

**The influence of perceived social norms and the availability heuristic on
consumer insurance decisions**

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Abstract

Understanding the factors influencing consumers' insurance decisions is still crucial in a time of persistent underinsurance. This research investigates the understated cognitive factors that influence South African customers' insurance decisions, placing emphasis on the way availability heuristics (rapid judgements drawn from vivid recollection) and perceived social norms steer purchase intentions.

This study employed a quantitative cross-sectional framework with 162 participants, challenging conventional assumptions about rational insurance-related decisions. The results show that availability heuristics had a strong influence on individuals purchase intention. This reflects the inclination by consumers to be swayed by a vivid personal recollection above pages full of detached numerical probabilities. Perceived social norms likewise showed a meaningful influence on purchase intention, yet this effect manifested independently and did not amplify availability heuristics.

These disclosures have significant implications for the insurance sector, which is experiencing significant changes. Behavioural science offers unique insights for improving product design and marketing strategies as the insurance industry struggles with economic pressures, climate-driven disasters, and rapid digital transformations. The research findings guide practitioners to use social norms to influence choices through conformity dynamics. Practitioners may use emotionally charged media coverage to boost insurance adoption rather than complex statistical presentations.

Keywords

Availability heuristics

Ecological rationality theory

Perceived social norms

Purchase intention

Quantitative research

Plagiarism Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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CHAPTER 1: INTRODUCTION TO THE RESEARCH PROBLEM

1.1. Background

Against a backdrop of rising uncertainties due to climate-driven disasters to economic volatility, consumer insurance decisions have become critical for protecting against catastrophic financial losses. Acquiring house, vehicle, health or life insurance, are important financial decisions that affect both financial security and personal well-being. However, underinsured risks are estimated to cause yearly economic losses over \$162.5 billion in 2018 (\$168 billion in 2012) (Lloyd's, 2018; Lloyd's, 2012). Making underinsurance a global concern. Catastrophic events are expected to cost around \$100 billion globally (Aon, 2025). This would be more than twice the 10-year average. Furthermore, insured losses are predicted to reach \$145 billion by the end of 2025 which highlights the protection gap that jeopardises the financial stability of many across the world (Swiss Re, 2025b). South Africa has the highest insurance penetration rate on the African continent of 11.54%, however many people within the country still face significant gaps due to financial and infrastructure constraints (Egosa, 2025). Economic strains and climate change being some of the main drivers leading to these disparities (Egosa, 2025).

Behavioural economics indicate that individuals do not always make rational decisions (Corcos et al., 2020; Richter et al., 2019). Human decisions frequently depart from strict logic; a pattern vividly illustrated in the seminal 1979 work of Amos Tversky and Daniel Kahneman. Their researched provided valuable insights into how people's decisions might be influenced by how information is framed. Kahneman and Tversky (2013) contradicted traditional economic theory, which assumed that people always decide rationally and prefer to minimize risk. Their worked showed that people often depend on mental shortcuts and familiar patterns instead of reasoning carefully through decisions, with the framing of information playing a crucial role in the outcome (Tversky and Kahneman, 1992). It clarifies why consumers often dismiss likely threats but take excessive precautions against rare events (Richter et al., 2019). Since prospect theory was developed, several decision biases have been identified in the literature (Ceschi et al., 2019).

Decision-making in insurance is especially challenging for individuals as they are required to make choices about uncertain future events against present expenses, which they often have very little knowledge about (Pattnaik et al., 2021). Traditional economic models, such as expected utility theory, assumes individuals maximise their return by assessing the probabilities and outcomes (Corcos et al., 2020; Richter et al., 2019). This deviates from the real-world behaviours where individuals are both risk-seeking for gains (buying lottery tickets) and risk-averse for losses (purchasing insurance). This paradox shows the influence of psychological variables on individuals' risk perception and how this can cause over-insurance for low probability catastrophic events or under-insurance for chronic conditions. A recent study showed a positive correlation between trust in an insurance company and intent to purchase insurance, as well as the decision to purchase insurance (Dragos et al., 2020). A lack of trust was found to discourage individuals from purchasing insurance in developing countries. The South African insurance market was estimated at a total premium volume of R887 397 million in 2024 (Swiss, 2025). Streamlining insurance comparisons by combining behavioural insights to match consumer preferences, can assist in providing long-term financial security (Corcos et al., 2020; Richter et al., 2019).

Considering the financial uncertainties mentioned and the insights behavioural economics brings to insurance, this research expands on prior studies exploring biases in insurance-related decisions (Corcos et al., 2020; Ceschi et al., 2019; Richter et al., 2019). It will more specifically focus on availability heuristics and social norms. The availability heuristic is a cognitive shortcut where the probability of an event occurring or the importance of such event, is based on past knowledge of similar instances (Keller, 2006; Tversky and Kahneman, 1973). In the evaluation of probabilities, people give priority to information that is readily available (Richter et al., 2019). This can be seen during emotionally charged (natural disasters), dramatic (shark attacks), or recent events. Consumers can easily over-insure or under-insure their assets by relying on these shortcuts (Corcos et al., 2020; Richter et al., 2019).

In addition to mental shortcuts, social norms are another key part of behavioural economics which drives decision making. Social norms are shared expectations or behaviours within a society that affect decision making (Cialdini et al., 1990; Germar et al., 2023; Schultz, 2022). They can be characterised as either descriptive norms

(society's behaviour) or injunctive norms (acceptable behaviour). Social norms are evaluations of behaviour upheld by society (Horne and Mollborn, 2020). The importance of descriptive norms and their influence on customers' purchase intent will be the primary focus of this study.

This study examines South Africa's insurance sector, providing a significant background for analysing how these behavioural characteristics manifest in real-world situations. The insurance sector in South Africa is well-established and functions under strict regulation. A few major companies dominate the industry, that together command over 80% of the market while providing crucial financial protection to consumers (Deloitte, 2025). The insurance industry continues to face many challenges like economic constraints (consumers have limited disposable income), legislative changes (insurers undergo costs to implement changes), and environmental shifts (climate related catastrophes) (Kirk, 2025). Digital advancements help tackle these issues by delivering tailored services and customer-focused solutions (Venessa, 2025). In a dynamic and uncertain market, understanding behavioural patterns enables insurers to enhance their risk evaluations significantly. This research offers a chance to explore how social influences and mental shortcuts, like availability heuristics, shape decisions in the fast-paced insurance industry, yielding valuable insights for personalising products and messaging.

1.2. Contribution

1.2.1. Academic and scholastic contributions

To better understand cognitive biases in insurance decisions, it is important to understand the development of prospect theory (Kahneman and Tversky, 1979). A study showed the purchase rate of insurance cover being influenced by reframing the premium as a monthly amount instead of annual (Bhatia, 2024). Prospect theory underwent refinement in cumulative prospect theory, which added probability weighting to better explain anomalies such as concurrent lottery ticket and insurance purchases by individuals which showed both risk-seeking (for gains) and risk-averse (for losses) behaviour (Kahneman and Tversky, 1992). The development of prospect theory in the lab has been criticised for having limited real-world application,

especially in dynamic markets where biases are moderated by experiences (Barberis, 2013).

Ecological rationality offers an alternative perspective to prospect theory. It explains heuristics as adaptive tools rather than the cause of bias (Gigerenzer and Gaissmaier, 2011). This research argues that human rationality arises from the alignment of cognitive strategies with environmental structures, rejecting the earlier “heuristics-and-biases” view that depicts shortcuts as irrational errors. Ecological rationality suggest that basic mental shortcuts often outperform intricate models. Additionally, decision-making is viewed as being constrained by time and uncertainty. This explains why individuals uses mental shortcuts to make decisions rather than engaging in detailed probability-based calculations. With regards to making insurance related decisions, individuals might use the information from a recent disaster or traumatic experience when purchasing cover. Gigerenzer et al. (2022) provides a prescriptive lens for making better decisions in uncertain insurance markets and highlights how ignoring information can lead to better outcomes. The approach blends economic and psychological insights, proposing that rationality is context-dependent instead of being based on logical rules.

Ecological rationality provides one view to explain consumer decision-making, although prospect theory is still widely used to explain how consumer behaviour is influenced by biases. These biases lead frequently to less-than-ideal choices and the literature contains several examples of various biases. The theory developed by Daniel Kahneman and Amos Tversky was expanded by Richter et al. (2019) which connected prospect theory to the demand in insurance. Richter et al. (2019) indicated the reason why consumers frequently act irrational and over-insure low risks products are because of loss aversion and framing effects. Key biases, such as present bias and the endowment effect, reveal how people interpret information and make decisions (Richter et al., 2019). Present bias is when individuals tend to favour short-term gains over their financial stability in the future which often leads to reduced interest in retirement savings plans. The endowment effect causes individuals to place an emotional value on their belongings which explains why old cars are frequently being over-insured.

Building on this foundation, this study explains two behavioural constructs: the relative and combined influence of availability heuristics and perceived social norms in consumer insurance decisions. Availability heuristics describe how people judge the likelihood or significance of events based on how easily they can recall similar past experiences (Keller, 2006). In assessing likelihood, individuals favor information that's most assessable in memory. This tendency is particularly evident with emotionally charged disasters, or dramatic incidents like shark attacks. Consumers can often over-insure or under-insure their assets if they depend on these mental shortcuts. Current behavioural economic studies confirm availability heuristics' importance by demonstrating how individuals overestimate risk when making decisions in uncertain domains like insurance (Zhang, 2023).

1.2.2. Contribution for business

It is anticipated that the South African insurance industry will experience numerous changes in the coming years (Deloitte, 2025). Understanding the impact behaviour influences have on consumers, can assist insurance companies to adapt their strategies to the changes in the industry (Venessa, 2025). Insurance companies' profits are being influenced by natural disasters which has worsened due to the impact of climate change as well as increased reinsurance expenses. Evolving regulations around sustainability and data protection add further challenges for compliance (Old Mutual, 2025). Although overall insurance penetration is less than 3% throughout the Sub-Saharan African continent, there are plenty of opportunities considering the youthful population across Africa (more than 70% under 30) (Global Reinsurance, 2025). Innovations like microinsurance are excellent examples of how insurers can design products for under-represented markets in an emerging economy. Understanding the behavioural factors that drive insurance adoption is essential for capitalizing on these opportunities. This makes the study more important since behavioural factors like perceived social norms and availability heuristics can shape how products change over time.

Understanding consumer behaviour is vital amid these market shifts. It is important for insurance companies to develop products and marketing efforts that resonate with customers, which is something they struggle with (Pattnaik et al., 2021; Guan et al., 2020; Richter et al., 2019). Recognising the influence of social norms and

availability heuristics on consumers' decisions can guide insurers in creating user-friendly offerings. Richter et al. (2019) suggests by designing targeted marketing strategies which is rooted in behavioural insights will increase sales. They posited that insurance companies should focus on designing simpler, more accessible insurance products for consumers. Additionally, nudging can be used during the sales process. Using scripted outbound calls, insurers can influence behaviour to drive customer satisfaction. This approach is even more valuable where decisions are largely driven by consumers' emotions, like life and health insurance (Richter et al., 2019). Pairing customers with sales agents from similar backgrounds can increase sales by as much as 30% (Becker et al., 2020). Beyond this, insurers can use behavioural techniques like nudges to improve retention.

Comprehending behavioural dynamics is particularly important considering the recent challenges faced by the insurance industry. The COVID 19 pandemic dealt a serious blow to the service industry by profoundly altering consumer psychology and behaviour (Tao et al., 2022). The growth was largely driven by consumers increased risk awareness. Heightened public sensitivity to risks, spurred by the pandemic, exemplified the role of availability heuristics in shaping perceptions (Du, 2022; Ceschi et al., 2019; Tversky and Kahneman, 1973). Following COVID 19, insurance companies were placing a greater emphasis on wellness-driven products, and customised experiences (Consumer & Retail Practice Team, 2024). This change is influenced by consumers perceived expectation of what is acceptable or desirable behaviour.

1.3. Conclusion

Prior research has shown cognitive biases influence how decisions are made, such as availability heuristics (relying on familiar patterns as opposed to objective reasoning) and social norms (decisions are influenced by society's expectations) (Huber et al., 2023; Guercini and Milanesi, 2020; Ceschi et al., 2019; Cialdini et al., 1990). Although many studies have explored these topics in isolation, few have studied their combined interaction on insurance decision-making (Gigerenzer et al., 2022; Ceschi et al., 2019). To explore this, the present study investigates: How do availability heuristics and perceived social norms influence insurance decisions made by South African consumers?

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

Insurance purchases remained a complex decision for consumers due to their unpredictable nature (Pattnaik et al., 2021). For example, families are provided with financial security in the event of unexpected tragedies by life insurance cover (Pattnaik et al., 2021; Guan et al., 2020). However, despite the obvious advantages of insurance, individuals are required to evaluate not only the required benefits, coverage and criteria but also decide on the best service provider. This demonstrated the complexity of decision-making in the insurance industry and showed how unprepared individuals were for the risks they faced (Pattnaik et al., 2021). For instance, as noted in the classic economic analysis by Akerlof (2002), known as “Market for Lemons”, suboptimal decisions resulted from asymmetric information between buyers and insurers in addition to cognitive overload from analysing multiple insurance options.

Traditional economic theories struggled to explain many real-world insurance behaviours. This was because these theories assumed decision-makers were perfectly rational and made optimal decisions by maximising expected benefits (Corcos et al., 2020; Richter et al., 2019; Kahneman and Tversky, 2013). Behavioural economics, which incorporated psychological understanding, provided a better explanation as to why individuals’ decisions frequently deviate from rational models (Corcos et al., 2020; Richter et al., 2019). Two key psychological factors that impact the insurance decisions of individuals were perceived social norms and availability heuristics (Jiang et al., 2023; Horne and Mollborn, 2020; Tversky and Kahneman, 1973). Perceived social norms were defined as the unwritten guidelines that direct a group or society’s behaviour. The concept of availability heuristic was defined as a cognitive shortcut which caused people to consider the likelihood of an event occurring based on past experiences. To fully understanding the interaction between these two constructs required a comprehensive review of past literature.

This literature review critically examined how consumer insurance decisions were influenced by perceived social norms and availability heuristics. Any gaps in the literature that pertained to the relationship between these constructs in the context

of purchasing decisions in the insurance industry were highlighted through a synthesis of key research. The review was arranged thematically, beginning with a discussion regarding the theoretical basis and moving on to perceived social norms, availability heuristics, and identified gaps in the research.

2.2. Theoretical foundation

The study of human decision-making was shaped by divergent perspectives as shown by ecological rationality theory which serves as the basis for this study (Gigerenzer and Gaissmaier, 2011). Unbounded rationality which portrayed the mind as an idealised decision-maker with perfect information, boundless time, and unlimited calculation power, dominated economics for a large part of the 20th century (Gigerenzer and Selten, 2002). The phrase bounded rationality was first coined by Herbert A. Simon to describe real-world decision-making where such insight was unattainable (Gigerenzer et al., 2022; Gigerenzer and Selten, 2008). This gave rise to two schools of thought on bounded rationality. The first school, the well-known “heuristics-and-biases” program, explored systematic biases by separating peoples’ beliefs and decisions from the optimal beliefs and decisions assumed in rational-agent-models (Gigerenzer and Gaissmaier, 2011). This view described heuristics as mental shortcuts that often lead to costly mistakes when measured against logic and probability (Gigerenzer et al., 2022; Gigerenzer, 2018; Goldstein and Gigerenzer, 2002). Barberis (2013) criticised its poor predictive ability in dynamic markets, where biases might have changed due to experience.

The second school of thought on bounded rationality reframed heuristics not as biases but as tools that allow for intelligent decision-making in a highly uncertain world (Gigerenzer and Selten, 2002; Goldstein and Gigerenzer, 2002). This method served as the foundation for this investigation which was traced back to Herbert A. Simon’s fundamental question which enquired about the reasoning process of individuals in the absence of rationality in neoclassical economics (Gigerenzer and Gaissmaier, 2011). On the foundational concept of ecological rationality, which predicated that a strategy’s “rationality” was measured by its adaptation to the structure of the environment in which it was used rather than being a feature of its logical framework (Gigerenzer et al., 2022; Gigerenzer and Gaissmaier, 2011; Goldstein and Gigerenzer, 2002).

Ecological rationality was the main idea behind this theoretical framework developed by Gigerenzer. A heuristic's performance depended on how well it fit its environment and was neither characterised as good nor bad, rational or irrational (Gigerenzer and Gaissmaier, 2011). This idea of rational human behaviour was described by Herbert A. Simon's scissor example, where the two blades are represented by the external world and the cognitive capabilities of people. To fully understand the decision-making process, both the external world and the cognitive strategy need to be understood. Given that the circumstances under which a specific heuristic was likely to work or not, studies on ecological rationality were prescriptive (Gigerenzer et al., 2022; Gigerenzer and Gaissmaier, 2011). Additionally, they focussed on the external environment that heuristics can exploit such as redundancy, uncertainty and variability in weights. Redundancy occurred when the correlation between different cues produced overlapping information, it was rational to rely on one and disregard the others. Uncertainty referred to the accuracy of predictions where the greater the uncertainty, the more reliance was placed on simpler models. Variability in weights was described as the predictive power among different cues where either simple heuristics are employed in the case of a dominant cue or if the cues were roughly equally weighted, they were more rational to use the $1/N$ rule (Gigerenzer et al., 2022).

To understand why heuristics were essential, it is important to distinguish between the two fundamentally different kinds of decision environments. The first was a risk scenario where all potential outcomes and their probabilities were known, which is referred to as "small world" (Gigerenzer et al., 2022; Gigerenzer and Gaissmaier, 2011). In these scenarios the assumptions of classical rational-agent models held true, and any deviation was classified as an error. Classical examples of these risk scenarios were lotteries or roulette. However, most real-world decisions took place in "large worlds" characterised by uncertainty where the future remained unpredictable and all unknown information is estimated using sample data (Gigerenzer and Gaissmaier, 2011). These large world environments were commonly referred to as VUCA (volatility, uncertainty, complexity, and ambiguity) and examples of these included organisational decisions, like hiring choices and project investments. Complex statistical models frequently failed to produce reliable predictions in large world scenarios as the optimal solution cannot be obtained

(Gigerenzer et al., 2022). In these instance, simple heuristics become essential in making informed decisions (Gigerenzer, 2018).

Social norms provided an additional theoretical element to ecological rationality theory for this study, as it assisted in understanding consumer decision-making (Cialdini et al., 1990). Schultz (2022) emphasised how social norms ultimately influenced decisions of consumers through injunctive norms (socially acceptable behaviour) and descriptive norms (behaviour of most people), acting as a so called “secret agents of influence”. According to Melnyk et al. (2010) and Cialdini et al. (1990), descriptive norms influenced decisions based on behaviour of others. For example, people will be more motivated to buy insurance after they witnessed an increase in insurance uptake (Lo, 2013). Conversely, individuals who were subjected to injunctive norms felt under pressure to behave in ways that were deemed suitable to win society’s acceptance (Melnik et al., 2010; Cialdini et al., 1990). An example of injunctive norms would be the expectation from society to protect one’s belongings which could influence insurance purchases. Finally, a large portion of the research on perceived social norms was synthesized by labelling it as “secret agents of influence” (Schultz, 2022). The “secret” element alludes to the underestimation of the influence of social norms on behaviour. This realisation drew significant attention to a possible flaw in methodology as individuals were unaware of certain behaviours as they lacked conscious access to the normative forces influencing their behaviour. Therefore, this study is anchored on the theory of ecological rationality, supported by perceived social norms as a supporting theoretical concept.

2.3. Influence of social norms on consumer decision-making

Social norms were known as unwritten rules govern what is considered as acceptable behaviour (Cislaghi & Heise, 2020; Horne & Mollborn, 2020; Van Kleef et al., 2019). These implicit or explicit rules foster conformity that affected consumer preferences through methods such as moral concerns and expectation alignment (Jiang et al., 2023). Studies identify two main types of norms: descriptive norms, which capture what one believed most people did in a particular context and offered a kind of social cue that encouraged action by suggesting what were practical or effective; and injunctive norms, which reflect what someone believed others approve

or disapprove of, influenced others' behaviour through the prospect of social approval or criticism (Cialdini et al., 1990).

Several studies have been conducted on the efficacy of these two norm types. The meta-analysis carried out by Melnyk et al. (2019), concluded each of the two social norm types had different effects. This analysis concluded injunctive norms showed a greater influence on attitudes whereas descriptive norms had a greater impact on behaviour. In a more recent meta-analysis, the researchers discovered a contradicting finding (Rhodes et al., 2020). The meta-analysis suggested injunctive norms were much more successful in altering behaviour than descriptive norms. The same analysis revealed descriptive norms were responsible for shaping what people perceived to be normal behaviour. This contradiction in findings could be explained by the inclusion of moderators in the Rhodes meta-analysis to establish whether a relationship was truly causal. Rhodes (2022) postulated the impact of norms had varying effects on different people depending on several circumstances, such as the cultural environment (group-oriented societies tend to respond stronger to normative nudges) and proximity to the reference groups (expectations from friends and family are more impactful than those of strangers). Individual characteristics like morality and the anticipated benefit of a specific action are just two examples of the many complicated ways in which social norms influenced behaviour (Huber et al., 2023). When someone observed their peers supporting a particular action, for instance, they often followed suit and viewed it as morally acceptable.

Researchers have examined how social norms operate in addition to assessing the relative effects of different norm types. Horne and Mollborn (2020) presented an integrated framework for understanding the impact social norms had on decision-making. They divided social norms into three approaches: consequentialist, relational, and agentic. The consequentialist approach posited that decision-making was driven by incentives, for example peoples' expectation of receiving rewards or punishment. The relational approach emphasized the preference of individuals to adhere to social norms to feel a sense of inclusion to society. The agentic approach challenged our thinking about the static nature of social norms and instead posited that social norms were an ever-evolving construct driven by individuals. This framework provided an opposing view to the earlier study done by Cialdini et al. (1990), stating crucial dimensions regarding how social norms operated were

ignored by mainly observing the construct in a controlled environment. Additionally, Cialdini et al. (1990) captured a very narrow view of a complex social process from which social norms are formed and behaviour was influenced. Ultimately, Horne and Mollborn (2020) argued that social norms were a dynamic process and evolved over time because of the influences from changing values and other peoples' expectations.

Social norms were shown to be both contextual and changing (Li et al., 2024). The research by Li et al. (2024), showed the existence of anti-bias norms when an observer witnessed prejudice attitudes and behaviours being addressed by society. By reinforcing the behaviour of descriptive anti-bias norms (bias was uncommon) and returning the perception of injunctive anti-bias norms (bias was incorrect) to the pre-bias state, they found that confrontation had a restorative effect. By demonstrating that norms were actively created and upheld by society through social interaction, the viewpoint differed from other perspectives which considered norms as fixed, pre-existing rules. Their work was conducted on scenario-based methods which provided a limitation with regards to its application to the real-world. Li et al. (2024) demonstrated that individuals who actively addressed prejudice behaviour created lasting effect on local social norms. Their research showed that through persistent intervention against prejudice behaviour, the social norms that are considered acceptable by society will change.

Individuals who challenged preconceived opinions about others helped society reject stereotypes (Li et al. 2024). The research suggested that calling out discriminatory statements clarified what a community stood for and labelled such behaviour as unacceptable. It was less about dismantling big stereotypes and more about setting the tone for what's considered acceptable by the group. This encouraged society to challenge biases and create awareness around bias being socially unacceptable behaviour, thereby strengthening the idea of injunctive norms and descriptive norms. Germar et al. (2023) provided additional insights regarding the visual interpretation of information in a group setting and how these influences decision-making. Their research showed a close relationship between social norms and decision-making remained while the visual information or group setting was present. A further conclusion was derived from the influence of learned social norms on the judgements regarding visual information, stating individuals made decisions based on learned

social norms which could cause them to perceive images differently. These findings concluded that social norms could cause biases to either be lessened or exacerbated.

Germar et al. (2023) provided an interesting finding in their research, which showed that social norms created permanent perceptual biases. According to their research, individuals' perceptions of decisions may change because of being exposed to social norms, which affected how they subjectively reacted to decisions going forward. This argument challenges previous literature, which argued that social norms had a cognitive influence on behaviour. Germar et al. (2023) posited that the influence of social norms was changing individuals' perceptions. The persistent nature at which individuals' perceptions were changed, indicated a high degree of internalization. This corresponds to social norms being referred to as the "secret agents of influence", as their impact goes largely undetected. The ecological validity of the laboratory-based methodology by Germar et al. (2023) were questioned, as the controlled environment would rarely mimic those of the uncertain insurance industry. Their experiment still asked valuable questions about the deeper, perceptual aspect to social norms. This approach suggested a successful way to internalise social standards that might have increased the influence of social norms on decisions beyond the conscious mind.

