Gordon Institute of Business Science
University of Pretoria

The impact of vehicle telematics-based insurance rewards on the driving behaviour of short-term insurance policyholders.

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Abstract

This thesis explores the impact of telematics-based reward schemes on the driving behaviour of policyholders in the South African insurance sector. Using data collected from a leading South African insurer's telematics database, this research employs a combination of descriptive and inferential statistics to investigate the relationships between demographic characteristics, telematics rewards, and driving behaviour.

The findings indicate that demographic characteristics when considered together, have a statistically significant relationship with telematics rewards. Telematics rewards, in turn, exhibit a substantial relationship with driving behaviour. While the relationships between demographic characteristics and driving behaviour were not statistically significant, their influence on driving behaviour is noteworthy.

This research contributes to the understanding of how telematics-based reward mechanisms can influence and incentivise safer driving practices among insurance customers. It has academic and practical implications, shedding light on the potential benefits for the insurance industry in offering personalised insurance premiums based on individual driving behaviour. The findings provide insights for policyholders, insurers, and policymakers seeking to promote road safety, reduce insurance premiums, and enhance customer satisfaction.

Keywords:

Telematics-based insurance, Driving behaviour, Telematics rewards, Personalised insurance premiums

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.

Mbongeni Ndlovu

1 November 2023

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INTRODUCTION TO THE RESEARCH PROBLEM

1.0 Overview of the short-term insurance sector

The current digital revolution has not excluded the short-term insurance industry, which is being impacted by a constant state of change marked by consumer rights, information access, shifting economic conditions and laws regarding privacy (Moodley, 2019). The adoption of big data analytics by the automobile insurance sector is facilitated by the advent of new data sources via social media sites and the internet (Guillen Nielsen & Pérez-Marn, 2021). According to Pesantez-Narvaez Guillen and Alcaiz (2019) significant changes in the short-term insurance market have attracted new participants who were not previously engaged in the provision of short-term insurance services. These participants use artificial intelligence systems to predict individualised insurance premiums. Two significant examples of these new entrants are the banking services sector, which introduced bancassurance services and the mobile telecoms sector, which offered short-term insurance services. The short-term insurance market has witnessed the penetration of new companies, who have brought with them a variety of service alternatives available to policyholders, raising the level of competitive intensity within the short-term insurance sector.

1.1 The adoption of telematics-based insurance rewards

Companies in the short-term insurance sector are exploring new strategies to encourage safe driving behaviours that lower the probability of traffic accidents in the face of technological development and the growing accessibility of telematics devices (Stevenson et al., 2021). Telematics devices are artificial intelligence systems installed on vehicles with the function of gathering driving behaviour, which includes speeds, acceleration and braking patterns that ultimately result in the calculation of personalised insurance premiums and discounts (Nielsen et al., 2019). The launch of telematics devices in the short-term insurance sector enables it to embrace the paradigm shift from the generic determination of insurance premiums to personalised insurance premiums based on individual driving behaviour (Pesantez-Narvaez *et al.*, 2019). Cevolini and Esposito (2022) concur that telematics-based insurance schemes have promoted the transition from actuarial modelling towards behavioural insurance pricing.

Telematics devices offer several advantages, which encompass providing incentives to policyholders and mitigating the magnitude of insurance payouts for insurance companies. This is primarily attributed to the anticipated shift in driving behaviour, marked by a decrease in the occurrence of traffic accidents. (Francois & Voldoire, 2022). The use of real-time information provided by telematics has a significant impact on the changing of historical information (Slavova, 2016). Eling and Kraft (2020) highlight that telematics-based insurance rewards provide policyholders with an opportunity to reduce their insurance premiums by exhibiting safe driving practices. Ziakopoulos Petraki et al., (2022) concur that the application of telematics-based insurance incentives results in fewer road accidents, lower insurance premium prices and safer roads that benefit the general population at large.

Technological development in the insurance industry, particularly concerning the implementation of telematics, comes against the backdrop of the short-term insurance sector being characterised by unsought services and interference in people's private lives (Jeanningros & McFall, 2020), where the market is likely to under demand insurance services if no active initiatives are taken to market them. Within this context, the efficacy of telematics-based insurance premiums is premised on the efficiency and reliability of big data analytics.

1.2 Research Problem

Francois and Voldoire (2022) indicated that the failure of telematics-based insurance rewards in France was attributed to organisational and cognitive limitations that prevented the smooth implementation of big data innovations, upon which telematics-based insurance is reliant. Guillen *et al.,* (2021) stressed that, though the telematics pay-as-you-drive motor insurance scheme is beneficial to policyholders, it also penalises some near-miss events. The South African short-term insurance sector has demonstrated limited adoption of Internet of Things (IoT) technologies that can improve policyholder insights, enhance service innovations and drive transformational change in value creation for policyholders (EY, 2017). The scope of vehicle telematics is advancing in relation to diversity, data volume and complexity (Wessels & Steyn, 2020, p. 1). On the other hand, the adoption of technological innovations in the short-term insurance sector has a direct influence on the protection of personal security and data privacy which raises propensity for fraudulent operationalisation of the telematics-based insurance platform by insurers (Blakesley & Yallop, 2020, p. 287). Moodley (2019) contends that information privacy and consumer rights are global factors that have a significant influence on policies and regulations within the short-term insurance sector. The conceptual attraction of using telematics-based insurance to track individual driving conduct seems to be constrained by these factors, which are subject to compliance with consumer and information privacy rights that govern service developments in the short-term insurance industry. The chances of applying telematics to forecast driver behaviour in the short-term insurance business are also negatively impacted by the poor acceptance of IoT technologies in this industry, as well as the failure of telematics due to organisational and cognitive limitations. Despite the theoretical appeal of telematics in the short-term insurance industry, insufficient research has been done about its application concerning various demographics and gender groups. Extant research has inadequately captured the sustainability of telematics and its comparative influence in relation to other financial incentives offered by the short-term insurance sector.

1.3 Research Purpose

1.3.1 Academic Rationale

Short-term insurance products are primarily difficult to market and sell since they do not provide immediate benefits for the prospective customer. This has primarily made such types of services regarded as "unsought services," based on the realisation that the market is most likely to under-demand such services. The rapid technological infusion in business, which in the context of this study is in the form of telematics-based insurance, has played a significant role in making customers realise the immediate benefits associated with the acquisition of short-term insurance that is individualised to one's driving behaviour.

Within this context, this research will make an academic argument that the digitalisation of insurance policies through the leveraging of innovative solutions like telematics insurance policies can play a significant role in influencing positive marketing prospects for short-term insurance companies in the face of mounting demands on the part of consumers. There has been a wealth of research undertaken with regard to the anticipated benefits linked with the adoption of telematics in the field of insurance. This research is meant to interrogate the sustainability of this approach towards short-term insurance as well as the applicability of telematics concerning individuals' demographic profiles.

The study will also highlight the coexistence of telematics-based insurance rewards within the context of traditional and existing insurance portfolios and reward systems. The study is also undertaken within the context of the realisation that there have been reported cases where the use of technology in insurance, particularly telematics, failed in other research contexts due to a variety of factors, including the potential violation of personal privacy and data protection threats (Jeanningros & McFall, 2020).

1.3.2 Business Rationale

The paradigm shifts from traditional insurance towards leveraging telematics is a potential disruptor in the short-term insurance industry given the rapid infusion of industry into digitalisation. This technology transition is bound to benefit both insurance companies in the form of low claims as well as the customers, who will also benefit from the rewards they get in response to good driving behaviour. The approach adopted for telematics-based short-term insurance is unique in its nature. It distinctly prioritises customer-centricity by personalising insurance premiums, in contrast to the previous paradigm that relied on standardised premium calculations via actuarial methods. (Cevolini & Esposito, 2022).

The adoption of telematics-based short-term insurance can also be seen as an extension of corporate social responsibility by short-term insurance companies to demonstrate their concern for the safety and welfare of their customers by giving them rewards in return for favourable driving behaviour, which limits claims on the part of short-term insurance companies. From a business perspective, this was taken as a proactive approach towards corporate social investments to anticipate and influence positive driving behaviour on the part of policyholders.

The adoption of telematics-based insurance can also open avenues for strategic alliances between fintech companies and insurance companies in the development of value-added services that can enhance the level of customer embeddedness in existing policyholders. In essence, the adoption of telematics-based insurance is a strong business case when it comes to the delivery of customer loyalty and rewards that can enhance customer retention given the unsought nature of short-term insurance products.

1.3.3 Strategic advantages of telematics to insurers

Pay-as-you-drive (PAYD) insurance schemes in South Africa offer significant benefits for insurers, as they directly link premiums to an individual's driving behaviour. Torra et al., (2023) reiterated that innovative approaches not only promote acceptable driving behaviour but also provide a business case for insurers. By adopting telematics-based insurance rewards, insurers can enhance their market share by attracting low-risk drivers and offering competitive pricing and attractive policy offerings. The use of telematics data allows insurers to accurately assess the risk associated with individual drivers, resulting in more personalised and fair pricing for insurance premiums. This approach encourages safer driving behaviour, resulting in a reduction in accidents, claims and associated costs for insurers. Safer drivers are rewarded with lower rates, making it appealing for responsible individuals and incentivising them to choose telematics-based insurance.

Reddy and Premamayudu (2019) stress that telematics systems can detect and provide evidence of fraudulent claims, thus reducing losses due to fraudulent claims. Telematics data also helps insurers identify new market segments, tailor policies and develop innovative products. This level of customer engagement can build stronger relationships, increase customer satisfaction and potentially lead to higher policy retention rates. Moodley (2019) emphasise that insurers can also benefit from telematics-based insurance rewards, which provide a novel way of assessing risk and rewarding safe driving habits. The ease with which telematics-based insurance award platforms collect data on individual driving behaviour promotes risk profiling of policyholders, offering customised insurance rates based on driving habits.

Ayuso *et al.,* (2019) stress that PAYD insurance schemes in South Africa offer significant benefits for insurers, including increased market share, better risk management and improved customer engagement. By leveraging advanced telematics and digital technologies, insurers can improve pricing accuracy, gain valuable insights into driving patterns and risk factors and align with regulatory requirements and consumer protection standards.

1.4 Research Objectives

This research aims to fulfil the following objective:

RQ1. To determine the impact of policyholder demographics on rewards (Ma *et al.*, 2018).

RQ2. To analyse the influence of policyholder characteristics on driving behaviour (Eling & Kraft, 2020).

RQ3. To evaluate the impact of telematics rewards on driver behaviour (Elias, 2021).

1.5 Research Scope

Within this purview, the current study is relevant to many stakeholders, including insurance companies, policyholders, policymakers, road safety organisations and the general public. This research could inform future policy and insurance initiatives to promote safer driving habits and reduce insurance premium costs. This study will focus on 7,000 policyholders from Activated Insurance, a telematics-based insurance company operating in South Africa.

The purpose of this study is to establish the impact of telematics-based insurance on the driving behaviour of policyholders. The ultimate goal is to determine the effectiveness of telematics-based insurance rewards in promoting safer driving habits characterised by a reduction in road accidents and providing financial incentives to policyholders concerning driving behaviours. The study will also examine possible benefits of telematics-based insurance rewards for policyholders, short-term insurance companies and the general public at large, including reduced insurance premiums, improved road safety and enhanced customer satisfaction. Through this research, valuable insights will be highlighted with regard to the use of telematics-based insurance rewards to promote safe driving habits and reduce the cost of insurance.

1.6 Layout of the Research Study

This study is organised into seven chapters. The introductory chapter outlines the background of the study, which gives way to the formulation of the research problem, purpose and objectives. The introductory chapter also outlines the business and academic rationale behind the study.

Chapter 2 provides a detailed review of the literature on the concept of telematics-based insurance and its benefits with respect to the behaviour of drivers. The literature review is based on the Unified Theory of Acceptance and Usage of Technology. The main purpose of a literature review is to critically analyse existing literature with the view of identifying areas of convergence and points of difference.

Chapter 3 is responsible for the formulation of research hypotheses that will guide the rest of the research in line with the concept of telematics-based short-term insurance. Chapter 4 will critically analyse the research methodological foundations that inspire the way in which data is collected, measured and analysed in line with empirical principles. Topics within the methodology section will focus on the research philosophy, research design, strategy and approach, research population sampling strategy, data collection and analysis techniques, validating reliability, as well as ethical considerations.

Chapter 5 is responsible for the presentation of research results that were collected from across the section of motor vehicles registered on the telematics platform. Research findings are presented in the analysis from a descriptive statistics point of view. Other approaches to digital analysis will include event studies and style analysis. These types of analyses correlate the data from the time you get the reward and analyse if the driving behaviour changes. Style analysis would involve grouping the drivers into categories and seeing if they change.

Chapter 6 is engaged with providing a detailed discussion of research findings through a comparison of extant literature on the concept of telematics-based short-term insurance and outcomes that were eliminated from this study. Chapter 7 summarises the entire research process by outlining the conclusions and recommendations in relation to managerial and practical implications and highlighting the research limitations and contributions made by the study in relation to methodological practise and theory.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This chapter is responsible for providing a balanced and critical review of the literature regarding the concept of telematics and the best insurance schemes as they are applied within the context of the South African insurance industry. The critical review of literature recognises that telematics-based insurance rewards are within the scope of insurance service innovations that are driven by emerging technology innovations that include data analytics, machine learning, artificial intelligence and virtual reality systems. These supporting technological systems are also included as part of the literature review because they enhance the ability of the telematics insurance reward system to positively influence driver behaviour and create benefits for both the policyholder and the short-term insurance company.

The scope of the literature review begins by highlighting the two most dominant and relevant theoretical frameworks that govern the adoption, acceptance and use of telematics-based insurance. These theories include the Diffusion of Innovation Model as well as the Unified Theory of Acceptance and Use of Technology (UTAUT). These two theoretical models are critically discussed with the view of highlighting their relevance to the case of the expansion of the telematics base insurance reward scheme, which is positioned as a novel innovation to improve favourable driving behaviours amongst policyholders. Given that telematics-based insurance schemes are driven by technology; the literature review also critically discusses the concept of service innovations as they apply to the short-term insurance industry in general.

The driving behaviour of short-term insurance customers is evaluated in relation to the Theory of Reasoned Action Model. The literature review also critically discusses existing knowledge within the field of telematics-based insurance schemes as well as what needs to be done regarding the relationship between telematics-based insurance schemes and demographics, the sustainability of telematics-based insurance schemes and the comparative analysis of the efficacy of telematics-based insurance schemes in comparison to alternative insurance models.

2.1 Theoretical framework guiding the study

The theoretical framework provides the basis upon which the relevance of the current study was put into perspective through a detailed comparison of existing models that seek to explain a phenomenon. This research is focused on the application of a telematics-based insurance scheme to influence driver behaviour. The use of telematics-based insurance schemes was linked with user adoption models relating to technological objects, such as the Diffusion of Innovations Model and the Unified Theory of Use and Acceptance of Technology model. These two models have been deemed particularly pertinent to research that centre on leveraging technology as a way of influencing the behaviour of drivers.

2.2 Diffusion of innovations

The Diffusion of Innovations Model is an adopter category model that has been applied in different research contexts and focuses on the pace with which people and organisations are prepared to adopt and use technological innovations. This adopter model has been selected in this research given that telematics-based insurance schemes are a typical innovation that has yet to be diffused across the diversity of short-term insurance customers. The diffusion of innovations model, proposed by Rogers (1995), is an adapter category theory to showcase the processes that technology uses and organisations go through in the process of adopting new technologies and innovations.

The main principle behind the model Is that emphasis is placed on the adoption of technologies by an innovative segment of the market, with adoption rates increasing with time (Lai, 2017). The diagrammatic depiction of the diffusion of innovations model symbolises a normal distribution curve with fewer outliers representing innovators and laggards at each end. The diffusion of innovations model is a demonstration of the technology life cycle of innovations as they are adopted by different classes of user categories, as illustrated in Figure 2.1.

