L-Università ta' Malta
Faculty of Economics, Management & Accountancy

Enhancing motor insurance underwriting through educational and occupational metrics

Submitted in partial fulfillment
of the requirements of the Degree of Master of Science in
Insurance and Risk Management

Sean Borda

September 2025

Abstract

Traditional motor insurance pricing relies on demographic proxies to assess risk. These methods often fail to capture individual nuances namely, risk appetite. This research delves into past literature from sociology, psychology, and behavioural economics to establish a grounding of behavioural theory and decision making processes. The ultimate goal is to establish whether educational level, proxied by occupation, can serve as an effective approximator for driving behaviour, claims frequency, and claims severity.

A dataset from Maltese insurers was used for the statistical analysis between the above mentioned factors where several statistical techniques were applied to assess correlations between education and claims outcome. The findings do suggest some correlations and associations, however they are not as statistically significant as the ones observed in other countries.

This study aims to enrich current literature associated with decision-making and risk appetite within the insurance industry, through thorough review of interdisciplinary literature.

Acknowledgements

I would like to express my sincere appreciation to everyone who has supported me throughout my academic journey and the completion of this dissertation.

I am grateful to my supervisor, Dr. Andre Farrugia, for his guidance, patience, and time. Additionally, I would like to thank my family for their unwavering support.

Table of Contents

Chapter 1 - Introduction

1.1 Background

Chapter 104 of the laws of malta stipulates that motor insurance is a legal requirement in Malta as well as many other countries. A motor insurance agreement is a contract whereby the insurer agrees to cover certain damages related to the use of a vehicle. Such costs can be repairing the insured vehicle after a claim or covering the damages of third parties. Third-party damages often relate to the reinstatement of third-party property or compensation for injuries caused. Motor insurance has been a legal requirement since 1947, since it ensures that innocent third parties are always protected from damage in the operation of motor vehicles. (MFSA, 2025)

The increasing prevalence of motor vehicles has been a persistent trend since the mid-20th century. According to data published by the National Statistics Office (NSO), the first quarter of 2024 saw the registration of 821 newly licensed vehicles, equating to an approximate daily average of 62 new registrations. The majority of these newly registered vehicles were passenger cars, which reflects the continuing importance of personal transportation across all age groups. Driving has become an essential element of daily life for the general public.

Insurance providers operate on the principle of risk assumption, wherein they underwrite risks that individuals prefer not to bear themselves. This is why it is crucial for insurers to carefully select the risks they take on to maintain sufficient loss ratios and thus be financially stable. A key part of this process involves choosing which risks to underwrite, helping them maintain a healthy balance between claims paid and premiums collected, known as loss ratios. To avoid excessive losses, insurers create an underwriting policy that outlines the procedures under which underwriters must evaluate potential policyholders, set relevant terms, and adjust premiums. These variables are then adjusted depending on the perceived risk of the potential policyholder.

Traditionally, insurers established risk profiles and levels through factors such as age, gender, geographic location, driving history, engine capacity, and type of vehicle. While these factors offer a general view of the risks insured, they may not sufficiently cover the nuances associated with individual characteristics and driving behaviour. As a result, a lot of innovation is happening in the underwriting sphere, such as the introduction of ai models that interpret telematics data. (Espinoza and Johnston, 2025)

Modern infrastructure developments, including speed enforcement systems, improved road quality, and evolving social attitudes toward road safety, have significantly contributed to a safer road environment. Even so, many insurance companies still employ traditional underwriting methods that rely on outdated risk models. These models are often rigid and fail to consider the dynamic aspects of the modern environment and culture. Shifts in driver behaviour or socioeconomic changes are often unaccounted for under these models. The use of traditional models, which are based on broad assumptions, can lead to premiums that are mismatched and may be unfair to drivers. This risk is further exacerbated when considering modern driving habits and road conditions.

1.2 Gap in the literature

There is extensive research that studies well-documented determinants of risk associated with motor insurance claims, namely age, gender, and past driving offences. However, there are minimal studies that explore the correlation between socioeconomic indicators, namely, education and occupation, and road risk behaviours.

In other fields, such as finance, health, and sociology, there is growing evidence that these factors influence people's risk behaviour; however, few studies extend this reasoning and research to the domain of driving behaviour. For example, Koekemoer (2019) found that people with higher education levels tend to be more risk-averse when making financial decisions. Koekemoer's research suggested that a positive relationship between one's level of education and their risk tolerance exists. His research was founded on prior research that had also reached the same conclusion. Similarly, a study by Lindblom and Weidenmark in 2022 assessed the role that education has on individuals' financial risk appetites. They found that education plays a significant role in one's risk appetite in the domain of financial risk tolerance.

