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Assessing the willingness of rural homeowners to insure their homes in South Africa using multilevel modelling

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Originality Declaration

I hereby declare that this work, submitted for the degree Master of Science in Actuarial Science, at the University of the Free State, is my own original work and has not previously been submitted, for degree purposes or otherwise, to any other institution of higher learning. I further declare that all sources cited or quoted are indicated and acknowledged by means of a comprehensive list of references. Copyright hereby cedes to the University of the Free State.

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29 November 2023

Date

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Abstract

There has been an increase in urbanisation in the last decade as more South African seeks better work opportunities in the urban areas. Despite this notable increase, there are individuals who still prefer to build houses and reside in rural areas. There are reasons why people in South Africa have opted to invest in properties in rural areas. Firstly, the process to obtain land in rural areas is through a traditional leader or chief of the village (much easier than in the urban areas). Secondly, the cost of the land in the rural areas is significantly lower than the cost of land in the urban areas. As valid as these reasons are, they have drawbacks such as owners of the not having a title deed for their land and an accurate amount of the value of their land. This makes it difficult to insure these homes. The absence of a rural home insurance in South Africa that focuses on these rural homeowners fitting the description above was the driving force behind the need for this study. Literature thus far has been focused on agricultural and crop insurance in rural areas. This study will explore the challenges in the rural insurance market in South Africa and factors affecting the willingness of these rural residents to insure their rural homes.

Keywords: Short-Term Insurance, rural insurance, multilevel modelling

List of Abbreviations

AIC - Akaike Information Criterion
AIC - Akaike Information Criterion Corrected
ASISA - Association for Savings and Investment South Africa
BIC - Bayesian Information Criterion
BoP - Bottom of Pyramid
FCIC - Federal Crop Insurance Corporation
FSB - Financial Services Board
GDP - Gross Domestic Product
GIMAR - Global Insurance Market Report
IAIS - International Association of Insurance Supervisors
ICC - Intra-class Correlation Coefficient
IFRS - International Financial Reporting Standard
IMF - International Monetary Fund
KZN – KwaZulu-Natal
LTI - Long-Term Insurance
MLR - Multilevel Logistic Regression
NPICC - National People's Insurance Company of China
OLS - Ordinary Least Squares
P2P - Peer-to-Peer Insurance
PPPs - Public-Private Partnerships
SAM - Solvency Assessment and Management
SARDF - South Africa's Rural Development Framework
SAS - Statistical Analysis System
STI - Short-Term Insurance

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Chapter 1 - Introduction

1.1. Research Title

Assessing the willingness of rural homeowners to insure their homes in South Africa using multilevel modelling.

1.2. Problem Statement

There are notable differences in the ownership of land in rural areas compared to the ownership of land in urban areas are prevalent. In an urban area, a title deed serves as a form of evidence that you own a particular piece of land, but the same cannot be said about the rural area. Instead, land in the rural areas is allocated to residents through the Tribal Authority. The Tribal Authority could be the king, a prince, a chief or a destined traditional leader of the village. Despite this difference, residents still seek ownership of land in rural areas and build homes, as they still find comfort in these areas. When residents build homes in rural areas, the properties are either funded through a personal loan acquired from a local bank or self-funded through savings or pension. Some of these properties are not insured. One can raise the issue that these properties are not insured as they do not meet the necessary underwriting criteria that speak to properties in the urban areas, or the residents are not willing to insure their homes. To simply assume of unwillingness amongst rural homeowners to insure their homes can be misleading. Therefore, it is necessary to perform a study to assess the willingness of rural homeowners to insure their homes.

1.3. Research Questions

The research study is underpinned by the following research questions:

- What are the factors that affect the willingness of rural homeowners to insure their homes?
- How can a comprehensive home insurance policy be designed for rural dwellers in South Africa?

1.4. Background

We encounter situations in which we must decide whether to take part in a particular activity or not. Our decision is mainly driven by the risk attached to each possible outcome. Risk can be defined as the uncertainty that an event will occur that could result in financial losses. To minimise the impact of unlikely events, risk management strategies such as risk avoidance, risk reduction, risk transferring and risk acceptance are employed (Enyinda et al., 2010). As the name suggests, risk avoidance entails avoiding taking risks altogether. While risk reduction is about finding ways to mitigate the effects of risk. On the other hand, risk acceptance is accepting risks attached to a particular event and taking the necessary measures to plan for these risks. Lastly but most importantly, risk transferring is reducing one's exposure by passing on all or some risk to another party. Insurance forms part of the risk-transferring strategy. In simpler terms, insurance is a contractual agreement between two parties. Mbonane (2018) points out that in this agreement the insured party (the insured) consents to give the other party (the insurer) a set sum of money known as the premium either on a monthly, quarterly or an annual basis in return for cover against a specified set of risks. The fundamental assumption of insurance is the sharing or spreading of risks to return the insured party to as close to his original position as is reasonably possible. makes an analogy of insurance as a prestige umbrella. An umbrella that offers protection from the intense tropical sun or acts as a covering against rain. One with an umbrella is better off than someone without one. The analogy is meant to illustrate how being insured puts you in a better position than not being insured should an uncertain event occur. Beyond putting an individual in a better position, insurance promotes economic activity by protecting people and property from dangers that can be insured. Insurance increases your chances of overcoming unforeseen circumstances like natural disasters that are beyond your control. The insurance offering in South Africa can be divided into two, namely, long-term and short-term insurance. Long-term insurance is mainly focused on life-changing events such as critical illness, retirement and death. On the other hand, car insurance, building insurance, home content insurance, movable possessions insurance and rural insurance form part of short-term insurance. Rural insurance is insurance designed for the rural populace. This form of insurance is subdivided into crop insurance, poultry and livestock insurance or rural home insurance. Within the South African insurance industry, much work has been done for insurance policies that are agri-orientated such as crop and livestock insurance, but little can be said about rural comprehensive home insurance.

1.5. Objectives of the Study

The objectives of the study are as follows:

- **Main Objective**: Performing a study that will assess the willingness of rural homeowners to insure their homes in South Africa using multilevel modelling.
- **Sub Objective**: Determining practical solutions that could help improve the rural home insurance industry.

1.6. Importance of the Study

This study aims to contribute to the current literature in South Africa and serve as a building block ensuring that the South African rural insurance market is developed. There are two main areas in which the study is significant: academic motivation and business motivation.

1.6.1. Academic Motivation

While there is some literature focused on agricultural and crop insurance in Africa, hardly any considers the South African situation (Mbonane, 2018). Therefore, this study serves to contribute significantly to South African literature that is focused on rural insurance.

1.6.2. Business Motivation

Most of the attention in the rural insurance market has gone into crop and animal insurance, with less attention going toward determining if full coverage for rural homes is necessary. This study seeks to shift that attention to comprehensive rural home insurance. Thereafter, possible solutions will be recommended on how the insurance offering for rural homeowners could be designed. By achieving this, the proposed offering could encourage rural landowners to invest in building properties that meet the necessary criteria to be insured. Ultimately, this research study could assist policymakers and rural insurance companies in identifying key economic and social determinants of rural insurance consumption across different parts of South Africa.

1.7. Limitations of the Study

A solid foundation for any study's literature review is referencing prior research material. The South African rural insurance industry is its earliest days of development so there is not much literature available. The lack of prior research material has been viewed as an opportunity for the sector to advance, nevertheless.

1.8. Importance of the Study

The structure of the thesis will be made up of seven chapters.

In **Chapter 1** we introduce the topic of the study and detailed background of the study.

In **Chapter 2** we provide a summary of the topic's essential points and discuss the relevant literature for the study.

In **Chapter 3** we explain the area of the study, sampling techniques, data collection and methodology in detail.

In **Chapter 4** we outline the results and findings.

In **Chapter 5** we discuss the implications of the results.

In **Chapter 6** we outline a possible rural home insurance product that could be developed for the rural market.

In **Chapter 7** we make recommendations from the study and the advances made through the work above are summarised.

Chapter 2 - Literature Review

2.1. Introduction

A variety of topics are covered in the literature review for this study. We have opted to employ a top-down approach for the structure of the literature review.

Figure 1: Overview of the Literature Review

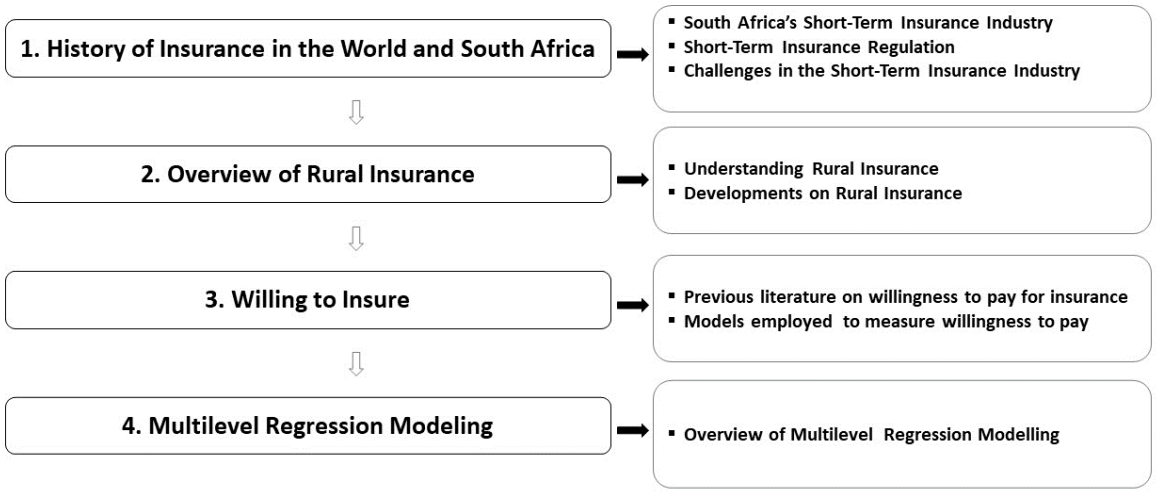


Figure 1 shows that the literature review of this study comprises of two main sections. The first section highlights the origin of insurance in the world and South Africa. This section outlines the development of regulations, the history of short-term insurance in South Africa and the difficulties the country's short-term insurance market has faced.

The second section shares literature on the overview of rural insurance both in the world and South Africa. Thereafter, South Africa's rural insurance market is compared to other nations in the world that have been invested in rural insurance. Finally, a summary of the past literature that is focused on the willingness to pay for rural insurance.

2.2. Origin of Insurance

The history of insurance goes all the way back to the ancient past. Babylonian and Chinese traders recorded the first insurance policies in antiquity. According to Masci (2011), Chinese traders came up with a strategy to safeguard themselves against cargo losses due to storms, pirates, or any other maritime mishaps. The merchants dispersed their goods across several ships to diversify their risks because they reasoned that anything that could sink or otherwise damage one ship in a single day wouldn't do the same to an entire fleet travelling over several days (Whit, 2022).

One of the first methods of insurance was described in the Code of Hammurabi, which was written circa 1750 BC, through a practice known as bottomry. According to Masci (2011), bottomry was defined by the Code of Hammurabi as a loan from A to B with the understanding that, should the voyage be successful, B would repay the loan plus a premium at a rate determined in the contract; if the voyage failed, A would forfeit both the loan and the premium and be left with nothing but the empty bottom of the ship. In addition to covering the risk of loss, A's premium had to be high enough to pay interest on the advance (Masci, 2011). The guilds, or associations of merchants, first formed as worker fraternities and took on the responsibility of protecting their members from fire and shipwrecks as well as providing appropriate assistance or burial in cases of illness, famine, or death as trade spread throughout Europe (Masci, 2011). The Danish guilds of the eleventh century stipulated that the entire organization was to reimburse a fellow brother for losses he suffered from shipwrecks, thefts, fires, or cattle burglaries (Masci, 2011). One characteristic of the guilds was the proximity of its members. People could get to know each other's traits and personalities because of proximity. This meant that adverse selection (i.e., when persons who pose a high risk cannot be distinguished from those who pose a low risk) and moral hazard (a potential difference in behaviour between a party shielded from risk and one that is fully exposed to it) were not a major issue. Proximity also allowed people to observe one another and learn more about each other. These precautionary measures are now features of a modern-day system known as mutual insurance.

According to (Masci, 2011), The Great Fire of London, which left approximately 100 000 people homeless and destroyed more than 13 000 homes, gave the fire insurance industry in England a significant boost. This led to the establishment of the first legitimate insurance firm in 1667 (Masci, 2011). A century later, the first insurance fund using actuarial and life expectancy calculations was established by two churches in Scotland. This fund was established using

premiums and was invested profitably. As a result, the return on investments would be used to pay the insurance recipients (Ferguson, 2009). Throughout the eighteenth century, insurance's reach expanded and the classification of risks emerged in the 1830s (Masci, 2011). Around 1840, the life insurance industry had a boom, in 1845, accident insurance started to become popular in Europe and liability insurance was subsequently introduced in 1876 (Masci, 2011). More types of insurance were developed and as a result, insurance was born in other nations, driven by countries with more experience.

2.2.1. South Africa's Short-Term Insurance Industry

The South African insurance industry began to grow when British rule over the Cape Colony began in the early 1800s (Alhassan, 2016). The British control made it easier for British businesses and residents to enter, which made insurance necessary (Alhassan, 2016). The first insurance brokers to offer any form of insurance (fire insurance) in the Cape of Good Hope were Alexander MacDonald and John Houghton. During the first week of August in 1806, the Phoenix Assurance Company of London appointed them (Alhassan, 2016). In the next 30 years, more than five British insurers penetrated the Cape Colony. The Zuid- Afrikaansche Brand en Levensversekering Maatschappij was established in Cape Colony as the first South African insurance firm in December 1835. The South African Mutual Life Assurance Society was established in 1845, ten years after this and it was modelled after the Scottish Equitable Mutual Life Assurance Society (now known as Old Mutual). By 1861, the insurance industry was still expanding, with over twenty companies operating in the Cape Colony (Alhassan, 2016). Following the discoveries of minerals in the late 1860s, many British businesses expanded into Johannesburg and insurance companies in Australia, the United States and New Zealand also looked to capitalise on the city's expanding urban populace and the mining industry's high risks. In the Cape alone, there were over fifty foreign insurance companies based by the year 1900 (Alhassan, 2016). The Council of Fire Insurance Companies, which is akin to the Fire Offices Committee of London, was established because of British dominance of the market (Alhassan, 2016).

It was in 1929 when businesses started submitting reports to the Registrar of Insurance and comprehensive statistics on the expansion of the insurance industry were accessible. The number of insurers in operation in South Africa rose from twenty-three to 176 between 1910 and 1950, a more than seven-fold increase. Over the same time, the percentage of domestic enterprises

compared to foreign companies increased from 39% to slightly over 50% (Verhoef, 2012). To provide more context on the size of the South African insurance industry and how it has grown in the past seven decades, Verhoef (2012) shared the contribution of short-term insurance (STI) and long-term insurance (LTI) premiums to gross insurance premiums from 1950 to 2000 in Table 1 below.

Table 1: Premiums of South Africa's short-term and long-term insurers

Years	Short-term		Long-term	
	Premiums (R ' mil)	% of Total Premium	Premiums (R ' mil)	% of Total Premium
1950	19	27,14%	51	72,86%
1960	75	35,71%	135	64,29%
1970	160	24,62%	490	75,38%
1990	7 580	25,79%	21 807	74,21%
2000	17 310	10,49%	147 747	89,51%

Source: Verhoef (2012), Alhassan (2016) and own compilation

Long-term (life) insurance has primarily dominated the South African insurance industry, as depicted in Table 1. At least 64% of the South African insurance market has been dominated by the long-term insurance sector since 1950. By 2000, approximately nine out of every ten insurers in South Africa were long-term insurers. This dominance of long-term insurers could be attributed to the increased demand for it. The affordable of life insurance products compared to short-term insurance products could be the reason for this dominance. For instance, one can get a funeral cover, but one can get car insurance for the same amount. Another important metric worth investigating is the number of insurers in South Africa. Tabulated below are the number of insurers in the South African insurance industry dating back to 1980.

Table 2: Insurers in the South African insurance industry

Years	Short-term		Long-term		Total Number of Insurers
	Primary insurers	Reinsurers	Primary insurers	Reinsurers	
1980	27	8	49	6	90
2000	86	7	62	3	158
2012	98	8	80	7	193
2014	97	7	74	7	185
2016	89	7	73	7	176
2017	88	7	72	7	174

Source: Verhoef (2012), Alhassan (2016) and own compilation

During the period 1980 to 2012, the number of insurance companies more than doubled from 90 in 1980 to 193 in 2012 (Verhoef, 2012). The main driver of this increase was the increase of short-term insurers from 27 to 98 in the respective period. In the last decade, there has been a decrease in the number of short-term insurers, from 98 companies in 2012 to 88 companies in 2017. The

number of reinsurers has been stable for both short-term and long-term insurance. In addition to the volume of premiums and several insurers, Ondruˇska et al. (2018) suggested the insurance penetration rate as another metric used to evaluate the success of the insurance sector. Okonkwo (2019) define insurance penetration rate to be a country's insurance premium as a percentage of its gross domestic product (GDP). As per the report titled "Emerging Markets: Growing Insurance and Challenges with a focus on Africa" compiled by Deloitte, the summary of South Africa's insurance penetration rate compared to the Sub-Saharan nations as of 2017 is depicted below.