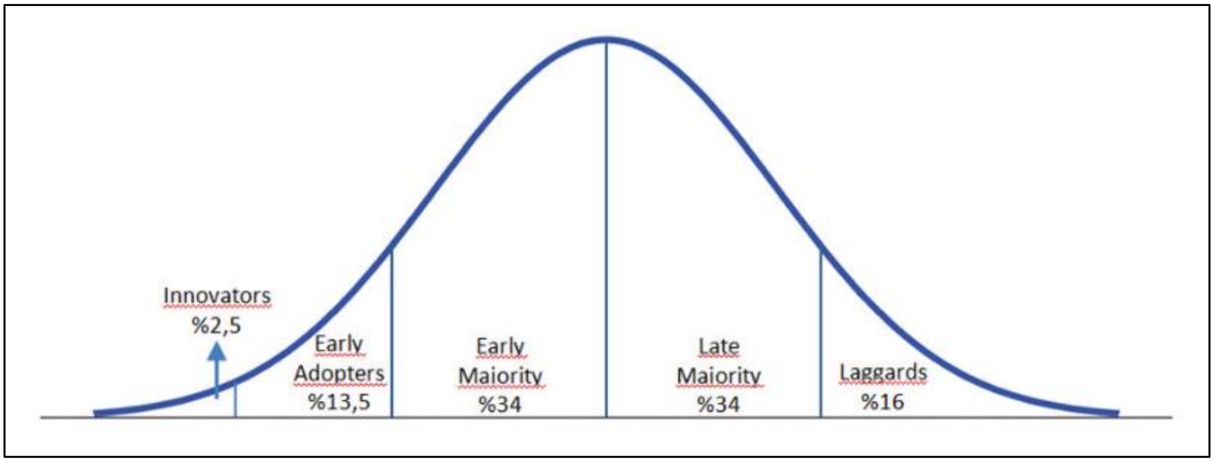


Figure 2.1: Diffusion of innovations model

Source: Adopted from Draycott *et al.,* (2019)

The theoretical significance of the Diffusion of Innovations Model to the current research is that it articulates stages that insurance customers as well as insurance companies can go through in the process of diffusing the telematics best insurance scheme, which is an innovative technology. The theory also articulates the strategies that organisations and technology users can utilise to adopt new technologies with relative ease and minimal resistance. With respect to the model, innovators are classified as “first movers”, who readily accept new technologies with much less resistance (Sanidewi & Paramita, 2018).

The Diffusion of Innovations Model explains different adopter categories that are not only peculiar to this study but have also been used in existing research. The model has been successfully applied to explain the adoption of different technologies in different industries as well as reduce the uncertainty associated with the adoption of technological innovations (Gilbert *et al.*, 2015). The basic principles behind the Diffusion of Innovations Model are that the benefits associated with adopting new technological innovations diffuse to the rest of the markets, which are risk-averse and look forward to innovators accessing their user experiences and efficacy of new technologies prior to their adoption (Anders, 2021).

The critical success factor behind the Diffusion of Innovation Model lies in the strategic fit that it presents to organisations that are preparing to embrace new technologies to enhance their level of competitiveness (Azhgaliyeva, 2019). The claim to fame of the Division of Innovations Model is related to key factors that include the reliability of technology, the observability of the advantages associated with technologies for innovators and first movers, the relative advantages provided to companies that adopt new technologies and the compatibility of new technologies with existing systems. These factors are critical in attracting companies and users towards the use of new technologies as a way of improving operational efficiency or customer satisfaction (Amati *et al.*, 2019).

The relevance of the Diffusion of Innovations Model to the current research is that it can assist short-term insurance companies in categorising and identifying specific customer categories that need to be targeted with the use of telematics. This approach towards positioning the telematics-based best insurance scheme optimises the allocation of the marketing budget for short-term insurance companies by identifying opinion leaders and innovators who can easily accept the use of telematics-based insurance schemes as a way of influencing their driving behaviour and, in the process, benefiting from some financial worlds. These innovators can then act as brand ambassadors or brand endorsers to spearhead the popularity of the telematics-based insurance scheme amongst their social circles and other adopter categories to improve and increase the usage and adoption of telematics-based insurance along its life cycle. The relevance of the Diffusion of Innovations Model is complimented by the Unified Theory of Use and Acceptance of Technology.

2.3 The Unified Theory of Acceptance and Use of Technology

This research is based on the application of a technology-based approach to collect the driving behaviour of short-term insurance customers. The efficacy of telematics-based insurance was analysed from the perspective of the Unified Theory of Acceptance and the Use of Technology (UTAUT). The basic principles of this model are that actual technology use is a result of behavioural intent. The main premise behind the Unified Theory of Acceptance and Use of Technology is that performance expectancy, effort expectancy, social influence and facilitating conditions influence behavioural intent that ultimately leads to use behaviour. These four constraints are moderated by gender, age, experience and voluntariness of use.

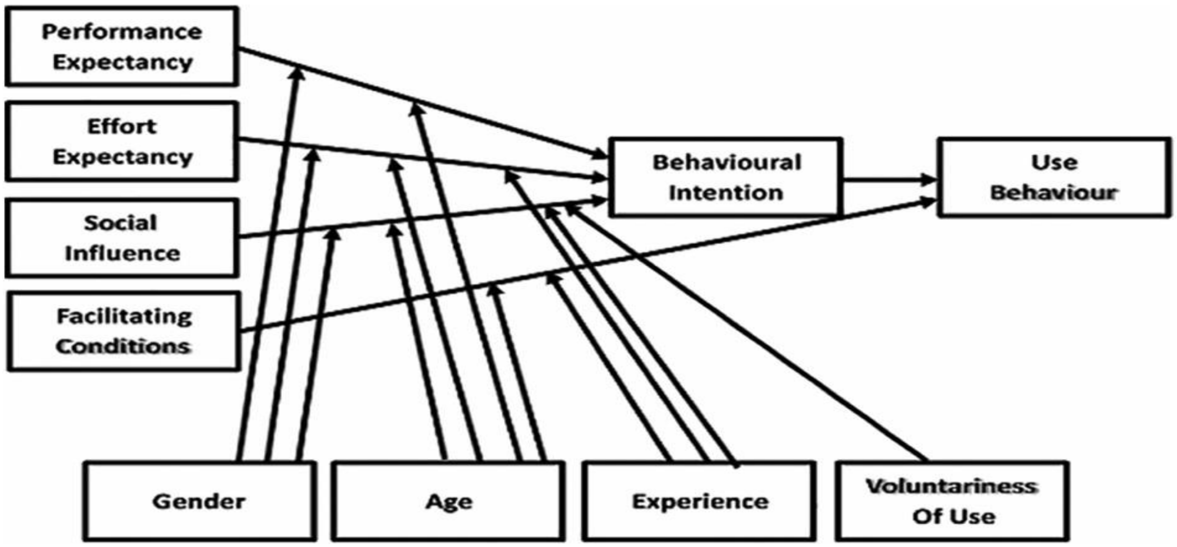


Figure 2.2: The UTAUT Model

Source: Adopted from Venkatesh *et al.*, (2003).

The Unified Theory of Acceptance and Use of Technology is illustrated in Figure 2.2 is composed of four main constructs that include performance expectancy, effort expectancy, social influence and facilitating conditions. The first three constructs have a direct influence on behavioural intention, while facilitating conditions influence user behaviour directly. Moderating conditions that support these constructs include gender, age, experience and voluntariness of the use of a technology (Johnson, 2020; Venkatesh *et al.*, 2003).

2.3.1 Performance Expectancy

Performance expectancy refers to the perception of the user, that their utilisation of technology is associated with an improvement in an activity (Lulin *et al.*, 2020). The effectiveness of performance expectancy is dependent on the competency that a user gains through the use of technology. Within the framework of this research, performance expectancy is viewed from the perspective of the utility value that short-term insurance policyholders perceive to benefit from the use of telematics-based insurance reward mechanisms. It is anticipated that leveraging technology through the use of telematics-based insurance schemes is likely to influence positive driving behaviour among short-term insurance policyholders (Shachak *et al.*, 2019). This view is justified by the existence of extant literature, which shows a significant relationship between performance expectancy and behavioural intention towards the use of technology in various social and economic contexts (Abbad, 2021; Mikalef *et al.*, 2019).

2.3.2 Effort Expectancy

With respect to the UTAUT, the effort expectancy constructs focus on the simplicity of use of telematics for end users determines effort expectancy, which leads to its acceptability. Because it examines the degree in which motorists are able to alter their driving conduct in response to the possible advantages of using telematics-based insurance rewards, effort expectancy is significant within the context of the current research. Positive behavioural intentions are likely to be influenced by the technology's perceived usability (Dimitriadis *et al.*, 2019).

2.3.3 Social Influence

Social influence acknowledges that the availability of a social infrastructure that supports individuals' behavioural goals affects how easily people can use technology (Abbad, 2021). The importance of social influence is examined within the context of the present investigation from the viewpoint of the knowledge that is disseminated among holders of short-term insurance policies on the purported benefits associated with the implementation of the telematics-based insurance incentive system. Therefore, the willingness of policymakers to capitalise on the telematics-based insurance incentive system to effectively change their driving habit depends on the development of a social infrastructure.

Given that experts exercise a great degree of autonomy and discretion, which suggests that they are likely to employ technology, Rouidi *et al.*, (2022) found that social influence is the lowest indicator of likelihood when it pertains to adoption of technology and acceptability. Less societal issues have an impact on technologies like telematics insurance reward programmes. Abbad (2021) believed that social influence determines behavioural goals when using technology, particularly in the digital era where there is a rise in the use of telematics-based Insurance schemes and people rely on the opinions and insights expressed by people in online communities to influence their own personal decisions.

2.3.4 Facilitating Conditions

According to Biruk and Abetu (2019), enabling conditions are the circumstances in which a person's use of technology is influenced by the availability of organisational and technical support infrastructure. According to Lulin *et al.,* (2020), the efficiency of these networks of assistance is predicted to have a direct impact on each person's behavioural goals when using the technological platform. The ability of the telematics-based insurance reward system to collect accurate information about policyholders' driving behaviour is key to creating the favourable conditions that encourage a positive change in driving behaviour.

2.3.5 Moderating Conditions

Moderating conditions have to do with an individual's experience, gender, age and willingness to use technology, among other personal traits. Although they are not anticipated to have a direct impact on behaviour, moderating factors are projected to have a moderating impact on performance expectancy, effort expectancy, social influence and enabling conditions as they affect behaviour intention and actual technology use (Lulin *et al.*, 2020). Identifying the impact of drivers' demographic traits on their propensity for safe driving behaviour is one of the goals of this study.

The adoption of technology is influenced by gender. The adoption of telematics-based insurance reward programmes is thought to be significantly influenced by gender diversity (Kernebeck *et al.*, 2022). Gender can influence a person's propensity to adopt telematics-based insurance reward programmes. Faida *et al.,* (2022) emphasised that females are more inclined to be guided by social influence and organisational intents than their male counterparts with regard to the acceptance and utilisation of telematics-based insurance rewards systems. This suggests that, in contrast to men who are more motivated by performance and effort expectations, women are probably more impacted by the assistance they receive from their peers when it comes to the adoption of telematics-based insurance incentive systems (Shachak *et al.*, 2019).

In terms of age, the research suggests that the generation gap operates so that the younger generation exhibits a larger inclination for telematics-based insurance incentives schemes than the more mature generation (Anirvinna *et al.*, 2021). Younger generations who were born during the pinnacle of the digital revolution are more likely to adopt telematics-based insurance rewards programmes technologies than older generations who are more likely to utilise paper-based ones (Abbad, 2021).

Through familiarity with various technology-enabled devices, experience increases the ease of adopting telematics-based insurance incentive systems, according to research (Shachak *et al.*, 2019). By adopting technologies like telematics-based insurance reward programmes, voluntary use has a huge impact on social influence (Hsu, 2018). According to the body of existing research, men are more likely than women to voluntarily adopt digital marketing practises with little need for social approval (Kernebeck *et al.*, 2022; Shachak *et al.*, 2019). In contrast, women need a strong social environment to support them in order to accept telematics-based insurance reward programmes.

2.4 Theory of Reasoned Action Model

The Theory of Reasoned Action, which was proposed by Fishbein and Ajzen (1975), has been included in this research as it explains the behaviour of people when they make decisions that are contrary to their attitudes. The Theory of Reasoned Action highlights that the behaviour of people is perceived from the urge of confirmation with an existing subjective norm, which influences the development of attitudes in line with an ideal behaviour. The intentions of people towards a behaviour are a key motivator in the execution of efforts that are aimed at achieving that behaviour (Branley & Covey, 2018). The underlying factors behind the Theory of Reasoned Action Model include attitude and normative factors that are determined by the expected outcomes that emanate as a result of performing a specific behaviour. The expected behavioural outcomes can either be positive or negative. This model is illustrated in figure 2.3.

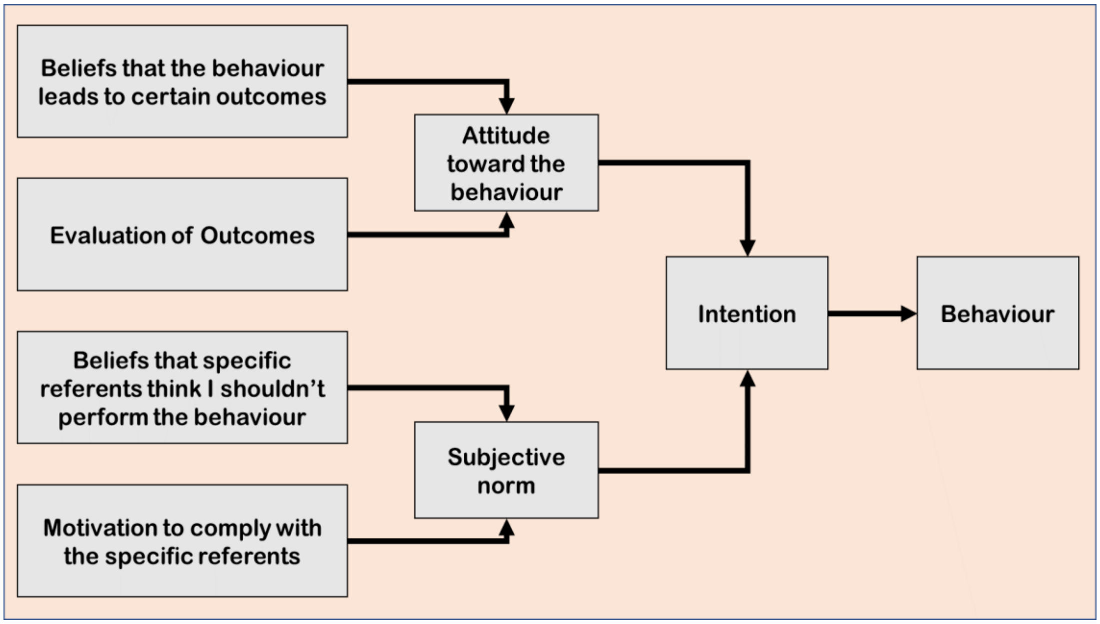


Figure 2.3: Theory of Reasoned Action Model

Source: Adapted from (Schiffman & Kanuk, 2012)

The normative beliefs underlying human behaviour determine the level of influence they receive within their social circles. The decision by short-term insurance customers to use telematics-based insurance systems is premised on their subjective norms and social influence received from reference groups. This position is adopted from the Theory of Reason and the Action Model appears to confirm the influence of social factors as proposed by the Unified Theory of Acceptance and Use of Technology with regards to the social influence construct.

The applications of the Theory of Reasoned Action Model in the measurement and determination of user subjective norms and attitudes may not be peculiar to this research alone since the model has been successfully used in determining levels of consumer behaviour in other research contexts. The Theory of Reasoned Action Model was applied in a study that focused on eLearning technology (Boateng *et al.*, 2016), the application of mobile learning technology (Park et al., 2012), social media marketing and networking (Rienetta *et al.*, 2017), the adoption of e-commerce (Bahtar, 2016), the application of technology in sports (Ibrahim, 2014) and the application of online consumer behaviour (Lim *et al.*, 2016).

This significance of the Theory of Reasoned Action within the context of the current research is based on its articulation of consumer attitudes towards an acceptable behaviour and subjective norms that influence the actual driving behavioural motives from the perspective of attitudes and the motives that might derive from short-term insurance adoption of favourable driving behaviours that might culminate in benefiting from telematics-based insurance rewards.

2.5 The scope of telematics-based Insurance

The application of black-box insurance schemes through the use of on-board devices, sensors have expanded the possibilities of collecting vital driver behaviour in real time through use of telematics (Torra *et al.*, 2023). Literature on the application of telematics-based insurance rewards is evolving. However, existing literature on this subject indicates that the shift in paradigm toward artificial intelligence-driven telematics-based insurance has yielded noteworthy advantages for short-term insurance companies, particularly in the context of claim payments, which aligns with the driving behaviour of policyholders. (Stevenson et al., 2021). In this regard, the use of telematics-base insurance rewards has enabled short-term insurance in the calculation and determination of individualised insurance premiums (Pesantez-Narvaez et al.,2019).

The use of telematics-based insurance rewards supports the categorization of clients in respect of their driving behaviours when it comes to determining insurance premiums payable and rewards that can be given in response to favourable driving behaviour (Winlow *et al.*, 2019). Boucher *et al.,* (2017) concur that the advent of disruptive innovations has made it possible to install Global Positioning Systems in vehicles for the purposes of determining the driving habits that underscore the telematics-based insurance schemes. Pesantez-Narvaez *et al.,* (2019) underscore that the pay as you drive insurance schemes are based on leveraging driving behaviour in the determination of insurance prices.

Existing literature on the application of telematics-based insurance programmes shows that participants exhibit several driving habits, such as decreased frequency of sudden braking, reduced speeds and avoiding sudden accelerations, which are key risk factors that can contribute to higher insurance premiums. Longhi and Nanni (2020) concur that policyholders are likely to engage in safe driving practises like wearing seat belts and avoiding accidents while driving. Jeanningros and McFall (2020), reiterate that telematics-based insurance rewards encourage insurance price personalisation based on individual level data. Medders et al., (2021) stressed that gender-based price discrimination is problematic for most insurers since the gender diversity is outside the control of the insured.