Previous studies have provided valuable insights on social norms and how they interact with purchase intent. According to studies on flood insurance, people were more likely to purchase insurance when they believed that others in their social circle supported or acted in a similar way, as opposed to just reacting to the perceived threat (Lo, 2013). This increase in individual flood insurance because of proximity to others with coverage, demonstrated the mediating role of social norms on perceived risk. Social factors that expressed through conversations and nonverbal cues, influenced risk perception. Recent research showed the influence on norms were driven by both the perceived level of risk and the degree of uncertainty surrounding risk (Zhuang & Carey, 2025). When people were unsure of their vulnerability and the extent of the risk, they were more likely to copy the actions of others and purchase insurance to guard against unforeseen circumstances. As this research focused on the moderating effect of perceived social norms on available heuristics and purchase

intent, the literature review on available heuristics would be discussed in the next section.

2.4. Availability heuristics

2.4.1. Availability heuristics

Our understanding of heuristics evolved greatly over the last 50 years. Tversky & Kahneman (1973) first introduced the idea of availability heuristics in 1973. Their research on availability heuristics showed that individuals relied on past experiences when making complex decisions rather than using statistical data to assess the probability of an event happening. Their theory simplified the elusive question of how often an event occurred by asking instead how easily it could be recalled. Considering that frequent events were generally easier to recall, Tversky and Kahneman concluded from their seminal work that the availability heuristic had ecological validity. However, the ease by which an event was recalled was influenced by more than just frequency. Additional non-frequency related factors such as uniqueness, how captivating an event was, and how much media attention it received, all contributed to how easy an event was remembered. Tversky and Kahneman, described this mental shortcut as a source of bias which cause errors in decision-making. This became the foundation to their research in understanding how individuals consistently deviated from the proposed best answer predicted by rational models.

The availability heuristic was conceptualised as a mental process through which an individual will retrieve, construct, and associate past experiences (Tversky and Kahneman, 1973). When considering the well-known example of determining word frequency, individuals tended to overestimate the number of words that start with the letter “K” as opposed to words having the letter in the third place. This was because words like “knowledge” were more memorable compared to words like “make” or “take”, despite the latter being more commonly used. Which creates a feeling of a higher frequency. A similar distortion happened when individuals unconsciously perceived events to frequently occur in pairs by the strong cognitive associations rather than the actual co-occurrence (Tversky & Kahneman, 1973). The brain association between “bacon and eggs” seemed to appear together more frequently

than they did. This was referred to as illusory correlations, where individuals' intuitive perception of frequency deviated from statistical reality. Tversky and Kahneman explained the existence of systemic biases in the way individuals viewed patterns in their environment and the deeper the mental connection between two concepts, the more they exaggerated their simultaneous occurrence.

Folkes (1988) research indicated unique experiences were one of the most important factors influencing availability heuristics. Individuals paid greater attention to unique events which made them easier to recall. In contrast to product failures associated with more popular brand names, an experiment showed that participants underestimated the frequency of product failures on unique and distinctive brand names. This occurred due to the perceived ease of recalling the more common brand names instead of recalling the actual failure rate. Folkes' research showed that unique experiences drove individuals' perception of risk which could lead to incorrect assessments. Siegrist (2021) continued to examine how perceived risk affected behaviour, highlighted how emotionally charged situations led people to make skewed risk decisions. Together, these studies demonstrated how availability heuristics shaped consumers' perceptions, causing them to prioritise risks related to emotional past experiences over those that are highly likely.

Prospect theory was used to further contextualise the availability heuristic's influence on decision-making. Tversky and Kahneman (1979) introduced the four fundamental principles of prospect theory in their seminal paper, which reconceptualized decision-making under risk. First, reference dependence suggested that people measured gains and losses against a neutral reference point which is usually their current position, rather than assumed by utility theory as their ultimate wealth position. Second, loss aversion captured the asymmetry in people's reactions to positive and negative changes. The value function was steeper in the loss domain, which reflected losses as more significant. Third was diminishing sensitivity which meant prospect theory's value function is S-shaped. This indicated a decreased sensitivity as you move away from the reference point which gave a significant disparity in risk attitude whether an individual is in the gain or loss domain. Fourth was probability weighting which was contrary to traditional utility theory, which assumed individuals processed probabilities linearly. The original formulation of prospect theory was able to effectively be explained experimental anomalies in the behaviour of individuals such

as why they are both risk seeking (in the form of gambling) and risk adverse (protect their assets by purchasing insurance) at the same time. This formulation occasionally encountered limitations when dealing with situations that posed multiple outcomes and therefore the cumulative prospect theory was created. Cumulative prospect theory addressed the earlier limitations by adopting a rank-dependent cumulative functional approach that changed the entire probability distributions rather than individual probabilities (Tversky and Kahneman, 1992). This ensured stochastic dominance, extending applicability to uncertain prospects with an arbitrary number of outcomes.

Gigerenzer and Gaissmaier (2011) contradicted the traditional view that availability heuristics are inherently flawed or error prone. They posited due to the simplicity and applicability of applying heuristics, it often outperformed complex models in high uncertainty environments. Comparing the definition of availability heuristics provided by Tversky & Kahneman (1973) to the definition of Gigerenzer and Gaissmaier (2011) did not suggest one approach to be superior in the context of insurance. Instead, each strategy demonstrated strong justification for insurance-related decisions. The fundamental incentive behind purchasing insurance was best explained by using Kahneman and Tversky's (1973) approach and applying prospect theory. A compelling argument was made towards the willingness to spend more to protect against future unlikely but catastrophic events. Additionally, it described how cognitive biases contributed to certain consumer preferences such as the desire for low deductibles. On the other hand, Gigerenzer and Gaissmaier's (2011) approach explained how individuals appropriately assessed the likelihood of hazards in an uncertain world. The evidence presented by Pachur et al. (2012), showed that a formalised availability heuristic can be viewed as a "smart heuristic" that is both straightforward and effective. Essentially, this demonstrated the accuracy and adaptiveness in heuristics when used to estimate the frequency of underlying risks (Gigerenzer and Gaissmaier, 2011). This study focused on the mental shortcuts that was applied during decision-making processes, ignoring earlier thinking of heuristics as a source of bias.

2.4.2. Availability heuristics and consumer purchase decisions

The influence of availability heuristics on consumer purchasing decisions was multifaceted. Prior research demonstrated that availability heuristics affected how individuals perceived risk, simplified complex decisions, and shaped consumer purchase intent. Despite the complicated nature of insurance decisions, individuals' subjective assessments of the chances of experiencing an insured event (such as mortality or loss of assets) were influenced by availability heuristics (Du, 2022; Siegrist and Árvai, 2020; Zain ul Abdin et al., 2017). Past literature showed a strong relationship between emotionally charged events and insurance decisions (Siegrist and Árvai, 2020; Richter et al., 2019). These findings suggested that risk management strategies should have accounted for how vivid, emotional experiences disproportionately influenced perceived likelihood and subsequent insurance purchases (Pachur et al., 2012; Keller et al., 2006).

Past literature has showed a strong relationship between emotionally charged events and insurance decisions. Siegrist and Árvai (2020) and Keller et al. (2006) indicated the effect an emotionally charged event had on individuals perceived risk and the influence on insurance uptake. Keller et al. (2006) showed even in the absence of firsthand experience, exposure to an emotionally charged event enhanced availability. A study showed that participants rated flooding as a high-risk event after viewing photographs of flooded houses compared to a control group that did not view similar images. This demonstrated how the media and advertising campaigns could manipulate availability heuristics and influence individuals' perception of risk (Du, 2022). For instance, pharmaceutical advertising can provide consumers with more knowledge about a particular condition which made the condition appear more common and possibly raising demand for insurance related treatment. Campaigns that highlighted uncommon but striking health risks, like heart disease, demonstrated this phenomenon and increased the perceived urgency for health or life insurance (Richter et al., 2019).

Availability heuristics had a considerable influence on ecological rationality (Gigerenzer and Gaissmaier, 2011). Ecological rationality argued that heuristics were adaptive tools that aligned with the structure of the environment, contrary to the heuristics-and-biases view that saw availability heuristics as a source of error

(Tversky & Kahneman, 1973). Consumers often operated in “large world” scenarios when it came to insurance decisions, where complete information about risk products and probabilities was unavailable. For example, an individual might have relied on the recent memory of an emotional experience rather than data, when deciding to purchase insurance. Additionally, availability heuristics clearly explained the variations in the demand for insurance. Insurance coverage often increased in the immediate aftermath of a disaster (Richter et al., 2019). For example, as climate change increased the frequency of flood and other natural disasters, insurance for property increased as individuals recalled graphic media depictions of devastations. Due to the availability and well publicised nature of the incident, the risk was considered high. As societies’ recollection of the event faded and media coverage diminished, the demand for insurance also declined. These examples are both described by the availability-by-recall model, which explained this relationship between availability and insurance decisions (Pachur et al., 2012). The model demonstrated individuals could accurately predict the frequency of a risk event by their capacity to recall examples of such events from their own social cues, such as stories shared within a community.

Availability heuristics played a significant role in reducing calculation time in complex environments, especially when limited information and processing capabilities existed (Ceschi et al., 2019). This highlights the influence availability heuristics have on decision-making. An individual’s risk perceptions were influenced by availability heuristics by how quickly information came to mind. In VUCA (volatility, uncertainty, complexity, ambiguity) environments, availability heuristics helped individuals make faster decisions by reducing the cognitive load placed on them (Gigerenzer et al., 2022). Dominiak and Duersch (2024) described cognitive load as the burden placed on individual’s mental capacity. They found cognitive load specifically influential on behaviour in complex environments. Gigerenzer and Gaissmaier (2011) showed individuals reduced decision fatigue by relying on memorable experiences to make complex choices, compared to doing thorough analysis of all available options. Guercini and Milanesi (2020) demonstrated the beneficial impact of availability heuristics on effective decision-making in the face of uncertainty. In practice, this means insurance customers often gravitate toward well-known companies or policies that seem appealing rather than performing comparisons.

These results showed that consumer insurance decisions were significantly shaped by availability heuristics as decisions were based on memorable, emotionally charged events over evaluating data. The influence of availability heuristics was demonstrated by the increase in insurance coverage after a catastrophic event or because of media coverage. Availability heuristics are an adaptive instrument that supports ecological rationality. Availability heuristics can aid individuals in comprehending complex situations but can also distort risk perception, making unusual events seem more likely while underestimating frequent ones.

2.5. The gap in the literature

Academic research indicated availability heuristics and perceived social norms exerted distinct yet significant influences on consumer decision-making (Huber et al., 2023; Cialdini et al., 1990). Prospect theory explained how individual's psychological aversion to loss and tendency to overemphasise low-probability events made insurance research more appealing (Corcos et al., 2020; Richter et al., 2019). The influence of personal risk assessments on insurance purchases was often mediated by individuals' perceptions of the behaviours and endorsements of others (Lo, 2013; Tversky and Kahneman, 1973). Meanwhile, studies on availability heuristics showed that a key factor in determining insurance decisions was individuals' capacity to recall pertinent experiences from memory (Zhuang and Carey, 2025). However, researchers have not yet fully explored how these constructs interact.

While researchers have extensively examined both social norms and availability heuristics separately, there is limited understanding of how these factors work together to influence intention to purchase (Ceschi et al., 2019; Tversky and Kahneman, 1973). The studies have mostly looked at these ideas independently. For example, the research on availability heuristics focused on individuals' perception of risk based on memory accessibility, while research regarding social norms mostly looked at the influence of society and conforming to socially acceptable ideas (Horne and Mollborn, 2020; Van Kleef et al., 2019; Tversky and Kahneman, 1973). Exploring the causal sequence proposed by the literature would be a promising avenue for future research. First, coverage of a traumatic event increases risk perception by making it more accessible to individuals. Secondly, the increase in risk perception

makes individuals more aware of others' risk mitigation practices which directly influenced insurance decisions.

Furthermore, the role uncertainty played require additional research. Recent studies showed that the influence of social norms was significantly moderated by uncertainty around individuals' risk judgements rather than the judgements themselves (Zhuang and Carey, 2025; Guercini and Milanesi, 2020). This raised questions regarding how this kind of uncertainty interacted with availability heuristics. For example, whether a consumer who vividly remembered a disaster but also acknowledged the potential for distortion in their perspective, which become influenced by societal standards. Previous studies showed a mismatch between the number of individuals with an intent to purchase insurance and those individuals that followed through with the purchase (Dragos et al., 2020). The literature indicated trust and product knowledge were critical in understanding how to close this gap.

This work addresses the scarcity of research on the influence of social norms on availability heuristics, either by strengthening or weakening the impact of cognitive shortcuts, in the context of insurance purchasing behaviour (Rhodes et al., 2020; Pachur et al., 2012). This study aims to add a theoretical contribution by integrating social norms alongside the availability heuristic, to enhance understanding of consumer insurance decision-making (Huber et al., 2023). This research assessed whether societies' expectations strengthened or weakened risk assessments based on past experiences, resulting in their influence on decision-making.

CHAPTER 3: RESEARCH HYPOTHESES

The goal of this study is to investigate how availability heuristics and social norms influence decisions when consumers purchase insurance products. As discussed in chapters 1 and 2, there are a few studies that investigate the moderating effect of perceived social norms on availability heuristics in the context of insurance purchasing intentions.

3.1. Conceptual research model

The relationships between the various constructs considered within the study are illustrated below in Figure 1 (the conceptual research model). The model offers a structured framework for testing the hypotheses and applying the statistical analysis to investigate any influences between constructs.

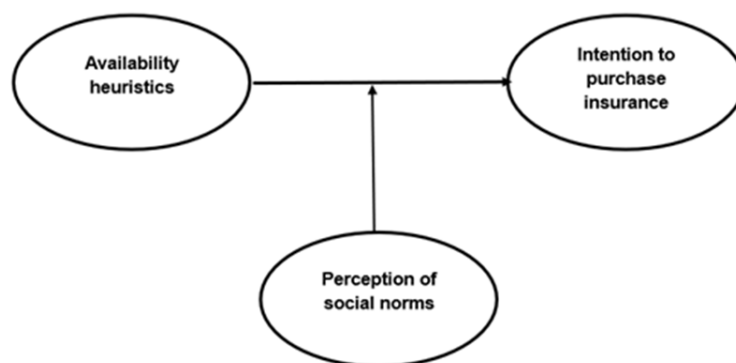


Figure 1: Conceptual research model

3.2. Research questions and hypotheses

3.2.1. Research question 1 (hypothesis 1)

RQ₁: Do perceived social norms have a significant influence on consumers' insurance purchase intention?

Existing literature highlights the significant role social norms play in consumer decision-making (Melnyk et al., 2022; Schultz, 2022). Horne and Mollborn (2020) support this theory by arguing that people tend to change their behaviour based on

what is socially acceptable as they seek to attract social relationships. Based on the literature review conducted in chapter 2, the study explores the extent to which perceived social norms influence consumers' intention to buy insurance.

Null Hypothesis (H_{10}): Perceived social norms have no significant influence on the intention to purchase insurance.

Alternative Hypothesis (H_{11}): Perceived social norms have a significant positive influence on the intention to purchase insurance.

3.2.2. Research question 2 (hypothesis 2)

RQ₂: To what extent does the availability heuristic influence South African consumers' intention to purchase insurance?

Research indicates that consumers often rely on availability heuristics when making financial decisions (Guercini and Milanesi, 2020; Zain ul Abdin et al., 2017). Additionally, people prioritize risks that are more personally memorable rather than those that are statistically more probable (Siegrist, 2021; Siegrist & Árvai, 2020; Folkes, 1988). Richter et al. (2019) and Zain ul Abdin et al. (2017) explain how cognitive shortcuts influenced complex financial decision-making, leading consumers to rely on familiar risks rather than conducting a thorough analysis.

Null Hypothesis (H_{20}): Availability heuristics have no significant influence on the intention to purchase insurance.

Alternative Hypothesis (H_{21}): Availability heuristics have a significant positive influence on the intention to purchase insurance.

3.2.3. Research question 3 (hypothesis 3)

RQ₃: Do perceived social norms moderate the relationship between availability heuristics and insurance purchase intention among consumers?

The literature shows extensive investigation regarding social norms and availability heuristics, however, there remains a significant gap in understanding their relative and combined influence, in insurance decision-making. The hypothesis below

determines if perceived social norms impact decision-making by strengthening or weakening risk evaluations based on availability heuristics.

Null Hypothesis (H_{30}): There is no significant interaction effect between perceived social norms and availability heuristics on consumers' intention to purchase insurance.

Alternative Hypothesis (H_{31}): There is a significant interaction effect between perceived social norms and availability heuristics on consumers' intention to purchase insurance.

CHAPTER 4: RESEARCH METHODOLOGY

4.1. Introduction

This research adopted a positivist research philosophy, meaning the study assumed an objective reality exists that can be captured and analysed through measurable data (Saunders and Lewis, 2018). Positivism relies on observable, quantifiable evidence rather than subjective interpretation. The study reflected this through its structured design methodology, that included standardised survey instruments, predetermined data cleaning and encoding processes. The systematic nature of these methods allows for replication, to make it possible for other researchers to replicate the results using the same methods. This chapter outlines the research methodology, population, unit of analysis, sampling method and size, measurement instrument, data gathering approach, data analysis process, quality controls, and limitations.

4.2. Research methodology and design

A cross-sectional research design was implemented to investigate whether perceived social norms moderated the relationship between availability heuristics and consumers' intention to purchase insurance (Zhuang and Carey, 2025; Stockemer et al., 2019). A cross-sectional approach was selected as it allows data collection at a single point in time because of time restrictions. A major limitation of the cross-sectional research design was its inability to establish clear causation since temporal precedence cannot be demonstrated. For clear causality to be proved, the changes in availability heuristics or perceived social norms must occur before changes in intent to purchase insurance. Therefore, only allowing correlation to be assessed by the study.

A mono-method, quantitative research methodology was used, given the nature of the instruments employed (Lim, 2025; Saunders and Lewis, 2018). Quantitative research followed a structured assessment to collect and analyse numerical data which is extremely valuable in obtaining objective, applicable and replicable results. The reliance on structured and standardized data collection methods, such as surveys, enables the detection of significant relationships between constructs

(availability heuristics, social norms, and intention to purchase), which allows the study to draw meaningful conclusions.

A deductive research approach was used to test the hypotheses as stated in chapter 3 (Stockemer et al., 2019; Saunders and Lewis, 2018). This approach ensured a structured research process, which allowed statistical controls that supported the hypothesis testing. The deductive method played an important role in behavioural economics research, as it allowed for the testing of predetermined theoretical assumptions, such as the moderating role of perceived social norms on availability heuristics and intent to purchase insurance (Sürücü and Maslakci, 2020). Examining a moderating (conditional) relationship was an example of diagnostic analysis in quantitative research, which investigates the relationships and underlying causes between constructs with an emphasis on conditional relationships and interactions (Lim, 2025).

4.3. Population

The study targeted South African adults aged 18 years and older who were the primary decision-makers for purchasing personal or household insurance products (for example, house, vehicle, health or life insurance). This age range was selected because it had captured all insurance decision-makers, from young adults (who had begun to make insurance decisions), middle-aged adults (who had more complex insurance needs), to older adults (who were making retirement and estate planning). It had been extremely valuable to obtain feedback from people in these varied life stages. This was aligned with the demographic standards of other quantitative studies in the field of behavioural economics. Zhuang and Carey (2025) performed a cross-sectional online survey that examined social norms on a sample of individuals which were 18 years and older. Similarly, a study that investigated private pensions and life insurance in Romania, examined a sample representative of the population which were between 18 and 65 years old (Dragos et al., 2020). Additionally, the population was aligned to the primary decision-makers from prior research conducted on risk management. Dragos et al. (2020) targeted the individuals responsible for making insurance decisions within the household. It is assumed that individual decision-makers were evaluating risks for themselves and

their dependents. The population included both current policyholders and potential buyers of insurance products.

4.4. Unit of analysis

The individual insurance consumer served as the unit of analysis, as this study focussed on decision-making on an individual level. By focussing specifically on consumers' perceptions, this study aimed to explore how perceived social norms and availability heuristics influence purchase intent in insurance.

4.5. Sampling method and size

The study employed non-probability sampling methods because of its practicality. While probability sampling methods (e.g. stratified random sampling) might have been a better choice, they weren't realistic options to implement within the available window. A structured survey was distributed using convenience sampling, by which participants were selected based on their proximity to the researcher as well as their willingness and availability to complete the questionnaire (Saunders and Lewis, 2012). Additionally, initial participants were encouraged to circulate the questionnaire to their professional networks which created a "snowball" effect. This process is referred to as snowball sampling. This secondary sampling technique was employed to increase the number of respondents.

The researcher personally monitored how data was collected too increases the accuracy of the results and allow a balanced representation across diverse demographics (e.g. race, gender, income levels). The researcher targeted a sample size of 120 to 150 respondents. The final sample size of $N = 162$ is confirmed as being large enough for multiple regression. The power test confirms $N = 162 > 50 + (8 \times k)$ where k is the number of predictors used in the test. This gives $N = 162 > 114$ as the researcher will use 8 predictors (moderator, independent variable, interaction term, and 4 control variables).

4.6. Measurement instrument

This study collected data to address the hypotheses stated in chapter 3 through a structured survey questionnaire. Control variables were included as part of the demographic section of the questionnaire. These included age (as a continuous variable), gender, household income, financial security and family situation. The use of control variables in the study on behaviour factors, perceived social norms and availability heuristics, allowed the researcher to reduce the influence of confounding effects on purchasing intent (Eling et al., 2021).

The questionnaire contained 15 questions, apart from the demographic information, to measure the following constructs:

- Perceived social norms
- Availability heuristics
- Intent to purchase

The below paragraphs, sets out how the questions were formulated to measure each construct.

4.6.1. Perceived social norms

The moderator for the purpose of this study was perceived social norms. Perceived social norms of consumers with regards to insurance purchases were measured using 7-point Likert scale, ranging from 'strongly disagree' to 'strongly agree', adapted from Lo (2013). In the fifth study conducted by Alex Lo, two questions were asked using a 7-point Likert scale to measure individuals perceived social expectations regarding flood insurance purchases. The researcher adopted and adapted the measurement from the study by Lo (2013), to measure the extent consumers believed that (1) their family or friends want them to purchase insurance, and (2) other individuals like themselves would purchase insurance. A limitation from the study by Lo (2013) was that the Cronbach alpha was not provided to confirm the reliability of the study.

This study focused specifically on the influence descriptive norms on behaviour. Therefore, a 7-point Likert scale which ranges from ‘strongly disagree’ to ‘strongly agree’, was used to measure the influence of descriptive norms (Huber et al., 2023). The measurement used by Huber et al. (2023), was adopted and adapted. Respondents were asked to comment on how many people around them had insurance.

Table 1 below shows the questions asked to participants, with the full survey questionnaire provided in Annexure A.

Table 1: Social norms measuring instrument

Construct	Item	Item code
Social norms	Q2.1 To what extent do you believe your family or friends want you to purchase insurance (e.g. a life insurance policy, health insurance and/or car insurance that is not provided as part of your employee benefits)?	SNORQ2.1
	Q2.2 To what extent do you believe other individuals like yourself would purchase insurance (e.g. a life insurance policy, health insurance and/or car insurance that is not provided as part of your employee benefits)?	SNORQ2.2
	Q2.3 How many people around you purchased insurance to protect their financial security?	SNORQ2.3

4.6.2. Availability heuristics

Availability heuristics were considered the independent variable in this study. Availability heuristics were measured using the 7-point Likert scale, ranging from ‘strongly disagree’ to ‘strongly agree’, developed by Zain ul Abdin et al., (2017). Section two in the study by Zain ul Abdin et al., (2017) was adopted and adapted by the researcher to measure the influence availability heuristics on individuals’ intention to purchase insurance. Participants were asked (1) if they prefer to buy insurance from insurers that they were more familiar with, and (2) if they consider the information received from family and friends as reliable and would base insurance decisions on it. The specific section of the study by Zain ul Abdin et al., (2017), had a Cronbach alpha of larger than 0.7.