Interestingly, a contrasting study from Iran, published in the Chinese Journal of Traumatology in 2013, found that there was an association between education level and road traffic accidents. This points to a valuable and unexplored link between education and behavioural risk factors. Existing work relies heavily on pre-established metrics such as age, experience, and gender. Many studies often default to age-based classifications with little or no analysis of any potential underlying factors.

1.3 Why is this project needed?

As previously mentioned, traditional underwriting models heavily rely on demographic stereotypes and historical data that may not be fully applicable or entirely relevant in modern contexts. As a result, certain policyholders may be unfairly categorised, leading to higher premiums.

On the other hand, other policyholders may be inaccurately assessed due to generalised underwriting strategies. These policyholders may benefit from premiums that are lower than their actual risk level. In both cases, a premium-to-risk mismatch is present.

A small motor insurance industry, such as Malta's, may benefit from refined risk models that incorporate indicators such as education and occupation. These variables may provide a clearer picture of the policyholder's risk perception, sense of responsibility, and long-term planning. Such factors can contribute to driving behaviour and may provide valuable insights into insurance underwriting procedures. Furthermore, the addition of such a metric to proposal forms comes at little to no cost to insurers, as it only involves the addition of a question or two during the underwriting stage.

People engaged in higher education or employed in roles that demand discipline, problem-solving, or compliance with safety standards often adopt these qualities in their everyday behaviour, including when driving. Such individuals may also have a stronger awareness of the personal, professional, and financial repercussions of reckless driving.

On the other hand, those with limited educational backgrounds or working in less specialised jobs may not demonstrate the same degree of caution. In such cases, short-term convenience or gratification can take precedence over long-term considerations, potentially leading to riskier driving habits.

Incorporating these factors into underwriting decisions allows insurers to tailor policies more closely to individual risk profiles. This can make pricing appear fairer and strengthen customer confidence. When policyholders believe that the coverage they receive aligns with their actual level of risk, they are more likely to remain loyal to their insurer. Furthermore, a product that feels tailored to an individual's circumstances is often perceived as more valuable. Lastly, the use of a personalised cover may provide a competitive advantage over competitors using traditional models, leading to a larger market share.

The objectives of this research are as follows:

- Explore existing literature that connects education and occupation to risk behaviour in various domains (finance, health, sociology, and economics), and evaluate its applicability to driving behaviour
- Analyse motor insurance claims data to examine the relationships between socioeconomic factors and claims frequency and severity.
- Provide a real-world interpretation of the results of the statistical analysis.

1.4 Importance and limitations

The Maltese insurance market is renowned for being both highly competitive and lucrative, with numerous companies vying for market share and continually seeking innovative ways to differentiate themselves from their competitors. In such a dynamic environment, insurance firms continually seek new opportunities and strategies that can give them a competitive edge.

Accurate risk modelling will not only benefit insurers through improved loss ratios and enhanced customer segmentation, but also benefit consumers by providing fairer and more customised coverage. Furthermore, the adoption of such metrics will ultimately benefit consumers by creating a more transparent insurance landscape. Lower-risk drivers, based on their educational level and occupation, can be rewarded with lower premiums, thereby encouraging safe driving.

1.5 Steps to complete the thesis

The first stage of the literature review involves a comprehensive review of the academic literature on education, occupation, and risk attitudes in the context of decision-making, level of risk aversion, and driving.

The second stage is that of data collection. The researcher will see anonymised claims data from Malta's leading motor insurers, GasanMamo Insurance, Mapfre Middlesea, Elmo Insurance, Atlas Insurance, and Citadel Insurance. These companies represent almost all of the Maltese motor insurance market, thus ensuring a representative dataset.

The next stage is data analysis. Claims data will be categorised by claims severity, person at fault, and the presence of injuries. These categories will be compared against occupation (acting as a proxy for level of educational attainment). Statistical methods will then be used to identify significant patterns.

The final stage will involve integrating the findings from the data analysis as well as insights from previous literature. Here, recommendations and suggestions for further research will also be made.

<u>Conclusion</u>

This thesis attempts to challenge traditional procedures of motor insurance underwriting by proposing the inclusion of education and occupation as supplementary indicators of risk. Traditionally, underwriting relied heavily on metrics such as age, claims history, and vehicle type; these will still be important; however, the addition of behavioural and personalised metrics will result in a fairer underwriting assessment that benefits both the insurer and the policyholder.

By exploring these indicators, this research hopes to contribute to the development of more accurate and innovative underwriting practices. Ultimately, as with any study, the objective is to keep enriching knowledge and create a more nuanced understanding of driving behaviour that aligns with modern practices.