Another dimensional benefit of telematics-based insurance comes in the form of cost savings for policyholders (Winlow *et al.*, 2019). Hence, policyholders who exhibit safe driving practises through the telematics-based insurance programmes are eligible to benefit from lower premiums. Guillen *et al.,* (2020) specified that these cost savings were substantial, with policyholders reporting discounts of up to 30% of their base insurance premiums. Existing literature appeared to support the implementation of telematics-based insurance rewards, as these have been linked with significant improvements in driving behaviour and the promotion of safer roads. Additional research is required to comprehensively appreciate the impact of telematics-based insurance rewards on driving behaviour and to identify the most effective strategies that can sustain the implementation of telematics-based insurance rewards (Tian *et al.*, 2020).

Despite the conceptual appeal of telematics-based insurance rewards, existing literature appears to place emphasis on the policyholder's behaviour as the main driver of telematics. It appears that other exogenous factors that increase the risk profile of drivers are ignored. These factors might include the threat of hijacking, which is common in South Africa, the behaviour of other road users, as well as the state of the roads themselves, which might pose a risk factor.

2.5.1 Business benefits of telematics-based Insurance scheme

Insurers in South Africa can benefit significantly from the use of pay-as-you-drive (PAYD) insurance schemes. PAYD insurance is an innovative approach where premiums are directly linked to an individual's driving behaviour. The proclivity towards telematics-based insurance schemes is not only earmarked at promoting acceptable driving behaviour on the part of policyholders, but there is also a business case to it. Insurance firms are making inroads towards the adoption of telematics-based insurance rewards after realising the benefits associated with such a paradigm shift in terms of risk leveraging, making accurate underwriting decisions, improve customers engagement. Insights from Torra *et al.*, (2023) specify that pay-as-you-drive insurance schemes benefit insurers in the sense that firms that are quick to adopt telematics-based insurance rewards, have the capacity to enhance their market share as they stand to attract low-risk drivers from other insurers that do not use the telematics-based insurance rewards schemes.

Cevolini and Esposito (2022) stress that the ability to attract low-risk drivers implies that the telematics-based insurers incur relatively lower insurance claims from clients hence preserving value for the insurer. PAYD insurance allows insurers to segment their customers into different risk groups based on driving behaviour. This segmentation enables insurers to specifically target low-risk drivers with more competitive pricing and attractive policy offerings. By tailoring their marketing and pricing strategies, insurers can attract safer drivers and potentially expand their customer base.

Cevolini & Esposito (2022) weigh in that telematics data allows insurers to accurately assess the risk associated with individual drivers based on their behaviour. This enables more personalised and fair pricing for insurance premiums through segmentation of the insurance market though the principle of actuarial fairness. PAYD insurance encourages safer driving behaviour as policyholders are financially incentivised to drive responsibly. This can result in a reduction in accidents, claims and associated costs for insurers. As safer drivers are less likely to make claims, insurers can potentially decrease their overall risk exposure. Safer drivers are rewarded with lower rates, making it appealing for responsible individuals and incentivizing them to choose telematics-based insurance.

Blakesley (2020) specify that telematics systems can detect and provide evidence of fraudulent claims. This helps insurance companies reduce losses due to fraudulent claims (Eling & Kraft, 2020). The works of Torra et al., (2023) reiterate that telematics data provides insurers with a deeper understanding of driving behaviour, enabling more accurate underwriting decisions and risk assessments. Moodley (2019) emphasise that in the event of an accident, the collected data can aid in claim handling, streamlining the process and reducing the need for lengthy investigations and disputes.

Ayuso *et al.*, (2019) stress that telematics-based insurance allows insurers to engage more closely with their customers through regular feedback and personalised insights about their driving habits. PAYD insurance schemes provide an opportunity for insurers to engage with their policyholders more consistently. This engagement fosters a sense of partnership and encourages safer driving practises, potentially leading to fewer accidents and claims. Pesantez-Narvaez *et al.*, (2019) concur that customers also benefit from lower premiums when they demonstrate good driving behaviour, further incentivizing loyalty to the insurance company.

The works of Kanta Reddy & Premamayudu (2019) highlights that telematics data provides valuable insights into driving patterns and customer preferences. Insurance companies can analyse this data to identify new market segments, tailor policies and develop innovative products. Insurers can provide real-time feedback on driving behaviour, offer suggestions for improvement and create personalized rewards for safe driving. This level of customer engagement can help build stronger relationships, increase customer satisfaction and potentially lead to higher policy retention rates.

Pesantez-Narvaez *et al.*, (2019) illustrates that by understanding the driving habits of young or inexperienced drivers, insurers can create specialised products to better meet their needs. Telematics systems enable insurers to automate data collection and analysis, reducing the need for manual processes and extensive paperwork. This leads to operational efficiency gains by streamlining underwriting, claims and policy management processes. Insurers can also optimise resources by focusing on high-risk areas or customers based on the insights provided by telematics. By reducing risk, insurers can enhance their profitability. With PAYD insurance, premiums are based on actual driving patterns, distance travelled and driving habits. This approach allows insurers to price policies more accurately, resulting in fairer premiums for policyholders and reduced claims pay-outs for the insurer.

Insights from Ziakopoulos *et al.,* (2022) reiterate that insurance companies are also sent to benefit from telematics-based insurance rewards, which provide a novel way of assessing risk and rewarding safe driving habits. The ease with which telematics-based insurance award platforms collect data on individual driving behaviour promotes the risk profiling of policyholders to offer customised insurance rates based on driving habits (Pesantez-Narvaez et al., 2019). Tian *et al.* (2020) are of the opinion that telematics-based insurance rewards play an important role in the reduction of road accidents, which improves general road safety to the benefit of the general public. PAYD insurance schemes heavily rely on advanced telematics and digital technologies to collect and analyse driving data. Insurers can leverage the use of mobile apps, connected devices and artificial intelligence to track driving behaviour accurately. This not only improves the accuracy of pricing but also enables insurers to gain valuable insights into driving patterns and risk factors. PAYD insurance schemes align insurers with regulatory requirements and consumer protection standards. With PAYD insurance, premiums are directly linked to objective driving indicators rather than traditional risk factors such as age, gender, or location. This can lead to more equitable pricing, reducing the potential for discriminatory practices.

2.6 Service Innovations

Service innovations related to technological advancements result in improvements in the quality of delivery to customers. Recent technological innovations have resulted in several innovations that optimise the quality of service delivery through leveraging artificial intelligence, blockchain technology (Sonkamble *et al.*, 2021), machine learning, big data analytics, cloud computing technologies, virtual reality and augmented reality, among others (Longworth & Longworth, 2020; Nivetha & Sudhamathi, 2019). The rise in the use of Internet technologies has also promoted an exponential rise in service innovations within the short-term insurance sector (Wang *et al.*, 2018).

Companies in the short-term insurance sector leverage the use of internet-based platforms to increase the volume of traffic through the use of internet and mobile insurance platforms that depend on technological innovations. The exponential approach used in the application of the Internet of Things phenomenon has also raised the profile of service innovations within the short-term insurance sector (Rayes & Salam, 2019). The application of service innovations is premised on the degree to which end users are technologically sophisticated and capable of applying various technologically driven solutions in their everyday lives (Kanta Reddy & Premamayudu, 2019). Short-term insurance companies have seized opportunities made available by service innovations to implement customer-focused insurance services that enhance increased usage rates across different customer categories.

The permanent use of Web 2.0 technologies has increased the popularity of service innovations in the insurance sector, provided that customers and other end users can use, generate and share content amongst themselves in a manner that enhances the brand profile of services offered by the insurance sector (Ukpere et al.,2017). Implementing insurance service innovations allows insurance companies to go a step ahead in integrating social media platforms as part of their insurance service channels to expand the scope of their market reach (Zia & Kalia, n.d.). It is realised that the insurance service sector disseminates information pertaining to their service innovations through the use of social media platforms as a way of enhancing the acceptability of innovations by leveraging the presence of a sophisticated online community with a high proclivity towards sharing information (Francois & Voldoire, 2022a).

Existing literature on the subject of technology, particularly on the use of social media platforms, appears to suggest that the use of social media platforms as a channel through which information is disseminated is more popular among the youth market segment as compared to the mature market segment (Ukpere *et al.*, 2017). Hence, the dissemination of information about insurance service innovations through social media platforms might fail to effectively reach mature customer segments if they are not the prime targets for the use of social media platforms as a credible source of information. Concerning the Diffusion of Innovation Model, given that mature market segments may not be kept abreast of recent technological developments, which might affect their adoption of telematics-based insurance policies,

The strategic implications of these realisations are that there is a gap in the dissemination of information pertaining to interest rate-based insurance services and platforms by which the mature market of the insurance sector might fail to get access to such information based on their advanced age, their location, their level of education and most importantly, their level of information literacy sophistication. From the perspective of insurance service innovations, the current research focus is on the strategic ways in which telematics-based insurance schemes were promoted to reach a broader segment of the market. Taking into consideration differences in the adoption of technologies by different groups, we can also be moderated by the age, gender, experience and voluntariness of use, as highlighted in the Unified Theory of Acceptance and Use of Technology.

2.6.1 Artificial Intelligence Systems

Various players in the insurance service sector in South Africa could partner with fintech companies to offer digital insurance services and solutions to enhance customer loyalty. This insurance service innovation has incorporated the augmentation of artificial intelligence technologies that imitate human behaviour to enhance the quality of service delivery (Shambira, 2020). Artificial intelligence systems that have been integrated with insurance systems or advanced analytics that are used for predictive maintenance can anticipate failures in service delivery and respond faster to critical situations (Rayes & Salam, 2019).

The application of artificial Intelligence systems provides technology-driven intelligence techniques to capture individual as well as collective knowledge, which promotes the expansion of the knowledge base with the view of improving the overall level of service quality for customers (Spanaki *et al.*, 2021). The works of Zia and Kalia (2022) reiterate that the application of artificial intelligence systems supports the operationalisation of telematics-based insurance schemes to enhance the service experience levels of customers. The relevance of artificial intelligence systems within the framework of innovative telematics-based insurance schemes is their leverage on computer-based systems that emulate human behaviour to accomplish physical tasks such as monitoring driving behaviour with the view of providing financial rewards in return for acceptable behaviour (Zia & Kalia, 2022). The application of artificial intelligence systems within the insurance service sector is therefore promoted by machine learning, which allows the creation of virtual systems that imitate reality (Longworth & Longworth, 2020; Pesantez-Narvaez *et al.*, 2019).

With the advancement in the development of artificial intelligence systems, it has become possible for the insurance sector to pay for human-based functions and make appropriate recommendations in real time through the use of technology (Huang & Meng, 2022). Such systems have culminated in the development of telematics-based insurance systems that capture the driving behaviour of customers in real-time. Although artificial intelligence applications may not exhibit the originality, complexity and generality of human intelligence, they have proven to play a pivotal role in the development of contemporary knowledge that enhances the quality of service delivery that the insurance sector stands to provide to its customers (Kanta Reddy & Premamayudu, 2019). In addition to artificial intelligence, the best telematics insurance schemes also demonstrate the application of expert systems to capture knowledge within the confines and limitations of human expertise (Rayes & Salam, 2019).

Within the context of the operation of our ability to provide the telematics-based insurance scheme, the incorporation of an additional intelligence system with a case-based reasoning approach has improved the quality of decision-making capabilities amongst short-term inference companies concerning capturing the behaviour of customers (Kanta Reddy & Premamayudu, 2019). Case-based reasoning captures the collective knowledge gathered over time with the view of minimising errors, improving the quality of decision-making and reducing the overall service turnover time (Hoyer *et al.*, 2020). The ultimate results of applying artificial intelligence systems within the short-term insurance sector have been an enhancement in the overall quality of services provided to customers with regard to financial rewards in exchange for favourable driving behaviour.

2.6.2 Big Data Analytics and Machine learning Systems

The massive volume of data required for the operationalisation of telematics insurance intensifies the complexity of telematics-based Insurance schemes (Torra *et al.*, 2023). Telematics-based insurance schemes are capable of collecting huge amounts of data pertaining to the driving behaviour of customers. This implies that the structure of the foundations of telematics-based insurance schemes is based on the incorporation of extensive data analytics systems to utilise analytical methods for managing vast volumes of complex data sets to improve the operational efficiency of short-term insurance companies (Rayes & Salam, 2019). The application of big data analytics is based on its predictive value for the future direction of short-term insurance companies in the collection of structured data pertaining to the driving behaviour of customers, which is distributed to a centralised server and analysed using complex query languages (Kim *et al.*, 2017).

The short-term insurance sector can make permanent use of big data analytics to gather data relating to customer behaviour with the view of coming up with targeted marketing strategies to increase usage rates in specific market segments. Nevertheless, developments in big data analytics within the short-term insurance sector demand summarised information which assists in the identification of the main risk factors for price determination (Torra *et al.*, 2023). This research is interested in establishing the strategic use of telematics-based insurance schemes based on big data analytics to collect the driving behaviour of customers, with the view of developing customised financial reward systems to improve usage rates.

The department of complex systems that utilise big data analytics through data centres has remarkably reduced the processes of collecting, transferring and analysing structured and unstructured data, which has better specific appeal when it comes to implementing telematics-based insurance schemes (Rayes & Salam, 2019). The effectiveness of big data analytics within the context of the short-term insurance sector depends on the availability of historical data to improve the scope of enterprise-wide decision-making. Even though big data analytics are not part of customer-focused service innovations, they help the short-term insurance sector improve the quality of customer service by leveraging innovative channels for collecting relevant customer data that were used to target the same customers with specific telematics-based insurance rewards.

Machine learning techniques are widely used within the short-term insurance sector to predict and classify problems through the application of sophisticated algorithms (Kashef *et al.*, 2020). Ramakrishna *et al.,* (2019) highlight that the focus of machine learning is on the prediction of outcomes from complex data sets through algorithms that learn from data and create a model for predicting and learning underlying patterns of user behaviour. Within the context of the application of telematics-based insurance schemes, it is apparent that insurance companies can leverage machine learning infrastructure to collect accurate data pertaining to the driving behaviour of customers and develop appropriate financial reward systems.

2.7 User Behaviour

The concept of “user behaviour” has been included in this study because it is a crucial output variable that results from the application of telematics-based insurance schemes. The increased use of telematics-based insurance schemes is likely to result in favourable driving behaviour among short-term insurance customers, hence the need to understand the end-user behavioural context concerning brand switching behaviour, usage intentions and consumer attitudes. The frequency models of insurance are linked with an increase in accident probability, which are used in the determination of insurance premiums (Torra *et al.*, 2023).

2.7.1 Usage intentions

The concept of usage intentions has been incorporated into this research, as have the usage rates of telematics-based insurance reward schemes that are positioned to regulate the driving behaviour of short-term insurance customers. The concept of usage intentions has been prominently researched in consumer behaviour changes (Koo et al., 2020).

Torra *et al.,* (2023) stress that telematics data has proven to be effective in the identification of driver behavioural traits in relation to age and place of residence as a basis for assessing the risk claims propensity of drivers (Torra *et al.*, 2023). The study represents customers' value judgements in their decision-making process (Zhang *et al.*, 2021). Usage intentions are a reflection of the extent of consumer perceptual awareness concerning the decision of whether to buy specific brands or not. Three processes are involved in the realisation of consumer usage intentions. These include the willingness to buy, the intention to buy and the likelihood of referring other customers to buy from a selected service provider (Kim et al. 2017). Torra *et al.,* (2023) reiterated that there is as association between telematics variables and the risk of an accident.

Existing literature highlights that these three concepts are interrelated and contribute to the existence of strong consumer behavioural intentions towards services. The need to be associated with specific brands (Mørk et al., 2019). Bahtar (2016) underscores that the willingness of consumers to buy brands is determined by the intensity of the information search processes they go through. Jin *et al.,* (2016) underscore that consumers go through an intensive information search process with the view of minimising social, financial and cognitive risks associated with making a consumption decision (Confente et al., 2020). From the perspective of this research, usage intentions are within the framework of the ease with which insurance customers are prepared to utilise telematics-based insurance schemes and increase their usage rates in terms of making referrals to other drivers (Liu & Wang, 2019).

2.7.2 Consumer Attitudes

Telematics enhances the capacity to differentiate and discriminate amongst insurers (Torra *et al.*, 2023). Consumer attitudes regarding the usage of technological products cause pre- or post-usage psychological dissonance, which were classified. Consumers who continually look for knowledge to support their usage decisions by drawing on their own past experiences as well as the past occasions of their significant others fall under the first kind of cognitive dissonance. The second type of the phenomenon of cognitive dissonance focuses on how consumers assess their own usage decisions in terms of the appropriateness of insurance spending and the general acceptance of such decisions (Makudza, 2020).