Figure 2: South Africa compared to Sub-Saharan African nations

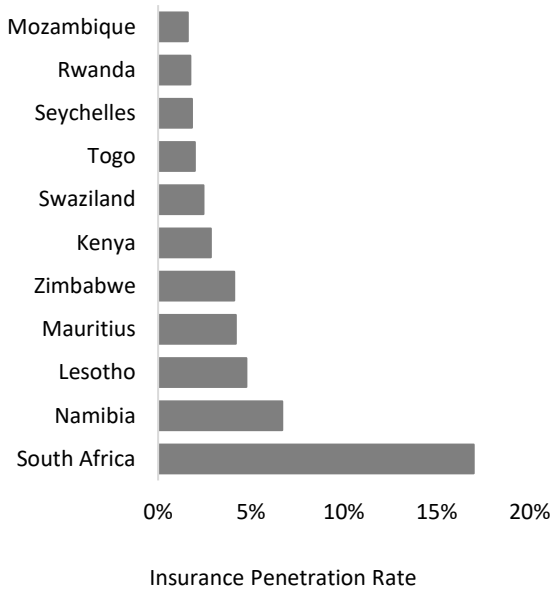
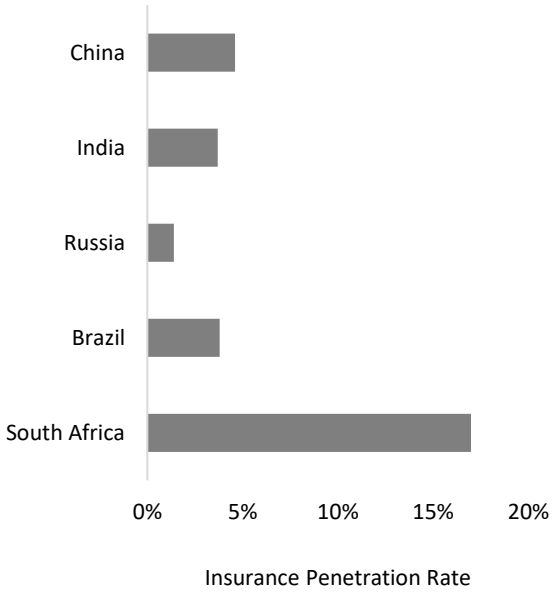


Figure 3: South Africa compared to BRICS nations

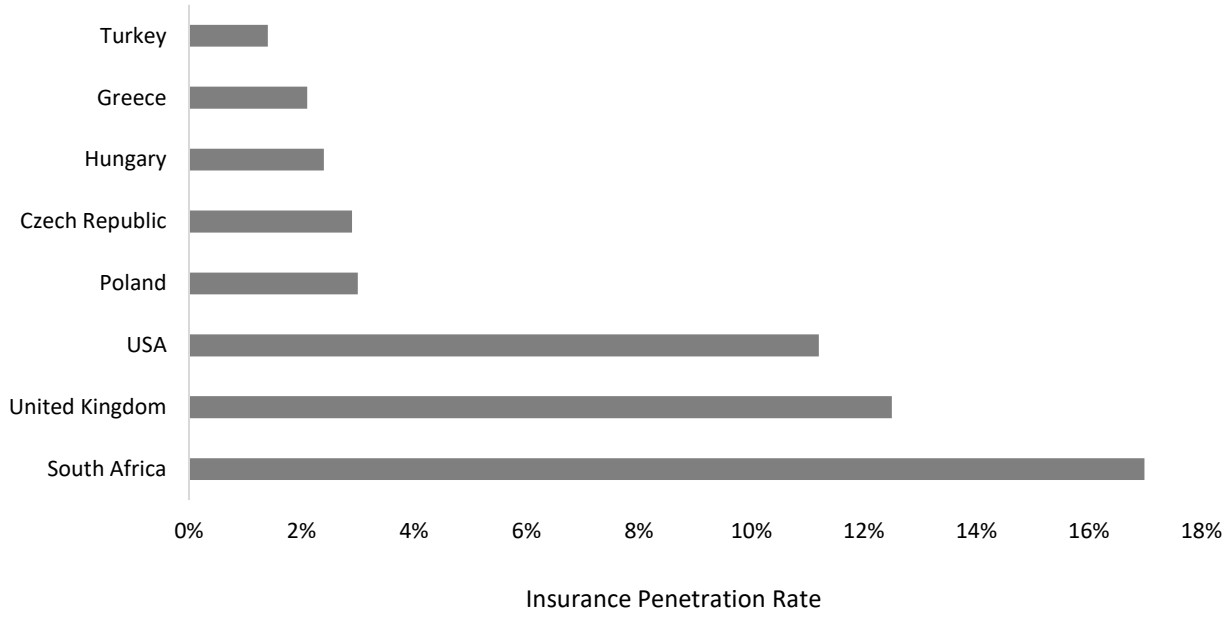


It is worth noting that South Africa's insurance penetration rate (16.99% as per 2017 numbers) is significantly better than the Sub-Saharan African countries (van der Merwe, 2018). In second place is Namibia with a penetration rate of 6.69%, which is below half of South Africa's rate. The main driver for the high overall insurance penetration rate in South Africa compared to their African counterparts is the high life insurance penetration rate.

Another driver is the ongoing development of the South African insurance industry by the entry of disruptive start-ups such as Naked's CoverPause, Pineapple and JaSure. Customers who use CoverPause can lower their premiums for days when they do not drive. JaSure is an insurtech that provides clients with on-demand insurance and Pineapple provides full personal insurance coverage through a scalable approach based on peer-to-peer lending. South Africa's insurance penetration remains higher even when compared to its BRICS counterparts. In second place is

China with a penetration rate of 4.60% and Russia has the lowest insurance penetration rate amongst the BRICS nations, with 1.40% which is more than ten times less than South Africa's penetration rate as per Statista numbers. Nerovnya (2018) flagged that Russia's low insurance penetration rate to the stagnant demand for insurance products. Figure 4 below shows South Africa's insurance penetration rate compared to the UK, the USA and some emerging markets in Europe as of 2017.

Figure 4: South Africa compared to the UK, the USA and EU emerging markets



South Africa's insurance penetration remains higher even when compared to the UK, the USA and some European emerging markets. The insurance penetration rates of the UK and USA are the closest to South Africa's insurance penetration. The UK and the USA reported an insurance penetration rate of 12.50% and 11.20% respectively as of 2017. On the other hand, European emerging markets such as Poland, Czech Republic, Hungary, Greece and Turkey reported insurance penetration rates below 4.00%. van der Merwe (2018) highlighted the following reasons as the potential drivers of low insurance penetration rates within emerging markets:

- Products offering similar benefits with complex terms and conditions that are not suitable to the market. For instance, a product suitable for the urban market is not guaranteed that it will perform the same in the rural area (van der Merwe, 2018). Socio-economic factors such as poor literacy and low income amongst potential clients have resulted in a lower than desired insurance penetration rate in South Africa (van der Merwe, 2018).

- van der Merwe (2018) added that a lack of trust between the insurers and potential customers is another driver for a low insurance penetration rate. An increase in the fraudulent claims, delays in payment of claims and poorly trained brokers has resulted in potential buyers having little to no trust in insurance companies.

- Lastly, insurance regulation has also contributed to the low insurance penetration within a country. For instance, the necessary administrative regulations that an insurer must undergo to register a company and later trade make entry to the industry a challenge.

2.2.2. Short-Term Insurance Regulation

Verhoef (2012) shared that in 1806, the Cape Colony appointed South Africa's first insurance agent. Thereafter, the regulation governing the South African industry underwent some historic changes.

Table 3: Historic changes in the South African insurance industry

Years	Milestone
1806	The Cape Colony's first insurance agent is appointed
1835	Establishment of the first native insurance company
1923	Passage of the First Union Insurance Act
1929	Mandatory filling and submission of returns to the Registrar of Insurance
1943	Passage of the Insurance Act No 27 of 1943
1980s	New Technological Advancements
1990	Passage of the Financial Services Act No 97 of 1990
	Establishment of the insurance department under the Financial Services Board (FSB)
1998	Long-Term Act 52 of 1998 and Short-Term Insurance Act 53 of 1998 were passed
2004	International Financial Reporting Standard of 2004 (IFRS 4)
2009	Introduction of the Solvency Assessment and Management (SAM) regulatory framework
2010s	Twin Peak Model
2013	The Rise of Insurtech
2017 onwards	International Financial Reporting Standard of 2017, Amendment to the Short-Term Insurance Act (IFRS 17) and Insurance Act of 2017

Source: Alhassan (2016), Chemhere (2019) and own compilation

Various initiatives have been taken to implement insurance regulation in South Africa. Prior to 1910, general mercantile law only included general insurance. Verhoef (2012) shared that the courts of the Orange Free State and the Cape Colony also applied English Insurance Law to life insurance cases, while the courts of Natal and the Transvaal did so under Roman-Dutch Law. The First Union Insurance Act of 1923 was the first piece of legislation to govern the insurance industry in South Africa. The Act combined elements of the legal framework for insurance markets in the UK, the USA and Canada to give foreign companies operating in South Africa the ability to provide

coverage for policies from their investments in their home countries (Verhoef, 2012). The Insurance Act No. 27, which was passed in 1943, brought about new improvements in the insurance market. Thereafter, in the early 1980s, the implementation of computer systems streamlined processes and simplified the administration of claims and policies. The government established the Melamet Commission, an inquiry commission that investigated the causes of the failure, in response to AA Mutual's closure in 1986. The Melamet study recommended increased financial services regulation (Verhoef, 2012). As a result, the Financial Services Board Act No. 97 of 1990 was passed and the Financial Services Board (FSB) was subsequently established. Alhassan (2016), the Insurance Act No. 27 of 1943 was replaced by the Long-Term Act 52 of 1998 and the Short-Term Insurance Act 53 of 1998 to keep the operations of long-term and short-term companies separate. The purpose of the Short-Term Insurance Act 53 of 1998 is to regulate certain short-term insurer and intermediary activities, as well as to make sure that short-term insurers are registered (Alhassan, 2016).

The new millennium saw a greater emphasis on market-wide prudential regulation. This was demonstrated by the introduction of the International Financial Reporting Standard (IFRS 4). IFRS 4 was established to provide guidance for the accounting of insurance contracts (Chemhere, 2019). The standard was made explicit that it covered the majority of financial guarantee contracts when it was updated in 2005 and released in March 2004 (Alhassan, 2016). Less than half a decade later, Solvency Assessment and Management (SAM) was established. The introduction of SAM allowed Solvency II to be adjusted to the South African market ensuring that local insurance market regulation would be brought up to par with international standards and a stable market will be encouraged to safeguard policyholders (Alhassan, 2016). In accordance with the SAM, the regulator aims to establish a framework for risk-based and group-wide supervision of the South African insurance market, which is supported by three pillars: quantitative requirements, risk and governance systems and reporting requirements (Alhassan, 2016).

The two thousand and tens saw the rise of insurtech which birthed start-ups with creative solutions that used technology to upend established insurance structures started to surface. Shortly after, the Twin Peaks was introduced after being first proposed in a 2011 policy "A Safer Financial Sector to Serve South Africa Better". Twin Peaks is a thorough and all-inclusive financial

industry regulation scheme. It aims to eliminate regulatory arbitrage and forum shopping, fix gaps in the regulatory framework and signify a clear departure from a disjointed regulatory approach.

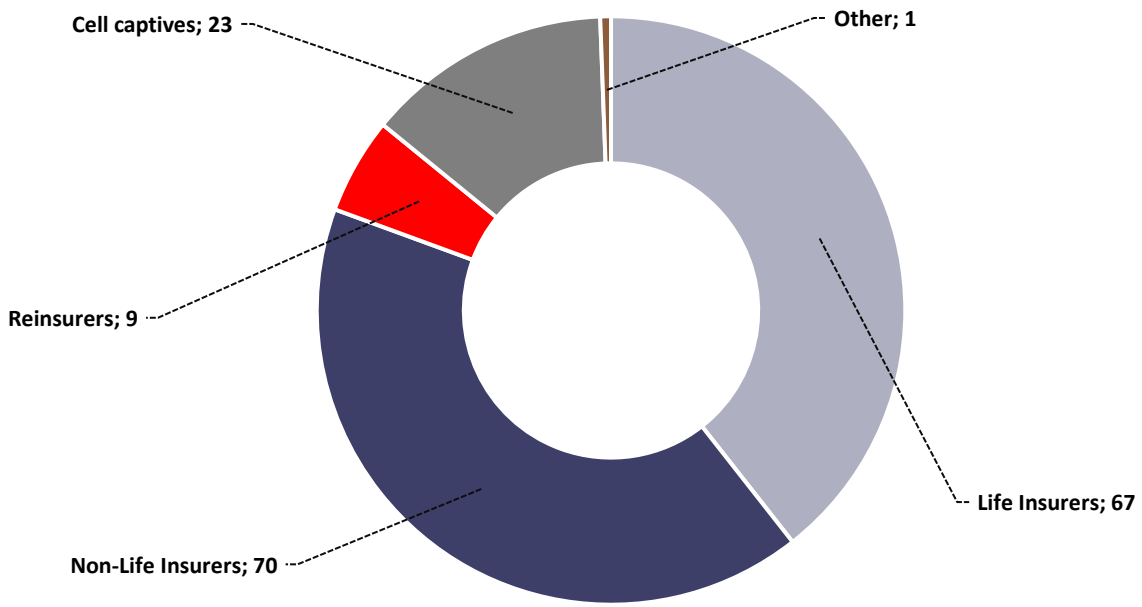
Thereafter, IFRS 17 was issued in May 2017 which was the first truly international standard for insurance contracts to replace IFRS 4 (Chemhere, 2019). IFRS 17 removed existing inconsistencies and paved the path for insurance to be able to apply consistent accounting principles for all insurance contracts (Chemhere, 2019). For instance, under IFRS 17, a multinational organisation can standardise how insurance contracts are measured across the group, making it simpler to compare outcomes by product and region. On 15 December 2017, amendments were made to the Short-Term Insurance Act of 1998 and became effective from 1 January 2018. Most of the changes made to the Short-term Insurance Act regulations concern the conditions under which an insurer may enter into a binder agreement, the rights and obligations of the insurer and the binder holder and the compensation that may be paid to the binder holder (Chemhere, 2019).

In 2021, the International Association of Insurance Supervisors (IAIS) released the tenth edition of the Global Insurance Market Report (GIMAR), which revealed that the total gross written premium worldwide was close to R129 trillion, which represented 7% of global economic activity. As of the end of 2021, the United States (USA) underwrote 38.1% of all premiums, with China (11.7%), the United Kingdom (UK), 6.7%, France (5.5%), Germany (5.4%) and Japan (5.3%), following in order. Although absolute numbers are instructive, it's also crucial to consider how much of a country's GDP this industry contributes to accurately gauge the contribution and significance of insurance to each nation's economy. In the USA, for instance, insurance accounts for 11.8% of GDP, while in some markets with much lower premium volumes, such as Great Britain (USD 399 billion), the industry's importance to the country's economy is larger, at a weight of 12%.

Although it is not evenly dispersed across Africa, reported in McKinsey's 2020 report titled "Africa's insurance market is set for take-off" revealed that Africa's insurance business is ranked amongst the top ten largest in the world. In monetary terms, it is valued at approximately R1.33 trillion in terms of gross written premium. The report points out that South Africa is the largest

and most established insurance market in Africa, accounting for 70% of all Africa's premiums. Furthermore, highlighted in the report is that approximately 54% of the premiums in Southern Africa are for life insurance which suggests that life insurance is the main insurance business in Southern Africa. The figure below shows the composition of the South African insurance industry as of 2018 as per IMF numbers.

Figure 5: South Africa's insurance industry as of 2018



Source: International Monetary Fund

In 2022, the IMF published a report which shared that the South African insurance industry accounts for 18.0% of South Africa's financial sector. As of 2018, there were a total of 170 insurance companies (67 life insurance, 70 non-life insurance, 9 reinsurers, 23 cell captives and 1 other). The top five insurance companies control 72% of the life insurance market and 48% of the non-life (general insurance, short-term insurance like house and auto insurance) market, suggesting that the business is still largely concentrated in the life insurance sector.

2.2.3. Challenges in the Short-Term Insurance Industry

Despite the evident growth in the South African insurance market, according to Alhassan (2016), there are challenges that the stakeholders in the South African short-term insurance market must deal with such as regulatory requirements and internal challenges. Insurers are faced with the challenge of complying with regulatory requirements. For instance, the International Financial Reporting Standard (IFRS), which mandates investments in systems and procedures and the SAM implementation preparation have increased the cost burden on insurance operations (Alhassan, 2016). Internally, short-term insurers are dealing with ongoing increases in operational costs items, mostly due to worse claims experience (Berg, 2014). Even though insurers are in the business of reducing risk, insurance companies frequently face risk in the form of fraudulent claims.

The Association for Savings and Investment South Africa (ASSIA) reported in 2022 that life insurers in South Africa had found 4 287 fraudulent claims worth a total of R787.6 million (ASISA, 2022) . This has led to insurers being more cautious and stricter terms and conditions for their customers which could later result in customer discontent. Moreover, if customers feel their needs and expectations have not been met by an insurer or service provider, it results in customer dissatisfaction. This usually has a snowball effect, with multiple things going wrong one after the other. In addition to the challenges mentioned above, one further difficulty for insurers in South Africa has been penetrating the underserved rural market.

2.2.4. Demand of Insurance

Literature from Lowe (1942), Cole et al. (2013), Levine et al. (2016), Atreya et al. (2015) and Moreno et al. (2017) have contributed to the literature focusing on the determinants of demand for insurance policies. These literature highlights factors such as the price of the insurance product, a person's risk appetite, salary level and finally educational level and financial literacy as the determinants of demand for insurance policies.

Price of Insurance

According to Lowe (1942), the Law of Supply and Demand states that an increase in the price of a commodity typically leads to a fall in demand and an increase in supply sooner or later. On the other hand, a price decrease tends to, sooner or later, raise demand while reducing supply. Atreya

et al. (2015) examined the variables affecting Georgia homeowners' decisions to purchase flood insurance. His research demonstrated a negative correlation between flood insurance pricing and demand. Levine et al. (2016) suggests that a price reduction improved the penetration of health insurance in Cambodia.

Risk Appetite and Salary Level

One of the reasons cited in studies by Platteau et al. (2017) and Salleh et al. (2018) for why people buy insurance products is the fear of uncertainty and risk aversion. An insurance product is viewed as a catastrophe prevention technique that people take to lessen their exposure to risks and uncertainty (Kelikume, 2022). Cole et al. (2013) reveals that people who are more risk-averse have more insurance demand. According to F. M. Moreno et al. (2017), understanding of consumer behaviour suggests that consumers are more likely to purchase more goods as their salary level rise. In the same vein, Cole et al. (2013) reported that households with more disposable income purchase rainfall insurance at a higher rate. However, other homeowners believe that their present resources will be sufficient to cover any losses in the event of an accident, thus they would rather go without insurance (Kelikume, 2022).

Education Level and Financial Literacy

Another key factor in the demand for insurance is education level. In general, educated people might be better knowledgeable of the dangers of having inadequate or no insurance. As a result, these people tend to demand more insurance than others with less education (Atreya, 2015). The same applies to financial literacy, individuals with better than average financial literacy tend to demand more insurance. Evidence from Bannier et al. (2016) revealed that there is a significant positive correlation between one's financial literacy and demand for insurance.