Chapter 2 - Literature Review

Understanding how individual characteristics influence driving behaviour has long been a focus of research across psychology, sociology, and behavioural economics. Among these disciplines, risk aversion is a concept that has been deeply studied. Ted O'Donoghue and Jason Somerville, in their paper "Modelling Risk Aversion in Economics," define risk aversion as a general tendency for a person to choose the option with the lowest likelihood of occurrence (O'Donoghue and Somerville, 2018). This can be portrayed using a simple example, if a person is offered two lotteries of equal value with different likelihoods of winning, the logical, risk-averse choice would be the one with the higher chance of winning. Thus, risk aversion is defined as the tendency to avoid situations that involve risk.

Determining risk aversion is crucial for this study, as it influences road safety, accident prevention, and future policies and legislation (Peltzman, 1975). This topic has been the subject of numerous studies over the years, particularly those examining how psychological and demographic factors influence driving behaviour (Rhodes and Pivik, 2011). However, the role of educational attainment as a predictor or determinant of risk aversion while driving has remained relatively underexplored.

To assess whether and how a person's educational attainment influences their inclination to engage in or refrain from risky driving behaviour, this literature review will examine the existing academic research. This study will take insights from different disciplines ranging from, theoretical models of risk perception from psychology, understanding the role of education from a sociological perspective, as well as behavioural economics to understand decision-making strategies and patterns.

Key terms, such as risk aversion, educational attainment, and risky driving behaviour, will be defined and explored in this review. Risk aversion refers to a behavioural tendency to prefer certainty over uncertainty, especially in contexts where potential adverse outcomes are involved (Kahneman and Tversky, 1979). In the context of driving, risk-averse individuals may be more likely to obey traffic laws, avoid speeding, and engage in defensive driving. In contrast, risk-tolerant individuals may be more prone to aggressive or inattentive behaviours.

A study was conducted in which researchers compared a questionnaire with a GPS tracking device in the participants' vehicles. Greaves and Ellison found that those who showed higher levels of risk aversion were less likely to engage in speeding. This would mean that individual personality traits, such as risk aversion, greatly influence driving habits (Greaves and Ellison, 2011). Such a conclusion is supported by a similar study conducted in China. Researchers used drivers' economic preferences as a measure of risk aversion and examined the relationship between the mentioned level of risk aversion and their propensity to commit traffic violations. It was discovered that economically more risk-averse people had fewer traffic violations, suggesting that individuals' risk preferences materialise when driving. (Hu et al., 2024)

Educational attainment refers to the highest level of formal schooling an individual has completed and is often used as a proxy for cognitive ability, social capital, and access to information (Cutler and Lleras-Muney, 2010).

This study assessed the foundational theories underlying risk-taking and general risk attitudes, and applied them in a driving context, using education as a measure of variation in risk aversion. To prepare the empirical portion of the thesis, which will examine the possible relationship between education and risk aversion in actual driving situations, this review identifies the advantages, disadvantages, and gaps in the body of existing literature.

2.1 Theoretical Foundations

Understanding the link between education and driving-related risk aversion is a complex issue with roots in multiple disciplines, including psychology, sociology, and behavioural economics. These disciplines provide context for interpreting how individuals make decisions and behave when dealing with uncertainty, such as driving. This section outlines the principal theories that underpin this area of research and inform the hypothesis that higher levels of education may be associated with greater risk aversion on the road.

Psychological Theories of Risk Aversion

The basis of psychological explanations for risk aversion is Prospect Theory, which was developed by Kahneman and Tversky (1979). This groundbreaking theory posits that individuals do not evaluate potential gain and potential loss equally; instead, individuals faced with uncertainty are drawn more to the prospective gain than to the potential loss. Kahneman and Tversky pose that an individual who is investing their money has an equal chance of making a return and an equal chance of making a loss; however, the possibility of the gain occurring is perceived as more significant. Kahneman and Tversky utilise the function below, which is concave for gains and convex for losses. (Kahneman and Tversky, 1979)

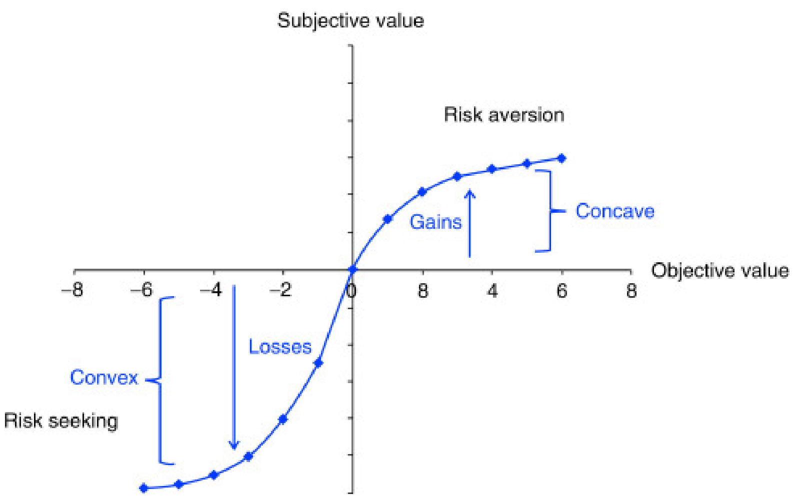

Figure 1: Theory value function (Sciencedirect.com, 2014)