According to a recent study; the insurance services industry has created consumer insurance services technologies that are well-positioned to impact customers' views in support of forging relationships that endure. Through obtaining pertinent information about customer preferences and online behaviour as foundational elements in order to capitalise on long-term connection-building, insurance technological advances are being integrated with such partnership-building impetus (Polonsky, 2017). The recognition that clients face usage risks related to the notion of cognitive dissonance, which encompasses the alleged hazards that customers encounter both prior to and after which make a usage decision, has made it necessary to leverage insurance technological advances towards building connections (Keegan & Rowley, 2017).

To minimise perceived risks that customers can experience when obtaining insurance services through online channels, the usage of insurance service innovations is optimised. In order to decide whether to use technology-driven insurance platforms, customers ask themselves several questions (Drahošová & Balco, 2017). These inquiries give rise to the concept of cognitive dissonance. Individuals' ideas about how they perceive hazards based on prior experience are reflected in their cognitive dissonance. The current research investigation concentrates on service enhancements primarily targeted towards policyholders. This particular group of clients is distinguished by a higher level of pre-usage emotional dissonance determined by prior knowledge and perhaps as a result of little acquaintance with technology-driven insurance systems.

2.7.3 Brand Switching Behaviour

According to Confente et al., (2020), brand switching behaviour is the process by which clients transfer their purchasing preferences from one service provider to another. According to Schiffman and Kanuk (2016), brand-switching behaviour is a representation of how consumers' brand loyalty and allegiance have changed from their current service providers to a new one. A brand relationship can cease due to brand switching behaviour, according to (Chigwende & Govender, 2021). Schivinski et al., (2020) concur that brand-switching behaviour persists in the presence of low switching costs due to a poor customer-provider connection. Aliff *et al.,* (2017) underline that a viewpoint based on relationships compared to a commercial orientation is why brand switching costs are significant.

In the South African insurance services industry, brand switching behaviour has become commonplace, as seen by customers who move from one insurance service provider to another in quest of superior customer experiences (Murwisi, 2018). Through enhancing the likelihood that consumers will stick with a specific insurance service brand due to the level of service they receive from online insurance platforms, insurance service innovations like mobile and internet insurance platforms have played a significant role (Makudza, 2020). The introduction of virtual interactions as a result of technological advancements within the insurance industry has increased the extent of brand-switching behaviours among consumers, who find it simple to shift their support from a single company to a different one.

According to Danbury (2017), customers who are happy with the level of service they are receiving from their existing supplier will not transfer providers. Advances in customer happiness result in increased conversion costs, according to research by Makudza (2020). Consumers might value the amenities offered by rival brands. However, Luturlean and Anggadwita (2015) made it clear that there is no direct correlation between their actual brand-switching behaviour and those services.

Similar opinions were voiced in the Imbug et al., (2018) study, which underlined how client interactions affect brand-switching behaviour. Adopting managing customer experiences as a tactic to increase brand switching costs and affect client loyalty is crucial. By raising the level of service delivery that is available to customers, innovations in the insurance industry serve as a panacea to reduce brand switching behaviour. The amount of technical proficiency of the end users, however, determines the perceived service quality that results from the implementation of insurance service innovation technologies. From the standpoint of the policyholder's market segment in the insurance services industry, the computer aptitude to use technology for insurance service innovations is analysed within the context of the current study.

2.8 Empirical Literature

Using accurate panel data based on monthly data, Torra *et al.* (2023) examined the impact of telematics variables and context on atmospheric conditions on the probability of complaints and liable collisions. According to the study, there is a lousy correlation among the number of complaints with the typical speed in metropolitan regions. The risk of an accident occurring is increased by heavy traffic quantity, accelerating, limited lanes, more lanes, urban roadway segments, low shoulder width and a smaller median width. While fatal car crashes have become more prevalent in rural regions, minor and catastrophic incidents are more frequent in metropolitan areas. The maximum velocity on motorways raises the possibility of complaints and the frequency of fatalities involving blame fluctuates over time in a self-regressive manner.

2.9 Gaps in knowledge

In addition to the crucial success criteria of telematics-based insurance rewards, a component of the study focuses on the drawbacks of the creative insurance programme. According to Francois and Voldoire (2022), the failure of telematics-based insurance incentives in France was caused by organisational and cognitive constraints that hampered the successful application of big data developments, which are essential to telematics-based insurance. According to Cather (2020), the inclusion of telematics data into insurance pricing schemes minimises prohibitions on discrimination and reduces heterogeneity with regard to age- and gender-based insurance prices, which leads to the selection of legislative representatives and asymmetrical information that favours particular applicants.

According to this viewpoint, little study has been done on the effects that telematics-based insurance rewards have on different demographics (Cather, 2020). The works of Stevenson *et al.,* (2021) recognise that even though a great deal of investigation has been done on the advantages of telematics-based insurance rewards, there nevertheless remains a lack of information regarding their impact on society, especially whenever it comes to demographic groups in terms of age, gender and cultural background. While the Internet of Things continues to develop, particularly in developing nations, the utilisation of telematics-based insurance is concentrated on a small market (Chen, 2018).

Studies have shown that the effect of this conduct could prove to be consistent over the long term, raising concerns about disasters and the capacity to rely on telematics-based insurance (Eling & Kraft, 2020). Concerns about driver privacy raised by the capacity misuse of driving behaviour data have also been brought up in relation to the prospective viability of telematics-based insurance, and they may have a significant impact on how widely this type of technology is adopted (Milanovi et al., 2020). In this light, more investigation is required to ascertain the effects of these incentives, with a particular emphasis on their viability and potential to alter the vehicular behaviours of holders of short-term insurance policies.

There has been a dearth of studies that compare telematics-based insurance benefits with alternative monetary promotions, recognition in society and price structures. Although the use of algorithms for machine learning is essential for utilization-based insurance pricing, Huang and Meng (2019) underline that an in-depth review reveals that the conventional logistic regression algorithms are the best suitable for insurance pricing. These opinions seem to support the telematics-based insurance pricing model, which harnesses the personalisation of insurance prices. In this light, more study is needed to reaffirm the value of telematics-based insurance payments as a customisation insurance pricing strategy that can hold its own against more conventional logistic regression-based insurance pricing. In this regard, additional research is required to ascertain which insurance incentives are most successful in encouraging safe driving practices among holders of short-term insurance policies. While additionally advancing the financial objectives of insurance firms.

Despite the conceptual appeal of telematics-based insurance, there are significant drawbacks associated with its use. Telematics policies that are designed to monitor driving performance are geared towards good drivers. The downside of this approach is that drivers with bad driving habits will see their premiums increase (Winn, 2019). Telematics-based insurance is not good for long-distance drivers since insurance coverage can get expensive as compared to a standard car policy (Ayuso & Perch, 2019). Telematics devices can monitor what speeds one is driving at. This implies that those drivers who frequently exceed the speed limit will face increased fines or even have their insurance policies cancelled (Verbelen & Antonio, 2018). Technology and monitoring costs may outweigh potential revenues, which results in dangerous drivers opting out.

Telematics car insurance is aimed at individual customers; however, the telematics-based system will not be able to tell who is driving the car at any particular point in time (Cevolini & Esposito, 2022). This implies that if there is a secondary driver who is not a particularly good driver, even their infrequent driving could negatively affect the entire insurance policy premiums. Telematics devices also cost money. Even if the insurance company gives you a box for free, you will be paying for the equipment in another way through higher premiums. Likely, good drivers will still receive lower insurance rates, but the premium will cover other expenses that are not covered by the telematics premium (Eling & Kraft, 2020).

Privacy concerns have also been raised about the use of telematics (Blakesley, 2020). While data is treated with the utmost privacy and security by insurance, there is also a risk that hackers could get hold of it, no matter how many precautions are put in place to protect it (Boucher & Steven, 2017). The cutting-edge approach to the installation of telematics devices is volatility. This can cause problems, however, in that good drivers will receive the benefits of lowered premiums, but bad drivers may not be paralysed to the same degree (Cevolini & Esposito, 2022). For good drivers, there is a financial incentive to have their behaviour monitored so that they are less likely to break the insurance system. However, that may be part of a low-premium demographic. There is an incentive not to use the technology. Insurance companies need to be able to match the lowered premiums for the good drivers by simply increasing the premiums for the bad drivers (Eling & Kraft, 2020). If their premiums are lower, then the overall running of the black box system will be more expensive for insurance companies.

2.10 Chapter Summary

The chapter touched on critical aspects revolving around the impact of telematics insurance schemes on the behaviour of short-term insurance policyholders. The basis for undertaking a literature review was discussing the main theoretical frameworks underlying the study, which included the Diffusion of Innovations Model, which depicts different adopter categories that were used to explain the proclivity towards the adoption of telematics-based insurance by short-term insurance policyholders. The Unified Theory of Acceptance and Use of Technology was also incorporated as the second theoretical framework in so far as it highlights constructs that on influence user behavioural intentions, particularly performance expectancy, effort expectancy, social influence and facilitating conditions. The conceptual appeal of the Unified Theory of Acceptance and Use of Technology primarily comes from the perspective of moderating conditions that include age, gender, voluntariness of use and experience since these were related to the demographic characteristics that the study looks forward to highlighting in relation to the uptake of telematics insurance by short-term insurance policyholders. The theory of Reasoned Action was also considered within the framework of theories for this research, which looks at the subjective norms and attitudinal effects that determine the extent of consumer behaviour from the perspective of the driving behaviour of short-term insurance policyholders. The chapter also focused on service innovation constructs from the perspectives of big data analytics, machine learning and artificial intelligence, which are key building blocks behind the successful implementation of telematics-based insurance schemes. The consumer behavioural variable was analysed from the perspective of usage intentions and consumer attitude, which are hypothesised to influence the driving behaviour of short-term insurance policyholders. The next chapter provides an outline of the research hypothesis.

CHAPTER 3

RESEARCH HYPOTHESIS

3.0 Introduction

The purpose of this chapter is to specify the formulation of a research hypothesis that guides the collection of data on the impact of telematics-based insurance rewards on the driving behaviour of insurance policyholders.

3.1 Impact of policyholder characteristics on rewards

Shi et al., (2022) established a significant correlation between driver age and the proclivity towards risky violations. Cai et al., Gaebler, Kaashoek, Pinals, Madden and Goel (2022) established that studies have found that black and Hispanic minorities are more likely than white drivers to be pulled over by the police for alleged traffic infractions, including combination of speeding and equipment violations. Tian et al., (2020) ascertained the role of perceived enjoyment, trust and social media as critical factors influencing millennials' attitudinal behaviour and intention to use insurance telematics.

H_1: *The policyholder characteristics have a statistically significant impact on telematics-based insurance rewards.*

3.2 The influence of policyholder characteristics on driving behaviour.

A study by Malekpour *et al.,* (2023) established that tangible financial incentives offered by telematics-based feedback are substantially connected with speeding driving behaviour. By noticeably lowering abrupt breaking and quick acceleration, Ruer *et al.,* (2020) confirmed that the use of telematics had a positive impact on driver behaviour. Meng et al., (2022) emphasised the potential for a supervised driving risk score neural network model to help telematics-based insurance uncover heterogeneity in their portfolio and draw in safer drivers by offering premium discounts. According to Guillen *et al.,* (2020), urban driving raises the risk of braking events, night-time driving lowers the risk of cornering events and speeding is linked to acceleration events.

H$_2$: *Policyholder characteristics have a statistically significant impact on the driving behaviour of the policyholders*

3.3 The impact of telematics rewards on driver behaviour

Torra et al., (2023) reiterate that telematics data provides insurers with a deeper understanding of driving behaviour, enabling more accurate underwriting decisions and risk assessments. Moodley (2019) emphasise that in the event of an accident, the collected data can aid in claim handling, streamlining the process and reducing the need for lengthy investigations and disputes. Ayuso *et al.*, (2019) stress that telematics-based insurance allows insurers to engage more closely with their customers through regular feedback and personalised insights about their driving habits. Pesantez-Narvaez *et al.*, (2019) concur that customers also benefit from lower premiums when they demonstrate good driving behaviour, further incentivising loyalty to the insurance company. Kanta Reddy and Premamayudu (2019) highlight that telematics data provides valuable insights into driving patterns and customer preferences. Pesantez-Narvaez *et al.*, (2019) illustrate that by understanding the driving habits of young or inexperienced drivers, insurers can create specialised products to meet their needs better. Telematics systems enable insurers to automate data collection and analysis, reducing the need for manual processes and extensive paperwork. In light of these outcomes, the current study seeks to test the following hypothesis:

H$_3$: *The telematics rewards have a statistically significant effect on driver behaviour.*

CHAPTER 4

RESEARCH METHODOLOGY

4.0 Introduction

This chapter outlines the research philosophy that influences the choice of the research design, strategy and approach. The chapter also articulates the research population, unit of analysis, sampling strategy, data collection, measurement and analysis approaches.

4.1 Choice of research design

The orientation of the research with regard to its approach to data collection, measurement and analysis was guided by the research design, which offers a road map. Utilising an empirical research design that fostered a satisfying answer to the research questions was the aim of this study. In the attempt to accomplish the goals of this study, a variety of research designs may be used. An exploratory research design, a design based on description, a case study research design and an explanatory research design are a few examples. Since it will enable the identification of correlations among research variables, an explanatory research design will be regarded as suitable in this regard (Saunders et al.,2019).

The foundation of an explanatory study design is its capacity to evaluate the hypothesis that telematics-based insurance programmes significantly affect the driving behaviour of holders of short-term insurance policies. In this regard, an explanatory research design offered a statistical basis for emphasising the impact that factors that determine the cost of insurance based on telematics have on the driving behaviour of holders of short-term insurance policies.

4.2 Purpose of research design

In the context of research methodology, a research design functions as a guiding framework delineating the approach to be taken for data collection, measurement, and subsequent analysis. (Bougie & Sekaran, 2019). In order to produce compelling answers to the study's objectives, the stages and procedures that must be followed during the research process must be outlined in the research design (Saunders et al.,2019). This occurs within the confines of the chosen research philosophy. Utilising an empirical research design that fosters a satisfying answer to the research questions is the goal of this study. Since it allowed for the identification of correlations between research variables, an explanatory research design was deemed to be appropriate (Saunders et al.,2019).

The foundation of an explanatory study design is in its capacity to evaluate the hypothesis that telematics-based insurance programmes significantly affect the driving behaviour of holders of short-term insurance policies. In this context, an explanatory study design offered a statistical basis for emphasising the impact of factors that contribute to telematics-based insurance rates on the driving behaviour of holders of short-term insurance policies. The use of secondary data sources is permitted by the explanatory research design. The scope of secondary data for this study was a database of 7,000 customers on the activated Insurance Rewards programme. Explanatory study also enabled the researcher to have a comprehensive understanding of telematics and to be vigilant for phenomena that surfaced during the research process.

4.3 Philosophy

Interpretivism, pragmatism, positivism and realism are just a few of the philosophical pillars that are used when conducting research (Saunders et al., 2019). These paradigms for study are applicable in various research contexts. A positivist research philosophy was used because of this study's quantitative research basis. Positivism is based on the idea that reality is objective and that statistical inference must be used to support the validity and reliability of study findings (Eisend & Kuss, 2019). Regarding the current study, positivism enabled the use of sample data for statistical analysis, which ultimately resulted in the generalisation of the research findings to a larger population of insurance policyholders.

According to Park et al., (2020), the philosophical foundation of positivism is to create an inquiry that produces explanatory linkages that ultimately result in the prediction and control of the phenomenon under consideration. In order to test hypotheses about how functional correlations were derived between the use of telematics-based insurance pricing and outcomes in the form of driving behaviour, positivist applications within this research rely on the hypothetical deductive technique.

The positivist paradigm was applied in this study under the presumption that there is a single, quantifiable reality that was recognised, comprehended and measured. This presumption allowed us to explain the cause-and-effect connections between the research variables. Positivism's core tenet was that knowledge may be created objectively without relying on the subjective values of the researcher or other participants (Park *et al.*, 2020). The foundation of positivism was the use of experimentation to isolate and regulate each factor's influence so that important research variables could be examined. In this sense, positivism is driven by the need to advance internal validity by emphasising the degree to which study design and obtained data provide support for causal inference assertions. Based on the degree to which the researcher can minimise threats to Internal validity, rigour in the implementation of the positivist paradigm was assessed.

4.3.1 Approach selected

A method of research is a general strategy and process for carrying out research that falls under the categories of deductive, inductive, or abductive (Bougie & Sekaran, 2019). The validity of presumptions, theories, or hypotheses is examined using a logical technique. This suggests that a deductive strategy is compatible with the quantitative research paradigm, which aims to establish the causality of research variables in a study. Through generalisation, an inductive technique generates new theories. A research procedure focused on the explanation begins with perplexing facts in an abductive manner.