In addition to the questions described above, respondents were asked to comment using a 7-point Likert scale, ranging from ‘strongly disagree’ to ‘strongly agree’, adapted from Ndawula et al. (2024). The study by Ndawula et al. (2024) was adopted and adapted by the researcher. Participants were asked to comment on (1) how premium relates to value, (2) whether they read their insurance policy, (3) provided the overwhelming amount of information they have access to, whether insurance protected against loss, and (4) whether they trust their own decision-making instincts. This section of the study by Ndawula et al. (2024), had a Cronbach alpha of 0.704.

Table 2 below shows the questions asked to participants, with the full survey questionnaire provided in Annexure A.

Table 2: Availability heuristics measuring instrument

Construct	Item	Item code
Availability heuristics	Q3.1 I am more likely to purchase insurance (e.g., house, vehicle, health, and/or life insurance) for risks (e.g. natural disasters, burglaries, car accidents) that are frequently discussed on TV, radio or social media because this information is readily available to me.	HEURQ3.1
	Q3.2 You consider the information received from family and friends as a reliable reference for your own insurance decisions.	HEURQ3.2
	Q3.3 I consider the premiums charged for an insurance policy (e.g., house, vehicle, health, and/or life insurance) to reflect the true value, if I know the premium charged are similar to other policies with the same terms and conditions.	HEURQ3.3
	Q3.4 I review all information provided in an insurance policy (e.g., house, vehicle, health, and/or life insurance) before I decide to buy it.	HEURQ3.4
	Q3.5 Given all the events discussed in the news and on social media about car accidents and burglaries, I associate an insurance policy (e.g., house, vehicle, health, and/or life insurance) with protection against losses.	HEURQ3.5
	Q3.6 I trust my instincts when making decisions about purchasing an insurance policy (e.g., house, vehicle, health, and/or life insurance).	HEURQ3.6

4.6.3. Consumer purchase intent

Consumer purchase intent was considered the dependent variable for the purposes of this study. Consumers' purchase intent was measured by using a 7-point Likert scale, ranging from 'strongly disagree' to 'strongly agree', adapted from Dragos et al. (2020). The study by Dragos et al. (2020) was adopted and adapted by the researcher. Participants were asked to comment on (1) their trust in insurance companies, (2) their experience regarding insurance companies, (3) whether they currently have insurance, and (4) whether they intent to purchase insurance, (5) consider insurance as an investment to secure their financial well-being, and (6) consider insurance to protect against financial risks. The study by Dragos et al. (2020), had a Cronbach alpha equal to 0.84.

Table 3 below shows the questions asked to participants, with the full survey questionnaire provided in Annexure A.

Table 3: Purchase intent measuring instrument

Construct	Item	Item code
Purchase intent	Q4.1 How much trust do you have in insurance companies?	PURCQ4.1
	Q4.2 Your experiences or those of your relatives (family, friends) regarding insurance companies have been ...?	PURCQ4.2
	Q4.3 Have you purchased, or do you have any type of insurance currently (e.g., house, vehicle, health, and/or life insurance)?	PURCQ4.3
	Q4.4 I intend to purchase a new insurance policy or renew my current insurance policy within the next 12 months.	PURCQ4.4
	Q4.5 I have purchased or intend to purchase an insurance policy because I consider it an investment to secure my financial well-being.	PURCQ4.5
	Q4.6 I have purchased or intend to purchase an insurance policy because I consider it as protection for financial support in case of unexpected events (e.g., illness or death).	PURCQ4.6

4.7. Data gathering process

Data collection was conducted through an online questionnaire which was developed on an online survey platform called Microsoft Forms. The researcher distributed the questionnaire through personal networks, via Email, WhatsApp, and LinkedIn. Collecting data through digital channels proved cost-effective and logistically easier (Stockemer et al., 2019; Saunders and Lewis, 2018). A limitation of online questionnaires was the possibility of misunderstanding by participants and the inability to clarify the meaning of the question.

Prior to formal data collection, a pre-test was conducted with seven individuals that resembled the population. The pre-test main purpose was to assess the clarity, consistency, and validity of the survey instrument (Stockemer et al., 2019; Saunders and Lewis, 2018). A well-structured pre-test enhances the reliability of the questionnaire by identifying potential ambiguities and measure the average completion time. The pre-test responses were excluded from the final data sample that was used for analysis (Stockemer et al., 2019).

4.8. Data analysis approach

A structured, multi-step approach was adopted by the researcher (Stockemer et al., 2019; Saunders and Lewis, 2018). The data analysis approach followed by the researcher included both descriptive and inferential techniques. The completeness of the survey results was checked. Following data cleaning, categorical variables were transformed into numerical codes (Stockemer et al., 2019).

Descriptive statistics (e.g., mean, median, and mode) and variability measures (e.g., standard deviation), were computed to analyse patterns across demographic groups (Lim, 2025; Stockemer et al., 2019). The initial insights into the dataset were visualised using histograms for numerical continuous variables (e.g., Likert scales responses) and bar charts for categorical variables (e.g., demographical information) (Stockemer et al., 2019). The reliability of each construct was assessed by Cronbach's alpha. A Cronbach alpha of larger than 0.7 indicated an acceptable reliability (Dragos et al., 2020; Sürücü and Maslakci, 2020).

According to Stockemer et al. (2019), regression models allowed for the testing of predictive relationships between constructs. When conducting multiple regression analysis, the following assumptions were tested prior to analysis: the dependent and independent variables were linear, all observations were independent, residuals were normally distributed, and the independent variable was uncorrelated with the error term (Lim, 2025; Stockemer et al., 2019). The researcher first confirm that all the assumptions held. Multiple regression analysis was used to assess the relationship between availability heuristics, perceived social norms, and consumers' intention to buy insurance. The interaction effects were examined to assess how norms interact with availability heuristics. Assumptions (such as normality and multicollinearity) were investigated to ensure accurate results were obtained.

4.9. Research ethics

Ethical clearance was obtained on the 24 August 2025 by submitting the Ethical Clearance Form and all supporting documents to the Gordon Institute of Business Science's Ethics Committee. Data collection commenced on attainment of approval.

4.10. Limitations

The gathered data at a particular point in time. The cross-sectional design provided significant constraints with regards to data collection which allowed causation and temporal relationships to be created (Zhuang and Carey, 2025; Stockemer et al., 2019). Causality cannot be confirmed since it cannot be established if the change in the independent variable occurred before the change in the dependent variable (Lim, 2025). This design offered limited contextual understanding of the constructs over a period. As data was collected at the same time and the independent and dependent variables were measured simultaneously using a Likert scale, there was a risk for common method bias (CMB) (Lim, 2025; Zain ul Abdin et al., 2017).

A mono-method quantitative methodology limited the study to a single method which could introduce measurement weakness (Zain ul Abdin et al., 2017). The methodology could also overlooked essential nuances, possibly affecting the depth of the study (Lim, 2025). Additionally, quantitative research could potentially

oversimplify complex ideas, and statistical models provided no flexibility around interpretation of information.

Convenience and snowball sampling, although it is faster and less resource-intensive than probability sampling, produced a dataset that might not have accurately depicted the population in the study (Lim, 2025; Stockemer et al., 2019). Convenience and snowball sampling are both examples of non-probability sampling techniques which introduced the potential for bias, as not every respondent had an equal chance of being selected. For this reason, the researcher monitored the demographic characteristics as the data was collected and attempted to adjust the sampling approach to reduce sampling bias.

This study depends on participants accurately disclosing their intention to purchase insurance. However, this does not reflect actual behaviour (Sharma, 2021; Dragos et al., 2020). Additionally, measuring the influence of social norms on availability heuristics, could introduce bias (Rhodes et al., 2020). Furthermore, individuals had limited exposure to risk events and therefore might have faced difficulty in making decisions based on availability heuristics (Pachur et al., 2012). Research identified the influence of heuristics on decisions however, there was some difficulty in understanding which heuristic, individuals relied on during the decision-making process (Siegrist and Árvai, 2020).

As stated by Lim (2025) and Stockemer et al. (2019), the application of multiple regression analysis assumes that all observations are independent of one other. If this assumption fails, bias will be introduced into the model. Additionally, the prediction accuracy will be reduced when there is no linear relationship between the dependent and independent variables.

CHAPTER 5: FINDINGS

5.1. Introduction

The objective of chapter 5 is to present the empirical results of the quantitative data collection and analysis process. This chapter connects the theoretical framework and methodology developed in earlier chapters with the findings' discussion in chapter 6. A systematic approach will be presented from the collection of the data to the description, concluding on the hypotheses testing. First, an explanation of the sampling characteristics and the response rates is discussed followed by demographic presentation of the data. Additionally, the chapter addresses the critical aspect of data quality by testing the validity and reliability of the measuring instruments used in the study. Finally, this chapter addresses each of the research questions and accompanying hypotheses stated in chapter 3, providing clear evidence to support the findings.

5.2. Description of sample data

Data were collected over a period of roughly one month by distributing the online survey using digital platforms such as Email, WhatsApp, and LinkedIn. The distribution of the survey took place from 2 September 2025 to 4 October 2025. During this time, 175 participants completed the survey and provided their consent to take part in the survey. Before the data was analysed, the information from the 175 survey questionnaires was subjected to a methodical data preparation and coding procedure. This is crucial to maintain the integrity of data which will enable meaningful interpretation of results (Stockemer et al., 2019).

Firstly, the data were reviewed for incomplete submissions. There were no missing data fields, which showed a 100% completion rate. The researcher conducted an analysis to identify outliers in the data by calculating the mean, minimum value, maximum value, Q_1 , and Q_3 of each construct (Lim, 2025; Stockemer et al., 2019). The identified quartile values and boundaries for each construct is specified in Table 4. Outliers were identified as values that fell outside the range ($Q_1 - 1.5 \times IQR$; $Q_3 - 1.5 \times IQR$) where the interquartile range (IQR) is the difference between Q_3 and Q_1 .

The analysis revealed 13 outliers which were subsequently removed from the sample, which left the final sample size of 162.

Table 4: Age by gender distribution

Name	Perceived social norms (SNOR)	Availability heuristics (HEUR)	Purchase intent (PURC)
Q1	4,33	4,67	4,17
Median	5,33	5,33	4,67
Q3	5,67	5,67	5,17
IQR	1,33	1,00	1,00
Upper bound	7,67	7,17	6,67
Lower bound	2,33	3,17	2,67

To facilitate quantitative analysis of the data, the survey questionnaire required systematically recoding (Stockemer et al., 2019). Appendix A contains the entire coding methodology used by the researcher (as part of the survey questionnaire).

5.3. Descriptive statistics

The demographic characteristics of the sample (N = 162) are essential in understanding the relevance of the findings to the South African insurance consumer. Additionally, the demographic data provides context to the researcher during the analysis of the results. Apart from the questions measuring the three constructs, the survey questionnaire included questions relating to the following control variables (age, financial situation, monthly income, and household situation) to account for any demographic variations in the analysis. Control variables are rarely the main focus of studies but are often included to assist in isolating the effect of the main explanatory variables (Siegrist and Árvai, 2020).

5.3.1. Descriptive statistics of the control variables

The study requested participants to provide details regarding their age, gender, monthly household income, household situation, as well as financial security. These specific control factors were chosen because of prior research indicated their possible influence (Eling et al., 2021; Dragos et al., 2020; Richter et al., 2019).

Gender distribution

Gender was recorded as part of this study as a control variable due to prior research indicating its influence on individuals risk perception and insurance purchase behaviour (Richter et al., 2019). Figure 2 shows a higher proportion of males (58%) completed the survey than females (42%). This is an example of the gender imbalance that is representative of males being the main insurance decision makers and should be considered while interpretation of the results.

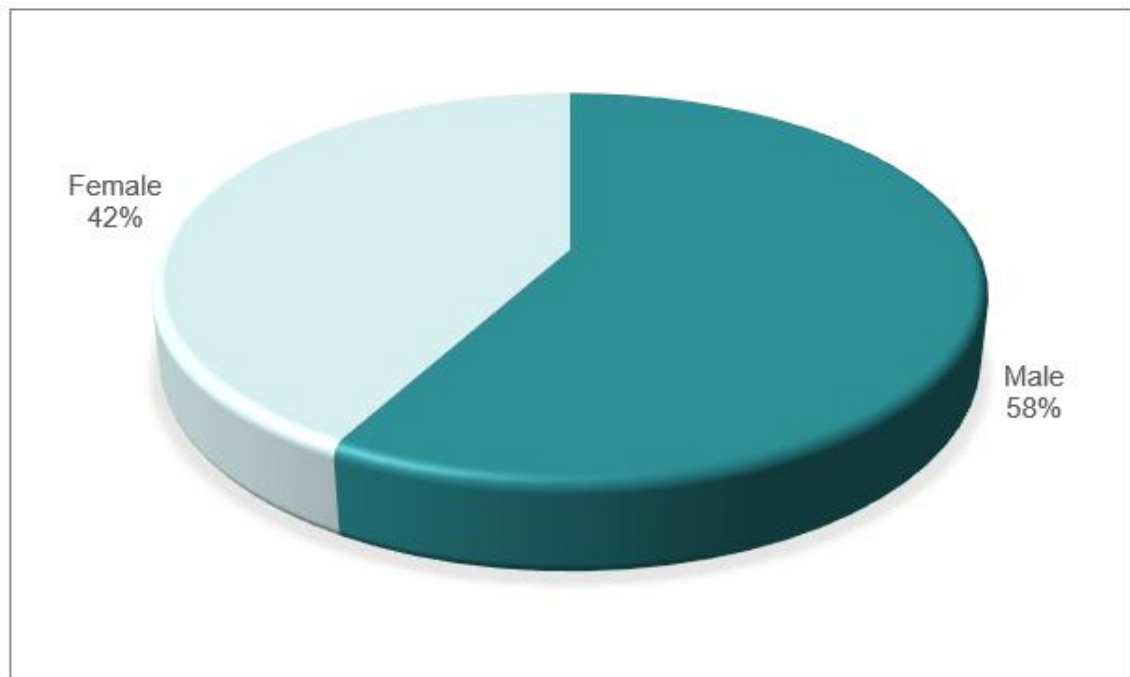


Figure 2: Gender

Age by gender distribution

The survey captured the actual age of the participants. The gender of the participants was plotted against the actual age of the participants which were grouped together in age bands. Figure 3 provide a graphical representation of the percentage of participants based on age and gender. Of the 162 participants, most were between the ages of 30 to 49 for both males and females. The age band 30 to 39 showed a completion percentage of 35% for males and 32% for females. The age band 40 to 49 had a slightly lower completion percentage for males of 26% but showed a 32% completion percentage for females.

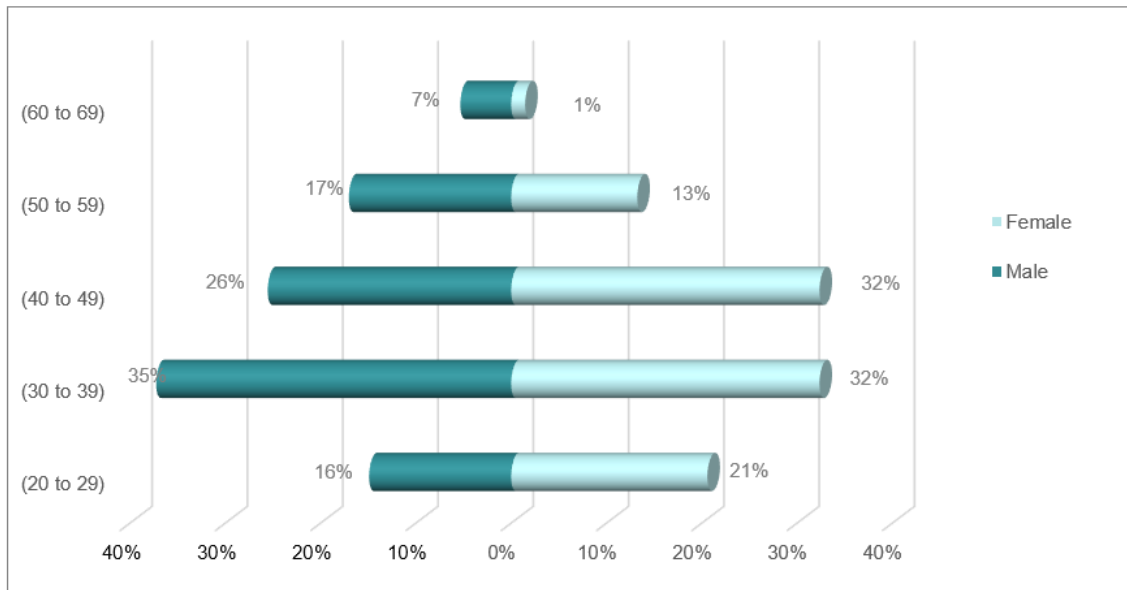


Figure 3: Age by gender distribution

Education attainment

Participants were requested to provide details with regards to their highest qualification obtained. Figure 4 shows that 68% of participants completed a postgraduate degree. The results show that participants may be more financially literate and have a more advanced understanding of insurance products than the population.

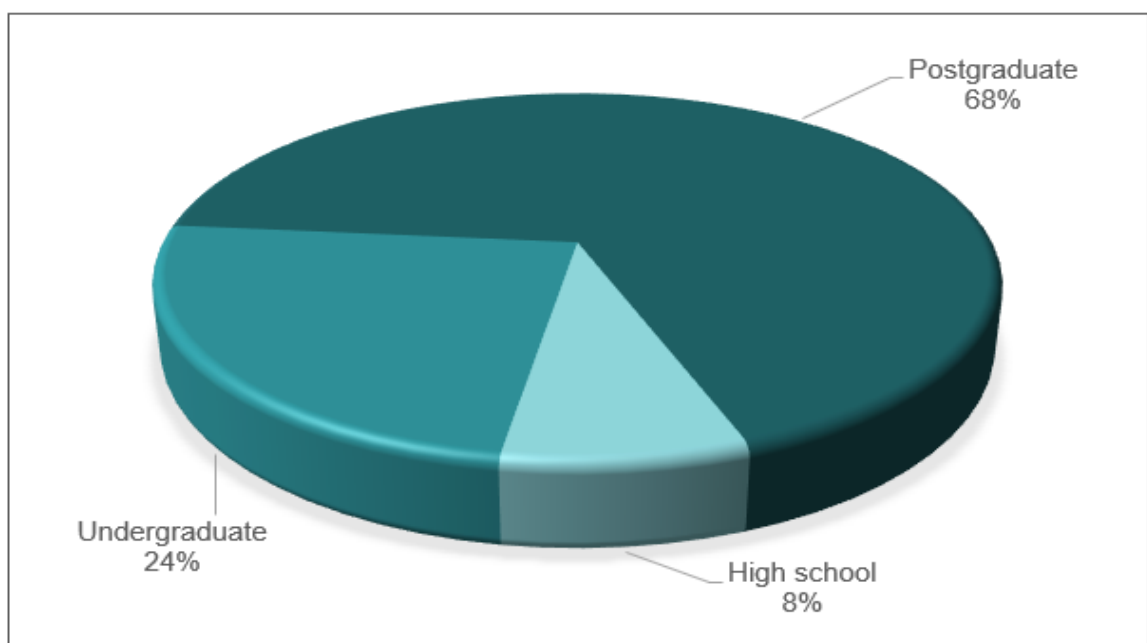


Figure 4: Education attainment

Monthly household income

Participants' monthly household income was requested using categorical ranges in the survey to account for sensitivity around providing exact salary data. Figure 5 shows the monthly household distribution of all 162 participants with 96 (59%) of the participants falling into the income category of above R50 000 per month. The ability by an individual to purchase insurance is significantly influence by their income level, which will have a direct impact on the perceived value of insurance. Households earning a higher income have more disposable income to spend on insurance compared to lower income households (Dragos et al., 2020).

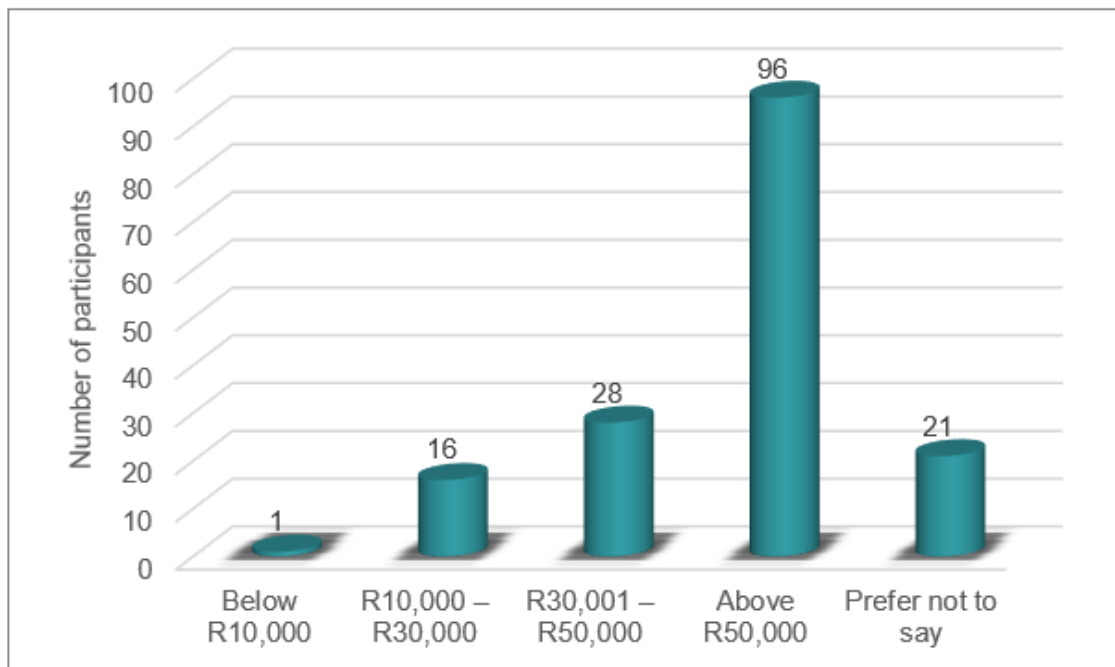


Figure 5: Monthly household income

Financial security

Figure 6 shows a 7-point Likert scale, ranging from 'not at all secure' to 'extremely secure' that was used to measure the participants' opinion of their current financial situation. It is noteworthy that 58% of participants indicated they are 'not at all secure' to 'moderately secure' with their financial situation. Despite the importance of insurance cover, individuals experiencing financial hardship will chose to prioritise other things above insurance (Dragos et al., 2020). This suggests that people's perceptions of their financial security have an impact on their insurance decisions.