As stated above, the value function is concave for gains. This indicates that the sensitivity to risk is increasing at a decreasing rate, suggesting that they are risk-averse. Therefore, it is evident that individuals prefer a certain gain over a probabilistic one of equal expected value. On the other hand, the function is convex for losses, which indicates that generally individuals are risk-seeking when it comes to mitigating losses. This means that individuals are more willing to gamble if it means avoiding a sure loss, which is the logical thing to do.

Furthermore, the function is steeper for losses than for gains. This captures a fascinating phenomenon called the ‘Loss Aversion Bias’. Under this phenomenon, losses are perceived as more psychologically impactful than equivalent gains. A study in 1990 called this phenomenon the ‘endowment effect,’ which is a manifestation of loss aversion bias, whereby people place a higher value on items they own compared to identical items not owned by them.

This research was conducted by means of three groups: buyers, sellers, and choosers. The sellers were given a mug and asked how much they would be willing to sell it for. The buyers were not given a mug but were asked how much they would pay for one. The choosers were asked whether they would prefer a certain sum of money or the mug. The findings were that he sellers demanded approximately double as much as the buyers were willing to pay for the mug, showing that they value their belonging more than it is actually worth, thus proving that the potential loss of giving up the item (for the seller) is perceived as more significant than the gain from acquiring it (from the perspective of the buyer). (Kahneman, Knetsch, and Thaler, 1990)

Therefore, the asymmetric S-shaped curve helps explain a wide range of real-world behaviours, such as why people may reject fair bets or make inconsistent choices depending on whether outcomes are framed as gains or losses.

The shape of the curve shows that individuals overall tend to exhibit loss aversion, meaning a preference for avoiding losses over an equivalent gain. On the contrary, individuals tend to value additional gains less and less, which results in the S-shaped curve. In the context of driving, this might explain why individuals avoid speeding or reckless manoeuvres that could lead to accidents or fines, even when time-saving is a potential gain.

Risk perception, another important psychological construct, refers to how individuals subjectively evaluate the danger associated with specific actions. Slovic (1987) emphasised that risk perception is influenced by both cognitive and emotional factors, including personal experience, perceived control, and familiarity, which will be further explored later.

<u>Sociological Perspectives on Education and Behaviour</u>

Education plays a significant role in society. Sociologists emphasise that education’s role is not simply a vehicle for transmitting knowledge and skills, but also plays a vital role in shaping identities, attitudes, and social behaviour. These institutions can be considered as agents of socialisation. Educational institutions serve the purpose of preparing students to navigate the world. This is done by embedding norms, values, and expectations that influence how individuals interact with the world. Such a function is central to understanding the role that education plays in the context of risk aversion, particularly in driving. (Hartlaub and Schneider, 2012)

One of the most influential frameworks for examining this phenomenon is Pierre Bourdieu's theory of cultural capital (Bourdieu, 1986). According to Bourdieu, education is a mechanism through which dominant cultural values are reproduced and internalised. Schools and universities transmit not only cognitive and technical competencies but also habits. These habits include attitudes toward authority, social norms, discipline, and delayed gratification, all of which are closely linked to risk-averse tendencies.

Since the role of educational institutions is to instil social norms and values, Bourdieu suggests that individuals with higher levels of educational attainment would be much more likely to have accepted and internalised social norms. This can materialise in many forms, such as respect for rules, obeying laws, and a more substantial commitment toward long-term outcomes. These factors will materialise in the context of driving through compliance with traffic laws, avoidance of aggressive manoeuvres, and most importantly, the awareness of social and legal consequences. From a Bourdieusian perspective, the effect of education goes far beyond intellectual competence and extends to ingrained social values and behavioural tendencies.