The deductive approach, which is founded on a theory and concludes in the testing of research hypotheses to either support or deny the claim based on the theory, was deemed vital given the quantitative nature of this research because it is based on data. The premise of this study is that using telematics-based insurance rewards has a significant impact on policyholders' driving habits. This hypothesis is logically evaluated using a detective research methodology, The study's findings are then statistically inferred from and generalised to the larger population of short-term insurance customers who might not currently be using telematics.

4.3.2 Methodological choices

According to Saunders et al., (2019), there are three basic methodological options: mono-methods, mixed methods and multi-methods. This study abided by the monomethod, which includes using a quantitative research strategy to establish the relationship between the use of telematics-based insurance benefits and policyholders' driving behaviour. The preexistence of a wealth of secondary telematics data that may be utilised to determine the relationship between telematics insurance benefits and client-driving behaviour justifies the use of quantitative approaches in this study. The relationship between the two research variables under consideration were statistically solved using telematics data. The results of a quantitative study can lead to the statistical inference that is used to generalise research findings to a larger population of holders of short-term insurance policies.

4.3.3 Strategy

A research strategy is a detailed plan that stipulates the manner in which data will be collected. There are several research strategies, which include experiments, surveys, action research, case studies, grounded theory, ethnography and archival research (Bougie & Sekaran, 2019). Given that this study relied upon secondary data, it is more relevant to use an archival research strategy that involves searching and extracting information and evidence from original archives. This group of secondary data that was used in this study includes 7,000 policyholders for Activated Insurance, which is a telematics-based insurance scheme operating in South Africa. Telematics incorporate historical data, documents and records relating to the driving behaviour of insurance customers, which forms the basis upon which data was analysed to establish the link between the efficacy of telematics-based insurance and the driving behaviour of short-term insurance policyholders.

The advantages provided by the use of an archival research strategy stem from the realisation that these already existing secondary data are reliable and relevant to satisfactorily resolve the objectives of the study (Lê & Schmid, 2022). In the context of the current study, over 7,000 short-term insurance policyholders have signed up to use the telematics insurance scheme offered by Activated Insurance. Archival research is cost-effective since large quantities of data are readily available at a relatively low cost, especially when filtering out aspects like travel and other expenses.

In the context of the current research, archival research data on the telematics of short-term insurance policyholders is easily accessible from the Activated Insurance platform. Archival research provides an advantage by enabling an unbiased selection of elements from within the population. Archival research provides overly inclusive data that incorporates large volumes of information that can benefit future research.

On the other hand, potential drawbacks of archival research include the possibility of getting incomplete data sets, which might not satisfactorily be relied upon to resolve the objectives of a study. Seeking the appropriate archival information might be time-intensive, as there is the possibility of overwhelming amounts of data. A significant amount of time must be spent curating and making sense of digital files (Bougie & Sekaran, 2019). Despite these shortcomings, archival research was considered irrelevant for undertaking a study of this nature, which is looking into the driving behaviour of short-term insurance customers. This behaviour can best be analysed through the utilisation of a pre-existing platform and software upon which telematics is leveraged.

4.4 Time Horizon

There are two main time horizons in research, namely the cross-sectional study and the longitudinal study (Saunders et al.,2019). This research adhered to a cross-sectional study design, given that data on the telematics of 7,000 short-term insurance policies was collected over a short period of one month. It presents the driving behaviour of short-term insurance policy policyholders under the telematics platform.

4.5 Proposed research methodology

The study used a quantitative research methodology, which is premised on objective reality and the use of a large population and probability sampling methods that provide a statistical chance of elements within the population to represent the population (Lê & Schmid, 2022). A quantitative research approach is operationalised through the use of statistical approaches in data analysis, which are calculated in the testing of the research hypothesis on the influence of telematics-based insurance schemes on the driving behaviour of short-term insurance customers.

A quantitative research methodology incorporated a combination of both descriptive and inferential statistical analysis to profile drivers by reflecting their demographic characteristics in relation to their age groups, gender and other demographic profiles. Such a descriptive account of correspondence or this study’s ability to develop a detailed understanding of variations in the risk profiles of drivers pertaining to their agenda characteristics when it comes to driving behaviours. Inferential statistics was then used to highlight any statistically significant relationship between the object of telematics-based insurance schemes and the driving behaviour of customers with respect to their demographic profiles.

4.6 Population, sampling method and size

A research population is a collection of individuals or items that have similar characteristics that are of interest to a study (Bougie & Sekaran, 2019). Within the scope of the current research, the researcher is interested in a population of short-term insurance policyholders who subscribe to the telematics-based insurance scheme. This population was collected from the Activate Insurance telematics insurance scheme.

4.6.1 Unit of analysis

A unit of analysis is considered as an entity that is the focus of analysis within a study. Concerning the current research, the unit of analysis composed of individual policy policyholders who have opted to sign up for the telematics business insurance program. Therefore, the study analysed telematics data collected from each individual policyholder's vehicle.

4.6.2 Measurement instrument

This research is entirely reliant on the use of secondary data obtained from the telematics data extracted from policyholder vehicles. The scope of telematics data includes the week start date, the weekend date, policy number, item number, item premium, trip count, late drive count, drive time, late drive time, distance, overall driving score, legal score, anticipative score, hard events score, hard brake score, smooth score, hard acceleration score, hard turn score, average speed, driving score discount, driving time discount, night driving discount, final discount and reward amount. These telematic data entries form the basis upon which the secondary data measurement instruments are conceptualised in this research, given that the study is making use of pre-existing secondary data on the driving behaviour of short-term insurance policyholders.

4.7 Analysis approach

To determine the effects of the telematics-based insurance incentives program on specific policyholders' driving behaviours, the data gathered from the telematics devices was analysed using a combination of time series analysis, events study and style analysis. The patterns and trends in the data over time will be examined using time series analysis. Events study investigated how particular events, such as earning a reward, affect driving behaviour. Style analysis was employed to find distinctive driving behaviour patterns or styles that were connected to getting a reward. These analytical techniques contributed to a thorough knowledge of how the telematics-based insurance rewards program affects specific policyholders' driving habits.

4.8 Quality controls

The purpose of implementing quality controls is to assure that all the data that was collected from the Activate Insurance telematics-based insurance rewards system is reliable, valid and were subjected to statistical inference. Data cleaning was utilised to ensure that only relevant data is extracted from the telematics-based insurance reward system in line with the objectives of this study. Sample randomisation was used to provide assurance that there is a statistical chance of selecting all policyholders who are registered on the telematics-based insurance reward system. The purpose of sample randomisation is to provide a statistical chance for all the individuals within the sampling frame to be selected for data analysis with the view of establishing a link between the use of telematics-based insurance rewards and individual driving behaviour.

4.9 Limitations

Limitations that were experienced in the process of data collection included incomplete data collected from the Activate Insurance Telematics data base, which was not adequate to resolve the objectives of this study fully. This was a paramount limitation given that the current study was purely reliant on the collection of secondary data to resolve the objectives of this study. Concerns were noted with respect to privacy and confidentiality in accessing user driving behaviour collected through the telematics insurance database. A potential ethical breach was identified in using consumer data pertaining to their driving behaviour without their expressed consent. Reliance on the exclusive use of a quantitative research approach that is premised on the application of secondary data collected from the Activated Insurance telematics-based reward system failed to capture the subjective views and opinions of individual drivers with respect to the influence that telematics has on their driving behaviour. One of the key assumptions that has been made so far in this research was that the behaviour of individual policyholders is exclusively determined only once they get through the telematic system.

However, there was a limitation in this scope of reasoning since a driver's behaviour might be influenced by events that take place within the vicinity of the driving environment, such as the behaviour of other drivers as well as the road conditions. These exogenous factors might possibly affect the driving behaviour of an individual. At the same time, the telematics system does not consider these factors as key in providing rewards for good driving behaviour.

CHAPTER 5

RESULTS

5.0 Introduction

This chapter presents the research results and their analysis for a study that was meant to assess the impact of telematics-based insurance rewards on the driving behaviour of short-term insurance policyholders in South Africa. This chapter provides valuable insights into how these rewards influence driving behaviour among policyholders, shedding light on their effectiveness and implications for both insurers and drivers. Data is analysed through the use of descriptive statistics, particularly on the demographic characteristics of policyholders, and the use of inferential statistics to establish the impact of telematics-based rewards on the driving behaviour of short-term insurance policyholders.

5.1 Description of the database

The research was based on the exclusive analysis of secondary data extracted from a database supplied by a telematics rewards insurer operating in the South African market. The original database consisted of a total of 189,300 from the rewards dataset and 137,701 from the item data dataset. This dataset contained some incomplete and null values. Null and incomplete entries were cleaned and removed prior to conducting data analysis using Microsoft Excel. The data set that was used for the purposes of analysis was for the period that spanned a 25-month period, as from the 1st of March 2021 to the 1st of April 2023. This study period gave sufficient time to understand the changes in the driving behaviour of policyholders as influenced by the use of telematics rewards. However, this database included entries that could not be used for the purposes of data analysis since they had some missing data, such as age, gender, average speeds, average distance, and monthly telematics rewards, which made them insufficient for the purpose of data collection. A Microsoft Excel sheet was used for the purposes of data cleaning by filtering entries for missing values. After the completion of data cleaning, the final size of the database that was used for the purposes of data analysis was composed of 101,290 valid entries.

This database had several categories that enabled the study to come up with valid and reliable results with respect to the impact of telematics-based insurance on the driving behaviour of insurance policyholders. The categories that were used for the purposes of data analysis included the age of policyholders, their gender, and the periods during which the policyholder held a driver's licence. Key telematics data included the premiums that were paid and the rewards that were awarded to drivers. The driving behaviour was provided in the form of the average distance travelled, the average late drive distance, the average late drive duration, the average trip duration, the average acceleration distance, the average smooth distance, the average speed, the average distance travelled, and the location where the car is usually parked overnight. These telematics data that incorporate weekly rewards, age, gender, average speed, average distance, and age of driver's licence as key variables were relevant because they provided valuable data that was used to inform decisions about driver behaviour, risk assessment, and driver safety programs.

5.2 Descriptive statistics

Descriptive statistics are important in interpreting telematics data since they incorporate criteria such as weekly rewards, age, gender, average speed, overnight parking location, average distance, and driver's licence age. These factors are useful in identifying patterns, trends, and potential linkages, allowing for a better understanding of driving behaviour and helps in making data-driven decisions about driver safety, reward programmes, and other pertinent issues.

5.2.1 Change in Telematics Rewards

By studying the distribution of rewards earned by different drivers, descriptive statistics on changes in telematics incentives aided in determining the efficiency of the telematics reward system. It revealed if telematics awards incentivize better driving behaviour and result in better telemetry data. Table 5.1 displays descriptive information on changes in telematics reward amounts.

Table 5.1: Descriptive statistics on changes in telematics rewards

	N	Range	Minimum	Maximum	Mean	Std. Deviation
Rewards	101290	4019.00	-2110.00	1909.00	105.1884	146.69158
Valid N (listwise)	101290					

Source: Telematics rewards and driver behaviour research (2023)

There are 101, 290 observations in the descriptive statistics on changes in telematics rewards. The range is 4019 showing a large range of observed reward values. The lowest possible value is 2110. This shows that the incentive was negative, implying that fines or deductions may be imposed in some situations. The maximum value of the telematics reward changes was 1909. This is the highest reward amount found in the data set. The mean (average) value of telematics reward changes is 105.1884. This provides a measure of the central tendency or typical value of the weekly prizes earned. The standard deviation measures the variability or dispersion of reward amounts around the mean. The standard deviation is 146.69158 indicating that the data is relatively stable.

5.2.2 Age of telematics-based insurance rewards policyholders

Descriptive statistics on age can help identify any patterns or differences in driving behaviour based on age. Descriptive statistics on age are analysed in relation to the age distributions and the descriptive statistics as 0depicted in Table 5.2 and 5.3 respectively.

Table 5.2: Age Distribution

	Age Groups	Percentage
18 - 25 years	2 662	2.63%
26 - 35 years	35 284	34.84%
36 - 45 years	35 591	35.14%
46 - 55 years	18 386	18.15%
56 - 65 years	7 429	7.34%
66 - 75 years	1 559	1.54%
76 - 85 years	322	0.32%
86 - 95 years	47	0.05%
total	101 290	100.00%

Source: Telematics rewards and driver behaviour research (2023)

With a total of 35 284 observations representing 35.14%, the 36-to-55-year age group was the most prevalent, followed by the 26-to-35-year age group with 34.84%. The age group 86 to 95 years was the least represented, with only 38 policyholders (0.05%). The distribution of age groups reveals that the number of drivers climbed exponentially to a peak of 34.14% and then steadily fell with age from 46 to 86 years. As a result, beginning at the age of 66, the number of drivers participating in the telematics incentives plan in each age category rapidly fell. Table 5.3 displays descriptive statistics on the age of drivers.

Table 5.3: Descriptive statistics on Age

	N	Range	Minimum	Maximum	Mean	Std. Deviation
Age	101290	69.29	18.84	88.13	39.9371	10.31709
Valid N (listwise)	101290					

Source: Telematics rewards and driver behaviour research (2023)

Descriptive statistics on age consist of 101,290 observations. The range is 69.29, indicating a wide range of ages observed. The minimum recorded age was 18.84 years. This indicates that the driver was way above the legally acceptable minimum age for driving on South African public roads. The maximum value of the age was 88.13. This represents the oldest driver on the telematics rewards scheme. The mean age is 39.9371. This provides a measure of the central tendency or typical value of the age of insurance policyholders. The standard deviation measures the dispersion or variability of the age around the mean. In this case, the standard deviation is ±10.31709, indicating a relatively small spread or variability in the data. The descriptive statistics suggest that the ages vary widely, with a range of 69.29 years between the youngest and oldest drivers. There is a slight variability in the data, with age deviating from the mean by an average of 10.31709.

5.2.3 Gender of telematics-based insurance rewards policyholders

Descriptive statistics on the gender of telematics-based insurance rewards policyholders are showcased in Table 5.4.

Table 5.4: Gender of policyholders

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	52043	51.4	51.4	51.4
	Female	49247	48.6	48.6	100.0
	Total	101290	100.0	100.0	

Source: Telematics rewards and driver behaviour research (2023)

The gender distribution of the policyholders indicates that the research included a relatively equal representation of both male and female participants. The percentages show a slight numerical difference, with males (51.4%) comprising a slightly larger proportion of the sample than females (48.6%). However, the difference is minimal, and the distribution is considered relatively balanced in terms of gender representation. It is important to note that the gender distribution in this research sample might not perfectly reflect the real-world gender distribution of the population in South Africa. The proportion of males and females could be influenced by various factors, such as the recruitment methods employed, the target demographic, or the specific context of the study. Nonetheless, with a near 50-50 split, the research sample appears to have made efforts to include a diverse range of participants in terms of gender.

5.2.4 Period of Driver's License for telematics-based insurance rewards policyholders

Descriptive statistics focusing on the period of driver licence ownership and licence insurance date are shown in Table 5.6. In South Africa, it is a legal requirement for drivers to possess a legitimate and valid driver's licence for them to be allowed to drive on South African roads. This implies that during the period that the policy order is possessed, the driver's licence is used as an indicator of their experience in navigating through the traffic system in South Africa, which can also determine their risk profiles when it comes to the determination of telematics-based insurance awards.

Table 5.5: Period of Drivers Licence ownership and Licence Issuance Date

	N	Minimum	Maximum	Mean	Std. Deviation
Period of licence (years)	101290	62.97	.57	63.55	14.1688
Valid N (listwise)	101290				

Source: Telematics rewards and driver behaviour research (2023)

The data shown In Table 5.6 show that the minimum period for holding a driver's licence is equivalent to 0.57, while the maximum period for one who holds a valid driver's licence is 62.97 years. The average period for holding a driver's licence was 63.55 years, with a standard deviation of 14.1688 years. These statistics indicated that there were minimal variations in the periods for possession of a valid driver's licence. The longevity of possession of the driver's licence is essential to the study as it helps identify if drivers with a longer history of holding a licence tend to exhibit safer driving habits.

5.2.5 Average Trip Duration

The duration of a trip was used as an indicator of the risk profile of a policyholder. Data on the trip duration is illustrated in Table 5.7.

Table 5.6: Average Trip Duration

	N	Minimum	Maximum	Mean	Std. Deviation
trip duration (minutes)	101290	690.25	.00	690.25	19.6682
Valid N (listwise)	101290				

Source: Telematics rewards and driver behaviour research (2023)

The data shown in Table 5.7 demonstrates the existence of outliers, given that the minimum trip duration was .00 minutes and the maximum trip duration was 690.25 minutes. The mean trip duration was 690.25 minutes with a standard deviation of 19.6682. These statistical data show that there were minimal variations in the duration of trips across all items examined despite the existence of outliers in the data set. The implications of trip duration are that it can show the extent of risk that a policyholder faces while driving. The higher the trip duration, the more risk the driver is exposed to on the road.

5.2.6 Weighted Speed for telematics-based insurance rewards policyholders

Descriptive statistics can help summarize and analyse the average speed of drivers within a specific dataset as shown in Table 5.8.