2.3. Overview of Rural Insurance

2.3.1. Understanding Rural Insurance

There is no one, agreed-upon definition for the terms “rural” and “rural area”. Researchersand academics have varied ideas about what rural areas are. According to Ward (2009), rural areas are characterised by tradition over modernity, agriculture over industry, nature over culture and changelessness over dynamism. Chigbu (2013) argued that this assertion is not fully accurate. Chigbu (2013) raised that every rural area experiences some sort of change, whether it is a shift in land use, population, economics, or social factors. For instance, the agriculture industry sector in South Africa, which is mostly based in rural areas has been instrumental in the increase in GDP of South Africa over the years. Another misleading assumption is that rural dwellers are poor, uneducated and disadvantaged. This is false because there are some rural places that are both wealthy and impoverished. The Niger Delta region of Nigeria is an excellent illustration of a rural area that is home to oil wealth (Chigbu, 2013). These communities are still impoverished, despite being wealthy locations. This demonstrates that poverty and riches may coexist inrural places and that these two conditions can exist side by side (Chigbu, 2013). The National Treasury (2011a) cited South Africa’s Rural Development Framework (SARDF) of 1997, which provided two definitions of rural areas. According to the first description, rural areas are those that are sparsely populated for their size and where the primary source of income for residents is agriculture. In many of these places, there are villages and small towns spread out over a large area. According to the second definition of the SARDF of 1997, rural areas are areas in which most households rely on remittances and social assistance from the government to survive. For this study, the definition of a rural area combines the definitions mentioned above into an area that is sparsely populated, on the outskirts of urban area with traditional authority.

2.3.2. Developments on Rural Insurance

Beyond the South African borders, Argentina is one of the first countries to explore rural insurance. The history of rural insurance in Argentina dates to more than a century ago, followed by the USA and Russia being the last country to explore rural insurance in the list of countries provided in the table below (Harfuch, 2021). Harfuch (2021) highlighted that there are three distinct periods in the history of rural insurance in China. The National People's Insurance Company of China (NPICC), a state entity that organized and marketed insurance goods through local governments, was solely responsible for the first one, which ran from 1982 to 2002 (Harfuch, 2021). The poor demand for insurance products, however, was brought on by the high loss ratio, which resulted in a decline in premiums collected between 1992 and 2002. Between 2002 and 2007, China's second era of rural insurance was characterised by a series of pilot projects launched in different provinces, now with a substantial premium subsidy structure, while private insurers operated the policies (Harfuch, 2021). Post 2007, the third era, China's rural insurance market has experienced tremendous growth. The table below presents countries' rural insurance systems when they started and the main insured products.

Table 4: Characteristics of rural insurance in the World

Country	History	Co-insurance	Insured Products	Government Interventions
Argentina	Started in 1874	No	Forestry, Agriculture, Livestock	Private
USA	Started in 1938	No	Forestry, Agriculture, Livestock	Public - Private Partnership
China	Started in 1982	No	Forestry, Agriculture, Livestock	
Brazil	Started in 1954	No	Forestry, Agriculture, Livestock	
India	Started in 1972	No	Agriculture, Livestock	
Russia	Started in 1993	Yes	Agriculture, Livestock	

Source: Agroicine - Rural Insurance Around the World and Alternatives for Brazil

The most common insured products in the rural insurance market are agricultural- oriented products such as crops, forestry and livestock. Amongst the countries mentioned in the table above, public-private partnerships (PPPs) are typically used to organise rural insurance (Harfuch, 2021). The primary tactic employed by PPPs is to absorb a portion of the premium in the form of an economic subsidy.

In America

Harfuch (2021) shared that the only country among the selected few where governmental subsidy schemes are non-existent is Argentina's rural insurance market structure. Argentina uses a strictly private system among the countries examined in the table above. In the USA, the origin of rural insurance is rooted in crop insurance. Following the aftermath of the Great Depression (1929 to 1939) and the Dust Bowl (1930 to 1936), the USA government introduced crop insurance through the Federal Crop Insurance Corporation (FCIC) as a measure to assist agriculture to cover.

In India

In India, the history of rural insurance is rooted in agriculture. Locals would join to help one another out after crop failure or natural calamities. During the 19th century, the idea of rural insurance started to take shape in the contemporary period (Harfuch, 2021). In addition to covering crops, rural insurance also includes coverage for livestock and rural homes and properties.

In Russia

Like India, in Russia, agriculture has a long history of being the foundation of rural insurance. Russia has the youngest rural insurance system with a different approach to other countries tabulated in Table 4. A co-insurance system has been used in Russia in which insurers join forces to form a pool of insurers with the intention of spreading out of risks, reducing information asymmetry and lowering transaction costs.

In South Africa

The history of rural insurance in South Africa also stems from crop insurance, which was first implemented as a pooling plan in Piketberg, Cape Town, in 1916. Thereafter, farmers

in the Eastern Free State established a Society for the purpose of crop insurance in 1929. This society eventually evolved into Sentra-Oes (Raghuvanshi, 2008). Sentra-Oes was established in 1970 after the program underwent numerous changes over the years (Raghuvanshi, 2008). Since then, the offering of rural insurance remains to be limited to agriculture. In a developing nation such as South Africa, a subsidy option would not be financially feasible since more than a third of South Africa's population are rural dwellers. On the other hand, the success of a co-insurance system is based on the experience and knowledge pool of insurers. Despite the increase in insurance penetration in South Africa, there is little development of rural insurers and rural insurance penetration from existing insurers that would enable insurers to join forces to form a pool of insurers that addresses this penetration issue in the rural market.

2.4. Willingness To Insure

It is evident that rural insurance is still within its early developmental stages both in the World and in South Africa. Existing challenges in the traditional insurance market do not make insurance penetration into rural areas any easier. This has prompted researchers to investigate whether the rural populace is willing to pay for insurance. A study by Tian et al. (2015) investigated the factors affecting people's willingness to pay for earthquake insurance in rural China. Tian et al. (2015) performed regression analysis using a probit and tobit model to look at the farmer's need for earthquake insurance. In their study, Tian et al. (2015) found that farmers who shared personal characteristics, like age, gender and educational level, have a big impact on the demand for earthquake insurance. Also, the socioeconomic components of the farmer, such as government propaganda aimed at reducing earthquakes, were a significant contributing factor in this study by (Tian, 2015).

Another study by Wang et al. (2012) focused on rural insurance in China and highlighted the insurance experience and disaster experience of rural homeowners as dominated factors that affect the overall acceptance of disaster insurance. Within a healthcare context, Mathiyazaghan (1998) assessed the willingness to pay for rural health insurance

in India. The results of the study suggested that the family size, occupational status and education level of the participants were significant in determining the willingness to pay for rural health insurance (Asgary, 2004).

Asgary et al. (2004) performed a similar study in Iran with the aim of estimating rural households' willingness to pay for health insurance. Asgary et al. (2004) results agreed with Tian et al. (2015) and Mathiyazaghan (1998), highlighting the age and educational level of the participants as significant factors in determining the willingness to pay for rural health insurance. In addition to these factors, Mathiyazaghan (1998) also shared that village general characteristics such as geographical location, village population and access to piped water or telephone also proved to be significant variables (Asgary, 2004). On the other hand. Asgary et al. (2004) deemed family size, income level and employment status of the participants to be insignificant in determining the willingness to pay for rural health insurance.

A study by Onwujekwe (2010) which focused on the willingness to pay for community-based health insurance in Nigeria shared different findings to the literature previously mentioned. Contrary to Asgary et al. (2004) findings about family size being an insignificant factor in determining the willingness to pay for insurance, Onwujekwe (2010) paper indicated that family size is a significant variable in determining the willingness to pay for health insurance. In addition, the geographical location and socio-economic status of the participants also proved to be significant variables. In another study within Africa that focused on the willingness to pay for community-based insurance in Burkina Faso, Dong et al. (2003) highlighted that the gender, age and marriage status of the participants are significant in determining the willingness to pay for insurance.

But results from Dong et al. (2003) disagreed with the results from Mathiyazaghan (1998) study. Dong et al. (2003) flagged the occupation status as being insignificant in determining the willingness to pay for insurance. The table below shows past literature that has accessed the willingness to pay, their area of study and the method or methods used to predict the willingness to pay.

Table 5: Previous literature and method used

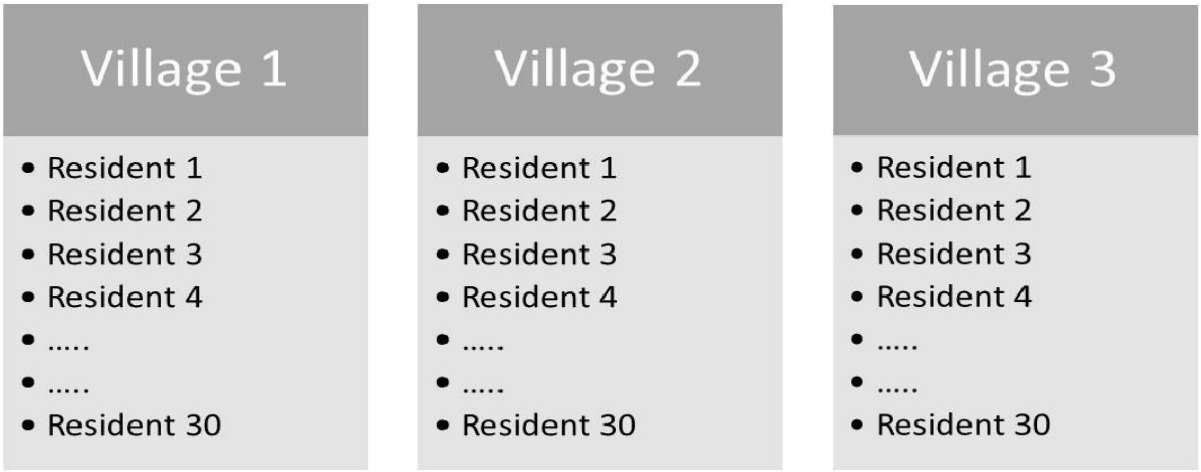
Author	Area of Study	Method Used
Tian et al. (2015)	China	Probit and Tobit Model
Wang et al. (2011)	China	Logistic Regression Model
Mathiyazaghan (1998)	Karnataka State, India	Logit Model
Asgary et al. (2004)	Iran	Ordinary Least Squares (OLS) Linear Regression
Onwujekwe (2010)	Nigeria	Full and reduced log OLS Regression Model
Mbonane (2018)	Swaziland	Probit Regression Model
Netusil (2021)	United States	Interval Tobit Model
Batbold (2021)	Mongoli	Logit Model and Ordinary Least Squares
Dong et al. (2003)	Burkina Faso	Logistic Regression Model
Azhar (2018)	Malaysia	Logistic Regression Model
Gulseven (2020)	Turkey	Logistic Regression Model

In assessing the willingness to pay for insurance in the previously mentioned studies, the willingness of individuals was treated as a binary variable (1 for willingness to pay and 0 for not willing to pay). From the past literature considered in the table above, often a logistic regression model has been employed in predicting willingness to pay.

2.5. Multilevel Regression Modelling

Multilevel models have been more prevalent during the past three decades in a variety of research domains, including education and health (Bryk & Raudenbush, 1987); (Raudenbush & Bryk, 2002)). Wang et al. (2011) recommended these models are ideal for hierarchically structured data. Below is an example of data structures in which multilevel modelling could be used.

Figure 6: Hierarchical data structure



In education, multilevel models have been used to assess learners nested within schools and in health, patients are nested within different hospitals. For this study, we will assess rural residents nested within different villages. For example, rural residents are members of their villages, organisations and communities. When assessing a resident's characteristics, characteristics of the villages or communities must be taken into consideration. Dash (2023) and Wang et al. (2011) raise the following advantages when using multilevel modelling for a study with a hierarchical structured data:

1. Clustered data can be inferred more accurately using multilevel modelling.
2. In the presence of longitudinal data, multilevel models can be extended to examine the change over time.
3. Multilevel modelling does not require the assumption of observation independence because it is intended to quantify and account for the intra-class correlation (ICC) in hierarchically structured data.

Some limitations of using multilevel modelling for a study with hierarchically structured data are noted below:

1. Wang et al. (2011) adds that it happens frequently that higher level units or groups be chosen out of convenience rather than at random from a pre-defined population (Wang, Haiyi, & Fisher, 2011). In these circumstances, extrapolating model parameter estimates to other groups may be inaccurate (Wang, Haiyi, & Fisher, 2011).
2. Due to the simultaneous modelling of result variance at the micro and macro levels, multilevel models are more sophisticated than ordinary regression models (Wang, Haiyi, & Fisher, 2011). As a result, the number of model parameters may increase, making the model less parsimonious (Wang, Haiyi, & Fisher, 2011).

2.5.1. Multilevel Logistic Regression

Under multilevel modelling, there is a subsection referred to as multilevel logistic regression modelling. Multilevel logistic regression (MLR) modelling uses several independent variables to predict a binary outcome. Wong (1985) highlighted that for the purpose of analysing data with group structure and a binary response variable, a multilevel logistic regression model is suggested. The specification is at both levels and the group structure is determined by the presence of micro-observations (Level 1 variables) contained within macro-observations (Level 2 variables). The regressors are the same across contexts, however, the micro regression coefficients can differ (Wong G. &., 1985). As shown by the past literature in the previous sub-section, the most common method to predict willingness to pay is a logistic regression model. Therefore, this study will employ a multilevel logistic regression model for assessing the willingness of rural homeowners to insure their homes.

2.6. Summary

The chapter is divided into four sections: the origin of insurance, an overview of rural insurance, willingness to insure and multilevel regression modelling. The first section outlines South Africa's short-term industry, short-term insurance regulation and its challenges and the determinants of the demand for insurance. The second section highlights the overview of rural insurance and the development of rural insurance in South Africa and other countries. The third section summarises previous literature that has focused on assessing willingness to insure in the short-term insurance industry and the models that have been employed to measure willingness to insure. Lastly, the fourth section provides a summary of the benefits and limitations of using multilevel regression modelling for hierarchically structured data.

Chapter 3 - Methodology

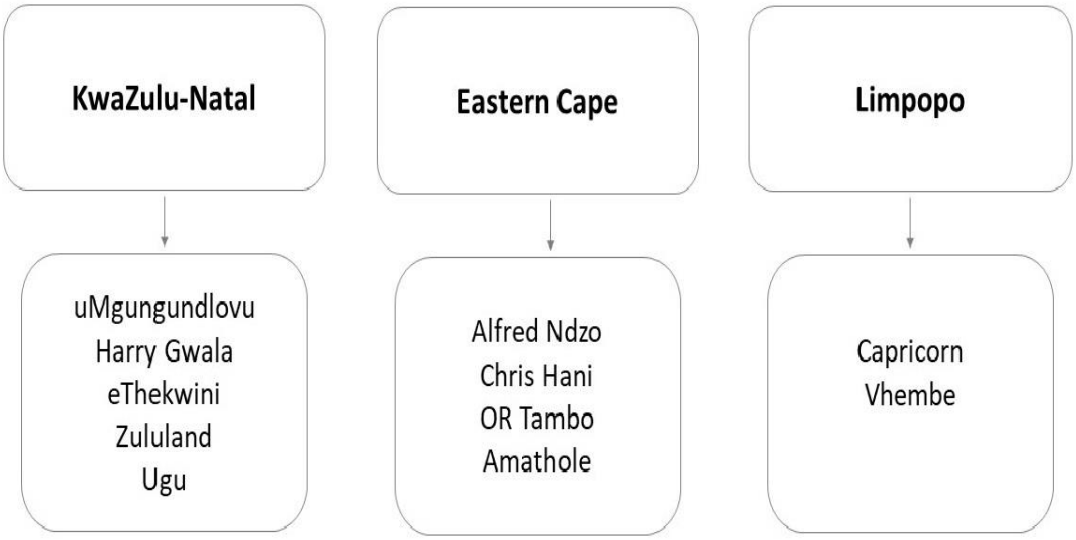
3.1. Introduction

This chapter outlines the methodology of this study. The chapter is subdivided into six sections: namely, area of the study, sampling methodology, ethical consideration, data collection, data variables and data analysis. The study will cover participants in rural areas within three provinces in South Africa, namely Limpopo, Eastern Cape and KwaZulu-Natal (KZN). The second section then discusses the sampling technique and the sample size of the study. The third section outlines that this study has adhered to the relevant ethical standards. The data collection sub-section outlines when the data was collected, how it was collected by whom. In addition, this section highlights the data collection issues the researcher encountered in the data collection process and they were addressed. The data variables sub-section highlights the dependent variable and the independent variables of the study. The dependent variable is the willingness of rural homeowners to insure their homes. The independent variables are divided into two, the rural resident variables and the village variables. Thereafter, the last section of the chapter describes the data analysis of the study. The data analysis will be split into two. The first part will focus on investigating how the dependent variable varies across the independent variables. The second part will fit the multilevel logistic regression model, assess the variables that are significant in the model and propose the final model that will be used to estimate the willingness to insure homes amongst rural homeowners.

3.2. Area of the Study

The study will cover participants in rural areas within three provinces in South Africa, namely Limpopo, Eastern Cape and KwaZulu-Natal (KZN). Figure 7 shows the three provinces that were under consideration for the study with their respective districts.

Figure 7: Provinces and their districts for the study



The eThekwini metro, uMgungundlovu, Harry Gwala, Zululand and Ugu districts were taken into consideration for the KZN province. Alfred Ndzo, Chris Hani, OR Tambo and Amathole districts were taken into consideration for the Eastern Cape province. Capricorn and the Vhembe district were taken into consideration for the province of Limpopo. Villagers from each of the districts were sampled.