So it is established that education plays a vital role in shaping social identity and social status. In fact, in many societies, educational attainment is the primary determinant of socioeconomic status. Research suggests that individuals with higher education, as well as socioeconomic backgrounds, generally align their everyday behaviour to reflect their social identity. This materialises in avoiding actions that can be considered irresponsible, deviant, or inconsistent with the values of their socioeconomic class. Therefore, behaviours such as aggressive driving may be seen as inconsistent with the traditional middle or upper-class values. This will result in individuals who form part of these socioeconomic classes often being more cautious and having more normative behaviour when driving. (Nickerson, 2024)

The relationship between education and social identity also relates to other sociological theories related to self-regulation and impression management. Individuals with higher education are often urged into professional environments where self-control, planning, and adhering to norms are expected and rewarded. Such traits start from the school level, and by the time the student is ready for their professional occupation, they are ingrained within them. Such traits are positively reinforced within an educational context using good grades, these continue to be positively reinforced in the occupational context using performance reviews and promotions. Such traits will continue to influence one's day-to-day decision-making patterns, resulting in a greater sensitivity to risk and a preference to minimise uncertainty, key characteristics of risk aversion. (Vaughn et al., 2012)

Furthermore, education exposes individuals to diverse social networks, institutional settings, and discourses about public health, legal systems, and civic responsibility. This exposure may allow individuals to develop a better understanding of social and systemic consequences; thus, they are automatically more cautious in avoiding situations that can harm them or bring legal consequences. (Vaughn et al., 2012)

In conclusion, this sociological perspective posits that education goes beyond the transfer of knowledge but also shapes behaviour through enhancing decision-making processes and embedding individuals into social systems, norms, and values. Such systems, norms, and values are traditionally risk-averse. This will result in educated individuals becoming law-abiding and disciplined citizens with an inclination towards safety over uncertainty and risk-taking. Thus, such individuals will be more risk-averse in all contexts, one of which is driving.

Behavioural Economic Models of Risk and Education

Behavioural economics integrates insights from psychology and traditional economic theory to better understand decision-making under uncertainty better. Economists measure the usefulness or satisfaction that a product or service offers an individual in terms of utility. When it comes to insurance, there is an element of uncertainty, which is why economists measure utility about uncertain events using expected utility.

The Expected Utility Theory was created by John von Neumann and Oskar Morgenstern in 1944. It establishes that individuals make decisions based on multiple factors and not necessarily the expected monetary value in isolation. People make decisions based on the expected utility that the commodity offers them. This can create added complications for economists since this expected utility is often subjective. Von Neumann and Morgenstern (1944).

Edwin Mansfield and Gary Yohe, in their 'Microeconomics Theory/Application, tenth edition, 2000), define risk averters as 'When confronted with gambles with equal expected monetary values, risk averters prefer a gamble with a more-certain outcome to one with a less-certain outcome.' Mansfield and Yohe (2000). Empirical research directly correlates evaluated risk aversion with personal traits (Hartog, Ferrer-i-Carbonell, and Jonker, 2002). Thus, risk aversion can be considered as one's attitude towards risk preference. In this context, risk aversion is often modelled through concave utility functions, as is shown below, where the marginal utility of wealth or outcomes decreases with increasing magnitude, as shown below. The y-axis represents the individual's utility, while the x-axis represents wealth or, in other words, monetary risk.

Conversely, risk-seeking individuals will have a convex expected utility function, meaning that as the wealth (or monetary risk) increases, so does their utility, as can be seen below.

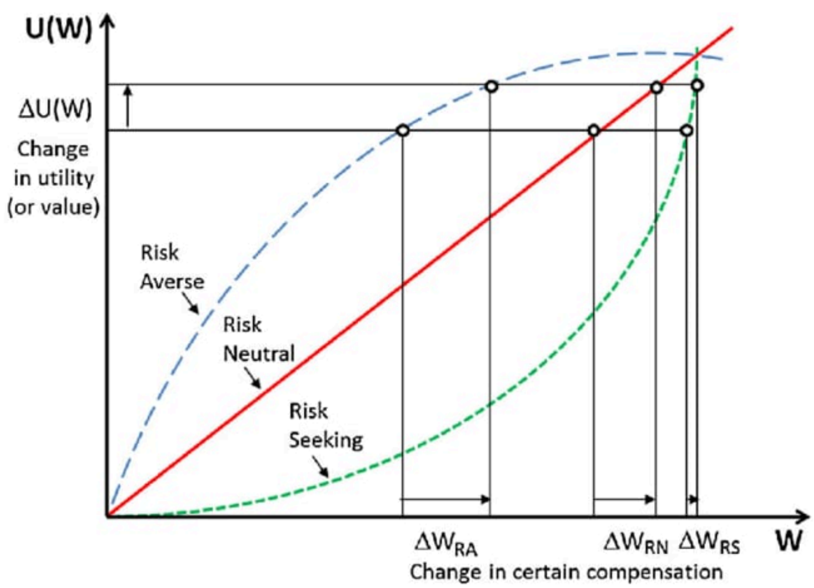

Figure 2: Risk Averse & Risk Seeking Utility Function (Harris and Wu, 2014)

Kenneth Arrow, in his paper 'Uncertainty and the Welfare Economics of Medical Care,' applied expected utility theory to demonstrate that risk-averse consumers were much more willing to purchase insurance. This is because the risk-averse individuals were much more content spending a proportionally small amount as an insurance premium than risk the loss of the underlying asset, which represents a proportionally larger amount. In economic terms, the utility obtained from peace of mind is greater than the monetary value of the premium itself.