Table 5.7: Weighted speed

	N	Range	Mini	Maxi	Mean	Std. Dev
Weighted speed (km/h)	101290	181.71	.00	181.71	48.4159	14.79853
Valid N (listwise)	101290					

According to Table 5.8 the weighted speed and distance coverage has a minimum weighted speed of 0.00 and a maximum weighted speed of 181.71 with an average weighted of 48.4159 kilometres per hour. There was a small variability in the weighted speed given a standard deviation of ±14.79853. An average speed of 48 kilometres per hour can explain fewer insurance claims that have been made over the period of the telematics rewards scheme as depicted in Table 5.5. This might be an indication that drivers are exhibiting safer driving tendencies as demonstrated by the relatively lower speeds and fewer number of insurance claims.

5.3 Inferential statistics

Inferential statistics were applied to test hypotheses on the relationship between policyholder demographics on rewards.

5.3.1 Impact of policyholder demographics on rewards

The impact of telematic rewards on the demographic characteristics of policyholders were tested through the application of a combination of correlation and regression model. A Pearson correlation coefficient assisted in discerning the magnitude and direction of relationship between telematics rewards and the demographics of policyholders as indicated in Table 5.9.

Table 5.8: Correlations between telematics rewards and demographics

		gender	Age	Rewards
Gender	Pearson Correlation	1		
	Sig. (2-tailed)			
	N	101290		
Age	Pearson Correlation	-.031**	1	
	Sig. (2-tailed)	.000		
	N	101290	101290	
Rewards	Pearson Correlation	.085**	.010**	1
	Sig. (2-tailed)	.000	.001	
	N	101290	101290	101290

The correlation statistics shown In Table 5.9 indicate that there is a weak positive and statistically insignificant correlation between gender and weekly telematics rewards ($r = 0.085$, $p = 0.000$). This might imply that though gender and telematics rewards are related, their effect is statistically small. This might indicate that there are slight differences when it comes to telematics rewards that are awarded based on gender differences. Given that telematics rewards are awarded based on driving behaviour, it might imply that there are minor differences in the awarding of telematics rewards based on the gender of policyholders.

The correlation statistics shown in Table 5.9 Indicate that there is a weak negative and statistically significant correlation between the age of the driver and weekly telematics rewards ($r = -0.031$, $p = 0.000$). This might imply that though the age of the driver and telematics rewards are related, their effect is statistically small. This might indicate that there are slight differences when it comes to telematics rewards that are awarded based on age differences. Given that telematics rewards are awarded based on driving behaviour, it might imply that there are minor differences in the awarding of telematics rewards based on the age of policyholders.

Table 5.9: Regression Coefficients telematics rewards and demographics Model 1

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	60.407	2.322		26.017	.000
	Age	.183	.045	.013	4.116	.000
	Gender	25.207	.919	.086	27.423	.000

a. Dependent Variable: Rewards

Given that the significance value of 0.000 was less than the critical value of 0.05, the telematics-based insurance benefits were determined to have a statistically significant effect on policyholder age. When it comes to telematics awards, this value implies that policyholder age has a statistically significant impact on driving conduct. As a result, age has a significant impact on telematics rewards. Telematics-based insurance reward policyholders, on the other hand, were found to have a statistically minor impact on driver gender (significance value = 0.000). These findings show that the gender of policyholders has a statistically significant on the of telematics-based insurance rewards.

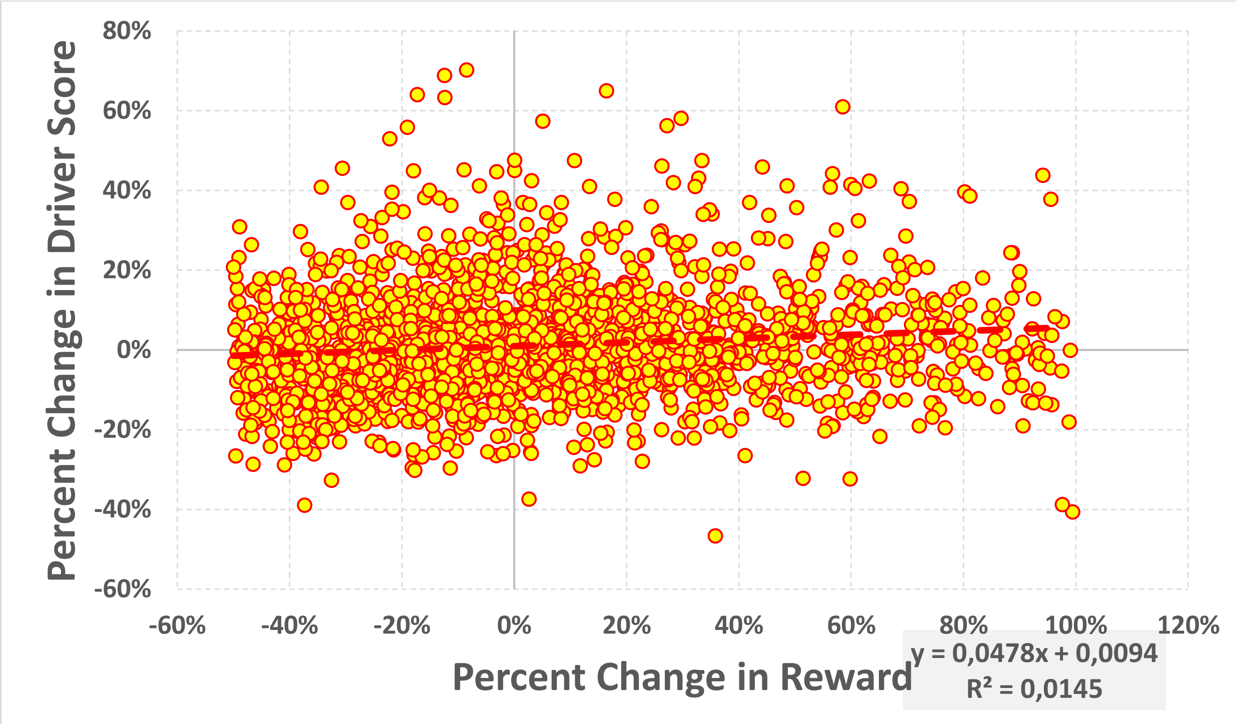
Table 5.10: Regression Coefficients telematics rewards and demographics Model 2

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
2	(Constant)	96.726	1.908		50.707	.000
	Demographics	.204	.045	.014	4.572	.000

a. Dependent Variable: telematics rewards

The combined model reveals an adverse association between policyholder demographics (age and gender) and telematics-based insurance benefits, despite the fact that the relationship is statistically significant because the computed significance value of 0.000 is less than the critical value of 0.05. When a negative beta coefficient is found between demographics and telematics rewards, it indicates that these two factors have a negative association. In a regression study, the beta coefficient measures the degree and direction of the association between two variables. The negative beta value in this situation indicates that as age and gender change, telematics benefits diminish. A positive beta coefficient indicates that there are no significant variations regarding the demographic distributions of telematics rewards. Hence, there is no possibility of reward disparities in which some demographic groups may be disadvantaged in terms of acquiring or benefiting from telematics incentives systems.

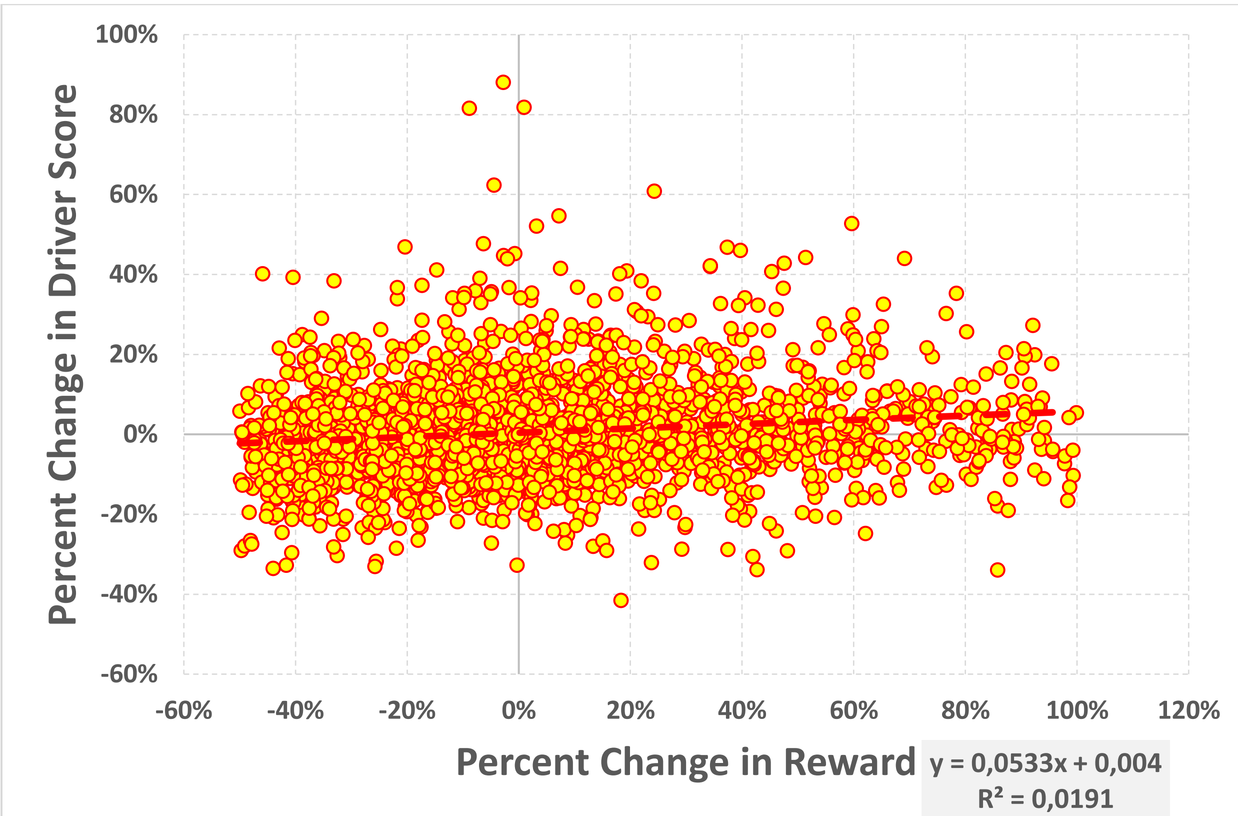
Figure 5.1: Change in driver score and reward for Male drivers



The statistical implications of the equation for male drivers Y = 0.0478x + 0.0094; R^2 = 0.0145. The equation provided suggests that the relationship between change in driver score (x) and change in rewards (Y) for male drivers can be represented by the equation Y = 0.0478x + 0.0094. The coefficient 0.0478 indicates that for every one unit increase in the driver's score, the change in rewards is predicted to increase by 0.0478. The intercept term 0.0094 suggests that when the driver's score is zero, the predicted change in rewards is 0.0094. The R-squared value of 0.0145 indicates that only 1.45% of the variation in rewards can be explained by the change in driver score, while the remaining 98.55% is attributed to other factors not included in the equation.

In terms of statistical implications, it is important to note that the low R-squared value suggests that the equation with this coefficient and intercept is not a very good fit for the data. There may be other variables, such as driver experience, customer ratings, or driving behaviour, that have a stronger influence on the rewards received by male drivers but are not accounted for in the current equation. The low R-squared value also indicates that the model does not provide a strong explanation for the relationship between change in driver score and change in rewards for male drivers. Therefore, caution should be exercised in interpreting or relying solely on this equation to predict or infer the exact relationship between these variables.

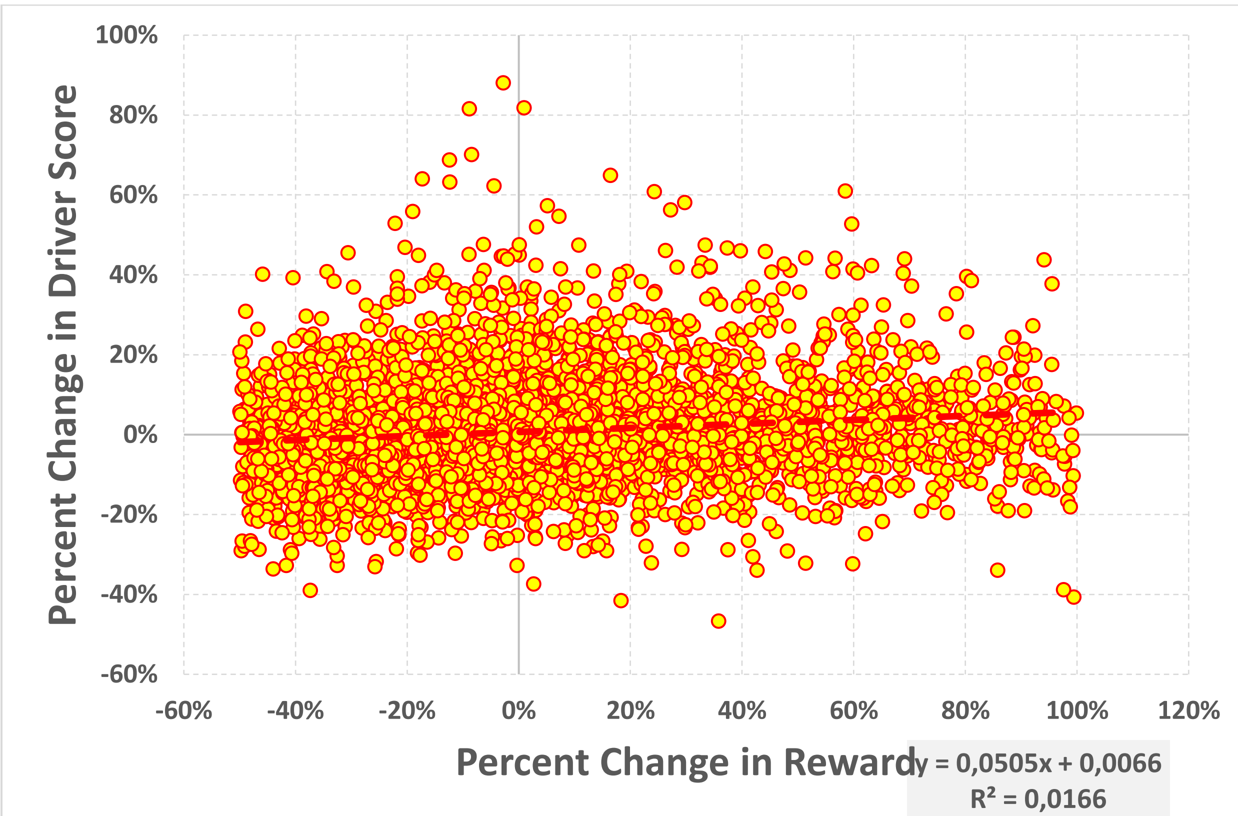
Figure 5.2: Change in driver score and reward for Female drivers



The statistical implications of the equation for female drivers Y = 0.0533 + 0.004; R^2 = 0.0191. The equation provided suggests that the relationship between change in driver score (x) and change in rewards (Y) for female drivers can be represented by the equation Y = 0. 0533 + 0. 004. The coefficient 0.0533 indicates that for every one unit increase in the driver's score, the change in rewards is predicted to increase by 0.0533. The intercept term 0.004 suggests that when the driver's score is zero, the predicted change in rewards is 0.004. The R-squared value of 0.0191 indicates that only 1.91% of the variation in rewards can be explained by the change in driver score, while the remaining 98.09% is attributed to other factors not included in the equation.

Figure 5.1 and 5.2 show the changes in the driver score and rewards for both males and females. The computed regression equations are Y = 0.0478x + 0.0094; R^2 = 0.0145 and Y = 0.0533x + 0.004; R^2 = 0.0191 respectively. These statistics imply that for every 1 unit of driving distance, the driving behaviour of females has a stronger predictive value on telematics rewards as opposed to male drivers. In essence, female drivers are more conscious on the roads as opposed to male drivers based on their driver scores for an equivalent distance and driving conditions on the road. As such female drivers are likely to get higher telematics rewards compared to male drivers for a similar driving distance and conditions.

Figure 5.3: Change in driver score and reward for both drivers



The equation Y = 0.0505x + 0.0066 represents a linear relationship between the change in driver score (x) and the change in rewards (Y). This equation can be interpreted as follows: for every one unit increase in the change in driver score, there will be an increase of 0.0505 units in the change in rewards, and there is also a fixed constant of 0.0066. The value of R2 = 0.0166 indicates the proportion of variance in the change in rewards that can be explained by the change in driver score. In this case, R2 is quite low, suggesting that only 1.66% of the variation in the change in rewards can be attributed to the change in driver score. This means that there are likely other factors not accounted for by the given equation that are influencing the change in rewards.

