	0.019	48.265	0.000
SN_4 <- SN	0.842	0.841	0.046	18.233	0.000
SN_5 <- SN	0.912	0.910	0.019	47.008	0.000
SN_6 <- SN	0.890	0.888	0.029	30.578	0.000
SN_7 <- SN	0.733	0.733	0.057	12.806	0.000
USE_2 <- USE	0.886	0.882	0.043	20.419	0.000
USE_3 <- USE	0.854	0.853	0.030	28.097	0.000
USE_4 <- USE	0.900	0.894	0.038	23.851	0.000