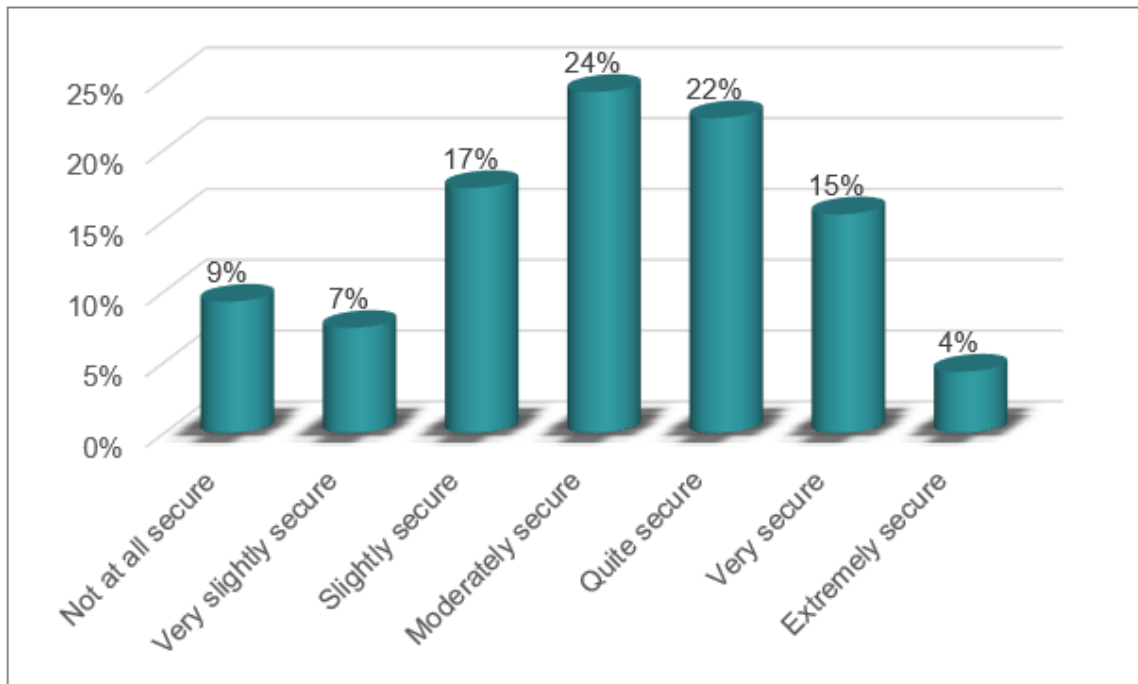


Figure 6: Financial security

Household situation

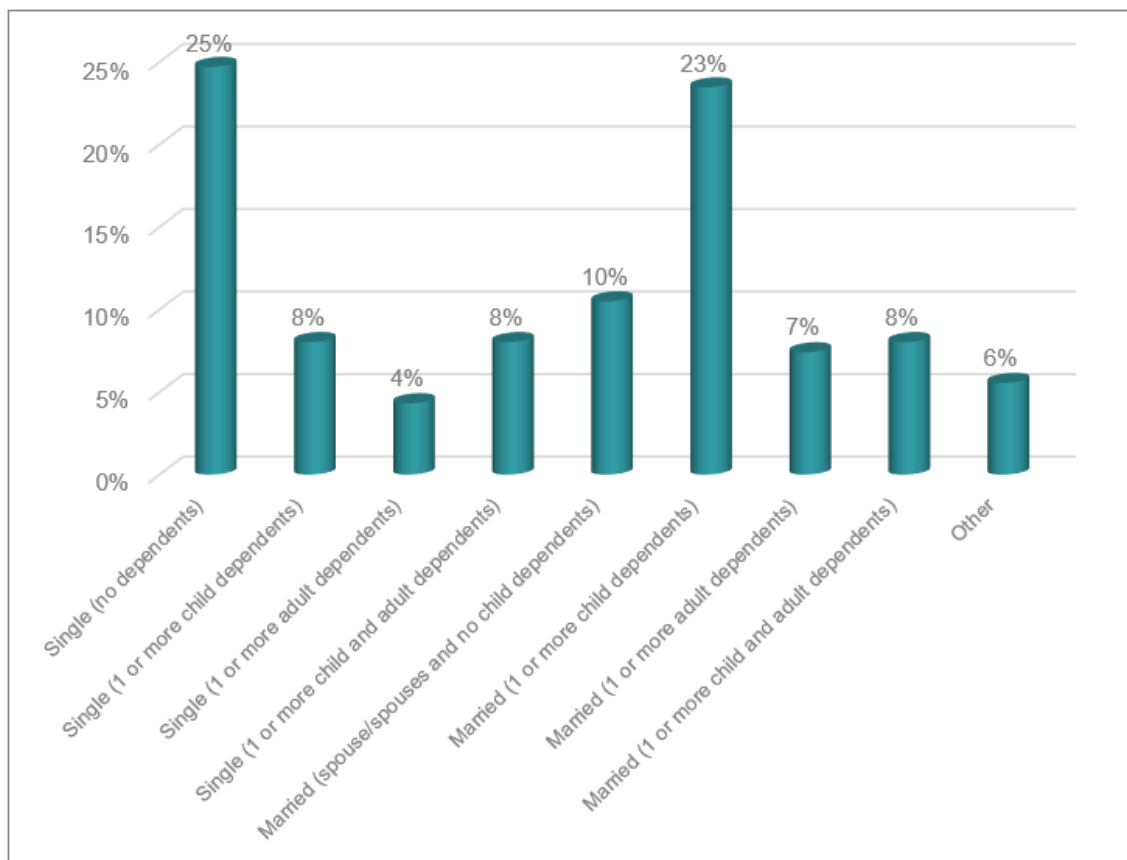


Figure 7: Household situation

The household situation of each participant was measured by enquiring about their living arrangements and the number of dependents. Figure 7 indicates 25% of participants are single with no child dependents and 23% indicated they are married with one or more child dependents. The insurance requirements of an individual are driven by their household situation. For example, individuals with multiple dependents tend to be more likely to obtain financial protection through life and health insurance (Dragos et al., 2020).

5.3.2. Descriptive statistics of key constructs

Descriptive statistics were calculated for each of the three constructs following the data cleaning process. The statistics in Table 5 provide insight into the distribution, dispersion and central tendency.

Table 5: Description statistics of key constructs

Construct	Item	N	Min	Max	Mean	Std. Dev
Perceived social norms	SOCN1	162	1	7	5,05	1,57
	SOCN2	162	1	7	5,78	1,09
	SOCN3	162	1	7	4,66	1,67
Availability heuristics	HEUR1	162	1	7	4,62	1,68
	HEUR2	162	1	7	4,72	1,46
	HEUR3	162	1	7	4,86	1,68
	HEUR4	162	1	7	5,64	1,43
	HEUR5	162	1	7	5,70	1,19
	HEUR6	162	1	7	5,62	1,26
Purchase intent	PURC1	162	2	7	4,31	1,19
	PURC2	162	1	7	4,35	1,03
	PURC3	162	1	4	3,57	0,81
	PURC4	162	1	7	5,01	1,88
	PURC5	162	1	7	5,35	1,43
	PURC6	162	2	7	5,96	1,04

5.4. Reliability and validity of instrument

The reliability and validity of the measuring instruments were established as part of ensuring the quality of the quantitative research conducted (Sürücü and Maslakci, 2020). This section outlines the tests used and results obtained in measuring perceived social norms, availability heuristics and purchase intent.

5.4.1. Pearson's coefficient

This study employed the Pearson's coefficient to investigate the bivariate correlations among perceived social norms, availability heuristics and purchase intent. Pearson's coefficient determines whether items measuring the same construct are strongly correlated (Sürücü and Maslakci, 2020). The results from the SPSS output are found in Appendix B.

The linear relationship between two continuous variables is quantified by Pearson's correlation coefficient (r) which (Stockemer et al., 2019). The Pearson's correlation coefficient provides values ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation). No linear relationship exists around 0. Conventional rules state the p-value for each of the items and the total of the items must be less than 0.05 for the item to be valid.

Moderating variable: Perceived social norms

Table 6: Pearson's correlation matrix for perceived social norms

Variable	SNORQ2.1	SNORQ2.2	SNORQ2.3	SUM_S
SNORQ2.1				
SNORQ2.2	0.38**			
SNORQ2.3	0.22**	0.26**		
SUM_S	0.75**	0.68**	0.73**	

** Indicates all p-values are smaller than 0.01.

Table 6 shows the Pearson's correlation's coefficient calculating the correlations among the sample size (N=162) received from the three items (SNORQ2.1 to

SNORQ2.3) measuring perceived social norms and the sum of the items (SUM_S). All the individual items and the sum of the items are showing a p-value of less than 0.01 which indicates every correlation is statistically significant (Stockemer et al., 2019). The findings show that all three items contribute significantly to the overall construct.

Independent variable: Availability heuristics

The Pearson's correlation's coefficient was used to calculate the correlations among the sample size (N=162) received from the six items measuring availability heuristics and the sum of the items together (i.e. total availability heuristics). There were multiple non-significant connections found, with inter-item correlations (r) ranging from -0.08 to 0.30. HEURQ3.1 and HEURQ3.2 had an inter-item correlation of 0.30 ($p < 0.001$) (Stockemer et al., 2019), which was found to be the strongest. A weak or non-significant correlation was noted by items HEURQ3.3, HEURQ3.4, and HEURQ3.6, which might indicate heterogeneity (Sürücü and Maslakci, 2020). All the individual items are showing a moderate to strong positive correlation to the sum (p-value of less than 0.05). The results may indicate the measuring instrument of availability heuristics is assessing different but related components of the underlying construct.

Table 7: Pearson's correlation matrix for availability heuristics

Variable	HEURQ3.1	HEURQ3.2	HEURQ3.3	HEURQ3.4	HEURQ3.5	HEURQ3.6	SUM_A
HEURQ3.1							
HEURQ3.2	0.30**						
HEURQ3.3	0.02	0.07					
HEURQ3.4	-0.02	0.05	0.13				
HEURQ3.5	0.16*	0.10	0.18*	0.23**			
HEURQ3.6	-0.08	0.01	0.21**	0.14	0.17*		
SUM_A	0.50**	0.51**	0.56**	0.49**	0.55**	0.42**	

*Indicates all p-values are smaller than 0.05; ** Indicates all p-values are smaller than 0.01.

Dependent variable: Purchase intent

The Pearson's correlation's coefficient was used to measure the correlations among the responses (N=162) received from the six items (PURCQ4.1 to PURCQ4.6) measuring purchase intent and the sum of the items (SUM_P). The inter-item correlations ranged from weak to strong ($r = 0.04$ to $r = 0.56$). It was shown that PURCQ4.1 and PURCQ4.2 had the largest inter-item correlation ($r = 0.56$, $p < 0.001$) (Stockemer et al., 2019), indicating that they share a significant amount of variance. On the other hand, all the items in PURCQ4.4 had a non-significant correlation. The overall sum of the items showed moderate to strong correlations with the individual items, with r ranging from 0.42 to 0.68. All these were significant at $p < 0.001$ and supported the measuring instrument's overall consistency.

Table 8: Pearson's correlation matrix for purchase intent

Variable	PURCQ4.1	PURCQ4.2	PURCQ4.3	PURCQ4.4	PURCQ4.5	PURCQ4.6	SUM_P
PURCQ4.1							
PURCQ4.2	0.56**						
PURCQ4.3	0.17*	0.3					
PURCQ4.4	0.04	0.3	0.14				
PURCQ4.5	0.20*	0.23**	0.24**	0.29**			
PURCQ4.6	0.25**	0.15	0.17*	0.25**	0.32**		
SUM_P	0.58**	0.52**	0.42**	0.63**	0.68**	0.59**	

*Indicates all p-values are smaller than 0.05; ** Indicates all p-values are smaller than 0.01.

5.4.2. Cronbach's alpha

A measurement instrument's stability and consistency throughout repeated administration refers to the reliability (Stockemer et al., 2019). Internal consistency is most often used to measure how well Items on Likert scales measure the same construct (Dragos et al., 2020). The main indicator for evaluating internal consistency is the Cronbach alpha, which has values ranging between 0 and 1 (Sürücü and Maslakci, 2020).

A Cronbach alpha of larger than 0.7 is commonly accepted in behaviour science research (Dragos et al., 2020; Zain ul Abdin et al., 2017). For descriptive or exploratory research, a Cronbach alpha between 0.6 and 0.7 might be appropriate (Sürücü and Maslakci, 2020). The Cronbach alpha was calculated for each of the three constructs. The software program SPSS was used to perform the analysis. The results from the SPSS output are found in Appendix D.

Moderating variable: Perceived social norms

The Cronbach alpha was used to evaluate the internal reliability of perceived social norms construct (Sürücü and Maslakci, 2020). The reliability of the original three-item measuring instrument (SNORQ2.1 to SNORQ2.3) demonstrated a questionable reliability ($\alpha = 0.523$, $N = 162$). The item analysis revealed the lowest item-total correlation ($r = 0.287$) is provided by SNORQ2.3, which is below the 0.3 value. After deletion of SNORQ2.3, the two-item measuring instrument increased the alpha slightly to 0.528. The removal of SNORQ2.3 provided a moderate inter-item correlation of between 0.3 and 0.4 ($r = 0.383$, $p < 0.001$). The results are shown in Table 9.

Table 9: Reliability statistics for perceived social norms

Variable	N items	Cronbach alpha
SNORQ2.1 to SNORQ2.3	3	0.523
SNORQ.1 to SNORQ2.2	2	0.528

It is unclear whether the measuring instrument can reliably measure the desired construct given the weak Cronbach alpha. There could be several reasons for this result. For example, the small number of items measuring the construct limits the potential for a high internal consistency (Sürücü and Maslakci, 2020). Additionally, the measurement inaccuracy may be because of item wording or response formatting issues (Stockemer et al., 2019). Although the researcher conducted a pilot test and no participants in the pilot test reported any structure issues, the researcher must consider the possibility of participants finding the measuring instrument confusing.

Independent variable: Availability heuristics

The Cronbach alpha was used to evaluate the internal reliability of availability heuristics construct (Sürücü and Maslakci, 2020). The reliability of the original six-item measuring instrument (HEURQ3.1 to HEURQ3.6) demonstrated a questionable reliability ($\alpha = 0.412$, $N = 162$), falling well below the conventional acceptable standards. The item analysis revealed the lowest item-total correlation ($r = 0.134$) is provided by HEURQ3.1, which is below the 0.3 value. The deletion of HEURQ3.1 had a slight improvement in the alpha to 0.415. The further removal of HEURQ3.2 provided a moderate improvement in the alpha to 0.453. The researcher decided to remove HEURQ3.2 because the item had the lowest inter-item correlation of 0.091. The results are shown in Table 10.

Table 10: Reliability statistics for availability heuristics

Variable	N items	Cronbach alpha
HEURQ3.1 to HEURQ3.6	6	0.412
HEURQ3.2 to HEURQ3.6	5	0.415
HEURQ3.3 to HEURQ3.6	4	0.453

To increase the dependability of the measuring instrument, the researcher attempted to identify all inter-item-total correlations of less than 0.3 that significantly decreased the overall Cronbach alpha. The researcher could not improve the reliability of the Cronbach alpha through removal of anymore items, which suggests the remaining items are not sufficiently homogenous (Sürücü and Maslakci, 2020). The Cronbach alpha of 0.453 means that approximately 45% of the observed variance represents true differences in the construct, while 55% can be attributed to the measurement error. The measurement error will likely cause the observed effect sizes to underestimate the true relationships which is an important limitation to this study.

Dependent variable: Purchase intent

After conducting a reliability analysis for purchase intent using SPSS, the Cronbach alpha was calculated as 0.577 (Sürücü and Maslakci, 2020). The reliability of the original six-item measuring instrument (PURCQ4.1 to PURCQ4.6) demonstrated a

questionable reliability ($\alpha = 0.577$, $N = 162$), indicating a questionable reliability. The item analysis revealed the lowest item-total correlation ($r = 0.252$) is provided by PURCQ4.4, which is below the 0.3 value. The deletion of PURCQ4.4 increased the alpha to 0.601. The five-item revised measuring instrument showed inter-item correlation ranging from 0.237 to 0.452. The results are shown in Table 11.

Table 11: Reliability statistics for purchase intent

Variable	N items	Cronbach alpha
PURCQ4.1 to PURCQ4.6	6	0.577
PURCQ4.1 to PURCQ4.3, PURCQ4.5 to PURCQ4.6	5	0.601
PURCQ4.1 to PURCQ4.2, PURCQ4.5 to PURCQ4.6	4	0.599

5.4.3. Factor analysis

Factor analysis is a method of data reduction which is employed to find underlying patterns and dimensions in a collection of variables (Stockemer et al., 2019). The output for this section on factor analysis, which was done in SPSS, can be found in Appendix E.

Principal component analysis (PCA) with varimax rotation was selection in SPSS as the extraction method, as this is expected to maximise the variance described by each factor (Ceschi et al., 2019). In addition to factor analysis with varimax rotation, the Kaiser-Meyer-Olkin (KMO) test were conducted to ensure the data were suitable to conduct factor analysis. The KMO measure of sampling adequacy assesses whether there is enough common variation in the data to support factor analysis (Stockemer et al., 2019). A value of 0.6 and above is deemed adequate, a value between 0.7 and 0.8 is considered good, and above 0.8 is considered exceptional.

Moderating variable: Perceived social norms

A principal component analysis (PCA) was performed to investigate the three-items of the measuring instrument of perceived social norms (Lim, 2025; Ceschi et al., 2019). The result testing whether a PCA is suitable to be performed on the data, is

shown in Table 12. The sample size of 162 was found to be large enough to conduct a factor analysis, as shown by the 0.601 value of the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO). This was slightly above the minimum suggested value of 0.50.

A statistically significant result obtained from the Bartlett's test of Sphericity ($\chi^2(3) = 39.795$) shows that the items are sufficiently intercorrelated on a 95% confidence level (Ceschi et al., 2019).

Table 12: KMO and Bartlett's test for perceived social norms

Test	Statistic	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	KMO	0.601
Bartlett's Test of Sphericity	χ^2	39.795
	df	3
	Sig.	<0.001

PCA (when eigenvalues are larger than 1.0) recovered a single component which accounted for 52.88% of the total variance in the measuring instrument, as shown in Table 13. Each of the three items in the measuring instrument loaded significantly on the single component as reflected in Table 14. SNORQ2.2 displayed the highest loading of 0.780, followed by SNORQ2.1 (0.755) and SNORQ2.3 (0.639).

Table 13: Principal component analysis total variance explained for perceived social norms

Comp	Initial Eigenvalues			Extracted Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.586	52.88	52.88	1.586	52.88	52.88
2	0.800	26.68	79.55	-	-	-
3	0.614	20.45	100.00	-	-	-

The range of communalities was 0.408 to 0.609, which indicates that the single component explained 41% to 61% of the variance between individual items. The PCA supports the use of the complete measuring instrument.

Table 14: Component matrix and communalities for perceived social norms

Variable	Component Loading	Communalities (Extracted)
SNORQ2.1	0.780	0.609
SNORQ2.2	0.755	0.569
SNORQ2.3	0.639	0.408

Independent variable: Availability heuristics

Factor analysis was used to analyse the underlying structure of the construct measuring availability heuristics (Lim, 2025; Ceschi et al., 2019). The researcher is concerned regarding the validity and reliability of the measuring instrument, as it was adopted and adapted by several sources. The KMO test were conducted to ensure the data where suitable. The KMO measure of sampling adequacy assesses whether there is enough common variation in the data to support factor analysis (Stockemer et al., 2019). A value of 0.6 and above is deemed adequate, a value between 0.7 and 0.8 is considered good, and above 0.8 is considered exceptional.

Table 15 indicates the KMO test indicates miserable-to-mediocre sampling adequacy. Bartlett's test of sphericity indicates that correlations among items are substantial enough ($\chi^2(15) = 39.49.314$) to move forward with factor analysis with a significance level of $p < 0.05$ (Ceschi et al., 2019). Table 16 shows that two components were identified using the Kaiser criterion with an eigenvalue of more than 1.0. Together these components accounted for 48.19% of the variance. After Varimax rotation, it was found that Component 1 and Component 2 explained 25.52% and 22.67% of the respective variance.

Table 15: KMO and Bartlett's test for availability heuristics

Test	Statistic	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	KMO	0.575
Bartlett's Test of Sphericity	X ²	49.314
	df	15
	Sig.	<0.001

Table 16: Principal component analysis total variance explained for availability heuristics

Comp	Initial Eigenvalues			Extracted Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.584	26.41	26.41	1.584	26.41	26.41
2	1.307	21.78	1.307	1.307	21.78	48.19
3	0.908	15.13	-	-	-	-
4	0.787	13.12	-	-	-	-
5	0.777	12.94	-	-	-	-
6	0.637	10.62	-	-	-	-

Table 17: Principal component analysis total variance explained (Varimax rotation) for availability heuristics

Comp	Initial Eigenvalues			Rotation (Varimax)		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.584	26.41	26.41	1.531	25.52	25.52
2	1.307	21.78	1.307	1.360	22.67	48.19
3	0.908	15.13	-	-	-	-
4	0.787	13.12	-	-	-	-
5	0.777	12.94	-	-	-	-
6	0.637	10.62	-	-	-	-

Table 18: Component matrix and communalities for availability heuristics

Variable	Component 1	Component 2	Communalities
HEURQ3.1	-0.047	0.815	0.666
HEURQ3.2	0.076	0.746	0.562
HEURQ3.3	0.611	0.043	0.375
HEURQ3.4	0.599	0.019	0.359
HEURQ3.5	0.613	0.307	0.470
HEURQ3.6	0.645	-0.209	0.459

Table 18 shows the rotated solution revealed two distinct components as the load is the highest on these components. Component 1 contains items 3 to 6 (HEURQ3.3 to HEURQ3.6) with loadings ranging from 0.599 to 0.645. Component 2 contains items 1 and 2 (HEURQ3.1 to HEURQ3.2) with loading of 0.815 and 0.746 respectively. According to communalities, between 36% and 67% of the variance is explained by the two components. It is evident from the results that the measuring instrument is made up of two different but related aspects.

Dependent variable: Purchase intent

A value of 0.6 and above is deemed adequate, a value between 0.7 and 0.8 is considered good, and above 0.8 is considered exceptional. Table 19 indicates the KMO test is adequate with a value of 0.611. Bartlett's test of sphericity indicates that correlations among items are highly significant at $\chi^2(15) = 127.052$ to move forward with factor analysis with a significance level of $p < 0.001$. Table 20 shows that two components were identified using the Kaiser criterion with an eigenvalue of more than 1.0. Together these components accounted for 55.39% of the variance. After Varimax rotation, it was found that Component 1 and Component 2 explained 28.41% and 26.98% of the respective variance.

Table 19: KMO and Bartlett's test for purchase intent

Test	Statistic	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	KMO	0.611
Bartlett's Test of Sphericity	X ²	127.052
	df	15
	Sig.	<0.001

Table 20: Principal component analysis total variance explained for purchase intent

Comp	Initial Eigenvalues			Extracted Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.055	34.25	34.25	2.055	34.25	34.25
2	1.269	21.14	55.39	1.269	21.14	55.39
3	0.884	14.73	70.12			
4	0.726	12.09	82.22			
5	0.663	11.05	93.27			
6	0.404	6.73	100..00			

Table 21: Principal component analysis total variance explained (Varimax rotation) for purchase intent

Comp	Initial Eigenvalues			Rotation (Varimax)		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.055	34.25	34.25	1.705	28.41	28.41
2	1.269	21.14	55.39	1.619	26.98	55.39
3	0.884	14.73	70.12	-	-	-
4	0.726	12.09	82.22	-	-	-
5	0.663	11.05	93.27	-	-	-
6	0.404	6.73	100..00	-	-	-

Table 22: Component matrix and communalities for purchase intent

Variable	Component 1	Component 2	Communalities
PURCQ4.1	0.151	0.857	0.757
PURCQ4.2	0.045	0.874	0.766
PURCQ4.3	0.538	0.057	0.293
PURCQ4.4	0.711	-0.142	0.526
PURCQ4.5	0.696	0.218	0.532
PURCQ4.6	0.633	0.222	0.450

Table 22 shows the rotated solution revealed two distinct components as the load is the highest on these components. Component 1 contains items 3 to 6 (PURCQ4.3 to PURCQ4.6) with loadings ranging from 0.538 to 0.711. Component 2 contains items 1 and 2 (PURCQ4.1 to PURCQ4.2) with loading of 0.857 and 0.874 respectively. Between 29% and 77% of the variance can be explained by the two components as can be seen in Table 22.

5.4.4. Conclusion

Perceived social norms: Final measuring instrument SNORQ2.1 and SNORQ2.2

The initial three-item instrument showed questionable reliability ($\alpha = 0.523$). The analysis revealed that SNORQ2.3 performed the worst with a correlation of less than 0.3 ($r = 0.287$). After removal of SNORQ2.3, the inter-item correlation improved to 0.383 ($p < 0.001$) and showed a slight increase in the Cronbach alpha to 0.528. This choice was reinforced by the PCA, which identified a single component that explained 52.88% of the variance. The SNORQ2.3 exhibited the weakest loading with the component (loading = 0.639), compared to SNORQ2.1 (loading = 0.780) and SNORQ2.2 (loading = 0.755). The Pearson's correlation analysis verified that all items correlated significantly with the total sum on a 95% confidence level. Even with the small sample size ($N = 162$) and low Cronbach alpha, the two-item measuring instrument (SNORQ2.1 and SNORQ2.2) provides the most consistent measure of perceived social norms.

Availability heuristics: Final measuring instrument HEURQ3.3; HEURQ3.4; HEURQ3.5; and HEURQ3.6

The initial six-item instrument demonstrated poor reliability ($\alpha = 0.412$) and required improvement. The Cronbach alpha was increased to 0.453 by eliminating the items with the lowest inter-item correlations. By sequentially removing HEURQ3.1 ($r = 0.134$) and HEURQ3.2 ($r = 0.091$) increased the alpha. No further improvements could be obtained by deleting any other items, even though the alpha is still far from the traditional threshold. The PCA revealed a two-component structure which accounted for 48.19% of the total variance. Component 1 (HEURQ3.3 to HEURQ3.6) explained 25.52% of the variance and Component 2 (HEURQ3.1 and HEURQ3.2) explained 22.67% of the variance. This confirms the removal of items (HEURQ3.1 and HEURQ3.2) loading on Component 2. The Pearson's correlation analysis showed a weak to moderate inter-item correlation (-0.08 to 0.30). However, all items showed a moderate to strong correlation with the total sum on a 95% confidence level.