In summary, the statistical data suggests a weak linear relationship between the change in driver score and the change in rewards, with the change in driver score explaining only a small proportion of the variation in the change in rewards. The combined change in the driver score and telematics reward for both drivers is characterised by the quadratic equation Y = 0.0505x + 0.0066; R2 = 0.0166. These statistics show that for both gender their driving behaviour positively influences their telematics rewards even though the predictive value for percentage change in reward and driver score is better for females (R2 = 0.0191) than for overall gender categories (R2 = 0.0166).

5.3.2 The effect of characteristics on driver score

The third essential objective was meant to evaluate the impact of characteristics on driver behaviour. The characteristics that were considered included vehicle make, age and gender as illustrated in Table 5.12.

Table 5.11: Characteristics and driver score Model 1

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.970	.000		4056.257	.000
	Vehicle	.001	.000	.039	12.130	.000
	gender	-.002	.000	-.079	-25.276	.000
	Age	-3.346	.000	-.025	-7.833	.000

a. Dependent Variable: Driver Score

The given regression coefficients provide information about the relationship between the predictor variables (vehicle make, gender, age) and the dependent variable (driver score). Vehicle Make (P = .000, Beta = .039) show that there is a statistically significant p-value suggests that there is enough evidence to conclude that the type of vehicle make has a significant effect on the driver score. The positive beta coefficient of .039 indicates a positive association between the vehicle make and driver score, but due to the non-significance, it is uncertain whether this association is truly meaningful or just due to random chance.

Gender has a p-value of 0.000 and a beta value of -0.079. these statistics imply that there is a statistically significant relationship between gender and the driver score. The negative beta coefficient of -0.079 might suggest that, on average, being male may be associated with lower driver scores compared to being female. On the other hand, age has a p-value of 0.000 and a beta value of -3.346. The statistically significant p-value indicates that age does have a statistically significant effect on the driver score. The negative beta coefficient of -3.346 suggests that, on average, older individuals tend to have lower driver scores compared to younger individuals.

Overall, based on the regression coefficients and p-values, it can be concluded that age is the only statistically significant predictor of driver score among the variables considered. Gender and vehicle make do not seem to have a significant impact on the driver score. It is important to note that regression analysis considers only these variables and may not capture the full complexity of factors that influence driver scores.

Table 5.12: Combined Model policyholder characteristics and Driver Behaviour

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.968	.000		5289.405	.000
	Characteristics	-2.291	.000	-.017	-5.496	.000

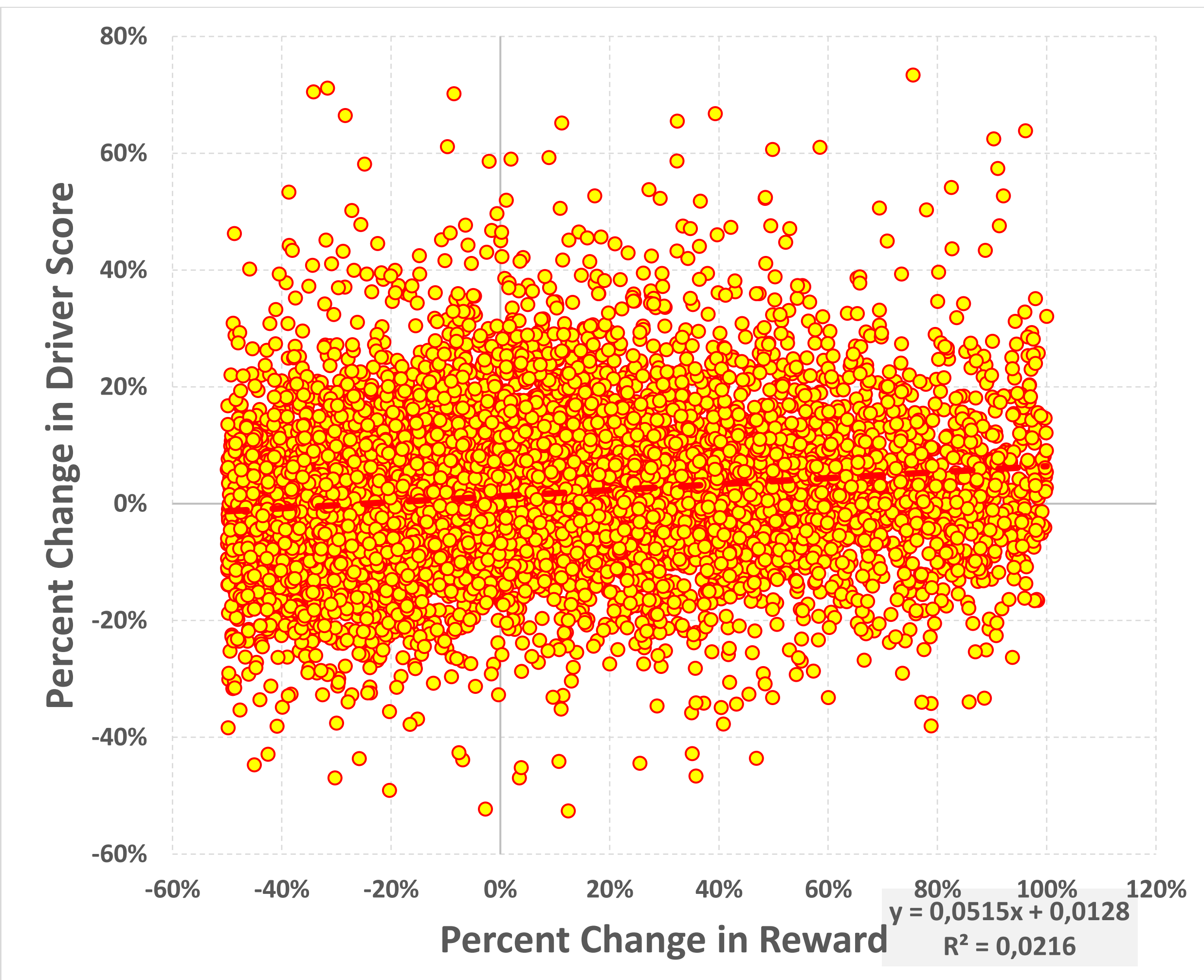
a. Dependent Variable: Driver Behaviour

The implications of a negative beta coefficient of -2.291, along with a significance value of 0.000, between characteristics and driver behaviour indicate several important insights when analysing telematics reward data. The negative beta coefficient suggests that as characteristics change, driver behaviour tends to be adversely affected. This implies that different characteristics exhibit different patterns of driver behaviour. The beta coefficient represents the magnitude of the relationship between demographics and driver behaviour. A larger negative coefficient signifies a stronger association between characteristics and driver behaviour. In this case, a significant coefficient of -2.291 indicates a small impact of characteristics on driver behaviour when analysing telematics reward data.

5.3.3 Telematics-based insurance rewards and the driving behaviour of policyholders.

This research objective was resolved through the use of regression model to predict the relationship between telematics-based insurance rewards and the driving behaviour of policyholders.

Figure 5.4: Telematics rewards and the driving behaviour of policyholders



The equation $Y = 0.0515x + 0.0128$ represents a linear relationship between two variables, where Y is the change in rewards and x is the change in driver score. The equation suggests that for every unit increase in the driver score, the rewards will increase by 0.0515 units, plus an additional fixed reward of 0.0128 units. The coefficient of determination (R2) measures the proportion of the variance in the change in rewards that can be explained by the change in driver score using the given equation. In this case, R2 = 0.0216, which means that only 2.16% of the variation in the change in rewards can be explained by the change in driver score using this equation.

Based on the low R2 value, we can conclude that the given equation may not be highly relevant or effective in accurately predicting the change in rewards based on the change in driver score. Other factors/variables may contribute significantly to the change in rewards that are not accounted for in this equation.

The driver score being a weak predictor of Telematics rewards with an R2 of 2.16% can be attributed to several factors. Driver score is typically calculated based on a few metrics like speed, distance driven, braking, and acceleration patterns. However, these metrics alone may not capture all the necessary information to predict Telematics rewards accurately. There might be other crucial factors such as road conditions, weather, traffic density, and driver experience that are not considered in the driver score but significantly impact the Telematics rewards.

The driver score does not take into account the specific circumstances under which certain driving behaviours occur. For instance, a sudden and hard brake might be necessary to avoid an accident, or aggressive acceleration might be required due to a merging lane. Without understanding the context, the driver score might unfairly penalize certain actions, leading to an inaccurate prediction of Telematics rewards. In addition, telematics rewards are influenced by other subjective factors such as insurance claims history, driver age, and region-specific risks. Although the driver score attempts to quantify driving performance, it fails to incorporate these individual preferences and risk factors effectively. As a result, the driver score alone might not sufficiently capture the complexity of driving behaviour and its correlation with Telematics rewards.

The accuracy of the driver score depends on the precision of the Telematics devices used to collect data. However, these devices can sometimes introduce measurement errors due to technical limitations or external factors such as GPS signal interference. Inaccurate or inconsistent data collection can significantly impact the reliability of the driver score as a predictor for Telematics rewards, leading to a weaker relationship between the two.

The combined impact of telematics rewards on driver behaviour is illustrated in Table 5.14

Table 5.13: The impact of telematics rewards on driver behaviour Model 2

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.966	.000		18148.156	.000
	Rewards	6.471	.000	.069	21.933	.000

a. Dependent Variable: Driver Score

The significance level of .000 implies a statistically significant relationship between telematics rewards and the driver score. This suggests that telematics rewards are likely to have a meaningful impact on driver behaviour and performance. A t-value of 21.933 indicates a very strong relationship between Telematics rewards and the driver score. This can be strategically important as it provides strong evidence to support the insurer's approach of incentivizing safe driving behaviour through Telematics rewards.

The unstandardized beta coefficient of 6.471 imply that a 6.471 change in the driver score is expected for every unit increase in Telematics rewards. This information can be helpful for insurers in determining the effectiveness of their rewards program and fine-tuning the incentives they offer. Standardized beta coefficient of 0.069 indicates a relatively weak relationship between Telematics rewards and the driver score. While the relationship is not as strong as the unstandardized beta coefficient suggests, it is still positive and indicates that Telematics rewards have a positive impact on driving behaviour.

The strategic implications of this data are that since driving at night is generally associated with increased risks, such as reduced visibility and a higher likelihood of encountering drunk drivers, a negative beta value suggests that drivers who spend more time driving at night tend to have higher insurance risks or lower telematics rewards. Drivers who spend more time on smooth roads and less time driving at night may be eligible for lower insurance premiums or higher rewards, reflecting their safer driving behaviours. Insurance companies often consider telematics data analysis to determine insurance premiums. A negative anticipative distance may indicate a higher risk of accidents, leading to increased insurance premiums for the driver. Telematics data analysis was used to identify drivers with negative anticipative distances and target them for driver training programmes. By addressing these unsafe driving behaviours, companies can improve road safety and reduce the number of accidents caused by drivers with a lack of anticipative distance.

5.4 Chapter summary

The chapter highlighted results emanating from a study that forecasted the impact of a telematics-based reward scheme on the driving behaviour of policyholders. The chapter was drafted from secondary data collected from the telematics database of a leading South African insurer. The data was analysed from a descriptive and inferential statistical perspective. The purpose of descriptive statistics is to describe the demographic characteristics of policyholders. Inferential statistics were used to establish the relationship between research variables as specified in the objective of the study. The research was focused on resolving three objectives. On the first objective, it was established that the combined module for demographics has a statistically significant relationship with telematics rewards. On the second objective, telematics rewards were found to have a previously significant relationship with driving behaviour. The third research objective highlighted that demographics have statistically significant relationships with driving behaviour, even though the relationship was not statistically significant. The next chapter provides a comprehensive discussion of current research findings in relation to existing literature that has been undertaken to test the nature of relationships between the application of telematics-based reward mechanisms and the driving behaviour of insurance customers.

CHAPTER 6

DISCUSSIONS

6.0 Introduction

The purpose of this chapter is to contextualise the research findings emanating from this study within the context of existing empirical literature. This contextualisation process discusses the similarities and differences between what has been established in this research and what has been found in existing literature. The chapter begins by reflecting the research objectives that guided the entire research process. These objectives are then linked to existing literature if they are presented in a related line of research. It analyses the extent to which the selected methodological scope achieved research objectives and these results are then discussed with respect to empirical literature with the view of identifying points of difference and areas of convergence between the current study and empirical literature.

6.1 Recap of research objectives

The main objective of undertaking the study was to evaluate the impact of telematics-based insurance on the driving behaviour of policyholders. This broad objective was dissected into three specific objectives. The first objective was to establish the influence of telematics-based insurance on driving behaviours based on the demographic characteristics of policyholders in terms of their age groups, gender and the period they held a driver's licence. The purpose of this objective was to evaluate whether telematics business insurance schemes could be differentiated based on the demographic characteristics of customers based on their age groups, gender and driving experience. The second search objective was to evaluate which telematics insurance had the best impact on the driving behaviour of policyholders by taking into consideration such driving behaviours as anticipated distance, hard acceleration, abrupt stops, average speed, hard turns, trip duration and night driving. The third research objective was meant to establish the impact of telematics rewards on driver behaviour.

6.2 Alignment with theoretical framework

The application of telematics-based insurance schemes within the South African insurance industry is a relatively new phenomenon. Telematics-based insurance rewards are in the experimental stages of commercialisation by insurance companies. Telematics-based insurance rewards are yet to be fully adopted by the driving community in South Africa. The database that was used for data analysis was gathered from a total of 18,300 policyholders who were drawn from a total of 2,275 residential locations across different provinces in South Africa. In light of this background, it was considered essential to apply the unified theory of acceptance that uses technology as the most appropriate theoretical framework that could explain the proclivity by which the driving community was willing to adopt and apply telematics-based insurance reward schemes as a paradigm shift from pre-existing insurance policies that are not necessarily based on user driving behaviour. The ease with which drivers are willing to migrate towards telematics-based insurance schemes was explained by four constructs of the Unified Theory of Acceptance and Use of Technology Model (Johnson, 2020; Venkatesh *et al.*, 2003). These constraints included performance expectancy, effort expectancy, social influence, facilitating conditions and moderating conditions.

The application of the unified theory of acceptance and use of Technology was relevant to this research, particularly with respect to moderating conditions that pertain to the demographic characteristics of users since demography was one of the key variables that was tested in ascertaining the extent of the relationship between telematics insurance awards and driving behaviour. Therefore, within the context of the current study, driver demographics with respect of their age groups, gender and driving experience were used as key moderating variables that could potentially influence favourable driving behaviour within the framework of telematics-based insurance rewards.

Given that the current study was principally focused on how the application of telematics-based insurance rewards could influence driver behaviour, it was considered necessary also to incorporate a theory that focused on consumer or user behaviour. In this context, the theory of reasoned action was considered an ideal theoretical framework, with particular emphasis on explaining and understanding driver behaviour (Fishbein & Ajzen, 1975). The theory of reasoned action was included as an additional theoretical framework for the study, given that it provides a convincing explanation of the behaviour of people when they make decisions that are usually contrary to their attitudes. This chapter will justify the inclusion of the theory of reasoned action by applying its critical principles with respect to the behavioural attributes that were established in the preceding chapter. It stands to reason that the behaviour of drivers in response to telematics-based insurance rewards could be explained concerning their subjective norms and intentions towards and ideal behaviour, which influences attitudes towards telematics-based insurance rewards.

The diffusion of Innovation model was also incorporated as part of the theoretical frameworks, which could explain the spread of the adoption of telematics-based insurance reward schemes to other drivers in South Africa who are still using alternative vehicle insurance schemes. This model was utilised in the realisation that the usage of telematics-based insurance reward schemes in South Africa is still in its infancy stages and was scared up by their diffusion to the, more significant population of the driving community through positive word of mouth and testimonies that scheme satisfied drivers under the telematics-based insurance scheme give.

Therefore, the three theoretical frameworks applied in this study, namely the Unified Theory of Acceptance and Use of Technology, the Theory of Reasoned Action and the Diffusion of Innovations module, complement each other in trying to explain the impact of telematics-based insurance rewards schemes on the driving behaviour of policyholders. The Unified Theory of Acceptance and Use of Technology and the Diffusion of Innovations model were applied to relate to the telematics insurance rewards parts as an innovative insurance scheme that gives rewards based on acceptable and good driving behaviour. The theory of reasoned action was applied to explain the driver's behavioural intentions and attitudes, which could not be satisfactorily explained by the other two theories used in this study.

6.3 Testing of research Hypotheses

The study tested three broad statements of hypothesis that were tested through comparison with the 0.05 threshold for the critical value and the computed significance values. The test criteria were based on the relative strength of the computer significance value in relation to the critical value. If the significance value was greater than the critical value, then the relationship was considered statistically insignificant; if the significance value was less than the critical value, then the relationship was considered statistically significant. The outcomes of hypothesis testing are showcased in Table 6.1.