3.3. Sampling Methodology

In a quest to use a sampling technique that is inexpensive and simple, convenience sampling was used for this study. Acharya (2013) defined convenience sampling as a non-probability technique in which the sample is selected based on the investigator's convenience. Acharya (2013) added that the choice of respondents depends on who is present at the appropriate time and place. After deciding on the sampling technique for a study, the appropriate sample size was the next crucial decision that must be made. Fitzner et al. (2010) argued that if the sample size is too small, it will be unable to reliably answer the research questions posed or test the research hypotheses. On the other hand, if the sample is too large, it can take time to get the results. To ensure an appropriate sample size was used, a power analysis was performed before the study to determine the appropriate sample size for the study. Fitzner et al. (2010) shared that a hypothesis, the difference between the true proportion and the suggested proportion in the null hypothesis, a significance level, effect size and the power size are needed in determining the sample size through power analysis. Claim statistics from short-term insurer Santam show that 33% of the homes in South Africa are underinsured, i.e. (H0: $\boldsymbol{\rho_o}$ = 0.33). The significance level ($\boldsymbol{\alpha}$) for the analysis was set at 5%. The difference between the true population proportion ($\boldsymbol{\rho}$) and the suggested proportion in the null hypothesis ($\boldsymbol{\rho_o}$) were set to 6%. A large proportion of past literature on power analysis has recommended a power of the test ($\boldsymbol{1-\beta}$) ranging between 80% and 90% (Fitzner & Heckinger, 2010). For this study, the power of the test was set at 90%. The effect size can be calculated as follows:

$$Effect\ Size\ (ES) = \frac{\rho - \rho_o}{\sqrt{\rho(1-\rho)}} = \frac{0.06}{\sqrt{\frac{1}{3}\left(1-\frac{1}{3}\right)}} = 0.1276$$

The effect size is 0.1276 and the sample size (n) can be calculated using the formula below:

$$Sample\ Size = \frac{\left(z_{1-\frac{a}{2}} + z_{1-\beta}\right)^2}{ES^2} = \frac{(1.96+1.28)^2}{0.1276^2} = 645.33$$

Initially, the proposed sample size for this study was estimated to be 645. During the collection data, there was low participation and limited resources to reach the target of 645, the final sample size for the study is 353 participants from a total of 28 villages.

3.4. Ethical Considerations

This study received ethical approval from the General/Human Research Ethics Committee of the University of the Free State. The ethical clearance number is UFS HSD2023/0409/3. All participants were informed about the consent form that included detailed explanations of the study's objectives and data confidentiality.

3.5. Data Collection

The survey was conducted in three provinces, EC, KZN and Limpopo between 26 June 2023 and 31 July 2023. The data was collected through questionnaires administered by the interviewer in a face-to-face setting, namely, the rural resident questionnaire and the village questionnaire. The questionnaires targeted rural residents who own homes in rural areas and their respective villages.

The rural resident questionnaire highlighted the socio-demographic characteristics, affordability of insurance and degree of knowledge of the rural residents about rural insurance. For example, the rural resident questionnaire includes questions such as "What is your highest level of education?", "What is the total estimated value of the property?" and "Would you sign up rural home insurance for your property?". The village questionnaire focused on the characteristics of each village, the surrounding area of the village and the proximity of each village to the urban area. For example, the village questionnaire includes questions such as Are the properties in the village built in a mountainous area? and how far is the village from the nearest town?

To increase the amount of information appropriate for this study, a lot of time and effort was put into reorganising the data. The following data collection issues were noted:

Refusal to participate

Some participants refused to participate in this research study purely because they were no form of compensation or benefit for them.

Participant withdrawal

The withdrawal rate from the participants of the study was minimal. While interviewing some participants, a total of five participants withdrew from the study. Reasons for withdrawal were driven by questions regarding monthly salary and education level. These participants raised concerns that these two questions were personal. These participants were omitted from the study.

Misunderstanding of the study objectives

Despite the researcher explaining the aims and objectives of the study, there were some participants who perceived the study as a way for the researcher to sell rural home insurance rather than a research study. This led to non-participation.

Missing and incorrect values

A total of 16 participants who did not complete their questionnaire. These participants were excluded from the study. Some participants entered incorrect values. For example, the rural resident questionnaire required the participants to input the name of their village and district and some participants did not complete this section. For entries with missing district names, the researcher used the village names to populate the district name. Moreover, some participants entered the name of the local municipality they reside in instead of district names, these were correct accordingly.

Multicollinearity

The linear relationship between two or more variables is referred to as multi-collinearity. (Alin, 2010) described multi-collinearity as an issue that could seriously undermine the

validity of the model parameter estimates. The larger a coefficient's standard error, the less probable it is to be statistically significant in a regression, according to Allen (1997), all other things being equal. Makhura (1994) added that if a variable is removed, the significance level of the coefficients of the remaining variables rises, indicating that the variable is a collineated variable. In Chapter 4, a correlation matrix will be constructed to assess if there is multicollinearity amongst the variables of the study. After addressing the data collection issues mentioned above, there were entries that had missing values and incorrect values that were omitted from the study resulting in a final sample size of 317 participants.

3.6. Data Variables

The influence of a village and resident-related factors on residents' willingness to sign up for rural home insurance will be analysed using multilevel modelling. For ease of reference, we use the notation "i" indexes for residents and "j" indexes for villages.

3.6.1. Dependent Variables

Participants were asked if they would be willing to insure their home which the dependent variable, later referred to as $Willing_{ij}$. The dependent variable is binary, meaning that the variable of interest takes the form of a 0 or 1 (yes or no).

3.6.2. Independent Variables

Guided by previous literature from Moreno (2017), Atreya (2015) and Bannier (2016), independent variables that will be considered are age, gender, education level, employment status, financial literacy and insurance awareness. In addition, village characteristics such as the estimated number of households in a village and the proximity of a village to national roads and urban areas.

Table 6: Rural resident and village variables

Rural Resident Variables	Village Variables
Age of the Resident	Name of the Village
Gender of the Resident	Name of the District
Education Background of the Resident	Proximity to Road
Employment Status	Proximity to Urban Areas
Monthly Salary	Number of Households in Village
Household Budget	Forest in Village
Missed Bills	Mountains in Village
Missed Loan Payments	Province
Financial Adviser of the Resident	
Financial Knowledge of the Resident	
Kind of Insurance Policies	
Number of Insurance Policies	
Claiming Experience	
Claiming Frequency	

Rural resident variables

Table 7: Rural variables and their descriptions

Variable	Short Variable	Description
Resident Age	Age_i	Age of the resident
Resident Gender	$Gender_i$	Gender of the resident
Education Background	$EduLevel_i$	Education background of the resident
Employment Status	$EmpStat_i$	Employment status of the resident
Monthly Salary	$Salary_i$	Monthly salary of the resident
Household Budget	$Budget_i$	Monthly budget of a household
Budget Utilisation	$BudgetLimit_i$	How often you say within monthly budget
Missed Bills	$MBill_i$	Number of missed bills per month
Missed Loan Repayment	$MLoan_i$	Number of missed loan repayments per month
Financial Advice	$FinAdv_i$	Source of financial advice for the resident
Financial Knowledge	$FinKnow_i$	Financial Knowledge of the resident
Insurance Policyholder	$Insurance\_i$	Is the resident an insurance policyholder
Kind of Insurance Policies	$KPolicy_i$	Kind of insurance policies the resident has
Number of Insurance Policies	$NPolicy_i$	Number of insurance policies the resident has
Claiming Experience	$ClaimExp_i$	The claiming experience of the resident
Claiming Frequency	$ClaimFreq_i$	Number of claims the resident has claimed
Value of Property	$Value\_i$	Total estimated value of the property
Building Material	$Material_i$	Material used to build the property
Registered Builder	$Builder_i$	Was the property built by a registered builder
Insurance Cover	$Cover_i$	What would you cover your property against

Table 8: Rural variables – Continuous variable

Variable	N	Mean	Std Dev	Minimum	Maximum
$FinKnow_i$	318	6,78	1,26	4,00	10,00

Table 9: Rural variables – Categorical variables

Variable	Category	Frequency	Percentage
Age_i	18 - 30	27	8,52%
	31 - 43	93	29,34%
	44 - 56	118	37,22%
	57 - 65	79	24,92%
Age_i	Female	163	51,42%
	Male	154	48,58%
$EduLevel_i$	No Matric	21	6,62%
	Matric	53	16,72%
	Degree / Diploma	157	49,53%
	Postgraduate Degree (Honours, Masters, or PhD)	86	27,13%
$EmpStat_i$	Full-time employed	256	80,76%
	Part-time employed	27	8,52%
	Seasonal employed	10	3,15%
	Unemployed	24	7,57%
$Salary_i$	R 0 - R10 000	46	14,51%
	R 10 001 - R 20 000	67	21,14%
	R 20 001 - R 30 000	87	27,44%
	R 30 001 - R 40 000	71	22,40%
	R 40 001 - R 50 000	26	8,20%
	R 50 001 or more	20	6,31%
$Budget_i$	No	85	26,81%
	Yes	232	73,19%
$BudgetLimit_i$	Almost always	88	27,76%
	Always	40	12,62%
	Never	10	3,15%
	Sometimes	94	29,65%
	Not applicable	85	26,81%
$MBill_i$	No	283	89,27%
	Yes	34	10,73%
$MLoan_i$	No	237	74,76%
	Yes	80	25,24%
$FinAdv_i$	Advice from financial adviser	129	40,69%
	Advice from friend or family	158	49,84%
	Internet	17	5,36%
	Magazines or Newspapers	1	0,32%
	Other	10	3,15%
	Radio or Television	2	0,63%
$Insurance_i$	No	29	9,15%
	Yes	288	90,85%
$NPolicy_i$	0	29	9,15%
	1	100	31,55%
	2	144	45,43%
	3	35	11,04%
	4 or more	9	2,84%
$ClaimExp_i$	No	165	52,05%
	Yes	152	47,95%
$ClaimFreq_i$	0	176	55,52%
	1	78	24,61%
	2	38	11,99%
	3	14	4,42%
	4 or more	11	3,47%
$Value_i$	R 0 - R 250 000	57	17,98%
	R 250 001 - R 500 000	125	39,43%
	R 500 001 - R 750 000	84	26,50%
	R 750 001 or more	51	16,09%
$Material_i$	Concrete brick	180	56,78%
	Face brick Concrete brick	108	34,07%
	Face brick	23	7,26%
	Mud Concrete brick	1	0,32%
	Other	2	0,63%
	Wood Concrete brick	3	0,95%
$Builder_i$	No	197	62,15%
	Yes	120	37,85%
$Cover_i$	All the above	218	68,77%
	Cover against natural disasters	14	4,42%
	Cover against theft only	0	0,00%
	Not applicable	85	26,81%

A proportion of 37.22% of the participants of the study were aged between 44 - 56 years, followed by 29.34% of the participants between 31 - 43 years and only 8.52% of the participants were aged 30 or younger. The gender of the participants split was almost even with 51.42% represented by females and 48.58% represented by males. When looking at the education level, approximately half of the participants have a degree or diploma and 27.13% have postgraduate studies (Honours, Masters, or PhD) then the remaining quarter either has Matric or No Matric. The employment numbers showed that 80.76% (256 out of 317) of the participants are full-time employed and 7.57% (24 out of 317) of the participants are unemployed.

The income levels suggest that a large proportion of the participants earn between R 10 000 to R 40 000 per month. Only 46 out of 317 participants earn R40 000 or more. A proportion of 73.19% (232 out of 317) claimed to have a monthly budget for their respective households. Of those with a budget, 128 out of 232 claimed to always or almost always stay within the monthly budget and the remaining 104 participants indicated that they sometimes or never stay within their monthly budget. When observing whether the participants have missed monthly bills and missed loan payments in the past year, 10.73% claimed to have missed two or more bills in the past year. On the other hand, more than double this (25.24%) claimed to have missed two or more loan payments in the past year.

The participants of the study rely on their financial advisers or family and friends for financial-related matters. A proportion of 49.84% claim to receive advice from friends or family, while 40.69% receive advice from a financial adviser and the remaining on the internet, magazines, newspapers, radio or television for financial advice. Approximately 9 out of every 10 participants claim to have some form of insurance. Within those with insurance, a large proportion of the participants have 1 or 2 insurance policies and suggest that they have claimed in the past year. When considering the estimated value of the properties of the participants, 39.43% of the participants suggested a worth

ranging between R 250 001 - R 500 000 for their property. Thereafter, a proportion of 62.15% suggested that their properties were not built by a registered builder or constructor. Finally, when looking at the nature of cover that the participants would be interested in, 68.77% suggested that they would cover their property against natural disasters and theft and only 4.42% would take cover against natural disasters only.

Village variables

Table 10: Village variables with long description

Variable	Short Variable	Long Description
Province	$Province_j$	Name of the province in which the village is located
Proximity to Road	$ProxR_j$	Proximity of village to national, regional, or municipal road
Proximity to Urban	$ProxU_j$	Proximity of village to urban areas
Number of Households	$NHouse_j$	Estimated number of households in village
Forest in Village	$Forest_j$	Checks whether properties are built near a forest
Mountain in Village	$Mountain_j$	Checks whether properties are built on mountainous area

Table 11: Village variables with basic statistics

Variable	Category	Frequency	Percentage
$Province_j$	EC	125	39,43%
	KZN	134	42,27%
	Limpopo	58	18,30%
$ProxR_j$	Below 1 kilometer	102	32,18%
	1 - 3 kilometers	132	41,64%
	3 - 5 kilometers	26	8,20%
	More than 5 kilometers	57	17,98%
$ProxU_j$	Below 10 kilometers	83	26,18%
	10 - 20 kilometers	110	34,70%
	20 - 30 kilometers	79	24,92%
	More than 30 kilometers	45	14,20%
$NHouse_j$	Less than 100	5	1,58%
	100 – 300	21	6,62%
	300 – 500	38	11,99%
	More than 500	253	79,81%

A total of 125 rural homeowners in EC took part in the study, 134 from KZN and 58 from Limpopo. A proportion of 32.18% have built their homes at most 1 kilometre from a regional or national road. Moreover, for the participants under consideration in the study, more than half (60.88%) have built their homes no more than 20 kilometres from the urban areas.

3.7. Data Analysis

In many social, health and medical research investigations, binary measures such as “yes” vs. “no,” “success” vs. “failure” are perhaps the most widely used as outcome indicators (Wang M. S., 2011) For such binary outcomes, Wang et al. (2011) suggest that a multivariate logistic regression model is utilised. The variable under investigation ($Willing_{\mathrm{ij}}$) will be shown to vary for each of the other independent variables. For this study, the analysis of the data will be divided into two, namely, descriptive statistics and multilevel logistic regression. The descriptive statistics will present the willingness to insure homes across rural resident variables. For instance, how the willingness varies between income levels and employment status. The multilevel logistic regression will model the probability of residents taking rural home insurance. The multilevel models in this study will be fitted with SAS PROC GLIMMIX. Wang et al. (2011) highlighted that a multilevel logistic regression can be expressed in two levels, namely Level 1 variables (rural resident variables) and Level 2 variables (village variables). Singer (1998) suggested the following steps when compiling a two-level logistic regression model:

- **Step 1**: The base model will be introduced. After obtaining the base model, the intra-class correlation coefficient (ICC) will be calculated. The ICC is used to determine whether there is a need to use multilevel modelling for this study’s analysis. Literature by Aguinis (2015) and Ukoumunne (2002) have indicated that a high ICC (usually more than 0.10) suggests that there is a need for multilevel modelling. As recommended by Merlo (2006), the formula to calculate the ICC is shown below:

$$ICC = \frac{Within\ variation}{Within\ variation + \frac{\pi^2}{3}}$$

- **Step 2**: The base model will incorporate the village variables. The village variables will be assessed their statistical significance (Ene, 2021).

- **Step 3**: The rural resident variables will be added to the base model and their statistical significance will be assessed (Ene, 2021).

- **Step 4**: The model created in Step 3 with rural resident and village variables will be supplemented (Ene, 2021).

- **Step 5**: The final model will be displayed and evaluated against the earlier ones.

For illustration purposes, suppose we consider two Level 1 variables, namely, Age_i and $Gender_i$ and two Level 2 variables, namely, $ProxR_j$ and $ProxU_j$ for the study. Then the Level 1, Level 2 and the combined model equations are expressed below:

Equation 1: Level 1 variable equation

$$\eta_{ij} = \log\left(\frac{\rho_{ij}}{1-\rho_{ij}}\right) = \beta_{0j} + \beta_{1j}Age_i + \beta_{2j}Gender_i + e_{ij}$$

η_{ij} represents the log odds of signing up for insurance for a rural resident i from village j, β_{0j} is the intercept or the average log odds of signing up for insurance at village j, X_{ij} is the resident-level predictor for a rural resident i in village j and β_{1j} represents the slope associated with X_{ij} which shows the relationship between the resident-level variable and the log odds of signing up for insurance (Ene, 2021).

Equation 2: Level 2 variable equations

$$\beta_{0j} = \gamma_{00} + \gamma_{01}ProxR_j + \gamma_{02}ProxU_j + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

Singer (1998) refers to γ_{00} as the overall intercept representing the overall mean of all the residents, $u_{0j} \sim N(0, \tau^2)$ and $e_{0j} \sim N(0, \sigma^2)$ (Ene, 2021). Then substitute the Level 2 equations into the Level 1 equation to get the combined model (Ene, 2021).

Equation 3: Combined equation

$$\eta_{ij} = \gamma_{00} + \gamma_{10}Age_i + \gamma_{20}Gender_i + \gamma_{01}ProxR_j + \gamma_{02}ProxU_j + u_{0j} + e_{ij}$$

3.8. Summary

This chapter outlined the study's methodology. Six components make up this chapter: the study area, sampling technique, ethical considerations, data collection, data variables and data analysis. The research will encompass individuals living in rural regions throughout three South African provinces: KwaZulu-Natal (KZN), the Eastern Cape and Limpopo. For the KZN province, the districts of eThekwini metro, uMgungundlovu, Harry Gwala, Zululand and Ugu were considered. For the province of the Eastern Cape, Alfred Ndzo, Chris Hani, OR Tambo and Amathole districts were taken into consideration. For the province of Limpopo, Capricorn and the Vhembe area were taken into consideration.

Convenience sampling was chosen for this investigation to employ a low-cost, straightforward sample strategy. Convenience sampling is a non-probability strategy where the sample is chosen according to the convenience of the investigator (Acharya, 2013). The study's sample size consists of 317 individuals from 28 different villages. The University of the Free State's General/Human Research Ethics Committee granted ethical permission for this project. The number for the ethical approval is UFS HSD2023/0409/3. A consent form outlining the goals of the study and the confidentiality of the data was signed by each participant.

The study considered villages in the three provinces namely, EC, KZN and Limpopo and the study was conducted between June 26 and July 31, 2023. The interviewer used two face-to-face questionnaires to collect data: the rural resident questionnaire and the village questionnaire. Data collection issues during the data collection process included participant withdrawal, refusal to participate and misinterpretation of the study's goals.