More educated individuals may demonstrate greater risk aversion due to enhanced analytical abilities and greater exposure to formal training in probability and logic, which can improve decision-making under uncertainty.

Researchers have also explored how education changes people's attitudes towards risk-taking. A study conducted by Tanaka, Camerer, and Nguyen (2010) studied individuals in Vietnam and found that those with higher levels of education were more willing to take calculated risks. Such a conclusion is corroborated by the conclusion of Vaughn et al. (2012). This Vietnamese study suggests that education helps people better understand and manage uncertain situations, a conclusion shared by Vaughn. However, the study also showed that this relationship depends on external factors such as personality traits. A key trait was that of the "locus of control," which essentially means whether someone believes they have control over their own life. So, while education can improve how people think about and respond to risk, their personality and confidence also play a role in their risk-related decision-making process.

Furthermore, the risk compensation theory (Peltzman, 1975) suggests that individuals adjust their behaviour in response to perceived safety. If more educated individuals have a better understanding of road safety systems and legal consequences, they may be more likely to adopt a cautious driving style. Conversely, overconfidence in knowledge or control might reduce perceived risk, thereby moderating the effect of education on actual behaviour.

2.2 Education and General Risk Aversion

As shown previously, a growing body of research supports the conclusion that education plays a crucial role in shaping an individual's risk preferences. However, most research is focused on financial or health-related risk preferences. These insights are helpful since they create a foundation for understanding the role of education and general risk aversion, and by extension, driving. (Obermeier and Schneider, 2015)

Education and Financial Risk Aversion

As stated above, a substantial amount of research has explored the relationship between educational attainment and risk preference. These studies generally conclude that education plays a crucial role in shaping people's perception, evaluation, and response to risk and risky situations. This relationship is founded on the idea that education is pivotal to the development of cognitive and analytical skills needed for sound decision-making in uncertain situations. (Cutler and Lleras-Muney, 2010)

A study in Turkey found that education, especially at a university level, enhances decision-making in key aspects such as cognitive capacity, numerical reasoning, and critical thinking. (İsmail Karakuş, 2024) Such abilities are crucial in assessing probabilities, understanding statistical risks, and weighing the consequences of different decisions. Furthermore, individuals with such educations are likely to have knowledge and training in disciplines such as economics and maths, which are largely logic-based disciplines. These disciplines will help in making logical and utility-based decision-making. As such, education equips individuals with the correct frameworks that allow for informed and less impulsive decisions when encountering uncertainty. (Cutler and Lleras-Muney, 2010)

Empirical evidence strongly supports this view. In their recent study, Le Fur and Outreville (2022) conducted a detailed survey among French university students. They uncovered a clear correlation between educational background, especially in economics and finance, and levels of financial risk aversion. They found that students enrolled in quantitative and analytical fields preferred safer and more predictable outcomes over those with more uncertainty and higher returns. Such a preference for certainty is a clear indicator of risk aversion. Furthermore, Le Fur and Outreville suggest that the relationship between these analytical fields and risk aversion is not simply due to financial knowledge but due to broader educational exposure, which results in more structured decision-making processes.

Barsky et al. confirm this pattern in their foundational study in 1997. The researchers used data from the US Health and Retirement Study and developed a measure of risk tolerance based on participants' reactions to hypothetical financial gambles with different income variations. Their results revealed that those participants with higher levels of education were much more risk-averse, often opting out of high-risk, high-reward scenarios, even if the expected reward was much greater than the guaranteed alternative. The researchers interpreted their findings as proof that education impacts both economic behaviours and preferences for risk.

These studies support the hypothesis that education has a pivotal impact on individuals' risk preferences and that education goes beyond fostering technical ability and provides a foundation for calculating and understanding risk. Furthermore, it creates a framework for a cautious, structured, and forward-thinking decision-making process. This results in a general preference for certainty and predictability, indicators of risk-averse behaviour.