Table 6.1: Summary of Research Hypotheses

Hypothesis	Test criteria	Decision
H_1: The characteristics of policyholders have an effect on rewards	0.000 < 0.05	Accept
H_2: Telematics-based rewards have statistically significant impact on the driving behaviour of policyholders	0.000 < 0.05	Accept
H_3: The impact of telematics rewards on driver behaviour	0.000 < 0.05	Accept

6.4 Discussions of Research Findings

A discussion of research findings is undertaken by comparing the outcomes of this study to empirical literature with the view of contextualising current research findings in the body of knowledge on the impact of telematics-based insurance rewards on the driving behaviour of insurance policyholders. A discussion of research findings is undertaken for each of the three broad objectives of this study.

6.4.1 Impact of policyholder demographics on rewards

The correlation statistics illustrated in Table 5.10 indicate that the correlation between gender and weekly telematics rewards is weakly positive and statistically significant, indicating that while there is a relationship between the two, it is statistically insignificant. This implies that telematics awards may vary slightly according to the driver's gender, age and length of licence. Additionally, there is a marginally negative and statistically significant association between the length of the driver's licence and the weekly telematics awards, indicating that policyholders with longer licence terms are probably going to get less in the way of rewards than new drivers. These results go against the risk distribution between novice and experienced drivers.

A negative beta value indicates a negative association, and the combined model shows an inverse relationship between demographics and telematics-based insurance benefits. This implies that telematics benefits decline as demographics change, potentially disadvantageous to some demographics. This might prompt insurance companies to review their incentive schemes and consider ways to boost benefits for underrepresented groups.

Organisations can better customise their programmes to appeal to and engage particular demographic groups by understanding demographic preferences and behaviours through analysis of the negative beta coefficient. It is possible to look into and address the factors that contribute to this link, such as technology limitations, perceived privacy violations and a lack of understanding.

Regarding driving experience, this study established that the novice driver had nine months of experience, and the most experienced driver had 62 years of experience. This implies that the difference between the acquisition dates for acquiring a driver's licence ranged from the 9th of November 1960 to the 11th of October 2022. The research showed that the more experienced the driver, the better driving behaviour they exhibit. These research findings corroborate what was established in a study by Shi et al., (2022), which established a significant correlation between driver age and the proclivity towards risky violations.

6.4.2 The influence of policyholder characteristics on driving behaviour

With regards to the number of claims made in relation to gender, it was established that males made more claims compared to females. Males made 54.8% of their claims once, while 66.7% of males made claims twice. This might indicate differences in driving behaviour between males and females. With respect to gender and driving behaviour, Magaña *et al.* (2019:9) observed that the average number of events per 100 km stretch obtained by women was 52.67% lower than that obtained by men. With respect to the break-acceleration pattern, the value obtained by women was 62.15% lower than that registered for men. This indicates that women are more safety conscious and they exhibit safer driving behaviours compared to men. These research outcomes support what has been established in this study: males made more claims compared to women. This might indicate that females are more careful drivers or exhibit safer driving patterns as compared to males.

Current research findings on the relationship between age and driving patterns are comparable to those that were established in a study by Magaña, Paeda, Garcia, Paiva and Pozueco (2021:8), where the acceleration-break driving pattern was best for older drivers compared to young and older drivers. Magaña *et al.* (2019) highlighted that all the drivers with more experience in driving exhibited better driving skills and patterns when compared to new drivers with less experience. Young drivers received the worst results in the positive kinetic energy category of driving patterns, mainly due to the higher levels of stress they experienced compared to older drivers. Research by Jing-si et al., (2020) confirmed that male drivers exhibit higher red light running severity compared to females. These findings confirm the assertion that males are more prone to safe driving patterns as compared to females.

6.4.3 Telematics-based insurance rewards and the driving behaviour of policyholders.

This study established an inverse relationship between demographics and telematics rewards, as indicated by a negative beta coefficient, which means that some groups will receive smaller rewards. This raises the possibility of underrepresentation in incentives and forces insurance companies to review their incentive programmes. Telematics incentive perception and usage were enhanced by comprehending demographic preferences and overcoming technological constraints, privacy breaches and ignorance.

Research results from the study by Malekpour *et al.,* (2023) established that speeding driving behaviour is highly correlated to the tangible financial incentives provided by telematics-based feedback. Outcomes from the study by Ruer *et al.,* (2020) confirmed that the application of telematics positively influenced driver behaviour by significantly reducing abrupt braking and sudden acceleration. Meng et al., (2022) highlighted that a supervised driving risk scoring neural network model could enable telematics-based insurance to discover heterogeneity in their portfolio and attract safer drivers who are provided with premium discounts.

These research outcomes appear to suggest that leveraging big data analytics and machine learning techniques associated with the use of telematics-based insurance schemes is associated with positive improvements in safe driving practises that are beneficial to both the insurance company in terms of love insurance claims and the clients with respect to receiving premium discounts. This outcome shows a statistically significant relationship was established between the promotion of telematics-based insurance schemes and safer driving tendencies by policyholders.

This study established that a negative anticipatory distance while driving is a sign of impaired driving practises and might increase accidents. An insurance risk or telematics reward diminishes as smooth distance rises, according to a negative beta value of -0.022. An insurance risk or reward decreases as stationary time rises, according to a negative beta value of -0.537. An insurance risk or return decreases as the night driving mean rises, according to a negative beta value of -0.281. Driving at night carries more risks, such as poor visibility and drunk driving. As a result of their safer driving habits, drivers who spend more time on smooth roads and less time at night may be eligible for cheaper insurance premiums or larger awards. These research outcomes corroborate existing literature from a study by So et al., (2021), which emphasise that telematics provides better features for predicting accident frequency than typical variables used for risk classification, such as gender and driver age. This outcome indicates that telematics variables were used to understand driver behaviour better.

CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS

7.0 Introduction

This chapter highlights answers to research questions and stipulates the contributions of the study in terms of theory and practise. It also relates to the extent to which current research findings have been able to resolve the objectives of the study successfully. The impact that telematics-based insurance schemes have on the driving behaviour of short-term insurance clients. Key factors that were looked at in the study included the democratic demographic characteristics of respondents in terms of their age groups, gender and driving experience. These were related to various driving behaviours that could potentially impact the use of usage-based insurance incentives. The chapter also highlights the extent to which findings were generalised to the greater population of insured-car drivers in South Africa and stimulates discussion of the limitations of the study.

This study provides valuable insights into the impact of telematics-based insurance schemes on driving behaviour. The findings suggest that these schemes have a significant positive influence on improving driving habits and promoting safer road practices. Through real-time feedback and personalised incentives, telematics empowers policyholders to adopt responsible and cautious driving behaviours, resulting in reduced accident rates, lower insurance premiums and overall enhanced road safety. This research highlights the potential of telematics to revolutionise the insurance industry by aligning incentives and promoting a proactive approach to risk management. As technological advancements continue to reshape our society, further studies and broader implementation of telematics-based insurance schemes are warranted to assess their long-term impact on road safety and to bring about a more sustainable and secure future for drivers worldwide.

7.1 Principal Conclusions

This study provides valuable insights into the impact of telematics-based insurance schemes on driving behaviour. The findings suggest that these schemes have a significant positive influence on improving driving habits and promoting safer road practices. Through real-time feedback and personalised incentives, telematics empowers policyholders to adopt responsible and cautious driving behaviours, resulting in reduced accident rates, lower insurance premiums and overall enhanced road safety. This research highlights the potential of telematics to revolutionise the insurance industry by aligning incentives and promoting a proactive approach to risk management. As technological advancements continue to reshape our society, further studies and broader implementation of telematics-based insurance schemes are warranted to assess their long-term impact on road safety and to bring about a more sustainable and secure future for drivers worldwide.

7.1.1 Impact of policyholder demographics on rewards

The study showed a link between driver demographics and telematics rewards. Telematics incentives encourage new drivers to develop safer driving practices. Telematic rewards provide feedback on speeding, abrupt braking, or aggressive manoeuvres. Offering incentives and savings based on their improved driving habits can encourage people to take greater responsibility and caution when driving. Telematics awards boost safe driving behaviours in senior drivers. Telematics incentives might encourage adherence to speed restrictions, smooth braking, or staying focused on the road. Telematics incentives can offer insightful feedback to assist older drivers in upholding safe driving practices. This helps to lower accident rates and ensures the safety of older drivers as well as other motorists.

For male drivers, who may be more likely to engage in riskier activities, telematics benefits play a crucial role in promoting safer driving practices. By maintaining legal speeds, abstaining from aggressive driving and obeying traffic laws, telematics benefits encourage male drivers to adopt safer practices and perhaps lower accident rates. Even though women tend to drive more safely, telematics incentives can still have positive side effects. Telematics promote positive behaviour, and help to further improve the existing safe driving habits of female drivers by monitoring and rewarding adherence to safe practises, such as avoiding distractions, keeping safe distances, or complying with speed restrictions.

For new drivers who are still honing their skills, telematics rewards might be very beneficial in terms of driving experience. Telematics devices give drivers feedback and encourage them to improve crucial areas of their driving, such as smooth acceleration, responsible handling, and maintaining safe speeds. This plays a crucial role in forming their driving habits at a young age and lowering the hazards related to inexperience. Experienced drivers can gain from Telematics awards since they can maintain safe driving habits. Long-term drivers can fall victim to complacency or bad habits. Telematics devices assist in highlighting areas that need development and reinforcing positive driving behaviours through routine monitoring and feedback, ensuring that seasoned drivers remain alert on the road.

7.1.2 The influence of policyholder characteristics on driving behaviour

A key component of employing telematics systems to encourage safer driving habits is the link between telematics rewards and driver behaviour. It has been discovered that telematics incentives act as a type of positive reinforcement that encourages drivers to develop safer driving practices. Discounts are given to drivers who consistently adhere to speed restrictions, brake smoothly, or maintain safe following distances. Telematics systems encourage drivers to be more attentive, responsible and cautious on the road by tying rewards to particular safe driving behaviours. Telematics systems track and document each driver's driving actions over time, building a detailed picture of their routines. With the help of telematics rewards, this self-reflection can raise drivers' awareness of risky actions and inspire them to make improvements.

When drivers receive telematics benefits, they become more competitive, especially if they are a part of a group or insurance scheme. Drivers may work to increase their prizes or their ranks in comparison to other drivers, which might motivate them to keep getting better behind the wheel. This competition encourages drivers to seek out safer driving actively practises and develops a better driving culture. Beyond the direct incentives, the usage of telematics rewards might affect driving behaviour. The constructive criticism and feedback provided by telematics systems over time can assist drivers in internalising safe driving practices and incorporating them into their natural driving style. Long-term behavioural changes that go beyond the first deployment of telematics rewards result in this shift towards safer driving.

7.1.3 Telematics-based insurance rewards and the driving behaviour of policyholders.

The study found that inexperienced and risk-taking behaviours are common among young drivers. Statistics show that teenage drivers are more prone to speed, drive while distracted, or break other traffic laws. It is vital to concentrate on enhancing safe driving practises in this group through education, training and enforcement because they frequently have higher accident rates. Physical restrictions that older drivers may experience, such as impaired eyesight, hearing, or reaction times, can impair their ability to drive safely. This group may be more prone to accidents because they make decisions more slowly or have more trouble managing challenging driving situations. The safety of older drivers on the road was helped by routine screening and periodic driver evaluations.

Males have traditionally been linked to more violent driving habits, including speeding, tailgating, or reckless driving. This propensity may make accidents more likely. It is important to remember that not all male drivers fit into these stereotypes, and everyone should be encouraged to drive safely. Although it is commonly accepted that women drive more cautiously, gender-based variances vary significantly amongst people. Although women are less prone to engage in risky behaviours, distractions and other harmful driving habits can still affect them.

Unsafe driving habits might result from a lack of expertise and exposure to various driving situations. Inexperienced drivers may have trouble making decisions, recognising hazards, or controlling their vehicles. Gradually enhancing their driving abilities was accomplished through the use of supervised practising and graduated driving licencing schemes. In general, experience enhances one's judgements and driving abilities, resulting in safer driving practices. Long-term experience can also result in overconfidence and complacency, which can result in unsafe behaviours such as driving while distracted or failing to adjust to shifting road conditions. Such dangers were reduced by promoting ongoing education, defensive driving lessons and regular driving evaluations.

7.2 Theoretical contributions

Research findings can make a variety of contributions to theories of innovation diffusion, unified technology acceptance and use and rational behaviour. The notion of innovation diffusion explains how novel concepts or innovations spread and become accepted in a society. Findings from research were used to pinpoint the variables that affect the adoption and spread of telematics-based insurance. The features of early adopters are revealed by the research, who were categorised according to their age groups, driving experience, or gender and how they view the advantages of utilising telematics as well as the obstacles to adoption. This knowledge can help us better understand how and why particular people or groups of people favour or disapprove of the adoption of telematics-based insurance benefits.

The results of the research shed light on the variables that affect users' acceptance of and intention to utilise telematics-based insurance. The results can provide a deeper understanding of users' attitudes and motives towards this specific technology by studying the correlations between characteristics like perceived utility, convenience of use and behavioural intentions in line with the UTAUT model.

The impact of telematics-based insurance on people's attitudes towards safe driving and their subjective norms connected to driving behaviour is examined in research findings that support this idea. The study showed that different demographic groups have good perceptions of telematics-based insurance and societal pressure to drive carefully, which supports the theory's claim that these attitudes and subjective standards affect driving conduct in line with the Theory of Reasoned Action.

7.3 Managerial implications

Factors like average speed and distance revealed a driver's habits and tendencies travelled, which can assist the insurance predicting the likelihood of accidents or claims. Younger or less experienced drivers may be more likely to get in accidents. Therefore, age and experience (as determined by the age required to obtain a driver's licence) are also significant risk indicators. The insurance can provide policyholders with tailored pricing by leveraging these factors. This method takes into account each driver's unique driving style and departs from typical rating elements like age and gender. Weekly incentives may be offered to drivers who consistently exhibit safer driving behaviours (lower average speed, shorter distances.

The telematics database's weekly rewards programme encourages policyholders to maintain safer driving habits continually. Drivers are encouraged to drive responsibly and avoid harmful behaviours on the road by monitoring their performance and providing incentives for good driving habits. Customers' interactions with the insurance were improved through telematics databases that offer customised feedback on their driving habits. Based on the data gathered, policyholders receive frequent updates on their driving performance, which can help them identify areas for improvement and promote safer driving practices.

The telematics database helps insurance service providers identify fraud in insurance claims as well. Suppose an accident happens and there are differences between reported data during policy application or claim submission and actual driving behaviours (such as a high average speed). In that case, it raises concerns that call for additional investigation. Insurance companies can assess trends and patterns among various demographic groups by combining these variables, which enables them to make data-driven decisions. Insurance companies can pinpoint particular age or gender groupings that are more likely to be involved in collisions or have riskier driving tendencies. To reduce risks and increase road safety, this information was utilised to create targeted education or awareness programmes.

7.4 Limitations of the research

Telematics data only records specific characteristics of driver conduct, such as speed, acceleration, braking and vehicle position. Hence it only offers a restricted picture. It does not take into account other crucial elements, including driver focus, judgement and obedience to traffic laws. Telematics data do not capture the context of some behaviours. For instance, abrupt acceleration or braking could be necessary to prevent an impending collision or adjust for traffic circumstances. Without knowing the context, it could result in inaccurate assumptions about the behaviours of the driver.

Telematics data cannot offer information about the driver's mental or emotional state. It is unable to distinguish between reckless driving and intentional driving that is aggressive. Telematics data by itself are insufficient to provide an accurate determination of human factors like fatigue, distraction, or impairment. Telematics data could be misinterpreted. If a single instance of forceful braking is an aberration in a driver's generally good driving history, it may not necessarily be a sign of poor driving behaviour. A comprehensive grasp of the driver's general behaviour and tendencies is necessary for accurate interpretation.

Drivers' privacy concerns are heightened when telematics data is largely relied upon. Some people could feel uneasy about having their driving habits constantly observed and recorded, which could result in resistance or non-compliance. Technical problems with telematics systems might result in inaccurate or insufficient data collecting. In some places, GPS signals may be interfered with, resulting in erroneous or missing position information. The dependability of the data collected can potentially be affected by hardware or software issues. Data from Telematics largely focuses on driving behaviour and does not offer insights into other crucial areas of driver behaviour, such as adherence to vehicle maintenance, abiding by corporate standards, or, in the case of commercial drivers, customer contacts.

7.5 Suggestions for future research

This study was based on the exclusive use of secondary data on the driving behaviour of policyholders through the use of telematics. Future research can leverage a randomised control trial where participants are divided into two groups – one group receives telematics-based insurance rewards, while the other group does not. Collect and analyse data on driving behaviour (speeding, harsh acceleration or braking, etc.) for both groups before and after the intervention period to measure the impact.

Future research can adopt a different methodological approach through the use of qualitative research methodologies, which incorporate focus group discussions or surveys with participants who have experienced telematics-based insurance rewards to understand their perception of how these rewards influence their driving behaviour. This qualitative approach can provide valuable insights into the motivations behind changes in driving habits and was used to complement quantitative data obtained through other methods.

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