To provide more understanding of the variables of the study, the dependent and independent variables are described in detail. Lastly, the chapter shares that the data analysis will be split into two. The first part will focus on a data analysis of the variables. The fitted multilevel logistic regression model's findings will be the main topic of the second section. The multilevel models in this study will be fitted with SAS PROC GLIMMIX.

Chapter 4 - Results

This chapter is presented in two sections, namely, a descriptive analysis of the key study variables and a multilevel logistic regression model. The descriptive analysis will investigate the willingness to insure across the rural resident and village variables. Thereafter, a build-up to the final regression model will be presented in five models. Model 1 will the base model with no Level 1 and 2 variables. Model 2 will be the base model with Level 1 variables and Model 3 will be the base model with Level 2 variables. Model 4 will present the base model with both Level 1 and 2 variables and the most significant variables will be investigated. Finally, Model 5 will be a final model with Level 1 and 2 variables that have been identified as important in estimating the willingness of rural homeowners to insure their houses. These two sections will assist in answering the following questions and hypotheses.

Questions:

- In which province was the highest willingness to insure rural homes reported?
- Does willingness to insure rural homes differ across the employment status and education level of the rural residents?
- Does the willingness to insure rural homes differ across the estimated value of the homes?

Hypotheses:

- The education level of rural homeowners is instrumental in determining their willingness to insure their rural homes.
- Salary level has no impact on determining the willingness of rural homeowners to insure their homes.
- Insurance awareness is significant in determining the willingness of rural homeowners to insure their homes.
- The proximity to national roads and urban has no significant impact on the willingness of rural homeowners.

4.1. Data Analysis of Variables

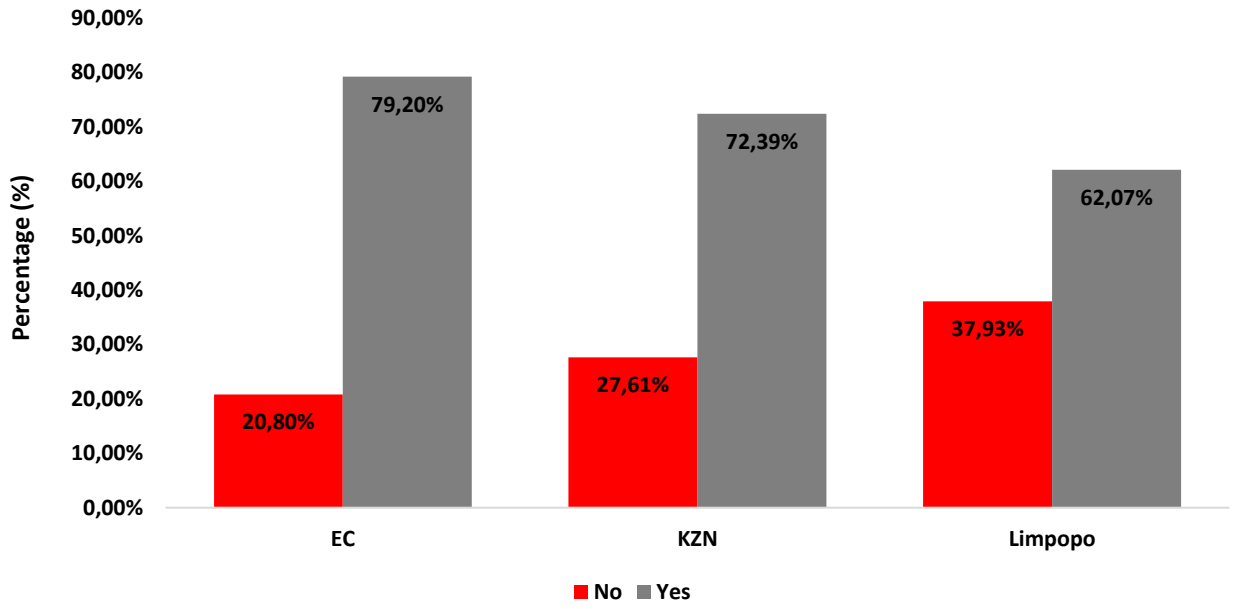
In this subsection, we investigated the willingness to insure across some rural resident and village variables such as province, education level, monthly salary, employment status, insurance awareness, claiming experience, proximity to road and proximity to urban areas to assess any notable trends. Thereafter, the dependent variables are dichotomised and reconstructed into binary variables to make them ideal to be incorporated in the multilevel logistic regression model in the second section of this chapter.

The results of the study indicated that 73.19% of respondents (232 out of 317) indicated they would be prepared to insure their homes, indicating that those living in rural areas were willing to do so.

4.1.1. Willingness across Provinces

The figure below shows the willingness of rural homeowners to insure their homes across the three provinces under the study.

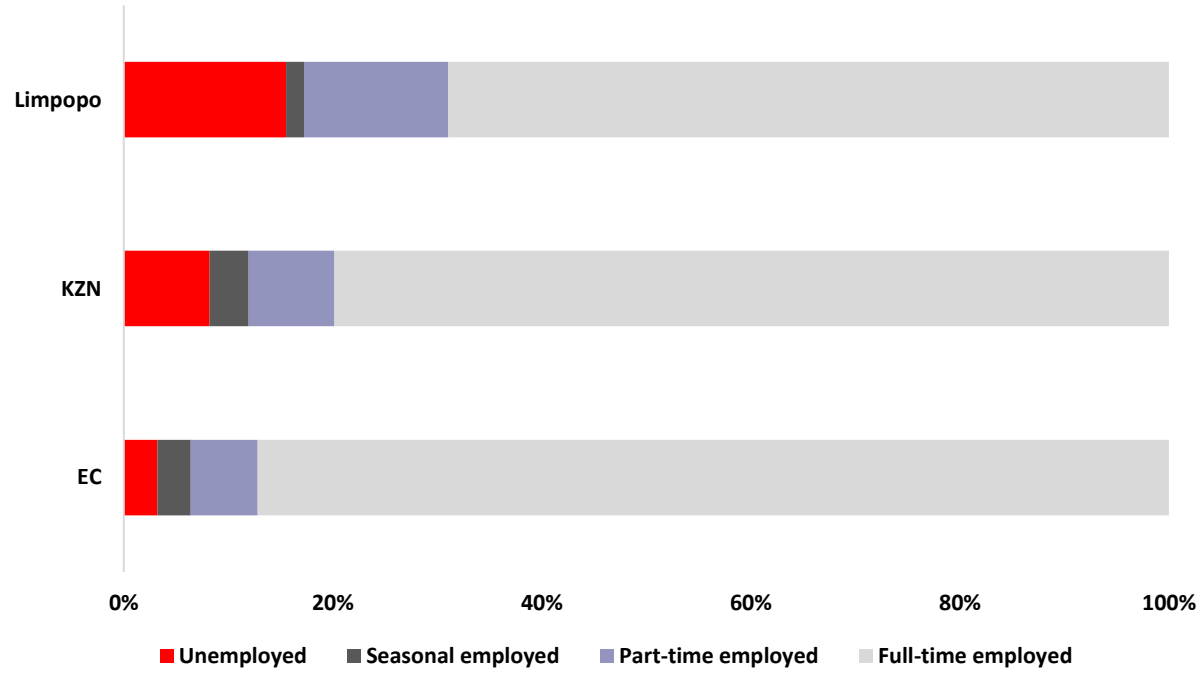
Figure 8: Willingness across provinces



The highest willingness to insure their homes was recorded in the EC province followed by KZN and the Limpopo province. A proportion of 79.20% of the rural residents who participated in this study in the EC would be willing to insure their homes. In KZN and Limpopo, 72.39% and 62.07% of the rural residents who participated in the study indicated that they would be willing to insure their rural homes. The main driver of the high willingness within the EC could be a result of the high-income earners and more stable workforce in the province and villages that are near the urban areas. The same reasons could be true for the KZN province, but one must take into consideration that during the time of the data collection, there was a tornado in KZN. This could have translated into participant's fear, resulting in high willingness to insure amongst residents in the KZN province. Moreover, Malatji (2020) highlighted that the low willingness to insure rural homes of residents could be attributed to the high unemployment rate and low literacy levels within the Limpopo province. Figure 9 depicts the employment status numbers across the three provinces.

4.1.2. Willingness across Employment Status

Figure 9: Employment status per province



Within our study sample, the highest unemployment numbers were reported in the Limpopo province followed by the KZN and EC. It is worth noting that our employment numbers depicted above agree with Malatji (2020) findings about the high unemployment rate in Limpopo. In Limpopo, 15.52% of the participants of the study are unemployed, 13.79% are part-time employed and 68.97% are full-time employed. Illustrated in Table 12 below is the willingness of the participants of the study across their employment status.

Table 12: Willingness across employment status

Employment Status	Actual Numbers			Proportion		
	No	Yes	Total	No	Yes	Total
Unemployed	14	10	**24**	58,33%	41,67%	**100.00%**
Part-time employed	13	14	**27**	48,15%	51,85%	**100.00%**
Seasonal employed	3	7	**10**	30,00%	70,00%	**100.00%**
Full-time employed	55	201	**256**	21,48%	78,52%	**100.00%**
Total	85	232	**317**	26,81%	73,19%	**100.00%**

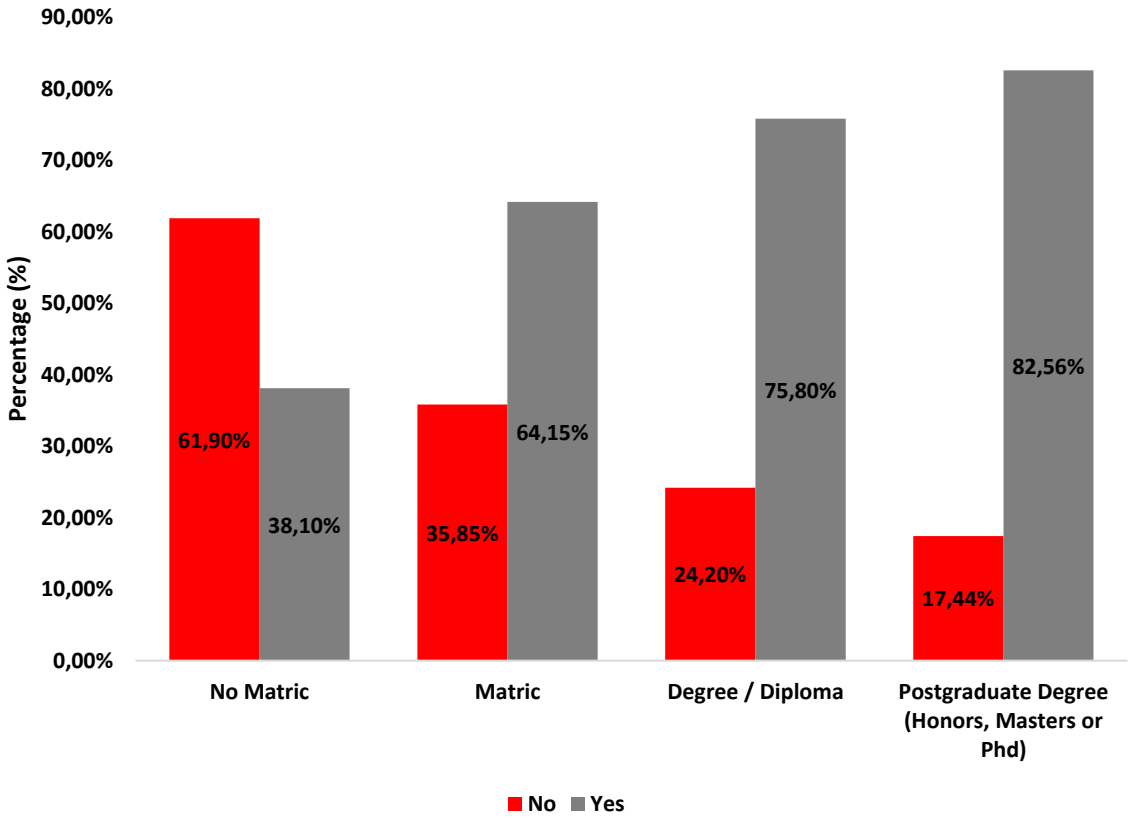
Table 12 shows that the more secure participants are with their employment status, the more likely they are willing to insure their homes. Amongst the unemployed participants, 41.67% (10 out of 24) suggested that they would be willing to insure their homes. Understandably so, one would not be willing to commit to paying for insurance monthly without any form of income. For the part-time employed and seasonal employed, the willingness is significantly better than the unemployed participants. The highest willingness was recorded amongst the participants who are full-time employed with 78.52% (201 out of 256) indicating that they would be willing to insure their homes.

4.1.3. Willingness across Education Level

The key takeaway from Figure 10 is that the willingness to insure increases with the rural resident's education level. For rural residents with No Matric, only 38.10% would be willing to insure their rural homes and 64.15% for the rural residents with Matric. This significant difference between the sub-categories shows the importance of education level is evident when comparing the willingness to insure. For rural residents with a degree or diploma, the

willingness to insure is 75.80% and 82.56% with a postgraduate degree would be willing to insure their rural homes.

Figure 10: Employment status per education level



4.1.4. Willingness across Insurance Awareness and Claiming Experience

The data analysis of the insurance awareness variable shows a low insurance penetration rate across the short-term insurance products, while there is a higher insurance penetration rate for the long-term insurance products. In our sample, 90.85% of the participants (288 out of 317) have an insurance product whether be it life insurance or short-term insurance. Of those with insurance, 47.92% (138 out of 288) have both life insurance and car insurance, which could be life insurance products ranging from life cover, funeral policies and informal burial societies. A proportion of 40.28% of the participants (116 out of 288) have life insurance, only 7.99% have some sort of home insurance or home content insurance and 2.43% have car insurance only. Figure 11 illustrates the claiming frequency of the participants who indicated that they currently have insurance and Figure 12 shows the willingness to insure across the claiming experience of the participants. A proportion of

55.47% (76 out of 137) of the participants with insurance suggested that they have claimed once in the past year and 44.53% (61 out of 137) suggested that they have claimed at least twice in the past year.

Figure 11: Participant's claiming experience

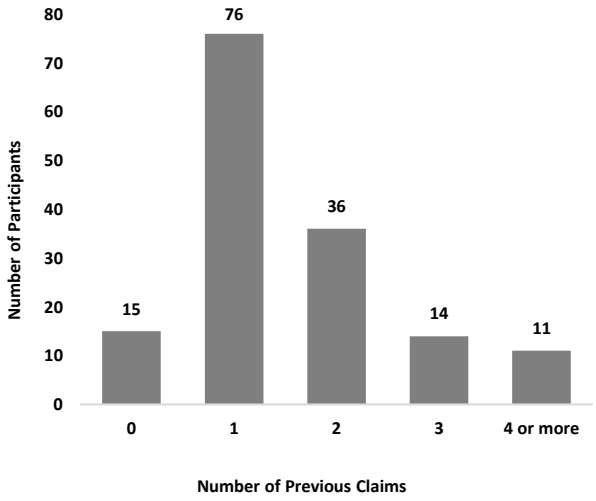
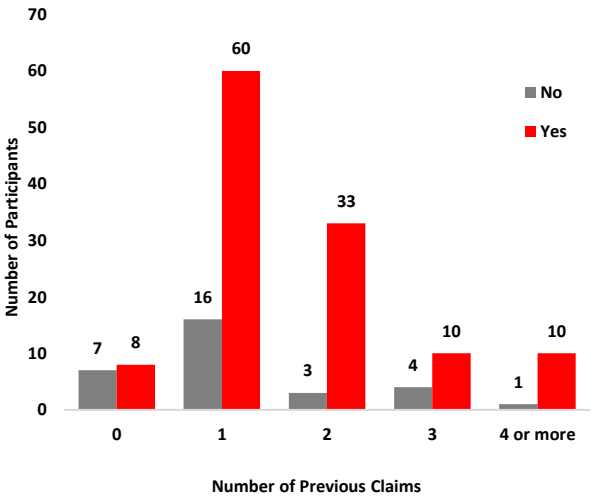


Figure 12: Willingness across claiming experience



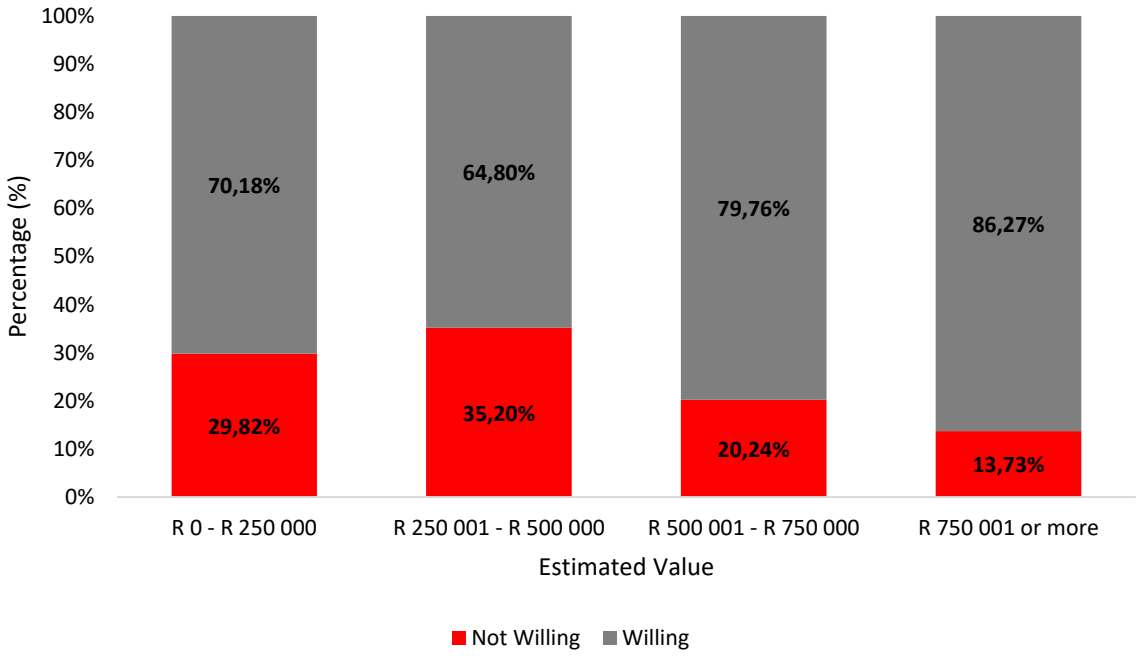
Moreover, it is worth noting Figure 12 illustrates the participants who have claimed in the past year have a higher willingness to insure homes compared to those participants who have not claimed in the past year. Of those participants who have claimed once in the past year, 78.95% (60 out of 76) suggested that they would be willing to insure their homes. Of those participants who have claimed once in the past year, 53.33% (8 out of 15) suggested that they would be willing to insure their homes. The high willingness of the participants with some claiming experience could be a result of participants understanding the value of having insurance, having experienced the benefit of it.