Purchase intent: Final measuring instrument PURCQ4.1; PURCQ4.2; PURCQ4.5; and PURCQ4.6

The initial six-item instrument demonstrated questionable reliability ($\alpha = 0.577$). The analysis revealed that PURCQ4.4 performed the worst with a correlation of less than the 0.3 threshold ($r = 0.252$). The Cronbach alpha was increased to 0.601 by eliminating PURCQ4.4. The remainder of the inter-item correlations ranged from 0.237 to 0.452. PURCQ4.3 was removed due to inter-item correlation being below 0.3. Although this reduced the Cronbach alpha slightly but improves the construct validity. The factor analysis revealed a two-component structure which accounted for 55.39% of the total variance. Component 1 (PURCQ4.3 to PURCQ4.6) explained 28.41% of the variance and Component 2 (PURCQ4.1 and PURCQ4.2) explained 26.98% of the variance. This confirms the removal of items (PURCQ4.1 and PURCQ4.2) loading on Component 2. The strong loadings on Component 1 (0.538 to 0.711) and Component 2 (0.857 and 0.874) showed that they measure complementary aspects of purchase intent. This supported the researcher's decision to keep the four-item instrument. The Pearson's correlation analysis showed variable

inter-item correlation (0.04 to 0.56). All items showed a moderate to strong correlation (0.42 to 0.68) with the total sum on a 95% confidence level.

5.5. Correlation analysis between variables

Prior to hypothesis testing, an extensive correlation analysis explored interconnections among the study's principal variables. The correlations provided valuable insights on relationships between constructs and control variables. This guided the interpretation of the regression results.

Table 23: Correlation matrix

Variable	1	2	3	4	5	6	7	8
PURC	-							
SNOR	0.22**	-						
HEUR	0.45***	0.38***	-					
Age	0.08	0.05	0.12	-				
Gender	-0.11	-0.04	-0.08	-0.02	-			
Monthly income	0.15*	0.11	0.18*	0.24**	-0.13	-		
Financial security	0.28***	0.19*	0.31***	0.16*	-0.05	0.35***	-	
Household situation	0.14	0.09	0.11	0.42***	-0.18*	0.29***	0.21**	-

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

5.6. Statistical testing and results

This section describes the analytical methodology and methodical approach used to test the hypotheses presented in chapter 3.

5.7. Research question 1: Hypothesis 1

H₁₀: Perceived social norms have no significant influence on consumers' intention to purchase insurance.

H₁₁: Perceived social norms have a significant positive influence on consumers' intention to purchase insurance.

A simple linear regression analysis was performed to test hypothesis 1. The regression analysis was performed with purchase intent (PURC) as the dependent variable and perceived social norms (SNOR) as the independent variable. The output from SPSS can be found in Appendix F.

5.7.1. Testing the assumptions for regression

To guarantee that parametric testing techniques are adequate to perform a linear regression analysis, the researcher conducted several statistical tests to ensure the required assumptions were being adhered to. The following assumptions are critical for regression analysis to be performed (Lim, 2025; Stockemer et al., 2019).

Both independent and dependent variables are measured at a continuous level. Since both variables were measured using a Likert-scale, it is confirmed that the condition of independence was satisfied.

The data should exhibit homoscedasticity, which means the variance of the residuals should be constant along the line of best fit. This assumption was checked by the visual examination of the residual plots which exhibit a relatively random scatter pattern. The spread of the data points appears to be consistent across the predicted values.

The observations should be independent. This assumption was tested by performing the Dublin-Watson test. Observations were found to be independent since the result of this test was within the range of 1 and 3, as shown in Table 24.

Table 24: Durbin-Watson test for SOCN and PURC

Model	R	R square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.216 ^a	0.047	0.041	0.78052	2.043

a. Predictor: (Constant) SOCN_IV

There should be no significant outliers in the data. From Table 25 it can be observed that the standardized residuals are within the required range of -3.29 and 3.29, which

is an indication of no significant outliers within the data. This is expected as the researcher remove any outliers during the data cleaning process.

Table 25: Residual statistics for SOCN and PURC

	Minimum	Maximum	Mean	Std. Deviation	N
Std. Residual	-2.986	2.558	0.000	0.997	162

The residuals of the regression line should be approximately normally distributed. The histogram exhibits a bell-shaped curve, and the normal P-P plot follow a diagonal line, which both confirms the residuals are normally distributed.

All regression assumptions are met, which confirms a simple regression analysis are acceptable to test this hypothesis.

Table 26: Results for hypothesis 1

Hypothesis	Statement	Result	Decision
H ₁₀	Perceived social norms have no significant influence on intent to purchase	$\beta = 0.216$; $p = 0.006$	Rejected
H ₁₁	Perceived social norms have a significant positive influence on intent to purchase	$\beta = 0.216$; $p = 0.006$	Accepted

There is sufficient evidence to reject the null hypothesis on a 95% confidence interval ($p = 0.006 < 0.05$).

5.8. Research question 2: Hypothesis 2

A simple linear regression analysis was performed to test hypothesis 2. The regression analysis was performed with purchase intent as the dependent variable (PURC) and availability heuristics (HEUR) as the independent variable. The output from SPSS can be found in Appendix G.

H₂₀: Availability heuristics have no significant influence on the intention to purchase insurance.

H₂₁: Availability heuristics have a significant positive influence on the intention to purchase insurance.

5.8.1. Testing the assumptions for regression

Both independent and dependent variables are measured at a continuous level. Since both variables were measured using a Likert-scale, it is confirmed that the condition of independence was satisfied.

The data should exhibit homoscedasticity, which means the variance of the residuals should be constant along the line of best fit. This assumption was checked by the visual examination of the residual plots which exhibit a relatively random scatter pattern. The spread of the data points appears to be consistent across the predicted values.

The observations should be independent. This assumption was tested by performing the Durbin-Watson test. Observations were found to be independent since the result of this test was within the range of 1 and 3, as shown in Table 27.

Table 27: Durbin-Watson test for HEUR and PURC

Model	R	R square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.449 ^a	0.202	0.197	0.71420	1.977

a. Predictor: (Constant) HEUR_IV

There should be no significant outliers in the data. From Table 28 it can be observed that the standardized residuals are not all within the required range of -3.29 and 3.29. This is slightly concerning but there is only one outlier in the sample of 162.

Table 28: Residual statistics for HEUR and PURC

	Minimum	Maximum	Mean	Std. Deviation	N
Std. Residual	-3.454	2.136	0.000	0.997	162

The residuals of the regression line should be approximately normally distributed. The histogram exhibits a bell-shaped curve, and the normal P-P plot follow a diagonal line, which both confirms the residuals are normally distributed.

All regression assumptions are met, which confirms a simple regression analysis are acceptable to test hypothesis 2.

Table 29: Results for hypothesis 2

Hypothesis	Statement	Result	Decision
H ₂₀	Availability heuristics have no significant influence on intent to purchase	$\beta = 0.449$; $p < 0.001$	Rejected
H ₂₁	Availability heuristics have a significant positive influence on intent to purchase	$\beta = 0.449$; $p < 0.001$	Accepted

There is sufficient evidence to reject the null hypothesis on a 95% confidence interval ($p < 0.001 < 0.05$).

5.9. Research question 3: Hypothesis 3

A multiple regression analysis was performed to test hypothesis 3. The regression analysis was performed with purchase intent as the dependent variable (PURC), availability heuristics (HEUR) as the independent variable, perceived social norms (SNOR) as the moderator and allowing for age, monthly income, financial status and household situation as the control variables. Incorporating the control variables into the regression model, allows the influences of perceived social norms and availability heuristics on purchase intent to be isolated which enhances the causal inference (Eling et al., 2021; Dragos et al., 2020).

This approach requires an interaction term to be created between availability heuristics (HEUR) and perceived social norms (SNOR). Both variables (SNOR) and (HEUR) were first centred before an interaction term was created, to reduce the possibility for multicollinearity between the main effects and the interaction term. Table 30 indicates the mean value deducted from each value.

Table 30: Mean value for centring the SNOR and HEUR variables

Variables	Mean
SNOR	5.4167
HEUR	5.4537

H₃₀: There is no significant interaction effect between perceived social norms and availability heuristics on consumers' intention to purchase insurance.

H₃₁: There is a significant interaction effect between perceived social norms and availability heuristics on consumers' intention to purchase insurance.

5.9.1. Testing the assumptions for multiple regression

Multiple regression requires a minimum sample size of $N = 162 > 50 + (8 \times k)$ where k is the number of predictors used in the test. This gives $N = 162 > 114$ as the researcher will use 8 predictors (SNOR, HEUR, interaction term, and 4 control variables) to test hypothesis 3. The sample size is confirmed as being large enough to use multiple regression.

The data should exhibit homoscedasticity, which means the variance of the residuals should be constant along the line of best fit. This assumption is confirmed as residual plot exhibit a relatively random scatter pattern. The spread of the data points appears to be consistent across the predicted values.

There should be no significant outliers in the data. The standard residual range is between -3.640 and 2.171 as indicated by From Table 31. Not all standardized residuals are within the required range of -3.29 and 3.29. This is slightly concerning and requires to be noted however it is not large enough to be removed.

Table 31: Residual statistics for HEUR, SNOR and PURC

	Minimum	Maximum	Mean	Std. Deviation	N
Std. Residual	-3.640	2.171	0.000	0.978	162

Table 32 indicates the VIF values obtained. The VIF values are all smaller than 3 which is an indication of no multicollinearity. Centring the SNOR and HEUR variables prior to creating the interaction term, was successful.

Table 32: Multicollinearity

	Tolerance	VIF
HEUR_CENTRE	0.988	1.01
SNOR_CENRE	0.979	1.02
SNOR_HEUR	0.951	1.03

The residuals of the regression line should be approximately normally distributed. The histogram exhibits a bell-shaped curve with mean = 0 and std. dev = 0.978. The normal P-P plot follows a diagonal line very closely with very minimal deviation. Both images confirm the residuals are normally distributed.

All regression assumptions are met, which confirms a multiple regression analysis are acceptable to test hypothesis 3.

5.9.2. Summary of model statistics

Table 33 indicate key findings of the multiple regression model. The researcher ran the multiple regression model in different stages. Model 1 only includes the four control variables. Model 2 was run by including the control variables (all four) and the independent variable (HEUR_CENTRE) and the moderating variable (SNOR_CENTRE). Whereas model 3 was systematically build up to include the control variables, the independent variable (HEUR_CENTRE), the moderating variable (SNOR_CENTRE), and the interaction term (SNOR_HEUR).

Table 33: Summary of model

Model	R	R ²	Adjusted R ²	R ₂ Change	F Change	df1	df2	Sig. F Change
1	0.28	0.079	0.250	0.079	3.351	4	157	0.012
2	0.527	0.278	0.250	0.199	21.328	2	155	<0.001
3	0.527	0.278	0.245	0.000	0.027	1	154	0.871

The p-value of the multiple regression test is 0.871 > 0.05 as indicated in Table 33.

The hierarchical regression analysis uncovered notable patterns across the three model. Model 1 tested demographic variables alone and found they explained 7.9% of the variance in the model ($R^2=0.079$, $F(5, 156) = 3.351$, $p = 0.012$). While this is a modest result, it does indicate that demographic background provides a valuable insight to intention to purchase insurance.

Model 2 incorporated the primary effects of availability heuristics and perceived social norms, yielding a marked rise in explained variance to 27.8% ($R^2 = 0.278$, $F(7, 154) = 9.922$, $p < 0.001$).

Model 3 introduced the interaction term to evaluate moderation. It accounted for 27.8% of the variance ($R^2 = 0.278$), reflecting negligible advancement beyond Model 2.

Table 34: Multiple regression model results

Variable	Model 1			Model 2			Model 3		
	B	SE	β	B	SE	β	B	SE	β
Control variables									
Age	0.003	0.008	0.030	0.002	0.007	0.023	0.002	0.007	0.024
Gender	-0.136	0.123	-0.085	-0.112	0.110	-0.070	-0.113	0.110	-0.071
Monthly income	0.038	0.074	0.079	0.002	0.068	0.002	0.003	0.068	0.003
Financial security	0.191	0.067	0.234*	0.124	0.062	0.152*	0.128	0.063	0.157
Household security	0.060	0.051	0.100	0.030	0.045	0.051	0.029	0.045	0.048
Main effects									
HEUR_CENTRE	-	-	-	0.323	0.057	0.415*	0.323	0.57	0.415*
SNOR_CENTRE	-	-	-	0.048	0.059	0.063	0.056	0.061	0.072
Interaction									
SNOR_HEUR	-	-	-	-	-	-	0.030	0.064	0.034

* $P < 0.05$

Table 35: Results for hypothesis 3

Hypothesis	Statement	Result	Decision
H ₃₀	There is no significant interaction effect between perceived social norms and availability heuristics on intent to purchase	$\beta = 0.011$; $p = 0.871$	Fail to Reject
H ₃₁	There is a significant interaction effect between perceived social norms and availability heuristics on intent to purchase	$\beta = 0.011$; $p = 0.871$	Rejected

There is insufficient evidence to reject the null hypothesis on a 95% confidence interval ($p = 0.871 < 0.05$).

CHAPTER 6: DISCUSSION OF RESULTS

6.1. Introduction

In this chapter, the theoretical framework developed in chapter 2 and the research questions outlined in chapter 3 are used to understand and conceptualize the empirical results reported in chapter 5. The three research questions and their associated hypotheses serve as the framework for the discussion, which links the statistical findings to previous research on availability heuristics, perceived social norms, and intent to purchase insurance. Prior to delving deeper into each study topic, the chapter will touch on the demographics of the sample. This is followed by a discussion on areas where the results support, expand, or challenge the existing research. The researcher will provide insights into the behavioural aspects influencing South African consumers intention to purchase insurance.

6.2. Demographic results

The sample's demographic composition provides significant characteristics that places the results into context. The sample (N = 162) was relatively wealthy individuals (59% earning more than R50 000 per month), well educated (68% having a postgraduate degree), and predominately male (58%). This demographic profile is significant for several reasons.

Firstly, comparing the high education level of participants reveals the sample was probably more financially literate than the population being considered. Previous research has clarified how education can shape the ways individuals make decisions (Dragos et al., 2020). Education can both improve the knowledge of financial products as well as the understanding of risk. Because less educated consumers may rely more on heuristics and social cues when making insurance decisions, the sample's concentration of highly educated participants might have an impact on the alternative hypotheses being rejected (Dragos et al., 2020; Siegrist and Árvai, 2020).

Second, the high-income levels show that most of the participants could possibly afford to purchase insurance. This is important for this study's analysis as income is a known factor in determining insurance uptake (Dragos et al., 2020). One of the

main obstacles to purchasing insurance is lowered when individuals can afford the premiums, which increases the influence of behavioural factors.

The demographic data provided a core finding. 58% of participants reported feeling moderately secure to less secure despite having high income levels. The finding reveal that objective financial standing doesn't always match up with subjective feelings of financial security (Richter et al., 2019; Barberis, 2013). This suggests other factors shaping individual's sense of financial well-being (Gigerenzer et al., 2022; Pachur et al., 2012). This conclusion is in line with earlier behaviour economic research that demonstrated the subjective insurance behavioural patterns is not compatible with those of a rational decision-maker (Richter et al., 2019).

The study's wide range of responses regarding household situation provides variation in the analysis. It allows the researcher to draw additional insights into how family responsibilities might interact with behavioural factors in insurance. According to prior research, individuals who are responsible for a family or dependents usually purchase more insurance (Dragos et al., 2020). This increase reliance on insurance products is due to the increased responsibility of ensuring their family's financial security.

6.3. Research question 1

6.3.1. Summary of findings

Addressing the initial research question, a simple linear regression analysis assessed whether perceived social norms (independent variable) shape intention to purchase insurance (dependent variable) (Lim, 2025; Stockemer et al., 2019; Saunders and Lewis, 2018). A simple linear regression analysis showed that perceived social norms explained 4.7% of the variance in intention to purchase insurance, which provided a significant positive connection between these two constructs at a 95% confidence interval ($\beta = 0.216$, $p = 0.006 < 0.05$). This finding supports hypothesis 1 which was accepted. This shows there are a strong relationship between social expectation and consumers' intention to purchase insurance.

This strong positive relationship is in line with prior research by Melnyk et al. (2019), which showed that social norms and the desire to conform can change the behaviour of individuals through both injunctive norms (perceptions of approval from others) and descriptive norms (perceptions of what others do). The modest R^2 (0.047) reveals that perceived social norms only account for a small percentage of the variance in intention to purchase.

6.3.2. Theoretical implications

This result validates prior research by Horne and Mollborn (2020), which suggests individuals follow social norms since they expect social rewards when society approves of their behaviour and dread society's disapproval for non-compliance. Applying this concept to the context of insurance, individuals could experience pressure to buy insurance to show they are financially responsible (Gross and Vostroknutov, 2022; Van Kleef et al., 2019). Social norms also include a relational component in which individuals comply with social norms in order not to lose their social bonds (Horne and Mollborn, 2020). The purchase of insurance is viewed by society as a sign that someone is responsible, mature, and shows concern for the financial security of their dependents (Dragos et al., 2020). All these factors can improve an individual's social connections and identity within society.

However, the predictive relationship that was found in the study, might have been weakened by the measurement instrument (Cronbach alpha = 0.528) (Dragos et al., 2020; Sürücü and Maslakci, 2020). The measurement instrument inaccuracy could have lessened the actual influence of perceived social norms on intention to purchase.

6.4. Research question 2

6.4.1. Summary of findings

A simple linear regression was performed to test whether availability heuristics act as a predictor of intention to purchase insurance (Lim, 2025; Stockemer et al., 2019; Saunders and Lewis, 2018). Availability heuristics explained 20.2% of the variance

in intention to purchase, which showed a strong significant positive connection between these two constructs at a 95% confidence interval ($\beta = 0.449$, $p < 0.001$). This finding supports hypothesis 2 and is also the study's strongest direct influence.

The findings from hypothesis 2 is consistent with the foundational work done on availability heuristics (Tversky and Kahneman, 1973). People rely on availability heuristics when they judge the likelihood of events based on whatever examples come to mind most easily, using mental shortcuts. In the insurance domain, people who readily summon memories of hazardous incidents tend to view such events as more probable and thus show greater propensity to acquire coverage.

The notable coefficient from the simple linear regression ($\beta = 0.449$) aligns closely with prior research (Richter et al., 2019). Richter et al. (2019) found that people's insurance choices are heavily influenced by whatever information is easier to recall, particularly when it involves emotionally charged events. The results agree with the findings of past research which showed that even in the absence of personal experience relating to the emotionally charged events, exposure to the event through visual representations is enough to increase insurance uptake (Keller et al., 2006).

The R^2 (0.202) indicates the percentage of the variance in intention to purchase that is explained by availability heuristics (Stockemer et al., 2019). The explained variance is substantially higher compared to the R^2 determined in the first research question which suggests that the intention to purchase insurance is influenced more strongly by cognitive shortcuts rather by social norms.

6.4.2. Theoretical implications

Using ecological rationality to interpret the findings provides a more nuanced approach (Gigerenzer et al., 2022; Gigerenzer and Gaissmaier, 2011). Heuristics are described as adaptive tools that can assist in decision-making, if used in the right context. Media coverage of emotionally charged events is often sensationalised to draw additional attention to the event; however, it is frequently highlighting serious risks. This results in individuals making generally reliable insurance decisions when they depend on availability, rather than performing extensive calculations which can be mentally exhausting.

It is important to recognise the weak measurement instrument in this study with a Cronbach alpha of 0.453, which is below the standard limits (Sürücü and Maslakci, 2020; Gigerenzer and Gaissmaier, 2011). The measurement instrument inaccuracy could have lessened the actual influence of availability heuristics on intention to purchase. The low reliability could reveal a multidimensional structure in the measuring instrument, which contains several different aspects of heuristics.

Despite the limitations of the measuring instrument, the correlation between availability heuristics and intention to purchase is so significant that the construct captures meaningful variance in decision-making processes (Stockemer et al., 2019). If the measurement instrument had a higher reliability score, the actual influence could be much higher.

6.5. Research question 3

6.5.1. Summary of findings

To test whether perceived social norms moderated the association between availability heuristics and the intention to purchase insurance, the researcher conducted a multiple linear regression model (Lim, 2025; Stockemer et al., 2019; Saunders and Lewis, 2018). No significant connection between these constructs at a 95% confidence interval was identified ($\beta = 0.011$, $p = 0.871$). This finding does not support hypothesis 3 and shows that perceived social norms have no influence on the association between availability heuristics and the intent to purchase insurance. Furthermore, the addition of control variables in the model eliminated the influence of perceived social norms ($\beta = 0.059$, $p = 0.421$) completely, while availability heuristics retained their strong influence ($\beta = 0.415$, $p < 0.001$).

The absence of a significant result in hypothesis 3, implies that perceived social norms and availability heuristics influence intention to purchase independently and possibly through different mental processes (as can be seen from hypotheses 1 and 2). Availability heuristics are mainly a function of cognitive retrieval of past experiences (Tversky and Kahneman, 1973). In comparison, social norms are the processes involved with conformity and approval-seeking (Horne and Mollborn,

2020; Cialdini et al., 1990). Rather than being interactive, these influences may be cumulative.

Considering the large direct influence availability heuristics ($\beta = 0.415$, $p < 0.001$) have in the study, indicates their dominance. This may indicate that there is no opportunity for social norms to act as a moderator in this study. When individuals have vivid memories of emotionally charged events, they do not necessarily consider society's approval when making decisions. This is consistent with prior research that showed a higher reliance on personal experiences than on social influences (Siegrist and Árvai, 2020).

The disappearance of the significant influence of social influences in the multiple regression model, despite the significant contribution in the simple linear regression model may indicate a theoretical connection between perceived social norms and availability heuristics. For example, viewing others performing risk mitigating practices such as buying insurance can encourage a similar behaviour (Cialdini et al., 1990; Tversky and Kahneman, 1973). This can simultaneously be seen as both recalling memories and conforming to society when making-decisions. Therefore, the positive correlation obtained from perceived social norms from the earlier test can easily be confused in the multiple regression model with availability heuristics (Rhodes et al., 2020). This view gains backing from the modest positive correlation linking availability heuristics with perceived social norms ($r = 0.38$, $p < 0.001$).

Earlier studies have demonstrated that social norms can either amplify or attenuate the effects of behavioural biases (Germar et al., 2023). This study contrasts with the findings obtained in this study. Germar et al. (2023) showed that social norms changed the subjective way in which people viewed information over the long-term. Their research was however conducted in a laboratory which lacked the factors applicable to real-world situations.

The findings are more in line with those of prior research that suggested the influence of social norms on other factors are complex and dependents on the context (Huber et al., 2023). Additionally, the influence of social norms should rather involve mediation through moral evaluation rather than the moderation that was tested in this study. Their findings showed that social norms interacted indirectly through several

different paths. Zhuang and Carey (2025) also concluded that social norms influence as a moderator was absent in their study on the relationship between risk perception and protective behaviour.

6.6. Conclusion

This chapter provides an overview of the results considering the current research and theory. The results of the regression analysis showed that the intent to purchase insurance is influenced by both perceived social norms and availability heuristics (Du, 2022; Melnyk et al., 2022; Schultz, 2022). Availability heuristics had a significantly higher influence than perceived social norms. Nonetheless, findings offered no support for perceived social norms moderating availability heuristics, underscoring the autonomy of these constructs (Huber et al., 2023; Gross and Vostroknutov, 2022). When all constructs and control variables entered the multiple regression model, availability heuristics emerged as the primary predictor.

These results contribute theoretically by delineating the comparative roles of behavioural factors in insurance decisions (Dragos et al., 2020; Zain ul Abdin et al., 2017). These results also carry further implications for insurance marketing and delivery of financial guidance to consumers (Richter et al., 2019). These results will be presented in the next chapter.

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

7.1. Introduction

This study investigated the moderating effect of perceived social norms on availability heuristics and intention to purchase insurance in the South African context. It has become increasingly important to understand the behavioural factors that influence consumers' insurance decisions. This chapter summarises the key findings, discusses the theoretical implications, recognises the limitations of this study, and provides suggestions for future research.