Education and Health Risk Behaviour

The relationship between education and risk aversion has also been observed in the domain of health behaviours. Cutler and Lleras-Muney (2010) conducted a study using large-scale databases that were representative of the United States. They found that education had a substantial effect on health behaviours. They concluded that individuals with a higher level of education were generally healthier and did not engage in practices that compromised their health, such as smoking, eating a poor diet, and not exercising.

This suggests that education may enhance forward-looking behaviour and awareness of negative externalities, both of which could translate into more cautious attitudes in other areas of life, including driving.

Education, Cognitive Ability, and Risk Preferences

Researchers have also considered whether education itself makes people more risk-averse, or whether the risk aversion observed among educated people is there just because those who seek education happen to be more cautious. Dohmen et al. (2011) studied this and found that cognitive ability is strongly related to lower risk-taking. When the variable of cognitive ability was controlled, the relationship between education and risk preference became weaker, thus indicating that cognitive ability is part of the reason why more educated people happen to be more risk-averse. Their results suggested that educated individuals tended to be more risk-averse; however, the reason for this risk-averse attitude may not be education itself. Instead, it is due to educated individuals having higher cognitive capacities, which leads them to pursue education. Education then improves their cognitive abilities, making them better at evaluating and avoiding risk, resulting in a risk-averse individual with a disposition to safer choices. (Ma et al., 2010) (Stephens & Ukpere, 2011)

This distinction is important because it implies that education is not merely a proxy for cognitive ability but rather an active agent that shapes behavioural tendencies. Education tends to instil structured problem-solving skills, formal reasoning, and consequence analysis that instil habits that favour risk-averse choices.

2.3 Risk Aversion in Driving Behaviour

The act of driving itself involves risk. All decisions, from speed to overtaking, require careful judgment of the danger involved. Researchers have been trying to identify what determines individuals' different risk tolerances behind the wheel for decades. Several factors have emerged as a result of these efforts.

<u>Demographics and Risk Profiles</u>

Many studies consistently show that young male drivers are the least risk-averse when compared to other groups (Williams, 2003).This group is often associated with risky driving, speeding, tailgating, and running red lights. A key factor in this group's risk-taking is the tendency towards sensation-seeking behaviour combined with an undeveloped perception of risk.

Similarly, gender also plays a significant role. Men generally have lower levels of risk aversion when it comes to driving. (Rhodes & Pivik, 2011) This is corroborated by the fact that before 2012, men were charged higher motor insurance premiums when compared to women due to the higher risk they posed. This practice was since changed due to legal intervention by the Court of Justice of the European Union, which made it illegal to use gender as a factor in setting insurance premiums. These patterns suggest that risk aversion in driving is subject to various individual characteristics and cannot be accurately generalised across populations.

Psychological Drivers of Risk-Taking on the Road

Fuller's (2005) general theory of driver behaviour offers a comprehensive framework for understanding how individuals assess and respond to risk while driving. According to Fuller, risk-taking behaviour in driving is determined by four factors: environmental conditions (such as traffic or road conditions), vehicle controls (the complexity of the vehicle's controls), weather, and the driver's perceived skill level. Confident drivers or drivers who perceive their skills as greater than the demands of the driving task tend to take more risks. These additional risks can materialise in the form of speeding, sudden lane changes, or aggressive overtakes. On the other hand, drivers who are not as confident or who perceive the situation as challenging are likely to be risk-averse and engage in defensive driving behaviour. (Danciu et al., 2012)

Under this model, risk perception acts as a 'cognitive filter', meaning mental biases through which drivers perceive, interpret, and respond to certain situations (Kouabenan, 2002). Wang et al. (2018) delve into the concept of a cognitive filter concerning driving behaviour. This study presents a framework that illustrates how various individual factors, such as perception, attention, and personality traits, shape a cognitive filter. One such factor that can shape one's cognitive filter is educational attainment. As shown previously, education can allow for more accurate assessment, information processing, and awareness of consequences. Such factors can result in a more accurate cognitive filter since the perceived risks can be more accurately measured, thereby promoting safer and more risk-averse behaviour while driving. (Wang et al., 2018), (Chung et al. 2021), (Piccardi et al. 2021)

2.4 Education and Driving Behaviour

The relationship between education and driving behaviour is less researched than similar studies that also incorporate education as a primary metric. However, in recent years, education's role in driving behaviour has been an evolving area. Currently, the primary focus of driver education programs is formal driving seminars that promote safer driving; however, there may be broader educational attainment factors that can influence attitudes towards road risks that are often overlooked.