4.1.5. Willingness across Estimated Value

As more South Africans look to metropolitan regions for greater employment possibilities, there has been an increase in urbanisation during the past ten years. Even with this noticeable rise, some people still favour home construction and rural living for various reasons. Amongst these reasons are that in rural area property owners do not pay rates and levies for their

property and the crime levels are significantly lower in rural areas compared to urban areas. When considering the relationship between a homeowner's willingness to insure their home and the estimated value of their property, it is fair to make the pre-empted conclusion that there is a positive correlation. In simpler terms, the higher the value of the house, the more likely that the owner of that house would be willing to insure it. Figure 13 below illustrates the willingness of rural homeowners across the estimated value of their properties.

Figure 13: Willingness across estimated value



The rural homeowners with houses valued between R 250 001 to R 500 000 have shown the lowest willingness rate, with only 64.80% of the participants in this category to insure their houses. Those who own houses valued at R 500 001 or more show increased willingness to insure and those above R750 001 even more so. Understandably, in the event of a loss because of a natural disaster, it would be easier to replace a house valued at R 200 000 compared to one valued at R 900 000. However, it is worth noting that as the estimated value of the rural houses increases, the willingness to insure their rural homes also increases.

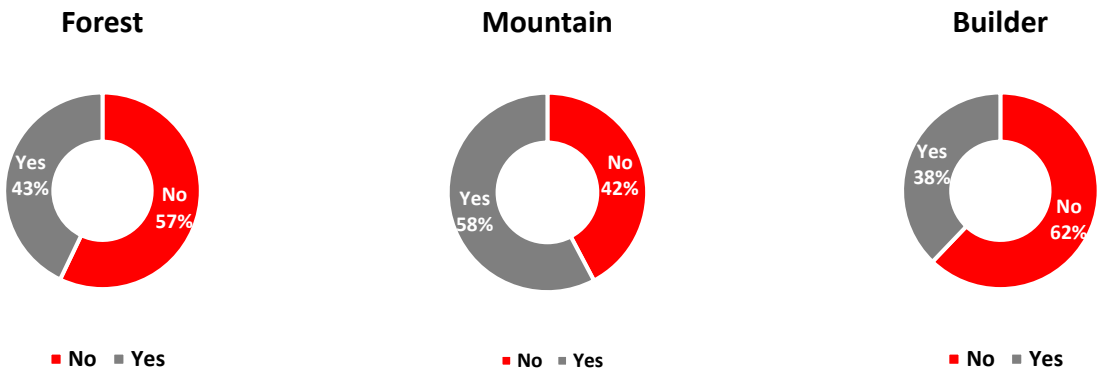
4.1.6. Willingness across Area

Despite high willingness rates amongst the participants of the study, the next questions that are crucial are “Are these properties built by registered builders and contractors?” or “Are they built near forest or mountainous areas?”. These two questions speak to the level of risk associated with these properties. The figure below illustrates the following:

- Rural residents who have built their houses near a forest or not.
- Rural residents who have built their houses near a mountainous area or not; and
- Rural residents who acquired the services of a registered builder or contractor for building their houses.

Figure 14 shows that 43% of the villages under the study are situated near a forest and 58% of the villages are situated on a mountainous area. These statistics could come as a surprise as to why a significant number of people would build in areas that could be considered high-risk areas (a forest or mountainous area). But most of the land in the rural areas is allocated based on ancestral history and lineage rather than being given the option to choose a land anywhere. When considering who built houses in the villages under the study, only 38% were built by a registered builder or contractor.

Figure 14: Location of villages



As rural areas are situated on the outskirts of the urban areas, the outsourcing of a builder from the urban area could prove to be costly. Therefore, 62% of rural homeowners indicated that their houses were not built by a registered builder or contractor. These statistics, which

are shown in the figure below from the perspective of insurers, are extremely concerning since they imply that many rural homes are constructed in high-risk zones and are consequently the most vulnerable in the case of catastrophic occurrences like severe fires and floods. From the prospective insured's point of view, this would suggest that there is a strong possibility that they would be paid hefty premiums to cover their homes if they are insured.

4.1.7. Dichotomised into binary variables

Table 13 demonstrates how the categorical independent rural resident variables are dichotomised into binary variables.

Table 13: Dichotomised rural resident variables

Variable	Category	Revised Category	Binary Category
Age_i	18 - 30	18 - 43	1
	31 - 43		
	44 - 56	44 - 65	0
	57 - 65		
$EduLevel_i$	No Matric	No Degree	0
	Matric		
	Degree / Diploma	Degree	1
	Postgraduate Degree (Honours, Masters, or PhD)		
$EmpStat_i$	Full-time employed	Employed	1
	Part-time employed		
	Seasonal employed		
	Unemployed	Unemployed	0
$Salary_i$	R 0 - R10 000	R 0 - R 30 000	0
	R 10 001 - R 20 000		
	R 20 001 - R 30 000		
	R 30 001 - R 40 000	R 30 001 or more	1
	R 40 001 - R 50 000		
	R 50 001 or more		
$BudgetLimit_i$	Almost always	Almost or almost always	1
	Always		
	Never	Never of sometimes	0
	Sometimes		
	Not applicable		
$FinAdv_i$	Advice from financial adviser	Financial Adviser	1
	Advice from friend or family	No Financial Adviser	0
	Internet		
	Magazines or Newspapers		
	Other		
	Radio or Television		
$NPolicy_i$	0	2 or less	0
	1		
	2		
	3	3 or more	1
	4 or more		
$ClaimFreq_i$	0	2 or less	0
	1		
	2		
	3	3 or more	1
	4 or more		
$Value\_i$	R 0 - R 250 000	R 0 - R 500 000	0
	R 250 001 - R 500 000		
	R 500 001 - R 750 000	R 500 001 - R 750 000	1
	R 750 001 or more		

Table 14 demonstrates how the categorical independent village variables are dichotomised into binary variables.

Table 14: Dichotomised village variables

Variable	Category	Revised Category	Binary Category
$ProxR_j$	Below 1 kilometer	Less than 5 kilometers	0
	1 - 3 kilometers		
	3 - 5 kilometers		
	More than 5 kilometers	More than 5 kilometers	1
$ProxU_j$	Below 10 kilometers	Less than 10 kilometers	0
	10 - 20 kilometers		
	20 - 30 kilometers		
	More than 30 kilometers	More than 30 kilometers	1
$Province_j$	Limpopo	Limpopo	0
	KZN	KZN and EC	1
	EC		
$NHouse_j$	Less than 100	Less than 100	0
	100 - 300		
	300 - 500		
	More than 500	More than 100	1

It is worth noting that a large proportion of the variables of the study are categorical variables (some with two or more sub-categories). To fit our multilevel logistic regression model, we will not get the best parameter estimates if a variable has more than two subcategories.

4.1.8. Multicollinearity Investigation

After dichotomising the variables into binary variables, the existence of strong collinearity between the independent variables should be investigated before proceeding to fit the regression models in the sub-section. When two variables are binary, the correlation is referred to as tetrachoric; when the correlation is more broadly defined, it is referred to as polychoric. For each variable in the study, tetrachoric or polychoric correlations will be computed. Previous literature suggests that a tetrachoric or polychroic correlation coefficient above 0.7 indicates multicollinearity. Table 15 on the next page shows the correlation matrix for the variables.

Table 15: Correlation matrix

	Value	Salary	Age	Budget	BudgetLimit	Builder	ClaimExp	ClaimFreq	EduLevel	EmpStat	FinAdv	Gender	Insurance	Material	MBill	MLoan	ProxR	ProxU	Forest	Mountain	Province
Value	1	(0.0546)	(0.0121)	0.0683	0.2061	0.1706	0.2005	0.2578	0.2175	0.168	0.21	0.0031	0.3729	0.3125	(0.0426)	(0.0618)	(0.0313)	(0.0852)	(0.0142)	(0.0288)	0.0526
Salary	(0.0546)	1	0.0053	(0.1901)	(0.999)	0.0335	0.0999	0.0752	(0.2706)	(0.51)	(0.0072)	(0.0003)	0.0611	(0.0411)	0.0512	0.0457	0.0826	(0.1355)	(0.2302)	(0.0923)	0.1322
Age	(0.0121)	0.0053	1	(0.0515)	(0.0236)	(0.2361)	(0.0678)	(0.0102)	(0.0502)	0.0623	(0.1237)	0.159	(0.1304)	0.0411	(0.0512)	0.1117	0.0707	(0.1032)	0.1676	0.1249	(0.0667)
Budget	0.0683	(0.1901)	(0.0515)	1	(0.999)	0.494	0.2981	0.3445	0.2931	0.6626	0.6409	(0.1643)	0.502	(0.0529)	(0.1483)	(0.2442)	0.0208	0.2077	0.0017	(0.16)	0.3369
BudgetLimit	0.2061	(0.999)	(0.0236)	(0.999)	1	0.999	0.402	0.3601	0.3416	0.3059	0.1554	0.2091	(0.9319)	0.963	(0.2719)	(0.2161)	0.1173	(0.1735)	(0.0114)	(0.1735)	0.3561
Builder	0.1706	0.0335	(0.2361)	0.494	0.999	1	0.3296	0.3407	0.2218	0.5996	0.4275	(0.1203)	0.4276	0.4084	(0.3061)	(0.3317)	(0.2173)	0.3317	(0.1423)	(0.1315)	0.0538
ClaimExp	0.2005	0.0999	(0.0678)	0.2981	0.402	0.3296	1	0.9875	0.3472	0.3216	0.3671	0.1525	0.9861	(0.0779)	0.0184	(0.2396)	(0.1046)	0.1072	0.0254	(0.0678)	0.2389
ClaimFreq	0.2578	0.0752	(0.0102)	0.3445	0.3601	0.3407	0.9875	1	0.3684	0.2638	0.4041	0.1389	0.9824	(0.2692)	0.089	(0.2536)	(0.1029)	0.1685	0.0361	(0.0437)	0.3678
EduLevel	0.2175	(0.2706)	(0.0502)	0.2931	0.3416	0.2218	0.3472	0.3684	1	0.2749	0.1779	(0.1147)	0.1782	(0.01)	(0.2814)	(0.3114)	(0.0812)	0.0272	(0.0771)	(0.0773)	0.0986
EmpStat	0.168	(0.51)	0.0623	0.6626	0.3059	0.5996	0.3216	0.2638	0.2749	1	0.6384	(0.2075)	0.5711	0.0312	(0.2997)	(0.2963)	(0.9656)	0.1919	(0.145)	(0.0788)	0.2163
FinAdv	0.21	(0.0072)	(0.1237)	0.6409	0.1554	0.4275	0.3671	0.4041	0.1779	0.6384	1	(0.1307)	0.4592	(0.0089)	(0.2295)	(0.2114)	(0.1777)	0.0175	(0.1328)	(0.1215)	0.3902
Gender	0.0031	(0.0003)	0.159	(0.1643)	0.2091	(0.1203)	0.1525	0.1389	(0.1147)	(0.2075)	(0.1307)	1	(0.0751)	0.0026	0.1287	0.1649	(0.0439)	(0.0462)	(0.0771)	0.0197	0.0984
Insurance	0.3729	0.0611	(0.1304)	0.502	(0.9319)	0.4276	0.9861	0.9824	0.1782	0.5711	0.4592	(0.0751)	1	0.1308	0.1059	(0.2247)	(0.1999)	0.3424	0.1035	(0.0633)	(0.0175)
Material	0.3125	(0.0411)	0.0411	(0.0529)	0.963	0.4084	(0.0779)	(0.2692)	(0.01)	0.0312	(0.0089)	0.0026	0.1308	1	(0.1955)	(0.9698)	0.1188	(0.1488)	(0.172)	(0.1238)	(0.0145)
MBill	(0.0426)	0.0512	(0.0512)	(0.1483)	(0.2719)	(0.3061)	0.0184	0.089	(0.2814)	(0.2997)	(0.2295)	0.1287	0.1059	(0.1955)	1	0.4745	0.0919	0.4224	0.3999	(0.0237)	0.1473
MLoan	(0.0618)	0.0457	0.1117	(0.2442)	(0.2161)	(0.3317)	(0.2396)	(0.2536)	(0.3114)	(0.2963)	(0.2114)	0.1649	(0.2247)	(0.9698)	0.4745	1	(0.1102)	0.2222	0.1264	0.0324	(0.1088)
ProxR	(0.0313)	0.0826	0.0707	0.0208	0.1173	(0.2173)	(0.1046)	(0.1029)	(0.0812)	(0.9656)	(0.1777)	(0.0439)	(0.1999)	0.1188	0.0919	(0.1102)	1	(0.9686)	0.9814	(0.6561)	(0.9969)
ProxU	(0.0852)	(0.1355)	(0.1032)	0.2077	(0.1735)	0.3317	0.1072	0.1685	0.0272	0.1919	0.0175	(0.0462)	0.3424	(0.1488)	0.4224	0.2222	(0.9686)	1	0.2199	0.1782	(0.1064)
Forest	(0.0142)	(0.2302)	0.1676	0.0017	(0.0114)	(0.1423)	0.0254	0.0361	(0.0771)	(0.145)	(0.1328)	(0.0771)	0.1035	(0.172)	0.3999	0.1264	0.9814	0.2199	1	0.0685	(0.5106)
Mountain	(0.0288)	(0.0923)	0.1249	(0.16)	(0.1735)	(0.1315)	(0.0678)	(0.0437)	(0.0773)	(0.0788)	(0.1215)	0.0197	(0.0633)	(0.1238)	(0.0237)	0.0324	(0.6561)	0.1782	0.0685	1	(0.3455)
Province	0.0526	0.1322	(0.0667)	0.3369	0.3561	0.0538	0.2389	0.3678	0.0986	0.2163	0.3902	0.0984	(0.0175)	(0.0145)	0.1473	(0.1088)	(0.9969)	(0.1064)	(0.5106)	(0.3455)	1

A large of proportion of the variables have a correlation coefficient below 0.7 except the ones highlighted in red. Some correlation coefficients are greater than 0.7 and 1. For instance, Budget and BudgetLimit. This is justifiable because one would have to have a budget to have a monthly budget limit. Another is ClaimExp and ClaimFreq, one would have to have a claiming experience to have a claiming frequency in the past year. When fitting the multilevel logistic regression in the next section, the results from this table will be considered.

4.2. Multilevel Logistic Regression Model

When fitting the logistic regression model, we created a training and testing set. The training set was set at 75% of the total sample of the study (237 participants) and the remaining 25% is the testing test (80 participants). Models 1 to 5 will be fitted using the training set. The testing set will be used to test the fitted final model.

4.2.1. Model 1

The first model to be fitted will be the base model (later referred to as Model 1). The base model is essential for two reasons. The first use of the base model is to test whether the grouping variable at Level 2 has an impact on the intercept (mean) of the dependent variable at Level 1. A multilevel modelling approach is required if it does. Secondly, researchers usually use it as a baseline model and thereafter add Level 1 and Level 2 variables. The covariance parameter estimates and the fixed effect solution for the base model are tabulated below.

Table 16: Covariance parameter estimates – Model 1

Covariance Parameter Estimates					
Cov Parm	**Subject**	**Estimate**	**Standard Error**	**Z value**	**Pr >Z**
Intercept	VillageName	0.4381	0.341	1.28	0.0994

Table 17: Solution for fixed effects– Model 1

Solutions for Fixed Effects					
Effect	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**
Intercept	1.1789	0.2322	36	5.08	<.0001

Table 18: Fit statistics – Model 1

Fit Statistics	
AIC (smaller is better)	274.15
AICC (smaller is better)	274.20
BIC (smaller is better)	277.37

To find out how much of the entire variation in the probability of willingness to insure is explained by the villages, the intra-class correlation coefficient (ICC) is calculated using the covariance parameter estimates in Table 16. Equation 4 shows the calculation of the ICC and Equation 5 shows the estimated probability of willingness using the results from Table 17.

Equation 4: Intra-class correlation calculation

$$ICC = \frac{\tau^2}{\tau^2 + \frac{\pi^2}{3}} = \frac{0.4381}{0.4381 + 3.29} = 0.1175$$

This suggests that the villages in our study account for around 11.75% of the variation in rural residents' willingness to purchase insurance, leaving the other 88.25% to be explained by the rural residents or other unidentified factors. The results also show that at a 10% level of significance, there is statistically significant variation among the villages in our sample in the log-odds of the willingness of rural homeowners to insure their properties (z-value = 1.28 and p-value = 0.0994 which is less than 0.1). The estimate of 1.1789 represents the log odds of willingness to insure at a typical village. To assess the probability of willingness to insure at a typical village from our sample can be calculated as:

Equation 5: Estimation of probability of willingness

$$P_{willing} = \frac{e^{1.1789}}{1 + e^{1.1789}} = 0.7647$$

The base model revealed that the probability of the willingness to insure amongst rural homeowners in a typical village is 76.47%. However, the probability of the willingness to insure varies considerably across villages. Therefore, it is important to add Level 1 and 2 variables and assess how the probability of willingness to insure changes. As seen from Table 18, the AIC (Akaike Information Criterion), the corrected AICC (AICC) and the Bayesian Information Criterion (BIC) for Model 1 are 274.15, 274.2 and 277.37. These statistics are important features in measuring how well a model fits the data. The lower the AIC, AICC and BIC, the better the model. These fit statistics will be monitored throughout the other suggested models in the next section.

4.2.2. Model 2

To assess the impact of the village variables, they are included in Model 1 to form Model 2 (the base model with only Level 2 variables). Tabulated below in Table 19 and Table 20 are the fixed effect solutions and the fitted statistics for Model 2.