This study considered two constructs, perceived social norms and availability heuristics, and investigated their influence on the intention to purchase insurance. The research topic was chosen because of the ongoing problem of underinsurance that is experienced worldwide, which resulted in a loss of more than \$162.5 billion in 2018 and is expected to reach \$145 billion by the end of 2025 (Swiss Re, 2025b; Lloyd's, 2018). South Africa has one of the highest insurance penetration rates in Africa (11.54%); however, large parts of South Africa are still exposed to coverage gaps (Egosa, 2025).

Conventional economic theories have not been able to address real-world insurance decision-making because they assume rational decision-making (Du, 2022; Richter et al., 2019). By including a behavioural component in decision-making offers a wider scope and a better understanding of the process (Corcos et al., 2020).

7.2. Research questions and methodology

7.2.1. Research questions

The stated three research questions are investigated further in this study.

RQ₁: Do perceived social norms have a significant influence on consumers' insurance purchase intention?

RQ₂: To what extent does the availability heuristic influence South African consumers' intention to purchase insurance?

RQ₃: Do perceived social norms moderate the relationship between availability heuristics and insurance purchase intention among consumers?

7.2.2. Research methodology

A cross-sectional, quantitative research design was implemented to circulate an online research questionnaire via digital platforms (Stockemer et al., 2019). The study adopted a positivist research philosophy to test the three hypotheses.

The final sample included a higher proportion of males compared to females, a high level of education, and a relatively high-income band. The three constructs, perceived social norms, availability heuristics, and intention to purchase, were measured using a 7-point Likert scale which was adopted and adapted from existing research.

The statistical analysis performed on the data included descriptive statistics, validity testing (Pearson's correlation and factor analysis), reliability testing (Cronbach's alpha), and simple linear and multiple regression analysis (Sürücü and Maslakci, 2020; Stockemer et al., 2019).

7.3. Discussion of key findings

7.3.1. Research question 1

A simple linear regression analysis showed that perceived social norms explained 4.7% of the variance in intention to purchase insurance, which provided a significant positive connection between these two constructs at a 95% confidence interval ($\beta = 0.216$, $p = 0.006 < 0.05$). This finding supports hypothesis 1 which was accepted. This shows there are a strong relationship between social expectation and consumers' intention to purchase insurance.

This strong positive relationship is in line with prior research by Melnyk et al. (2019), which showed that social norms and the desire to conform can change the behaviour of individuals through both injunctive norms (perceptions of approval from others) and descriptive norms (perceptions of what others do).

However, the predictive relationship that was found in the study might have been weakened by the measurement instrument (Cronbach's $\alpha = 0.528$) (Dragos et al., 2020; Sürücü and Maslakci, 2020). The measurement instrument's inaccuracy could have lessened the actual influence of perceived social norms on intention to purchase.

7.3.2. Research question 2

A simple linear regression model revealed that availability heuristics explained 20.2% of the variance in intention to purchase insurance, which showed a strong significant positive connection between these two constructs at a 95% confidence interval ($\beta = 0.449$, $p < 0.001$). This finding supports hypothesis 2 and is also the study's strongest direct influence.

Ecological rationality can be used to interpret the findings as it provides a more nuanced approach (Gigerenzer et al., 2022; Gigerenzer and Gaissmaier, 2011). Heuristics are described as adaptive tools that can assist in decision-making if used in the right context. Media coverage of emotionally charged events is often sensationalised to draw additional attention to the event; however, it is frequently highlighting serious risks. This results in individuals making generally reliable insurance decisions when they depend on availability, rather than performing extensive calculations which can be mentally exhausting.

The result is consistent with prior research which demonstrated that insurance decisions are significantly influenced when individuals make decisions based on readily available information (Richter et al., 2019). This is especially true when those decisions involved emotionally charged events that receive extensive media attention. The results agree with the findings of past research which showed that even in the absence of personal experience relating to the emotionally charged events, exposure to the event through visual representations is enough to increase insurance uptake (Keller et al., 2006).

With a Cronbach's α of 0.453, which is below the standard limits, it is important to recognize the study's weak measurement instrument (Sürücü and Maslakci, 2020;

Gigerenzer and Gaissmaier, 2011). The weak measurement instrument could have influenced the effect of availability heuristics on intention to purchase.

7.3.3. Research question 3

Within a 95% confidence interval, the multiple linear regression analysis indicated no discernible association between perceived social norms and availability heuristics ($\beta = 0.011$, $p = 0.871$). This finding does not support hypothesis 3. Furthermore, upon incorporating control variables into the model, the moderating effect vanished ($\beta = 0.059$, $p = 0.421$). However, the strong influence of availability heuristics is retained from the simple linear regression analysis ($\beta = 0.415$, $p < 0.001$).

The lack of significance for the moderating influence of perceived social norms on availability heuristics and intention to purchase is likely because perceived social norms and availability heuristics use distinct cognitive pathways (as can be seen from hypotheses 1 and 2). Availability heuristics are mainly a function of cognitive retrieval of past experiences (Tversky and Kahneman, 1973). In comparison, social norms are the processes involved with conformity and approval-seeking (Horne and Mollborn, 2020; Cialdini et al., 1990). These influences might be cumulative rather than interactive.

Considering the large direct influence availability heuristics ($\beta = 0.415$, $p < 0.001$) have on intention to purchase insurance, indicates the dominant impact availability heuristics have in the study. This may indicate that there is no opportunity for social norms to act as a moderator in this study. When individuals have vivid memories of emotionally charged events, they do not necessarily consider society's approval when making decisions. This is consistent with prior research that showed a higher reliance on personal experiences than on social influences (Siegrist and Árvai, 2020).

The absence of social norms showing a substantial impact in the multiple regression model, despite the significant contribution in the simple linear regression analysis may suggest a theoretical link between perceived social norms and availability heuristics. For instance, by watching friends and family take risk mitigating steps like buying insurance can spark the same behaviour in others (Cialdini et al., 1990;

Tversky and Kahneman, 1973). This can simultaneously be seen as both recalling memories and conforming to society when making decisions. In the multiple regression analysis, it's difficult to separate the effects of perceived social norms from availability heuristics since they may be measuring overlapping influences (Rhodes et al., 2020).

Prior studies have shown that social norms can influence behavioural biases by strengthening or weakening it (Germar et al., 2023). The findings presented herein contradict with those of Germar et al. (2023), who found that social norms influenced people's subjective perceptions of knowledge over time.

The results are more consistent with earlier research that indicated social norms have a complicated and context-dependent influence on other constructs (Huber et al., 2023). Additionally, the influence of social norms should rather involve mediation through moral evaluation rather than the moderation that was tested in this study. Their findings showed that social norms interacted indirectly through several different paths. On their study on the relationship between risk perception and protective behaviour, Zhuang and Carey (2025) also concluded that the influence of social norms did not act as a moderator.

7.4. Research limitations

The study's biggest limitation was the low reliability of the measurement instrument. The Cronbach's alpha values of perceived social norms (0.528), availability heuristics (0.453), and intention to purchase (0.599) fell below the conventional threshold levels (Sürücü and Maslakci, 2020). The low reliability values probably contributed to a weaker association between the tested relationships.

Convenience and snowball sampling were used during the data collection process and although its use was practical given the time and budget constraints of the researcher, the final sample might not fairly represent the population of South Africa (Stockemer et al., 2019; Saunders and Lewis, 2018). The sampling method may have introduced bias as not every possible respondent had an equal chance of being chosen. It is clear from the profile of the participants that indicated an overwhelming

response rate from highly educated males, earning more than R50 000 per month (Dragos et al., 2020; Guan et al., 2020).

The sample size ($N = 162$) was large enough for the statistical tests performed as part of this study, a larger sample size would allow more complex statistical analysis and provide greater statistical power (Saunders and Lewis, 2018).

The study focussed on consumers within the South African context. The South African insurance sector has unique characteristics which might not translate directly to other insurance markets and countries (Dragos et al., 2020; Guan et al., 2020).

7.5. Recommendations for future research

A focus for future research should be to formulate more reliable measuring instruments for perceived social norms, availability heuristics, and intention to purchase. This can be accomplished by expanding the items measuring each construct and eliminating the multidimensional structures within the constructs (Ceschi et al., 2019). The researcher can conduct a qualitative study to assess how these constructs are conceptualised by consumers which can ultimately inform the construction of the research questionnaire (Stockemer et al., 2019).

The inclusion of multiple heuristics to determine the influence of different cognitive shortcuts on the intention to purchase insurance, could potentially advance future research (Zain ul Abdin et al., 2017; Gigerenzer and Goldstein, 2011). Future studies could investigate whether social norms act as a mediator between availability heuristics and intention to purchase insurance (Huber et al., 2023; Lo, 2013).

7.6. Conclusion

This study has shown that both perceived social norms and availability heuristics influence South African customers' intention to purchase insurance. The findings of this study measuring the relative significance of cognitive and social aspects on purchase decisions, add valuable insights to existing research. By showing that perceived social norms have no moderating effect on availability heuristics and intention to purchase insurance provides important theoretical insights.

This study highlights why insurers need to grasp how behavioural economics shapes choices and apply it to tailor insurance offerings (Corcos et al., 2020; Richter et al., 2019). People rarely dive deep into details when choosing insurance, so products ought to match the process they use to decide (Ceschi et al., 2019). This study ultimately aims to bridge the underinsurance problem facing South Africans (Corcos et al., 2020).

Future research might shift from exploring people's plans to buy insurance to examining their real insurance decisions (Dragos et al., 2020; Guan et al., 2020). By inviting insurance companies to participate in the study, researchers can assess real insurance policy uptake alongside different behavioural factors (Huber et al., 2023; Rhodes et al., 2020).

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APPENDIX A: SURVEY QUESTIONNAIRE

Consumer Insurance Purchase Intent

Dear Respondent,

I am a student currently studying at the University of Pretoria's Gordon Institute of Business Science and I am conducting research toward the fulfilment of my qualification. Thank you for your interest in participating in this research study on consumer purchase intent in the insurance industry.

Your insights are vital in understanding the influence of availability heuristics and perceived social norms on consumer purchase intent.

The primary goal of this 10-minute questionnaire is to gather information about your attitudes, perceptions, and behaviours as it relates to purchasing insurance.

If you have any questions or concerns about this questionnaire or the research study, please contact me or my Research Supervisor at any time.

Student:

Chantel McPhail
24204022@mygibs.co.za

Supervisor:

Prof. Charlene Lew
lew@mygibs.co.za

Participation in this study is entirely voluntary. However, if you choose not to participate or wish to discontinue at any point during the questionnaire, you are free to do so without any consequences. We want to assure you that your responses are completely confidential. No personally identifiable information will be collected, stored, or used in this research.

Thank you for your time and valuable contribution to this study.

Section 1: Demographic Information

Q1.1 How old are you (Eling et al., 2021)? (Please state current age in years).

Q1.2 Gender (Eling et al., 2021; Lo, 2013; Zain ul Abdin et al., 2017):

- ☐ Male (1)
- ☐ Female (2)
- ☐ Non-binary (3)
- ☐ Transgender (4)
- ☐ Not listed (5)
- ☐ Prefer not to say (6)

Q1.3 Race/Ethnicity:

- ☐ Black (1)
- ☐ Coloured (2)
- ☐ White (3)
- ☐ Indian/Asian (4)
- ☐ Other (5)
- ☐ Prefer not to say (6)

Q1.4 Education attainment (Lo, 2013; Zain ul Abdin et al., 2017):

- ☐ Primary school (1)
- ☐ High school (2)
- ☐ Undergraduate (3)
- ☐ Postgraduate (4)

Q1.5 Monthly household income (Lo, 2013; Zain ul Abdin et al., 2017):

- ☐ Below R10,000 (1)
- ☐ R10,000 – R30,000 (2)
- ☐ R30,001 – R50,000 (3)
- ☐ Above R50,000 (4)
- ☐ Prefer not to say (5)

Q1.6 What would best describe your household situation (Eling et al., 2021)? Child dependents are younger than 18 and adult dependents are classified as older than 18. An Adult dependent is defined as a spouse, adult child, and/or extended family).

- ☐ Single with no dependents (1)
- ☐ Single with 1 or more child dependents (2)
- ☐ Single with 1 or more adult dependents (3)
- ☐ Single with 1 or more child dependents and 1 or more adult dependents (4)
- ☐ Married (spouse/spouses and no child dependents) (5)
- ☐ Married with 1 or more child dependents (6)
- ☐ Married with 1 or more adult dependents (7)
- ☐ Married with 1 or more child dependents and 1 or more adult dependents (8)
- ☐ Other (9)

Q1.7 How secure do you feel with your current financial situation? Please indicate your response to the following statement by choosing the most appropriate choice.

Not at all secure (1)	Very slightly secure (2)	Slightly secure (3)	Moderately secure (4)	Quite secure (5)	Very secure (6)	Extremely secure (7)
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Q1.8 What is the year of your most recent purchase of an insurance policy (e.g., house, vehicle, health, or life insurance)? If you have never purchased insurance, please indicate "Never."

Section 2: Perceived Social Norms

The following question examines how your insurance choices are influenced by what society deems socially acceptable behaviour (i.e. what is known as injunctive norms). Please indicate your response to the following statements by choosing the most appropriate choice. Question 2.2 is adapted from Lo (2013); Zhuang & Carey (2025).

Q2.1 To what extent do you believe your family or friends want you to purchase insurance (e.g. a life insurance policy, health insurance and/or car insurance that is not provided as part of your employee benefits)?

Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
(1)	(2)	(3)	(4)	(5)	(6)	(7)

The questions that follow will investigate how your insurance decision-making is influenced by the perceptions of other individuals around you (i.e. what is known as descriptive norms). Please indicate your response to the following statements by choosing the most appropriate choice. Question 2.2 is adopted and adapted from Lo (2013). Question 2.3 is adopted and adapted from Huber et al. (2023); Zhuang & Carey (2025).

Q2.2 To what extent do you believe other individuals like yourself would purchase insurance (e.g. a life insurance policy, health insurance and/or car insurance that is not provided as part of your employee benefits)?

Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Q2.3 How many people around you purchased insurance to protect their financial security?

Nobody	Very Few	Few	Some	Many	Most	Almost All
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Section 3: The Availability Heuristic

The questions that follow will investigate how your insurance decision-making is influenced by mental shortcuts of similar events. Please indicate your response to the following statements by choosing the most appropriate choice. Question 3.1 and 3.2 were adopted and adapted from Zain ul Abdin et al. (2017). Question 3.3 and 3.6 were adopted and adapted from Ndawula et al. (2024).

Q3.1 I am more likely to purchase insurance (e.g., house, vehicle, health, and/or life insurance) for risks (e.g. natural disasters, burglaries, car accidents) that are frequently discussed on TV, radio or social media because this information is readily available to me.

Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Q3.2 You consider the information received from family and friends as a reliable reference for your own insurance decisions.

Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Q3.3 I consider the premiums charged for an insurance policy (e.g., house, vehicle, health, and/or life insurance) to reflect the true value, if I know the premium charged are similar to other policies with the same terms and conditions.

Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Q3.4 I review all information provided in an insurance policy (e.g., house, vehicle, health, and/or life insurance) before I decide to buy it.

Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Q3.5 Given all the events discussed in the news and on social media about car accidents and burglaries, I associate an insurance policy (e.g., house, vehicle, health, and/or life insurance) with protection against losses.

Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Q3.6 I trust my instincts when making decisions about purchasing an insurance policy (e.g., house, vehicle, health, and/or life insurance).

Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Section 4: Consumer Purchase Intent

The questions that follow will assess your intention to purchase or renew an insurance policy based on your perception of its purpose. Please indicate your response to the following statements by choosing the most appropriate choice. Question 4.1 to 4.6 were adopted and adapted from Dragos et al. (2020).

Q4.1 How much trust do you have in insurance companies?

Not at all	Very little	Slightly	Moderately	Quite a bit	Very much	Extremely
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Q4.2 Your experiences or those of your relatives (family, friends) regarding insurance companies have been ...?

Extremely unpleasant	Very unpleasant	Unpleasant	Neutral	Pleasant	Very pleasant	Extremely pleasant
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Q4.3 Have you purchased, or do you have any type of insurance currently (e.g., house, vehicle, health, and/or life insurance)?

- ☐ No, I have never purchased any type of insurance. (1)
- ☐ Yes, I have purchased only compulsory insurance (e.g., life insurance and/or health insurance as part of my employee benefits). (2)
- ☐ Yes, I have purchased only voluntary insurance (e.g., vehicle insurance). (3)
- ☐ Yes, I have purchased both compulsory and voluntary insurance. (4)

Q4.4 I intend to purchase a new insurance policy or renew my current insurance policy within the next 12 months.

Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Q4.5 I have purchased or intend to purchase an insurance policy because I consider it an investment to secure my financial well-being.

Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Q4.6 I have purchased or intend to purchase an insurance policy because I consider it as protection for financial support in case of unexpected events (e.g., illness or death).

Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
(1)	(2)	(3)	(4)	(5)	(6)	(7)

Note on questionnaire

1. The APA references were removed in the final questionnaire that was sent out to respondents.

APPENDIX B: DATA CODING

Construct	Item	Item code
Social norms	Q2.1 To what extent do you believe your family or friends want you to purchase insurance (e.g. a life insurance policy, health insurance and/or car insurance that is not provided as part of your employee benefits)?	SNORQ2.1
	Q2.2 To what extent do you believe other individuals like yourself would purchase insurance (e.g. a life insurance policy, health insurance and/or car insurance that is not provided as part of your employee benefits)?	SNORQ2.2
	Q2.3 How many people around you purchased insurance to protect their financial security?	SNORQ2.3
Availability heuristics	Q3.1 I am more likely to purchase insurance (e.g., house, vehicle, health, and/or life insurance) for risks (e.g. natural disasters, burglaries, car accidents) that are frequently discussed on TV, radio or social media because this information is readily available to me.	HEURQ3.1
	Q3.2 You consider the information received from family and friends as a reliable reference for your own insurance decisions.	HEURQ3.2
	Q3.3 I consider the premiums charged for an insurance policy (e.g., house, vehicle, health, and/or life insurance) to reflect the true value, if I know the premium charged are similar to other policies with the same terms and conditions.	HEURQ3.3
	Q3.4 I review all information provided in an insurance policy (e.g., house, vehicle, health, and/or life insurance) before I decide to buy it.	HEURQ3.4
	Q3.5 Given all the events discussed in the news and on social media about car accidents and burglaries, I associate an insurance policy (e.g., house, vehicle, health, and/or life insurance) with protection against losses.	HEURQ3.5
	Q3.6 I trust my instincts when making decisions about purchasing an insurance policy (e.g., house, vehicle, health, and/or life insurance).	HEURQ3.6

Construct	Item	Item code
Purchase intent	Q4.1 How much trust do you have in insurance companies?	PURCQ4.1
	Q4.2 Your experiences or those of your relatives (family, friends) regarding insurance companies have been ...?	PURCQ4.2
	Q4.3 Have you purchased, or do you have any type of insurance currently (e.g., house, vehicle, health, and/or life insurance)?	PURCQ4.3
	Q4.4 I intend to purchase a new insurance policy or renew my current insurance policy within the next 12 months.	PURCQ4.4
	Q4.5 I have purchased or intend to purchase an insurance policy because I consider it an investment to secure my financial well-being.	PURCQ4.5
	Q4.6 I have purchased or intend to purchase an insurance policy because I consider it as protection for financial support in case of unexpected events (e.g., illness or death).	PURCQ4.6

APPENDIX C: TESTING FOR NORMALITY

i. Purchase intent (Dependent variable)

Case Processing Summary

	Valid		Cases Missing		Total	
	N	Percent	N	Percent	N	Percent
MEAN_P	162	100,0%	0	0,0%	162	100,0%

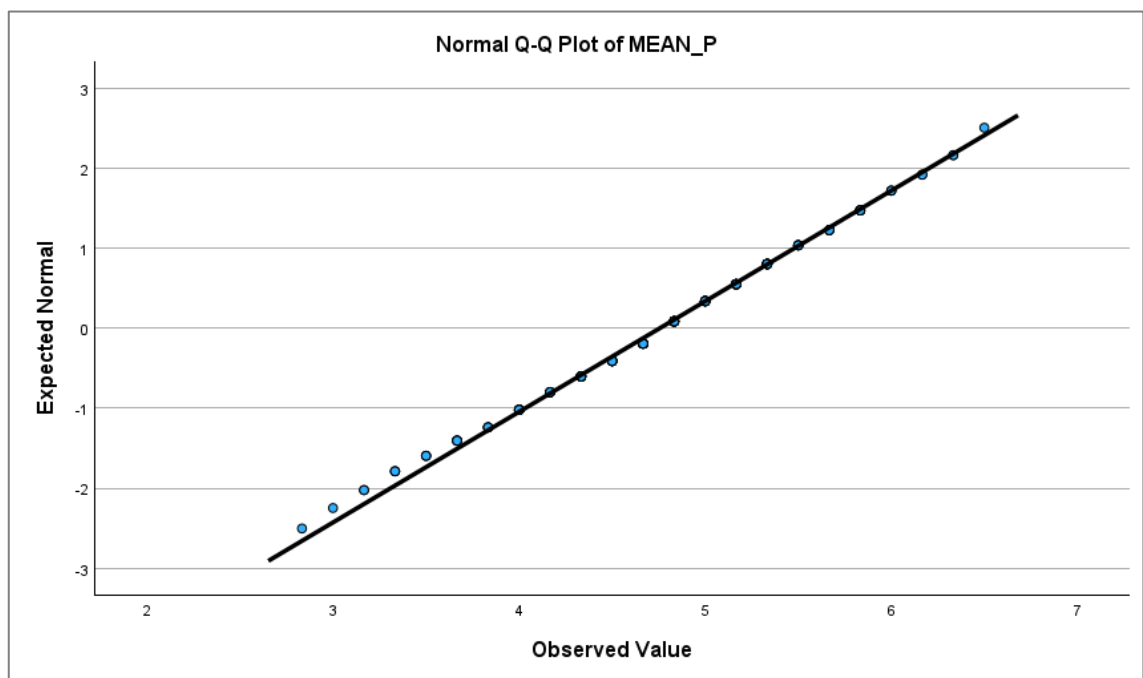
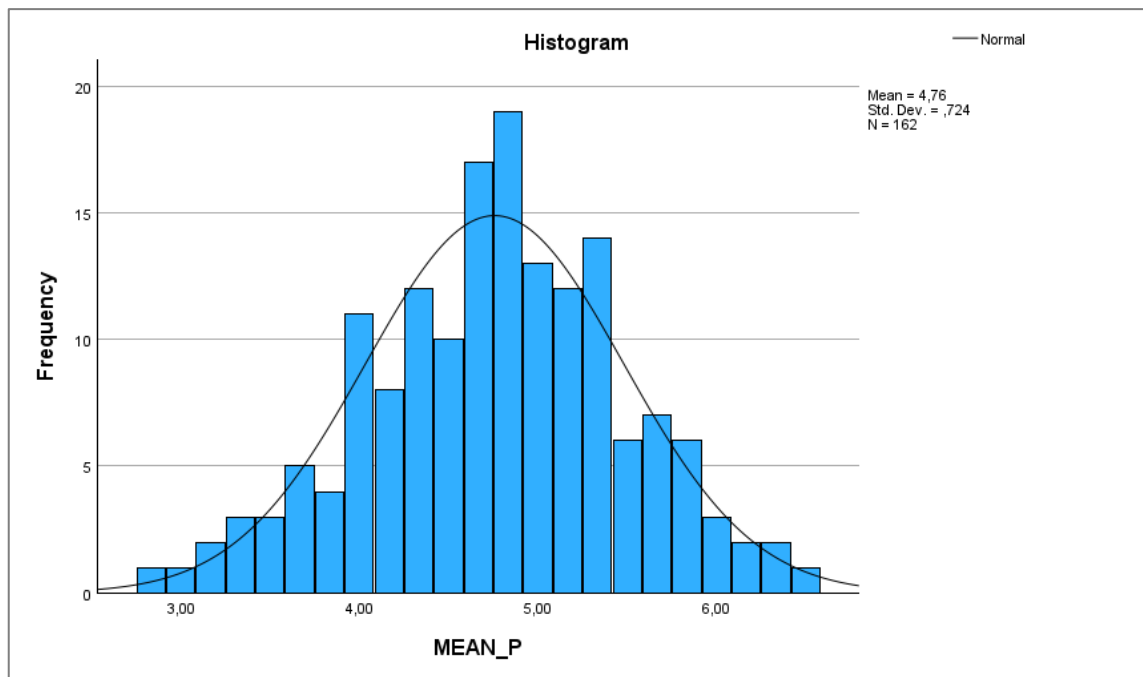
Descriptives

		Statistic	Std. Error
MEAN_P	Mean	4,7572	,05685
	95% Confidence Interval for Mean	Lower Bound	4,6449
		Upper Bound	4,8695
	5% Trimmed Mean	4,7638	
	Median	4,8333	
	Variance	,523	
	Std. Deviation	,72353	
	Minimum	2,83	
	Maximum	6,50	
	Range	3,67	
	Interquartile Range	1,00	
	Skewness	-,149	,191
	Kurtosis	-,138	,379

Tests of Normality

	Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
MEAN_P	,080	162	,013	,991	162	,433

a. Lilliefors Significance Correction



APPENDIX C: PEARSON'S CORRELATION

ii. Perceived social norms

		Correlations			
		SNORQ2.1	SNORQ2.2	SNORQ2.3	SUM_S
SNORQ2.1	Pearson Correlation	--			
	N	162			
SNORQ2.2	Pearson Correlation	,383**	--		
	Sig. (2-tailed)	<,001			
	N	162	162		
SNORQ2.3	Pearson Correlation	,224**	,263**	--	
	Sig. (2-tailed)	,004	<,001		
	N	162	162	162	
SUM_S	Pearson Correlation	,752**	,678**	,734**	--
	Sig. (2-tailed)	<,001	<,001	<,001	
	N	162	162	162	162

** . Correlation is significant at the 0.01 level (2-tailed).

Confidence Intervals				
	Pearson Correlation	Sig. (2-tailed)	95% Confidence Intervals (2-tailed) ^a	
			Lower	Upper
SNORQ2.1 - SNORQ2.2	,383	<,001	,243	,507
SNORQ2.1 - SNORQ2.3	,224	,004	,073	,366
SNORQ2.1 - SUM_S	,752	<,001	,676	,812
SNORQ2.2 - SNORQ2.3	,263	<,001	,114	,401
SNORQ2.2 - SUM_S	,678	<,001	,585	,753
SNORQ2.3 - SUM_S	,734	<,001	,654	,798

a. Estimation is based on Fisher's r-to-z transformation.

iii. Availability heuristics

		Correlations						
		HEURQ3.1	HEURQ3.2	HEURQ3.3	HEURQ3.4	HEURQ3.5	HEURQ3.6	SUM_A
HEURQ3.1	Pearson Correlation	--						
	N	162						
HEURQ3.2	Pearson Correlation	,298**	--					
	Sig. (2-tailed)	<,001						
HEURQ3.3	N	162	162					
	Pearson Correlation	,017	,073	--				
HEURQ3.3	Sig. (2-tailed)	,834	,357					
	N	162	162	162				
HEURQ3.4	Pearson Correlation	-,017	,051	,131	--			
	Sig. (2-tailed)	,830	,517	,097				
HEURQ3.4	N	162	162	162	162			
	Pearson Correlation	,157*	,098	,181*	,234**	--		
HEURQ3.5	Sig. (2-tailed)	,046	,217	,021	,003			
	N	162	162	162	162	162		
HEURQ3.6	Pearson Correlation	-,084	,001	,209**	,142	,167*	--	
	Sig. (2-tailed)	,287	,987	,008	,071	,033		
HEURQ3.6	N	162	162	162	162	162	162	
	Pearson Correlation	,497**	,513**	,562**	,488**	,553**	,424**	--
SUM_A	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001	<,001	
	N	162	162	162	162	162	162	162

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Confidence Intervals				
	Pearson Correlation	Sig. (2-tailed)	95% Confidence Intervals (2-tailed) ^a	
			Lower	Upper
HEURQ3.1 - HEURQ3.2	,298	<,001	,151	,433
HEURQ3.1 - HEURQ3.3	,017	,834	-,138	,170
HEURQ3.1 - HEURQ3.4	-,017	,830	-,171	,138
HEURQ3.1 - HEURQ3.5	,157	,046	,003	,304
HEURQ3.1 - HEURQ3.6	-,084	,287	-,235	,071
HEURQ3.1 - SUM_A	,497	<,001	,371	,605
HEURQ3.2 - HEURQ3.3	,073	,357	-,082	,225
HEURQ3.2 - HEURQ3.4	,051	,517	-,104	,204
HEURQ3.2 - HEURQ3.5	,098	,217	-,058	,248
HEURQ3.2 - HEURQ3.6	,001	,987	-,153	,155
HEURQ3.2 - SUM_A	,513	<,001	,390	,619
HEURQ3.3 - HEURQ3.4	,131	,097	-,024	,280
HEURQ3.3 - HEURQ3.5	,181	,021	,028	,327
HEURQ3.3 - HEURQ3.6	,209	,008	,057	,352
HEURQ3.3 - SUM_A	,562	<,001	,447	,659
HEURQ3.4 - HEURQ3.5	,234	,003	,083	,375
HEURQ3.4 - HEURQ3.6	,142	,071	-,012	,290
HEURQ3.4 - SUM_A	,488	<,001	,361	,598
HEURQ3.5 - HEURQ3.6	,167	,033	,013	,313
HEURQ3.5 - SUM_A	,553	<,001	,436	,651
HEURQ3.6 - SUM_A	,424	<,001	,289	,543

a. Estimation is based on Fisher's r-to-z transformation.

iv. Purchase intent

		Correlations						
		PURCQ4.1	PURCQ4.2	PURCQ4.3	PURCQ4.4	PURCQ4.5	PURCQ4.6	SUM_P
PURCQ4.1	Pearson Correlation	--						
	N	162						
PURCQ4.2	Pearson Correlation	,558**	--					
	Sig. (2-tailed)	<,001						
	N	162	162					
PURCQ4.3	Pearson Correlation	,174*	,031	--				
	Sig. (2-tailed)	,027	,693					
	N	162	162	162				
PURCQ4.4	Pearson Correlation	,043	,030	,142	--			
	Sig. (2-tailed)	,590	,706	,071				
	N	162	162	162	162			
PURCQ4.5	Pearson Correlation	,195*	,227**	,237**	,292**	--		
	Sig. (2-tailed)	,013	,004	,002	<,001			
	N	162	162	162	162	162		
PURCQ4.6	Pearson Correlation	,247**	,148	,170*	,249**	,317**	--	
	Sig. (2-tailed)	,002	,060	,031	,001	<,001		
	N	162	162	162	162	162	162	
SUM_P	Pearson Correlation	,581**	,519**	,422**	,634**	,683**	,585**	--
	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001	<,001	
	N	162	162	162	162	162	162	162

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Confidence Intervals

	Pearson Correlation	Sig. (2-tailed)	95% Confidence Intervals (2-tailed) ^a	
			Lower	Upper
PURCQ4.1 - PURCQ4.2	,558	<,001	,442	,656
PURCQ4.1 - PURCQ4.3	,174	,027	,020	,319
PURCQ4.1 - PURCQ4.4	,043	,590	-,112	,196
PURCQ4.1 - PURCQ4.5	,195	,013	,042	,339
PURCQ4.1 - PURCQ4.6	,247	,002	,097	,387
PURCQ4.1 - SUM_P	,581	<,001	,469	,675
PURCQ4.2 - PURCQ4.3	,031	,693	-,124	,185
PURCQ4.2 - PURCQ4.4	,030	,706	-,125	,183
PURCQ4.2 - PURCQ4.5	,227	,004	,075	,368
PURCQ4.2 - PURCQ4.6	,148	,060	-,006	,296
PURCQ4.2 - SUM_P	,519	<,001	,397	,623
PURCQ4.3 - PURCQ4.4	,142	,071	-,012	,290
PURCQ4.3 - PURCQ4.5	,237	,002	,086	,377
PURCQ4.3 - PURCQ4.6	,170	,031	,016	,316
PURCQ4.3 - SUM_P	,422	<,001	,286	,541
PURCQ4.4 - PURCQ4.5	,292	<,001	,145	,427
PURCQ4.4 - PURCQ4.6	,249	,001	,099	,389
PURCQ4.4 - SUM_P	,634	<,001	,531	,718
PURCQ4.5 - PURCQ4.6	,317	<,001	,171	,449
PURCQ4.5 - SUM_P	,683	<,001	,591	,757
PURCQ4.6 - SUM_P	,585	<,001	,474	,678

a. Estimation is based on Fisher's r-to-z transformation.

APPENDIX D: CRONBACH ALPHA

i. Perceived social norms (Cronbach alpha calculated using Q2.1 to Q2.3)

Case Processing Summary

		N	%
Cases	Valid	162	100,0
	Excluded ^a	0	,0
	Total	162	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,523	,551	3

Item Statistics

	Mean	Std. Deviation	N
SNORQ2.1	5,05	1,571	162
SNORQ2.2	5,78	1,090	162
SNORQ2.3	4,66	1,669	162

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,290	,224	,383	,159	1,708	,005	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SNORQ2.1	10,44	4,932	,357	,163	,389
SNORQ2.2	9,71	6,431	,411	,180	,366
SNORQ2.3	10,83	4,972	,287	,087	,528

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
15,49	9,891	3,145	3

ii. Perceived social norms (Cronbach alpha calculated using Q2.1 to Q2.2)

Case Processing Summary

		N	%
Cases	Valid	162	100,0
	Excluded ^a	0	,0
	Total	162	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,528	,554	2

Item Statistics

	Mean	Std. Deviation	N
SNORQ2.1	5,05	1,571	162
SNORQ2.2	5,78	1,090	162

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,383	,383	,383	,000	1,000	,000	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SNORQ2.1	5,78	1,189	,383	,147	.
SNORQ2.2	5,05	2,470	,383	,147	.

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
10,83	4,972	2,230	2

iii. Availability heuristics (Cronbach alpha calculated using Q3.1 to Q3.6)

Case Processing Summary

		N	%
Cases	Valid	162	100,0
	Excluded ^a	0	,0
	Total	162	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,412	,427	6

Item Statistics

	Mean	Std. Deviation	N
HEURQ3.1	4,62	1,680	162
HEURQ3.2	4,72	1,455	162
HEURQ3.3	4,86	1,685	162
HEURQ3.4	5,64	1,435	162
HEURQ3.5	5,70	1,185	162
HEURQ3.6	5,62	1,262	162

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,111	-,084	,298	,382	-3,543	,010	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HEURQ3.1	26,53	14,984	,134	,120	,415
HEURQ3.2	26,43	15,054	,210	,097	,360
HEURQ3.3	26,28	14,006	,214	,074	,358
HEURQ3.4	25,51	15,407	,184	,074	,376
HEURQ3.5	25,45	15,156	,323	,119	,307
HEURQ3.6	25,53	16,400	,152	,080	,393

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
31,15	19,543	4,421	6

iv. Availability heuristics (Cronbach alpha calculated using Q3.2 to Q3.6)

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	162	100,0
	Excluded ^a	0	,0
	Total	162	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,415	,425	5

Item Statistics

	Mean	Std. Deviation	N
HEURQ3.2	4,72	1,455	162
HEURQ3.3	4,86	1,685	162
HEURQ3.4	5,64	1,435	162
HEURQ3.5	5,70	1,185	162
HEURQ3.6	5,62	1,262	162

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,129	,001	,234	,233	175,296	,005	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HEURQ3.2	21,81	11,953	,091	,014	,453
HEURQ3.3	21,67	9,540	,250	,074	,331
HEURQ3.4	20,90	10,765	,229	,072	,348
HEURQ3.5	20,83	11,220	,297	,096	,311
HEURQ3.6	20,91	11,483	,223	,070	,356

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
26,53	14,984	3,871	5

v. **Availability heuristics (Cronbach alpha calculated using Q3.3 to Q3.6)**

Case Processing Summary

		N	%
Cases	Valid	162	100,0
	Excluded ^a	0	,0
	Total	162	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,453	,463	4

Item Statistics

	Mean	Std. Deviation	N
HEURQ3.3	4,86	1,685	162
HEURQ3.4	5,64	1,435	162
HEURQ3.5	5,70	1,185	162
HEURQ3.6	5,62	1,262	162

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,178	,131	,234	,103	1,789	,001	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HEURQ3.3	16,95	6,867	,255	,071	,396
HEURQ3.4	16,18	7,949	,240	,071	,399
HEURQ3.5	16,12	8,527	,292	,090	,358
HEURQ3.6	16,20	8,458	,259	,069	,382

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
21,81	11,953	3,457	4

vi. Purchase intent (Cronbach alpha calculated using Q4.1 to Q4.6)

Case Processing Summary

		N	%
Cases	Valid	162	100,0
	Excluded ^a	0	,0
	Total	162	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,577	,606	6

Item Statistics

	Mean	Std. Deviation	N
PURCQ4.1	4,31	1,192	162
PURCQ4.2	4,35	1,030	162
PURCQ4.3	3,57	,810	162
PURCQ4.4	5,01	1,878	162
PURCQ4.5	5,35	1,429	162
PURCQ4.6	5,96	1,036	162

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,204	,030	,558	,528	18,675	,017	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PURCQ4.1	24,23	14,252	,352	,357	,517
PURCQ4.2	24,20	15,265	,313	,336	,536
PURCQ4.3	24,98	16,534	,251	,094	,560
PURCQ4.4	23,53	12,039	,252	,120	,601
PURCQ4.5	23,20	12,420	,435	,209	,471
PURCQ4.6	22,59	14,654	,393	,168	,507

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
28,54	18,846	4,341	6

- vii. Purchase intent (Cronbach alpha calculated using Q4.1 to Q4.3, Q4.5, Q4.6)

Case Processing Summary

		N	%
Cases	Valid	162	100,0
	Excluded ^a	0	,0
	Total	162	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,601	,599	5

Item Statistics

	Mean	Std. Deviation	N
PURCQ4.1	4,31	1,192	162
PURCQ4.2	4,35	1,030	162
PURCQ4.3	3,57	,810	162
PURCQ4.5	5,35	1,429	162
PURCQ4.6	5,96	1,036	162

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,230	,031	,558	,527	17,871	,018	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PURCQ4.1	19,22	7,636	,452	,357	,490
PURCQ4.2	19,19	8,574	,399	,335	,526
PURCQ4.3	19,96	10,160	,237	,091	,599
PURCQ4.5	18,19	7,183	,368	,167	,552
PURCQ4.6	17,57	8,817	,349	,142	,550

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
23,53	12,039	3,470	5

viii. Purchase intent (Cronbach alpha calculated using Q4.1, Q4.2, Q4.5, Q4.6)

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	162	100,0
	Excluded ^a	0	,0
	Total	162	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,599	,611	4

Item Statistics

	Mean	Std. Deviation	N
PURCQ4.1	4,31	1,192	162
PURCQ4.2	4,35	1,030	162
PURCQ4.5	5,35	1,429	162
PURCQ4.6	5,96	1,036	162

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	,282	,148	,558	,410	3,771	,020	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PURCQ4.1	15,65	6,093	,449	,340	,472
PURCQ4.2	15,62	6,747	,440	,327	,492
PURCQ4.5	14,62	5,853	,328	,134	,589
PURCQ4.6	14,01	7,224	,335	,137	,561

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
19,96	10,160	3,187	4

APPENDIX E: FACTOR ANALYSIS

i. Perceived social norms

Correlation Matrix

		SNORQ2.1	SNORQ2.2	SNORQ2.3
Correlation	SNORQ2.1	1,000	,383	,224
	SNORQ2.2	,383	1,000	,263
	SNORQ2.3	,224	,263	1,000

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,601
Bartlett's Test of Sphericity	Approx. Chi-Square	39,795
	df	3
	Sig.	<,001

Anti-image Matrices

		SNORQ2.1	SNORQ2.2	SNORQ2.3
Anti-image Covariance	SNORQ2.1	,837	-,286	-,121
	SNORQ2.2	-,286	,820	-,170
	SNORQ2.3	-,121	-,170	,913
Anti-image Correlation	SNORQ2.1	,588 ^a	-,345	-,139
	SNORQ2.2	-,345	,578 ^a	-,197
	SNORQ2.3	-,139	-,197	,674 ^a

a. Measures of Sampling Adequacy(MSA)

Communalities

	Initial	Extraction
SNORQ2.1	1,000	,569
SNORQ2.2	1,000	,609
SNORQ2.3	1,000	,408

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,586	52,875	52,875	1,586	52,875	52,875
2	,800	26,675	79,549			
3	,614	20,451	100,000			

Extraction Method: Principal Component Analysis.

Component Matrix^a

	Component 1
SNORQ2.1	,755
SNORQ2.2	,780
SNORQ2.3	,639

Extraction Method:
Principal Component
Analysis.

- a. 1 components
extracted.

Reproduced Correlations

		SNORQ2.1	SNORQ2.2	SNORQ2.3
Reproduced Correlation	SNORQ2.1	,569 ^a	,589	,482
	SNORQ2.2	,589	,609 ^a	,499
	SNORQ2.3	,482	,499	,408 ^a
Residual ^b	SNORQ2.1		-,205	-,258
	SNORQ2.2	-,205		-,235
	SNORQ2.3	-,258	-,235	

Extraction Method: Principal Component Analysis.

- a. Reproduced communalities
b. Residuals are computed between observed and reproduced
correlations. There are 3 (100,0%) nonredundant residuals with
absolute values greater than 0.05.

Rotated Component Matrix^a

- a. Only one
component was
extracted. The
solution cannot
be rotated.

ii. Availability heuristics

Correlation Matrix

		HEURQ3.1	HEURQ3.2	HEURQ3.3	HEURQ3.4	HEURQ3.5	HEURQ3.6
Correlation	HEURQ3.1	1,000	,298	,017	-,017	,157	-,084
	HEURQ3.2	,298	1,000	,073	,051	,098	,001
	HEURQ3.3	,017	,073	1,000	,131	,181	,209
	HEURQ3.4	-,017	,051	,131	1,000	,234	,142
	HEURQ3.5	,157	,098	,181	,234	1,000	,167
	HEURQ3.6	-,084	,001	,209	,142	,167	1,000

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,575
Bartlett's Test of Sphericity	Approx. Chi-Square	49,314
	df	15
	Sig.	<,001

Anti-image Matrices

		HEURQ3.1	HEURQ3.2	HEURQ3.3	HEURQ3.4	HEURQ3.5	HEURQ3.6
Anti-image Covariance	HEURQ3.1	,880	-,258	,004	,050	-,141	,094
	HEURQ3.2	-,258	,903	-,052	-,038	-,027	-,003
	HEURQ3.3	,004	-,052	,926	-,067	-,115	-,163
	HEURQ3.4	,050	-,038	-,067	,926	-,186	-,080
	HEURQ3.5	-,141	-,027	-,115	-,186	,881	-,116
	HEURQ3.6	,094	-,003	-,163	-,080	-,116	,920
Anti-image Correlation	HEURQ3.1	,495 ^a	-,290	,005	,055	-,160	,105
	HEURQ3.2	-,290	,542 ^a	-,057	-,042	-,031	-,003
	HEURQ3.3	,005	-,057	,641 ^a	-,072	-,127	-,176
	HEURQ3.4	,055	-,042	-,072	,613 ^a	-,206	-,087
	HEURQ3.5	-,160	-,031	-,127	-,206	,596 ^a	-,129
	HEURQ3.6	,105	-,003	-,176	-,087	-,129	,600 ^a

a. Measures of Sampling Adequacy(MSA)

Communalities

	Initial	Extraction
HEURQ3.1	1,000	,666
HEURQ3.2	1,000	,562
HEURQ3.3	1,000	,375
HEURQ3.4	1,000	,359
HEURQ3.5	1,000	,470
HEURQ3.6	1,000	,459

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,584	26,407	26,407	1,584	26,407	26,407	1,531	25,517	25,517
2	1,307	21,780	48,187	1,307	21,780	48,187	1,360	22,670	48,187
3	,908	15,132	63,319						
4	,787	13,118	76,437						
5	,777	12,944	89,382						
6	,637	10,618	100,000						

Extraction Method: Principal Component Analysis.

Component Matrix^a

	Component	
	1	2
HEURQ3.1	,316	,753
HEURQ3.2	,395	,637
HEURQ3.3	,568	-,230
HEURQ3.4	,546	-,246
HEURQ3.5	,685	,007
HEURQ3.6	,488	-,471

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Reproduced Correlations

		HEURQ3.1	HEURQ3.2	HEURQ3.3	HEURQ3.4	HEURQ3.5	HEURQ3.6
Reproduced Correlation	HEURQ3.1	,666 ^a	,604	,006	-,013	,222	-,200
	HEURQ3.2	,604	,562 ^a	,078	,059	,275	-,107
	HEURQ3.3	,006	,078	,375 ^a	,367	,388	,385
	HEURQ3.4	-,013	,059	,367	,359 ^a	,373	,382
	HEURQ3.5	,222	,275	,388	,373	,470 ^a	,331
	HEURQ3.6	-,200	-,107	,385	,382	,331	,459 ^a
Residual ^b	HEURQ3.1		-,306	,010	-,004	-,065	,116
	HEURQ3.2	-,306		-,006	-,008	-,178	,108
	HEURQ3.3	,010	-,006		-,236	-,206	-,176
	HEURQ3.4	-,004	-,008	-,236		-,138	-,240
	HEURQ3.5	-,065	-,178	-,206	-,138		-,164
	HEURQ3.6	,116	,108	-,176	-,240	-,164	

Extraction Method: Principal Component Analysis.

a. Reproduced communalities

b. Residuals are computed between observed and reproduced correlations. There are 11 (73,0%) nonredundant residuals with absolute values greater than 0.05.

Rotated Component Matrix^a

	Component	
	1	2
HEURQ3.1	-,047	,815
HEURQ3.2	,076	,746
HEURQ3.3	,611	,043
HEURQ3.4	,599	,019
HEURQ3.5	,613	,307
HEURQ3.6	,645	-,209

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Component Transformation Matrix

Component	1	2
1	,899	,439
2	-,439	,899

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

iii. Purchase intent

Correlation Matrix

		PURCQ4.1	PURCQ4.2	PURCQ4.3	PURCQ4.4	PURCQ4.5	PURCQ4.6
Correlation	PURCQ4.1	1,000	,558	,174	,043	,195	,247
	PURCQ4.2	,558	1,000	,031	,030	,227	,148
	PURCQ4.3	,174	,031	1,000	,142	,237	,170
	PURCQ4.4	,043	,030	,142	1,000	,292	,249
	PURCQ4.5	,195	,227	,237	,292	1,000	,317
	PURCQ4.6	,247	,148	,170	,249	,317	1,000

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,611
Bartlett's Test of Sphericity	Approx. Chi-Square	127,052
	df	15
	Sig.	<,001

Anti-image Matrices

		PURCQ4.1	PURCQ4.2	PURCQ4.3	PURCQ4.4	PURCQ4.5	PURCQ4.6
Anti-image Covariance	PURCQ4.1	,643	-,353	-,122	,028	-,002	-,127
	PURCQ4.2	-,353	,664	,086	,018	-,121	,012
	PURCQ4.3	-,122	,086	,906	-,058	-,150	-,055
	PURCQ4.4	,028	,018	-,058	,880	-,186	-,149
	PURCQ4.5	-,002	-,121	-,150	-,186	,791	-,173
	PURCQ4.6	-,127	,012	-,055	-,149	-,173	,832
Anti-image Correlation	PURCQ4.1	,559 ^a	-,541	-,160	,037	-,003	-,174
	PURCQ4.2	-,541	,537 ^a	,111	,024	-,167	,017
	PURCQ4.3	-,160	,111	,638 ^a	-,065	-,177	-,063
	PURCQ4.4	,037	,024	-,065	,665 ^a	-,223	-,174
	PURCQ4.5	-,003	-,167	-,177	-,223	,682 ^a	-,213
	PURCQ4.6	-,174	,017	-,063	-,174	-,213	,714 ^a

a. Measures of Sampling Adequacy(MSA)

Communalities

	Initial	Extraction
PURCQ4.1	1,000	,757
PURCQ4.2	1,000	,766
PURCQ4.3	1,000	,293
PURCQ4.4	1,000	,526
PURCQ4.5	1,000	,532
PURCQ4.6	1,000	,450

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,055	34,248	34,248	2,055	34,248	34,248	1,705	28,411	28,411
2	1,269	21,142	55,390	1,269	21,142	55,390	1,619	26,979	55,390
3	,884	14,733	70,123						
4	,726	12,093	82,216						
5	,663	11,050	93,266						
6	,404	6,734	100,000						

Extraction Method: Principal Component Analysis.