Table 19: Solution for fixed effects – Model 2

Solutions for Fixed Effects						
Parameter		**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**
Intercept		1.1635	0.2888	32	4.03	0.0003
ProxR	Less than 5 kilometers	1.0782	0.7137	32	1.51	0.1407
ProxU	Less than 10 kilometers	-0.9203	0.3681	32	-2.5	0.0177
Forest	No	-0.4153	0.3703	32	-1.12	0.2705
Mountain	No	0.7491	0.3357	32	2.23	0.0328

The inclusion of the Level 2 variables to the base model has shown that the proximity of rural residents to urban areas (ProxU) and whether the village is in a mountainous area (Mountain) to be significant at a 5% level of significance in determining the willingness of rural homeowners to insure their homes. The proximity to municipal or regional roads (ProxR) variable does not have a significant effect on the willingness of rural homeowners to insure their homes at a 5% level of significance. Moreover, the same can be noted about the presence of a forest near a village (Forest), the results from the table above that this variable is also not significant at a 5% level of significance.

Table 20: Fit statistics – Model 2

Fit Statistics	
AIC (smaller is better)	270.64
AICC (smaller is better)	271.01
BIC (smaller is better)	280.31

There has been a reduction in both the AIC and AICC from Model 1 to Model 2. The AIC was reduced by 1.28% and the AICC was reduced by 1.26% when Level 2 variables were added to Model 1.

$$AIC_{change} = \frac{AIC_{Model\ 1} - AIC_{Model\ 2}}{AIC_{Model\ 1}} = \frac{274.15 - 270.64}{274.15} = 1.28\%$$

$$AICC_{change} = \frac{AICC_{Model\ 1} - AICC_{Model\ 2}}{AICC_{Model\ 1}} = \frac{274.20 - 271.01}{272.20} = 1.26\%$$

4.2.3. Model 3

To assess the impact of rural resident variables, we included rural resident variables in the base model to form Model 3 (the base model with only the Level 1 variables). Model 3 will assist in answering the question "Which rural resident variable is significant in determining the willingness to insure?" Tabulated below are the fixed effect solutions for Model 3 after including the Level 1 variables in Model 1.

Table 21: Solution for fixed effects – Model 3

Solutions for Fixed Effects						
Parameter		**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**
Intercept		2.6762	0.4737	36	5.65	<.0001
EduLevel	Matric or No Matric	-0.3751	0.4193	15	-0.89	0.3851
Salary	R30 000 or less	0.6737	0.4205	17	1.6	0.1275
Budget	No	-0.7112	0.3745	14	-1.9	0.0783
FinAdv	No	-0.9004	0.4039	16	-2.23	0.0405
Insurance	No	-1.1053	0.5569	11	-1.98	0.0727
ClaimExp	No	0.171	0.375	19	0.46	0.6537
Builder	No	-1.172	0.4236	17	-2.77	0.0132

Earlier in our data analysis section we showed that a large proportion of rural residents seek financial advice from family or friends rather than a financial adviser. Model 3 shows that the FinAdv variable is statistically significant in Model 3. The willingness to insure a home of a rural resident who seeks financial advice from a family or friend is only 40% of a rural resident who seeks financial advice from a financial adviser. Model 3 suggests that rural residents who do not have a monthly budget (Budget) have proven not to be significant at a 5% level of significance. In addition, the insurance variable (Insurance) is also not significant at a 5% level of significance. This implies that rural residents currently with no form of insurance (whether it is life or car insurance) are less willing to insure their homes.

Non-significant results are shown in the table for education level, monthly salary and claiming experience of the rural residents in determining their willingness to insure their homes. Outreville (1990) shared similar findings regarding the demand for property insurance in both the education level and income variables (referred to as monthly salary in this study). Moreover, the

findings of Ondruška et al. (2018) also did not support the significance of education level in determining the demand for property insurance. However, the results from Model 3 which suggest insignificance for the education level variable contradict the findings shown in Figure 10 which showed that as the education level of a rural resident increases, the probability of willingness to insure also increases. To investigate this contradiction, we include the education level only in the base model to assess whether it is totally statistically insignificant or it becomes insignificant when included with other rural resident variables.

Table 22: Model 1 with education level only

Solutions for Fixed Effects						
Parameter		**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**
Intercept		1.3147	0.2458	36	5.35	<.0001
EduLevel	Matric or No Matric	-0.7208	0.3859	15	-1.87	0.0814

Table 22 shows that the education level variable is significant at a 10% level of significance in determining the willingness to insure amongst rural homeowners. However, as a result of multicollinearity or the small sample size, the inclusion of other Level 1 variables resulted in the education level variable being insignificant in Model 3.

4.2.4. Model 4

Model 4 is the base model with both the Level 1 and 2 variables. Model 4 will assist in answering the questions such as:

- Do the variables included in Model 1 and Model 2 remain significant?
- Does a rural resident who has a monthly budget influence the willingness to insure their rural homes?
- Does the proximity to urban areas have a significant impact on the willingness to insure their rural homes?

Tabulated below are the fixed effects solutions for Model 4 after including both the Level 1 and 2 variables into Model 1.

Table 23: Solution for fixed effects – Model 4

Solutions for Fixed Effects						
Parameter		**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**
Rural Resident Variables						
Intercept		2.7245	0.5803	31	4.69	<.0001
EduLevel	Matric or No Matric	-0.4385	0.4233	15	-1.04	0.3167
Salary	R30 000 or less	0.6644	0.42	17	1.58	0.1321
Budget	No	-0.6448	0.3874	14	-1.66	0.1182
FinAdv	No Financial Adviser	-0.9438	0.4074	16	-2.32	0.0341
Insurance	No	-0.9834	0.5812	11	-1.69	0.1188
ClaimExp	No	0.2087	0.3752	19	0.56	0.5845
Builder	No	-1.1092	0.4229	17	-2.62	0.0178
Village Variables						
ProxR	Less than 5 kilometers	0.993	0.7476	31	1.33	0.1938
ProxU	Less than 10 kilometers	-0.6317	0.3835	31	-1.65	0.1096
Forest	No	-0.6239	0.3687	31	-1.69	0.1006
Mountain	No	0.5114	0.3576	31	1.43	0.1628
NHouse	Less than 100	0.5449	0.4783	31	1.14	0.2633

As seen in Model 3, variables FinAdv (the source of a rural resident's financial advice) and Builder (whether the property was built by a registered builder) remain statistically significant in Model 4. On the other hand, the model deems the remaining variables insignificant both at a 5% and 10% of significance. However, that does not mean these variables are completely insignificant in determining the willingness to insure amongst rural residents. There could be other reasons that drive these variables to be insignificant in this model. Reasons such as the size of our study sample or multi-collinearity amongst the variables shown in the table can lead to these variables being insignificant (this is discussed further in Chapter 5).

4.2.5. Model 5

Based on the developments from the three previous models, a final model (Model 5) is presented with some Level 1 and 2 variables and a cross-level interaction and compared to the preceding model (Model 1 to Model 4). The following questions will be addressed in the table below:

- Do the variables included in the preceding models remain significant in Model 5?
- Are there any cross-interactions between the variables that are significant in determining the willingness to insure?

Table 24: Solution for fixed effects – Model 1 to Model 5

Parameters		Model 1	Model 2	Model 3	Model 4	Model 5
Intercept		1.1789 ***	1.1635 ***	2.6762 ***	2.7245 ***	3.0994 ***
Rural Resident Variables						
EduLevel	Matric or No Matric			-0.3751	-0.4385	-0.4537
Salary	R30 000 or less			0.6737	0.6644	0.2692
Budget	No			-0.7112 *	-0.6448	-0.5699
FinAdv	No Financial Adviser			-0.9004 **	-0.9438 **	-1.0441 **
Insurance	No			-1.1053 *	-0.9834	-1.605 *
ClaimExp	No			0.171	0.2087	0.1739
Builder	No			-1.172 **	-1.1092 **	-1.0068 **
Village variables						
ProxR	Less than 5 kilometers		1.0782		0.993	
ProxU	Less than 10 kilometers		-0.9205 **		-0.6317	-1.426 ***
Forest	No		-0.4153		-0.6239 *	
Mountain	No		0.7491 **		0.5114	0.4573
NHouse	Less than 100				0.5449	
Province	Limpopo					-0.499
Cross Level Interaction						
Salary*ProxU	R 30 000 or less, Less than 10 kilometers					1.7817 *
Insurance*ProxU	No, Less than 10 kilometers					1.3588
Fit Statistics						
AIC		274.15	267.93	243.11	241.82	241.32
AICC		274.20	268.30	243.90	243.45	243.20
BIC		277.37	277.60	257.61	262.77	263.87

* means p-value <0.1, ** means p-value <0.05 and *** means p-value<0.01

From the table above, the final model has the equation shown below:

$$\eta_{ij} = 3.0994 - 0.4537 * EduLevel + 0.2692 * Salary - 0.5699 * Budget - 1.0441 * FinAdv - 1.605 * Insurance + 0.1739 * ClaimExp - 1.0068 * Builder - 1.426 * ProxU + 0.453 * Mountain - 0.499 * Province + 1.7817 * Salary * ProxU + 1.3588 * Insurance * ProxU$$

Throughout the four models (Model 3 to Model 5), at a 5% level of significance, the FinAdv variable remains significant in determining the willingness to insure rural homes. A similar trend is noted for the Builder variables but with a 5% level of significance. In addition, the ProxU is the significant Level 2 variable in Model 5. Other Level 2 variables were kept in Model 5 as they were significant in the preceding models and have some contribution in reducing the AIC, AICC and BIC of Model 5.

Like any interaction, a cross-level interaction aims to contrast variations in the value of a variable at one level in the hierarchy with variations in its influence on that level. Including a cross-level interaction of the variables Salary and ProxU, for instance, would only evaluate the impact of a person's salary and proximity to urban on their willingness to insure their rural home. Results from Model 5 indicate that the cross-level interaction of Salary and ProxU is statistically significant.

All the fitted statistics from Model 1 to Model 5 have reduced significantly. Model 1 presented an AIC of 274.15, an AICC of 274.10 and a BIC of 277.37, while Model 5 presented an AIC of 241.32 (11.98% reduction compared to Model 1), an AICC of 243.20 (11.31% reduction compared to Model 1) and a BIC of 262.87 (4.87% reduction compared to Model 1). The changes in the fit statistics suggest that Model 5 is the best model amongst the five models in predicting the willingness of rural homeowners to insure their homes. With the proposed final model in Chapter 4 consider the following scenarios with their log odds ratio, odds ratio and subsequent probabilities.

- Scenario 1: A rural resident who has a monthly budget, relies on a financial adviser for financial advice and resides in a mountainous area that is more than 10 kilometers away from the urban areas. The log odds ratio for this resident will be:

$$\eta_{ij} = 3.0994 - 0.5699(1) - 1.0519(1) + 0.4573\,(1) - 1.4326(1) = 0.5023$$

Subsequently, the odds ratio will be 1.6525 and thereafter the probability of willingness to insure for this resident will be $\frac{1.6525}{1+1.6525} = 0.6229$.

- Scenario 2: A rural resident who has a monthly budget, relies on a financial adviser for financial advice and does not reside in a mountainous area that is less than 10 kilometers away from the urban areas. The log odds ratio for this resident will be:

$$\eta_{ij} = 3.0994 - 0.5699(1) - 1.0519(1) + 0.4573\,(0) - 1.4326(0) = 1.4776$$

Subsequently, the odds ratio will be 4.3824 and thereafter the probability of willingness to insure for this resident will be $\frac{4.3824}{1+4.3824} = 0.8142$.

Scenarios 1 and 2 stress that the area that a village is situated in and how far they reside from the urban areas is important in determining the willingness of a rural homeowner to insure their homes.

4.3. Summary

This chapter is subdivided into two, namely, the data analysis of the variables and the multilevel logistic regression model. The data analysis section investigates how willingness to insure changes across each province, employment status, education level, the estimated value of the house, claiming experience and area of the village. The results of the study in this chapter indicated that 73.19% of respondents (232 out of 317) indicated they would be prepared to insure their homes, indicating that those living in rural areas were willing to do so. Provincially, the Eastern Cape showed the highest level of willingness to insure, followed by KZN and Limpopo. The province of Limpopo recorded the highest unemployment rates within our study sample, followed by the provinces of KZN and EC. With only 64.80% of participants in this group wanting to insure their homes, rural homeowners with homes worth between R 250 001 and R 500 000 have the lowest willingness rate. In contrast, homeowners who own properties valued at R 500 001 or more are more willing to insure them. The statistical analysis of the regression findings revealed monthly budget ($Budget$), financial advice ($FinAdv$), registered builder ($Builder$) and proximity to urban areas ($ProxU$) to be statistically significant in predicting the willingness of rural homeowners to insure their rural homes. In the next chapter, the results of the model will be discussed further, the model estimation will be performed and how the results can be utilised in an academic and business context.

Chapter 5 - Discussion

5.1. Introduction

It is important to review the study's research questions before going into further detail about this chapter. These are the research questions for the study:

- What are the factors that affect the willingness of rural homeowners to insure their homes?
- How can a comprehensive home insurance policy be designed for rural dwellers in South Africa?

The explanation of the model results, an examination of how the results differ from previous research, model estimation and recommendations for utilising the study results comprise the four sections that make up this chapter. The purpose of the first section is to highlight the first research question and how the results have addressed the research question. The second section evaluates the independent variables that were found to be significant and insignificant (i.e. what may be the cause of the insignificance) and compares the findings of this study with those found in earlier research. After that, the third section performs model estimation and assesses the effectiveness of the model in predicting the willingness of rural residents using an unseen dataset. The fourth section is to offer suggestions on how the findings should be applied in an academic context and business context.

5.2. Research Question 1

The purpose of the first research question was to determine the variables influencing rural homeowners' propensity to obtain homeowner insurance. A questionnaire focusing on village and rural resident variables had to be filled out by the participants. The variables pertaining to rural residents encompassed their demographics, financial acumen, building features in rural areas, insurance knowledge and financial literacy. The villages' geographic location was the focus of the variables, which included things like whether the village was close to a mountain or forest and whether it was close to a regional road or an urban area.

5.2.1. Research Findings

The study research results found the following variables to be influential in determining the willingness of rural homeowners to insure their homes:

- Education level of a rural resident.
- Salary of a rural resident.
- Whether a rural resident has a monthly budget.
- Source of financial advice for a rural resident.
- Insurance awareness of a rural resident.
- Claiming experience of a rural resident.
- Whether a rural home was built by a registered builder or contractor.
- Proximity of village to regional road or urban areas.
- Whether a village is situated near a forest or mountainous terrain.

The next section evaluates the independent variables that were found to be significant and insignificant (i.e. what may be the cause of the insignificance) and compares the findings of this study with those found in earlier research.

5.3. Retrospective Comparison of Results

This study started by first performing a data analysis of the study variables, to investigate any notable trends within our variables. Thereafter, a multilevel logistic regression model was fitted using a model development comprising of five models. The final model has the equation shown below:

$$\begin{aligned}\eta_{ij} = {} & 3.0994 - 0.4537 * EduLevel + 0.2692 * Salary - 0.5699 * Budget \\ & - 1.0441 * FinAdv - 1.605 * Insurance + 0.1739 * ClaimExp \\ & - 1.0068 * Builder - 1.426 * ProxU + 0.453 * Mountain \\ & - 0.499 * Province + 1.7817 * Salary * ProxU + 1.3588 * Insurance \\ & * ProxU\end{aligned}$$

5.3.1. Education Level

According to this study, the more educated a rural resident is, the more likely they are to insure their home. For example, only 38.10% (8 out of 21) of rural residents without a high school education would be willing to insure their rural homes, whereas 82.56% (71 out of 86) of rural residents with a

postgraduate degree (Honours, MSc, or PhD) would be willing to do so. The final model's results demonstrated that, at both 5% and 10%, a rural resident's educational attainment has no discernible impact on the demand for rural home insurance. Regarding education level, the results of this study agree with those of Ondruška et al. (2018), who in a related study deemed education to be statistically significant in determining insurance demand.

5.3.2. Salary

The study has revealed that the monthly salary of a rural resident is statistically significant in the final model at a 5% level of significance in determining the probability of a rural resident insuring his/her home. This finding contradicts the results from the studies of Browne et al. (2000), Esho et al. (2004) and Ondruška et al. (2018). The differing factor between our results and Ondruška et al. (2018) is that the salary variable is a binary variable in our study while Ondruška et al. (2018) has more than three categories for salary.

5.3.3. Insurance Awareness and Claiming Experience

The willingness of rural residents to insure their homes was found to be unaffected by factors such as insurance experience, whether they currently have insurance products, claiming experience, or whether they have made claims for any of their other current insurance products in the previous year. The strong correlation between the two variables was the primary cause of their insignificance.

5.3.4. Geographical Location

The village variables that were considered in this study were Forest, Mountain, ProxR (proximity to regional roads) and ProxU (proximity to urban areas). When it came to rural homeowners' willingness to insure their homes, the proximity to regional roads, Forest and Mountain were not statistically significant, but the proximity to urban areas was significant.

5.3.5. Monthly Budget

A household's ability to manage its finances is demonstrated by the existence of a monthly budget. Participants who reported having a monthly household budget made up 232 out of 317, or 73.19%. A proportion of 55.17% of participants of the study (128 out of 232) who had a monthly budget said they "Almost always" or "Always" stick to their monthly budget. The regression model revealed that the budget variable was significant in predicting rural residents' willingness to insure their homes.

5.3.6. Financial Advice

The financial advice ($FinAdv$) variable was used to evaluate whether financial advisers were used for financial decisions. Out of the 317 participants in the sample, 40.69% recommended consulting a financial adviser, while the remaining 59.31% said they get their financial advice from friends, family, the internet, radio, television, magazines and newspapers. The regression model results revealed that the financial advice variable had a significant impact on rural homeowners' willingness to insure their homes when it was included in the regression model. The main conclusion drawn from the final model is that when a rural resident switches from not using a financial adviser to consulting one, the likelihood that they will be willing to insure their rural home will increase by a factor of more than five.

5.3.7. Builder

Most villages are located far from the major cities that are home to most hardware stores, building companies and licensed builders. Because of this, constructing a home in a rural location is more expensive since significant transportation expenses must be included. According to the sample data, a mere 37.85% of the houses under investigation were constructed by licensed contractors or builders. According to this research study, the builder variable has a statistically significant impact on whether rural homeowners are willing to get home insurance. Considering the potentially higher costs involved in building in rural regions, it makes sense that homeowners whose homes were built by registered builders would be more likely to insure them if theft or natural disasters cause losses to their properties.