Component Matrix^a

	Component	
	1	2
PURCQ4.1	,684	-,538
PURCQ4.2	,617	-,621
PURCQ4.3	,439	,317
PURCQ4.4	,435	,580
PURCQ4.5	,664	,302
PURCQ4.6	,620	,257

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Reproduced Correlations

		PURCQ4.1	PURCQ4.2	PURCQ4.3	PURCQ4.4	PURCQ4.5	PURCQ4.6
Reproduced Correlation	PURCQ4.1	,757 ^a	,756	,130	-,015	,292	,286
	PURCQ4.2	,756	,766 ^a	,074	-,092	,222	,223
	PURCQ4.3	,130	,074	,293 ^a	,374	,387	,353
	PURCQ4.4	-,015	-,092	,374	,526 ^a	,464	,419
	PURCQ4.5	,292	,222	,387	,464	,532 ^a	,489
	PURCQ4.6	,286	,223	,353	,419	,489	,450 ^a
Residual ^b	PURCQ4.1		-,197	,044	,057	-,097	-,038
	PURCQ4.2	-,197		-,043	,122	,004	-,075
	PURCQ4.3	,044	-,043		-,232	-,150	-,183
	PURCQ4.4	,057	,122	-,232		-,171	-,169
	PURCQ4.5	-,097	,004	-,150	-,171		-,172
	PURCQ4.6	-,038	-,075	-,183	-,169	-,172	

Extraction Method: Principal Component Analysis.

a. Reproduced communalities

b. Residuals are computed between observed and reproduced correlations. There are 11 (73,0%) nonredundant residuals with absolute values greater than 0.05.

Rotated Component Matrix^a

	Component	
	1	2
PURCQ4.1	,151	,857
PURCQ4.2	,045	,874
PURCQ4.3	,538	,057
PURCQ4.4	,711	-,142
PURCQ4.5	,696	,218
PURCQ4.6	,633	,222

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Component Transformation Matrix

Component	1	2
1	,745	,667
2	,667	-,745

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

APPENDIX F: SIMPLE LINEAR REGRESSION (HYPOTHESIS 1)

Descriptive Statistics

	Mean	Std. Deviation	N
PURC_DV	4,9907	,79687	162
SOCN_IV	5,4167	1,11490	162

Correlations

		PURC_DV	SOCN_IV
Pearson Correlation	PURC_DV	1,000	,216
	SOCN_IV	,216	1,000
Sig. (1-tailed)	PURC_DV	.	,003
	SOCN_IV	,003	.
N	PURC_DV	162	162
	SOCN_IV	162	162

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	SOCN_IV ^b	.	Enter

a. Dependent Variable: PURC_DV

b. All requested variables entered.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,216 ^a	,047	,041	,78052	2,043

a. Predictors: (Constant), SOCN_IV

b. Dependent Variable: PURC_DV

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4,763	1	4,763	7,819	,006 ^b
	Residual	97,473	160	,609		
	Total	102,236	161			

a. Dependent Variable: PURC_DV

b. Predictors: (Constant), SOCN_IV

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	4,155	,305		13,619	<,001	3,553	4,758
	SOCN_IV	,154	,055	,216	2,796	,006	,045	,263

a. Dependent Variable: PURC_DV

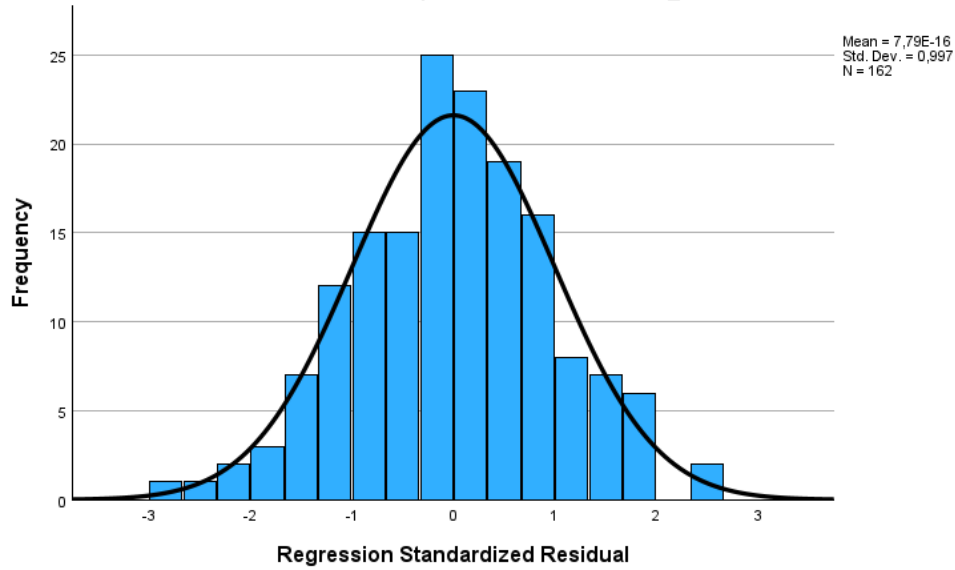
Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	4,3093	5,2350	4,9907	,17201	162
Residual	-2,33074	1,99640	,00000	,77809	162
Std. Predicted Value	-3,961	1,420	,000	1,000	162
Std. Residual	-2,986	2,558	,000	,997	162

a. Dependent Variable: PURC_DV

Histogram

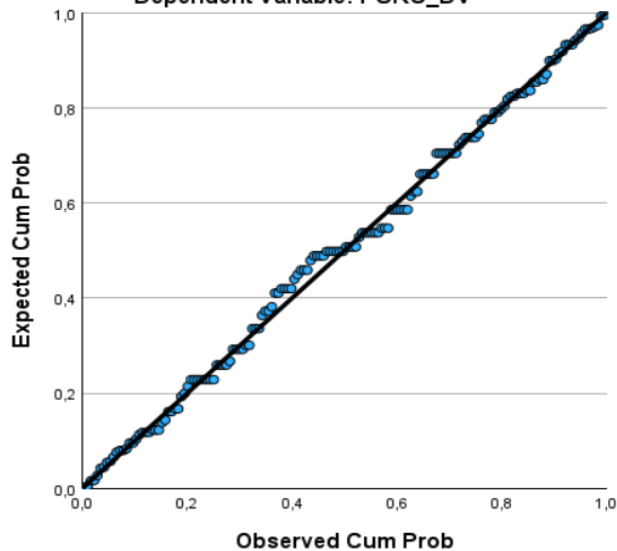
Dependent Variable: PURC_DV

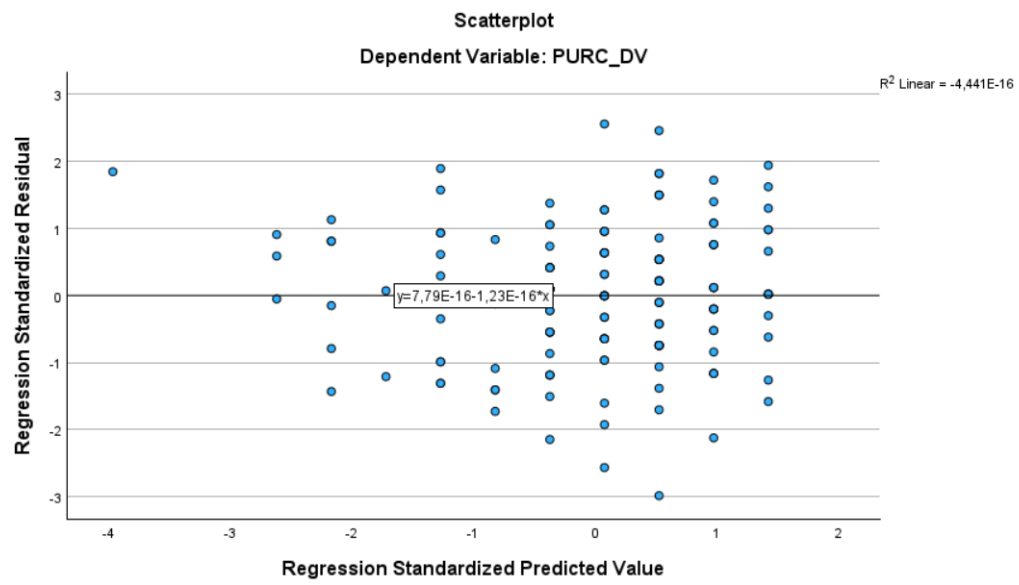


Regression Standardized Residual

Normal P-P Plot of Regression Standardized Residual

Dependent Variable: PURC_DV





APPENDIX G: SIMPLE LINEAR REGRESSION (HYPOTHESIS 2)

Descriptive Statistics

	Mean	Std. Deviation	N
PURC_DV	4,9907	,79687	162
HEUR_IV	5,4537	,86433	162

Correlations

		PURC_DV	HEUR_IV
Pearson Correlation	PURC_DV	1,000	,449
	HEUR_IV	,449	1,000
Sig. (1-tailed)	PURC_DV	.	<,001
	HEUR_IV	,000	.
N	PURC_DV	162	162
	HEUR_IV	162	162

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	HEUR_IV ^b	.	Enter

a. Dependent Variable: PURC_DV

b. All requested variables entered.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,449 ^a	,202	,197	,71420	1,977

a. Predictors: (Constant), HEUR_IV

b. Dependent Variable: PURC_DV

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20,624	1	20,624	40,433	<,001 ^b
	Residual	81,612	160	,510		
	Total	102,236	161			

a. Dependent Variable: PURC_DV

b. Predictors: (Constant), HEUR_IV

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2,732	,360		7,599	<,001	2,022	3,443
	HEUR_IV	,414	,065	,449	6,359	<,001	,285	,543

a. Dependent Variable: PURC_DV

Casewise Diagnostics^a

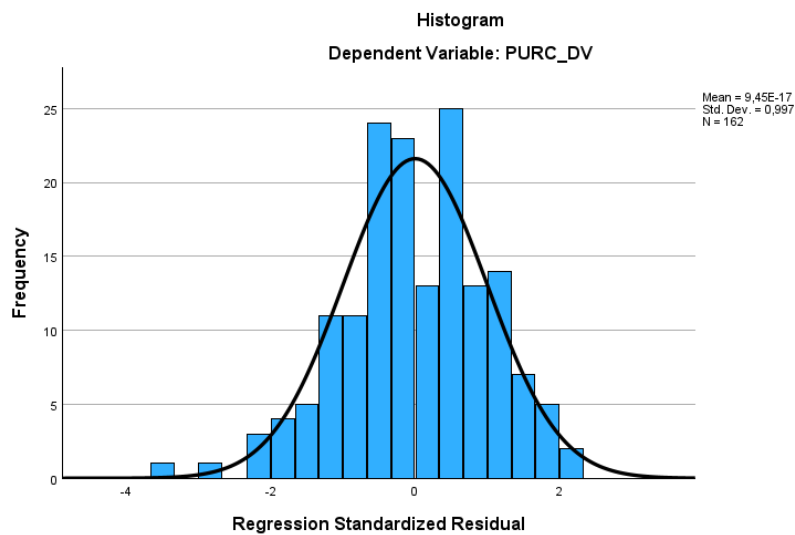
Case Number	Std. Residual	PURC_DV	Predicted Value	Residual
101	-3,454	2,75	5,2170	-2,46696

a. Dependent Variable: PURC_DV

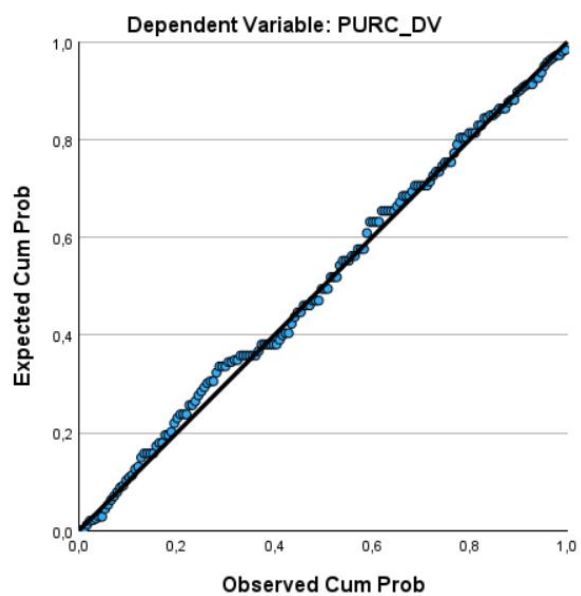
Residuals Statistics^a

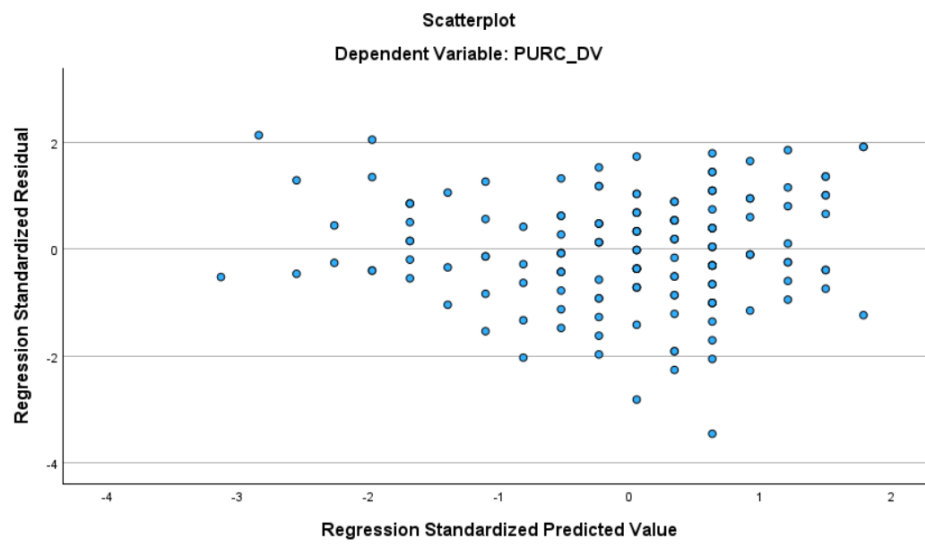
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3,8712	5,6310	4,9907	,35791	162
Residual	-2,46696	1,52531	,00000	,71197	162
Std. Predicted Value	-3,128	1,789	,000	1,000	162
Std. Residual	-3,454	2,136	,000	,997	162

a. Dependent Variable: PURC_DV



Normal P-P Plot of Regression Standardized Residual





APPENDIX H: MULTIPLE LINEAR REGRESSION (HYPOTHESIS 3)

Descriptive Statistics

	Mean	Std. Deviation	N
PURC_DV	4,9907	,79687	162
Actual_age	39,85	10,248	162
Monthly_Income	3,74	,831	162
Financial_situation	4,06	1,595	162
Household_situation	4,45	2,609	162
HEUR_CENTRE	,0000	,86433	162
SNOR_CENTRE	,0000	1,11490	162
SNOR_HEUR	,1952	,91613	162

Correlations

		PURC_DV	Actual_age	Monthly_Income	Financial_situation	Household_situation	HEUR_CENTRE	SNOR_CENTRE	SNOR_HEUR
Pearson Correlation	PURC_DV	1,000	,222	,139	,184	,039	,449	,216	-,056
	Actual_age	,222	1,000	,141	,166	,367	,074	-,010	,086
	Monthly_Income	,139	,141	1,000	,397	,232	,039	,007	-,018
	Financial_situation	,184	,166	,397	1,000	,084	,087	,106	-,114
	Household_situation	,039	,367	,232	,084	1,000	,062	,074	,071
	HEUR_CENTRE	,449	,074	,039	,087	,062	1,000	,204	-,150
	SNOR_CENTRE	,216	-,010	,007	,106	,074	,204	1,000	-,056
	SNOR_HEUR	-,056	,086	-,018	-,114	,071	-,150	-,056	1,000
Sig. (1-tailed)	PURC_DV	.	,002	,038	,010	,309	<,001	,003	,238
	Actual_age	,002	.	,037	,017	,000	,175	,451	,139
	Monthly_Income	,038	,037	.	,000	,001	,309	,466	,410
	Financial_situation	,010	,017	,000	.	,143	,137	,090	,074
	Household_situation	,309	,000	,001	,143	.	,215	,175	,186
	HEUR_CENTRE	,000	,175	,309	,137	,215	.	,005	,029
	SNOR_CENTRE	,003	,451	,466	,090	,175	,005	.	,238
	SNOR_HEUR	,238	,139	,410	,074	,186	,029	,238	.
N	PURC_DV	162	162	162	162	162	162	162	162
	Actual_age	162	162	162	162	162	162	162	162
	Monthly_Income	162	162	162	162	162	162	162	162
	Financial_situation	162	162	162	162	162	162	162	162
	Household_situation	162	162	162	162	162	162	162	162
	HEUR_CENTRE	162	162	162	162	162	162	162	162
	SNOR_CENTRE	162	162	162	162	162	162	162	162
	SNOR_HEUR	162	162	162	162	162	162	162	162

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	Household_situation, Financial_situation, Actual_age, Monthly_Income ^b	.	Enter
2	HEUR_CENTRE, SNOR_CENTRE ^b	.	Enter
3	SNOR_HEUR ^b	.	Enter

a. Dependent Variable: PURC_DV

b. All requested variables entered.

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			
						F Change	df1	df2	Sig. F Change
1	,280 ^a	,079	,055	,77457	,079	3,351	4	157	,012
2	,527 ^b	,278	,250	,69033	,199	21,328	2	155	<,001
3	,527 ^c	,278	,245	,69250	,000	,027	1	154	,871

a. Predictors: (Constant), Household_situation, Financial_situation, Actual_age, Monthly_Income

b. Predictors: (Constant), Household_situation, Financial_situation, Actual_age, Monthly_Income, HEUR_CENTRE, SNOR_CENTRE

c. Predictors: (Constant), Household_situation, Financial_situation, Actual_age, Monthly_Income, HEUR_CENTRE, SNOR_CENTRE, SNOR_HEUR

d. Dependent Variable: PURC_DV

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8,043	4	2,011	3,351	,012 ^b
	Residual	94,193	157	,600		
	Total	102,236	161			
2	Regression	28,371	6	4,728	9,922	<,001 ^c
	Residual	73,865	155	,477		
	Total	102,236	161			
3	Regression	28,383	7	4,055	8,455	<,001 ^d
	Residual	73,853	154	,480		
	Total	102,236	161			

a. Dependent Variable: PURC_DV

b. Predictors: (Constant), Household_situation, Financial_situation, Actual_age, Monthly_Income

c. Predictors: (Constant), Household_situation, Financial_situation, Actual_age, Monthly_Income, HEUR_CENTRE, SNOR_CENTRE

d. Predictors: (Constant), Household_situation, Financial_situation, Actual_age, Monthly_Income, HEUR_CENTRE, SNOR_CENTRE, SNOR_HEUR

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3,891	,348		11,186	<,001	3,204	4,578
	Actual_age	,017	,006	,216	2,597	,010	,004	,030
	Monthly_Income	,073	,082	,076	,885	,377	-,089	,235
	Financial_situation	,062	,042	,124	1,467	,144	-,021	,145
	Household_situation	-,021	,026	-,068	-,807	,421	-,071	,030
2	(Constant)	4,025	,311		12,948	<,001	3,411	4,639
	Actual_age	,016	,006	,205	2,757	,007	,005	,027
	Monthly_Income	,083	,073	,087	1,138	,257	-,061	,228
	Financial_situation	,037	,038	,074	,982	,328	-,038	,112
	Household_situation	-,030	,023	-,097	-,1293	,198	-,075	,016
	HEUR_CENTRE	,371	,065	,403	5,748	<,001	,244	,499
3	SNOR_CENTRE	,096	,050	,134	1,911	,058	-,003	,196
	(Constant)	4,025	,312		12,906	<,001	3,409	4,641
	Actual_age	,016	,006	,204	2,722	,007	,004	,027
	Monthly_Income	,083	,073	,087	1,132	,259	-,062	,228
	Financial_situation	,038	,038	,076	,991	,323	-,038	,113
	Household_situation	-,030	,023	-,098	-,1295	,197	-,076	,016
	HEUR_CENTRE	,373	,065	,404	5,694	<,001	,244	,502
	SNOR_CENTRE	,096	,050	,135	1,907	,058	-,003	,196
	SNOR_HEUR	,010	,061	,011	,163	,871	-,111	,131

a. Dependent Variable: PURC_DV

Excluded Variables^a

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	HEUR_CENTRE	,429 ^b	6,193	<,001	,444	,988
	SNOR_CENTRE	,214 ^b	2,824	,005	,221	,979
	SNOR_HEUR	-,056 ^b	-,722	,472	-,058	,973
2	SNOR_HEUR	,011 ^c	,163	,871	,013	,951

a. Dependent Variable: PURC_DV

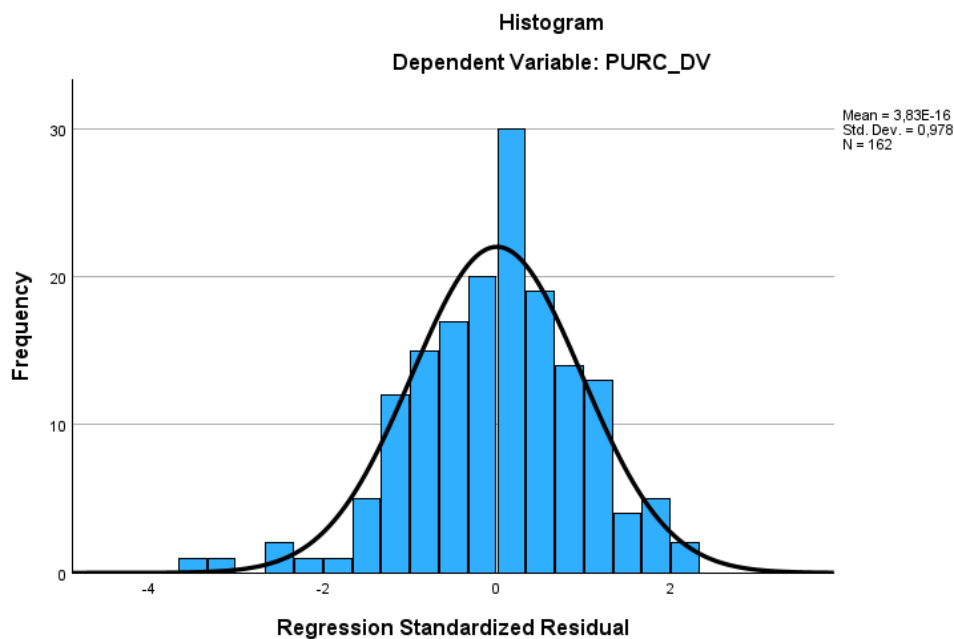
b. Predictors in the Model: (Constant), Household_situation, Financial_situation, Actual_age, Monthly_Income

c. Predictors in the Model: (Constant), Household_situation, Financial_situation, Actual_age, Monthly_Income, HEUR_CENTRE, SNOR_CENTRE

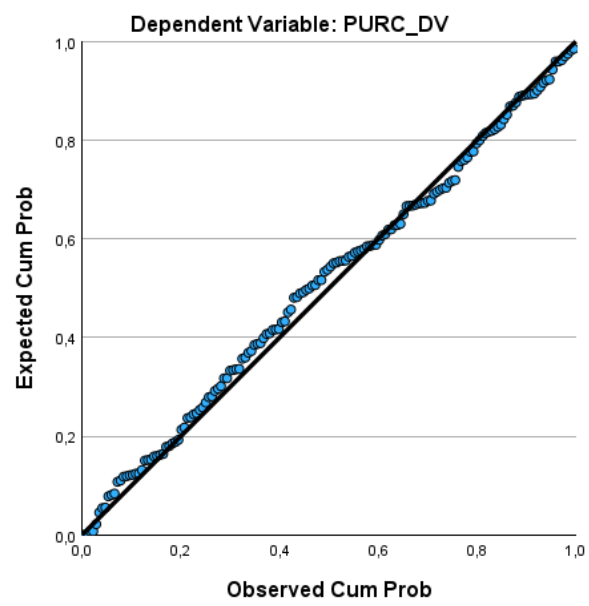
Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3,8291	5,9082	4,9907	,41987	162
Residual	-2,52095	1,50339	,00000	,67728	162
Std. Predicted Value	-2,767	2,185	,000	1,000	162
Std. Residual	-3,640	2,171	,000	,978	162

a. Dependent Variable: PURC_DV



Normal P-P Plot of Regression Standardized Residual



Scatterplot