5.4. Model Estimation

5.4.1. Model Prediction Accuracy

The multilevel logistic regression model presented in Chapter 4 was fitted using the training set (75% of the study sample). The remaining 25% of the study sample was deemed the testing set which will be utilised to predict the willingness to insure. The resultant predicted probability is then compared to a cut-off probability value ranging from 0.4 to 0.9.

Table 25: Confusion matrices for different cut-off values

Cut-off value = 0.4

		Predicted	
		1	**0**
Actual	**1**	48	10
	0	20	2

Cut-off value = 0.5

		Predicted	
		1	**0**
Actual	**1**	42	16
	0	18	4

Cut-off value = 0.6

		Predicted	
		1	**0**
Actual	**1**	39	19
	0	16	6

Cut-off value = 0.7

		Predicted	
		1	**0**
Actual	**1**	35	23
	0	16	6

Cut-off value = 0.8

		Predicted	
		1	**0**
Actual	**1**	26	32
	0	13	9

Cut-off value = 0.9

		Predicted	
		1	**0**
Actual	**1**	15	43
	0	10	12

The chance of getting a "positive" result (which is recorded as a 1 in the data table) is calculated using logistic regression. The least probability that would be regarded as a "positive" observation must be specified as the cut-off value to apply logistic regression to forecast if a new observation is "positive" or "negative." According to previous studies, a standard cut-off of 0.5 should be used. This indicates that an observation is categorized as "positive" (or simply as 1) if the expected probability is higher than 0.5. Using the confusion matrices provided in the table above, we can calculate results such as precision, recall, accuracy and F1-score of the model.

Table 26: Results from confusion matrices

Measures	**Cut-off values**					
	0.4	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Precision	70.59%	70.00%	68.63%	70.91%	66.67%	60.00%
Recall	82.76%	72.41%	60.34%	67.24%	44.83%	25.86%
Accuracy	62.50%	57.50%	51.25%	56.25%	43.75%	33.75%
F1-score	66.30%	63.14%	58.68%	62.73%	52.83%	43.20%

When the cut-off value is 0.5, the precision of the model is 70.00%, suggesting that 7 out of 10 times, the model will be correct in predicting willingness to insure. The recall is 72.41% which is reasonably high, suggesting that the model will be good at predicting some instances of willingness correctly. Finally, the accuracy of the model is 57.50% and the F1-score of the model is 63.14%.

5.5. Utilisation of Results

5.5.1. Academic Context

While there is some literature focused on agricultural and crop insurance in Africa, hardly any literature considers the South African situation (Mbonane, 2018). Therefore, this study serves to contribute significantly to South African literature that is focused on rural insurance. Not only does it add to the literature but also sheds some light on the factors that influence the willingness of rural homeowners to insure their homes. Furthermore, most of the research to date has been theoretical, with resultant studies concentrating on determining demand or willingness to insure rather than offering advice on what reasonable premiums people would be willing to pay.

5.5.2. Business Context

The results in Chapter 4 have shown that there is a willingness amongst rural homeowners to insure their homes. However, for a business case, the willingness alone is not enough to raise a discussion for a business case. In the event of tapping into unfamiliar markets, large data would be required to understand the patterns and trends in the market. With minimal data available that is focused on the informal market within the South African context, the data used for this study serves as a good foundation for further investigation. Based on our study sample, there is a willingness to insure homes amongst rural homeowners. However, willingness is the first step in eventually signing up for a product or service. Other factors such as the price of the product, the ease of claim and complaints and quality of service are also key in signing up for insurance. Amongst the participants of the study, the biggest concern was the price, claim lodgement and subsequently claim pay-out.

Within the rural insurance market, most of the attention has been given to livestock and crop insurance and less focus on investigating whether there is a need for a comprehensive rural home insurance. This study seeks to shift that attention to a comprehensive rural home insurance. Thereafter, possible solutions will be recommended on how the insurance offering for rural homeowners could be designed. By achieving this, the proposed offering could encourage rural landowners to invest in building properties that meet the necessary criteria to be insured.

Chapter 6 - Product Development

6.1. Introduction

This chapter is presented in three sections. The first section highlights where the idea of rural insurance comes from. The second section provides an overview of the current rural insurance offering in South Africa. The third section addresses the following research question:

- How can a comprehensive home insurance policy be designed for rural dwellers in South Africa?

6.2. Ideation

Land ownership in rural areas differs significantly from that of urban areas, with widespread differences. A title deed proves your ownership of a specific plot of land in an urban setting, but in a rural one, that is not the case. Rather, the Tribal Authority distributes land to the locals in the rural areas. The village's king, prince, chief, or predestined traditional leader could all be considered the Tribal Authority. Despite this, people continue to build homes and pursue land ownership in rural areas because they continue to find comfort there. When people build houses in rural areas, they either finance the construction themselves with savings or pensions or they obtain a personal loan from a nearby bank. A portion of these properties lack insurance. It is possible to argue that either the owners are unwilling to insure their homes, or these properties are not insured because they do not fit the underwriting requirements specific to properties located in metropolitan areas.

6.3. Current Market Offering

In South Africa, the leading insurers that offer rural insurance with a focus on the agricultural component are OUTsurance, King Price, Santam, Hollard and Old Mutual. OUTsurance’s rural insurance offering is agri-business focused. Their benefit offering covers farmers on their livestock, tools, vehicles and trailers and personal accident insurance. Personal accident insurance covers farm workers and pays out in the event of death or bodily harm and vehicle and trailer insurance provides a variety of insurance options for the vehicles and trailers on the farm.

There is no significant difference between King Price and OUTsurance's rural insurance offering, King Price also provides agricultural cover for all farmers' vehicles and implements property for both personal business assets. Moreover, other insurance players such as Santam, Hollard and Old Mutual have a similar offering, with much focus on the agri-business sector. Most recently, Sugar Insure, a company underwritten by GENRIC Insurance Company Limited, is an insurance start-up that launched a niche product. Their product offering targets homes in townships, rural villages and informal settlements. The insurance product is offered in two products, namely, "Legacy" and "Level Up". The Legacy product is a brick-and-mortar home insurance solution. It offers cover from damage to your building or household contents. The Level Up policy is a shack-home insurance option, that offers coverage for the building and belongings of your shack-home if it is damaged by fire, storm, wind or flooding. However, Sugar Insure has its shortfalls such as benefit limits. Sugar Insure covers any property built with brick and mortar for a minimum replacement value of R50 000 and a maximum of R2 million. The key takeaway is that in South Africa insurance when referring to rural insurance crop and agriculture insurance are the big players.

6.4. Research Question 2

The purpose of the second research question was to suggest how a comprehensive home insurance product can be designed for rural dwellers in South Africa.

6.4.1. Research Recommendations

Community-based Home Insurance

A rural community which could broadly defined as any public entity that is led by the designated traditional leader in that community, could set up insurance coverage for its members under a community-based home insurance (CBHI) product. The CBHI could be set up as a formal cell captive. A formal cell captive insurance company has its drawbacks and benefits. Management of a cell captive is that it would require time and a traditional leader of that specific village to possess skills such as administration. On the upside, as a formal cell captive, communities can leverage their size to seek assistance from the government with managing administration costs. Also, if registered as a formal captive, should there be any growth, there is a possibility to be underwritten by a larger

insurer which would potentially translate into lower premiums for the policyholders. Insurance coverage for rural residents may be mandatory or a voluntary benefit with clear requirements set to be considered for coverage. These requirements could range from ensuring that a property is built by a registered builder and not near a mountainous or forest-filled terrain.

Stokvel Fund

The establishment of an unofficial savings fund, or "stokvel fund," is a further option. A lump sum pay-out is made to members of a stokvel fund at the end of a predetermined time, in exchange for regular contributions of a predetermined amount. The establishment of stokvel funds by rural communities, to which rural residents would contribute monthly, would provide financial relief to the residents if their houses are destroyed by natural disasters or theft. One of the advantages of this fund is that stokvel members can readily modify informal rules for internal claim processes to better suit their needs. Another advantage of a stokvel fund is that it entails less administration compared to a formal cell captive. The disadvantages of a stokvel could offset its advantages. As an illustration, the funds are kept in a low-interest bank account to provide prompt access when required. This could result in the fund's member contributions not being sufficient to pay for every claim submitted. Moreover, without guidelines and documented policies of the fund, it would be challenging to implement risk management techniques, such as a waiting period before a policyholder can claim. Lastly, because stokvels are not recognised by the government as legitimate businesses and are therefore viewed as pyramid schemes, they are not protected by the law. Many considerations are necessary to ensure that rural insurance ameliorates rural development. A rural comprehensive insurance can be offered as a peer-to-peer insurance product.

Peer-to-Peer Insurance

Peer-to-Peer (P2P) Insurance is a new trend in the insurance industry that encourages group buying to make insurance more affordable. P2P is built on the fundamentals of a stokvel fund - based primarily on the concept of mutual risk pooling. Peer-to-peer insurance attempts to decrease overhead costs, improve transparency, decrease inefficiencies and most importantly, lessen the inherent friction that arises between insurance companies and their policyholders during a claim. For instance, rural dwellers in the same local municipality could pool funds to purchase insurance

(Saha, 2016). The benefit of P2P are potential money back and easy claiming processes. P2P insurance claims can be processed more quickly. Less paperwork is needed and many operations are now digital. As peer-to-peer insurance is not for profit, participants shouldn't have much trouble getting claims paid. Pineapple is the first peer-to-peer insurance firm in South Africa and it seeks to improve the insurance market's value, fairness, client transparency and affinity. Through a mobile application, Pineapple allows users to insure their goods with just the snap of a picture. The business model Pineapple employs is mainly focused on transparency amongst their customers on premium utilisation, underwriting process and profit use. Such a model could be instrumental in the development of a comprehensive rural home insurance. This model would bring like-minded rural residents together and revive the original community protection concept of insurance in the rural area.

Chapter 7 - Conclusion

7.1. Introduction

There are three sections to this chapter. It starts with an overview of the research study before presenting the results and conclusions. Finally, it makes suggestions for additional investigation and further research.

7.2. Summary

Insurance can be defined more simply as a contract between two parties. In exchange for coverage against a certain set of risks, the insured party (the insured) agrees to pay the other party (the insurer) a predetermined amount of money known as the premium on a monthly, quarterly, or yearly basis. Sharing risks to get the insured party back to as close to his initial position as is reasonably achievable is the core goal of insurance. In addition to improving an individual's situation, insurance stimulates the economy by shielding individuals and assets against risks that fall within the insurance policy. Insurance makes it more likely that you will survive uncontrollable unanticipated events, such as natural catastrophes. With a major contribution to the GDP of the nation, the insurance sector in South Africa is an important one. South Africa has the highest insurance penetration rate in Africa, at 16.99%, according to 2017 Statista data. Even though the country has a higher insurance penetration rate than other countries, a significant share of the insurance market is made up of long-term insurance (life insurance), with less money invested into short-term insurance-related industries like rural insurance. Now, people's perception of rural insurance is that it is primarily focused on agriculture and pays little attention to the needs of rural residents.

The primary goal of the research is to use multilevel modelling to evaluate rural South African landowners' willingness to insure their homes. The second goal is to suggest practical recommendations that can enhance the rural house insurance market. A review of the pertinent literature showed that several variables, including age, gender, educational

attainment, employment status, size of family, geography and population of the village, are important in predicting people's desire for insurance or their willingness to pay for it.

The study covered participants in rural areas within three provinces in South Africa, namely Limpopo, Eastern Cape and KwaZulu-Natal (KZN). The data was collected through questionnaires administered by the interviewer in a face-to-face setting, namely, the rural resident questionnaire and the village questionnaire. The questionnaires were carried out from 26 June to 31 July 2023 in the three provinces sample size for the study is 353 participants from a total of 28 villages. Data collection issues that were noted by the researcher were refusal to participate, participant withdrawal and misunderstanding of study objectives. After addressing the data collection issues, there were entries that had missing values that were omitted from the study resulting in a final sample size of 317 participants.

7.3. Results and Conclusion

The data analysis is divided into two sections, namely, data analysis of the variables and fitting a multilevel logistic regression model.

7.3.1. Data Analysis of Variables

The study's findings showed that rural residents were willing to insure their homes, as demonstrated by the 73.19% of respondents (232 out of 317) who said they would be willing to do so. The EC showed the highest willingness to insure, with KZN and Limpopo following closely behind. All participants' willingness to insure revealed that those with higher levels of education were more likely than those with lower levels of education to be willing to insure their homes.

A low insurance penetration rate is observed throughout short-term insurance products, but a larger insurance penetration rate is observed for long-term insurance products, according to the data analysis of the insurance awareness variable. A proportion of 90.85% (288 out of 317 participants) in our sample claimed to own an insurance product, whether it be short-

term or life insurance. Approximately half of those insured (138 out of 288 participants) have both car and life insurance; these products may include life insurance policies, burial societies and informal burial protection. Only 7.99% of the participants (116 out of 288) have a home or home content insurance, 2.43% have only car insurance and 40.28% of participants have life insurance only. Moreover, participants who work either full-time or part-time have a higher willingness to cover their rural homes when willing to insure across job status is examined.

7.3.2. Multilevel Logistic Regression

Five types of models were examined to arrive at the final regression model. Model 1 presented the base model with no rural resident and village variables. The base model with the village variables was shown by Model 2, while the base model with the rural resident variables was shown by Model 3. Model 4 showed the base model containing the rural resident and village variables and investigated their significance. The final model, Model 5, included the rural resident and village variables that have been found to be important in determining rural residents' desire to insure their homes. The statistical analysis of the regression findings revealed the following variables to be statistically significant in predicting the willingness of rural homeowners to insure their rural homes.

Monthly Budget

A monthly budget indicates that a household can handle its finances. Of the 317 participants, 232 (73.19%) reported having a monthly household budget. 128 out of 232 research participants, or 55.17% of the total, reported that they "Almost always" or "Always" adhered to their monthly budget. According to the regression model results, the desire of rural individuals to insure their homes was significantly predicted by the budget variable.

Registered Builder

Just 37.85% of the residences under examination were built by licensed builders or contractors, based on the sample data. The builder variable had a statistically significant effect on rural homeowners' willingness to obtain home insurance, according to this research study.

Financial Advice

A proportion of 40.69% of the 317 sample participants recommended consulting a financial professional, while 59.31% of the participants said they get their financial advice from friends, family, the internet, radio, television, periodicals and newspapers. The findings of the regression model revealed that the inclusion of the financial guidance variable had a substantial impact on rural people's desire to insure their homes.

Geographical Location

The village variables that were considered in this study were Forest, Mountain, ProxR (proximity to regional roads) and ProxU (proximity to urban areas). When it came to rural homeowners' willingness to insure their homes, the proximity to regional roads, Forest and Mountain were not statistically significant, but the proximity to urban areas was significant.

7.4. Further Research and Recommendations

Insights from this study will be useful for future investigations across insurers across the nation. To draw conclusions, the results of this study might be compared to those of other related investigations. A more comprehensive picture of the readiness to insure rural properties in South Africa can be obtained by conducting a survey among a bigger and more diverse population throughout all parts of the country. Moreover, the study's findings have determined that there is a gap in the market and can assist with insurance companies' marketing strategies, particularly when it comes to targeting the groups of prospective customers who lack insurance or have inadequate coverage. Secondly, insurance companies should provide services with accountability and openness. This will guarantee that consumers' perceptions of insurance will change from one of a capitalist industry to one that seeks to benefit society and further economic growth. In conclusion, policymakers ought to allocate more resources towards educating underdeveloped markets, like the rural market, about insurance and support programs that enhance their financial literacy.

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Appendices

Appendix A: Questionnaires

Rural Resident Questionnaire

1. Age	18 - 30
	31 - 43
	44 - 56
	57 - 65
2. Gender	Male
	Female
3. What is the name of the village you stay in?	
4. What is the name of the district you stay in?	
5. What is your highest level of education?	No Matric
	Matric
	Degree / Diploma
	Postgraduate Degree
6. What is your employment status?	Unemployed
	Employed
	Part-time employed
	Full-time employed
7. How much is your monthly salary?	R 0 - R 10 000
	R 10 001 - R 20 000
	R 20 001 - R 30 000
	R 30 001 - R 40 000
	R 40 001 - R 50 000
	R 50 001 or more
8. Does your household have a monthly budget?	Yes
	No
9. How often do you stay within your monthly budget?	Always
	Almost always
	Sometimes
	Never
10. In the last 12 months, were you ever behind two or more months in paying bills?	Yes
	No
11. In the last 12 months, were you ever behind two or more months in making loan payment?	Yes
	No
12. What sources most influence your financial decisions?	Magazines or Newspapers
	Radio or Television
	Internet
	Advice from financial adviser
	Advice from friend or family
	Other

Rural Resident Questionnaire continued

13. Out of 10, how would you rate your financial knowledge?	
14. Do you have an insurance policy?	Yes
	No
15. What kind of insurance policies do you have? Select all the ones you have	Home insurance
	Car insurance
	Livestock insurance
	Crop insurance
	Life insurance
	Home content insurance
16. How many insurance policies do you currently have?	0
	1
	2
	3
	4 or more
17. Have you ever claimed for any of the insurance policies?	Yes
	No
18. If yes, how many times in the past 12 months?	1
	2
	3
	4 or more
19. Do you own a property in the rural area?	Yes
	No
20. What is the total estimated value of the property?	R 0 - R 250 000
	R 250 001 - R 500 000
	R 500 001 - R 750 000
	R 750 001 or more
21. Which material was used in building your property?	Mud
	Wood
	Face brick
	Concrete brick
	Other
22. Was your property build by a registered builder or contractor?	Yes
	No
23. Would you sign up for rural home insurance for your property?	Yes
	No
24. If so, what cover would you consider for your property?	Cover against natural disasters
	Cover against theft or damage of home contents
25. If so, what cover would you consider for your property?	Full estimated current value
	80% of the estimated current value
	60% of the estimated current value

Village Questionnaire

What is the name of the village you stay in?	
What is the name of the district you stay in?	
How far is the village from urban areas?	Below 10 kilometers
	10 - 20 kilometers
	20 - 30 kilometers
	More than 30 kilometers
How far is the village from municipal road or regional road?	Below 1 kilometer
	1 - 3 kilometers
	1 - 3 kilometers
	More than 5 kilometers
Estimated number of households in village	Less than 100
	100 - 300
	300 - 500
	More than 500
Is the village near a forest?	Yes
	No
Is the village near a mountain?	Yes
	No