Driver Education and Training

Traditional driver education programs' syllabi aim to teach knowledge of fundamental driving operations such as traffic rules, vehicle operation, and safe practices. Evaluations of these programs reveal mixed results. A study conducted by Lonero and Mayhew in 2010 found that drivers who attended such seminars and programs had better knowledge and awareness than those who did not. Similarly, Topolšek et al. (2019) showed that road safety education affects the relationship between driving mistakes, infractions, and engagement in accidents. However, attendance at such programs did not consistently reduce crash involvement. Thus, researchers have been trying to determine whether general education levels, not just driving-specific training, can truly impact risk attitudes.

General Education and Risk-Taking in Traffic

As seen above, a growing body of interdisciplinary research suggests that general education plays a pivotal role in influencing individuals' risk attitudes and likelihoods of engaging in risky driving behaviours. Empirical findings indicate a negative correlation between educational attainment and risk-taking, a sentiment that also extends to risky driving behaviour. A study by Sivak et al. (2007) discovered that educated individuals were significantly less likely to be involved in a fatal motor vehicle crash. This is consistent with research by Borrell et al. (2005), who found a direct correlation between variations in educational attainment and the mortality rate from transport accidents. Under the same premise, educated individuals were less likely to commit traffic violations such as speeding and reckless driving. This conclusion suggests that education enhances cognitive ability by improving judgment, understanding, and decision-making, thus creating safer driving patterns.

Such safe driving patterns may be created by multiple factors. Firstly, individuals with higher education may possess higher cognitive abilities, allowing for better information processing skills, therefore making them more effective at making decisions under pressure. Secondly, individuals with higher education may be better at regulating their emotions, limiting road rage, aggressive driving, or impulsive decisions. Lastly, education can be considered a socialising factor by instilling norms, civic responsibility, and legal compliance, all factors that are relevant in safe driving behaviour. (Sivak, et. al, 2007)

In summary, general education appears to function as a protective factor against risky driving through a combination of cognitive, behavioural, and social pathways. Furthermore, it enhances cognitive ability, leading to increased information processing, effective emotional control, adherence to norms and rules, and increased sensitivity to the consequences of breaking rules. Therefore, educational attainment may serve as a predictor of safe driving practices. (Abdul Aziz Sabri, 2015) Furthermore, it can be used for future methods aimed at reducing driving-related risks and providing a broader driving education syllabus.

2.5 Gaps in the Literature

Despite a strong theoretical and empirical foundation linking education, risk aversion, and driving behaviour, the existing literature reveals several critical gaps that require further research. Firstly, there is a lack of direct studies that examine the influence of educational attainment on risk aversion in driving as a construct. Education has been well studied when associated with general risk aversion as well as safe driving practices; however, few studies connect these areas and assess the impact of education on driving risk preferences. Secondly, there is a population-specific focus of much of the current research, with particular focus on populations such as university students or urban drivers. Few studies consider the broader population as a whole. This lack of diverse samples limits studies. There is a need for general frameworks to be set in place to understand how education interacts with general risk aversion and driving among different cultures and populations. Thirdly, the literature is restrained in disciplinary boundaries, without proper collaboration among disciplines. A more interdisciplinary approach, incorporating economics, psychology, and sociology, could yield more profound insights into the complex mechanisms at play.

Chapter 3 - Methodology

This chapter outlines the methodology employed to investigate whether education is a determining factor in individuals' risk appetite while driving. The subject of measuring risk-taking behaviour is quite complex and challenging to examine without long-term observation of direct driving behaviour. Therefore, this study employs an indirect approach by analysing insurers' claims data, focusing on key variables such as occupation, claim severity, fault, and injuries. The primary variable is occupation, as it serves as an indicator of educational attainment. Insurers do not directly ask for the level of education; therefore, assessing claimants' occupations, i.e., 'professional' or 'non-professional', will allow the researcher to determine whether individuals with differing education levels exhibit distinct patterns in driving-related risks.

A practical methodology is essential to ensure a valid and reliable analysis. This chapter will detail the research design, data sources, variables, analysis techniques, ethical considerations, and even limitations.

3.1 Research Design

This study employs a quantitative and correlational research design, utilising secondary data collected from multiple insurance companies in Malta. The central objective is to determine whether the level of education is correlated with driving behaviour. A key challenge encountered was the lack of direct data on the policyholders' educational levels. Therefore, occupation was used as an approximation to claimants' level of education. To more accurately measure driving risk appetite, several variables were taken into consideration. Namely, the occurrence of injury in the claim, the severity of the claim, and the fault determination. Since this is an observational study of the data, the objective of the study is to explore associations rather than establish causality; therefore, a non-experimental research approach was taken.

A cross-sectional design was employed, which analyses the data collected at a single point in time. Such an approach was deemed suitable due to the large amount of data, allowing for the practical examination of patterns and relationships. This cross-sectional design enables the simultaneous assessment of multiple variables. The evaluation of these variables enables the discovery of associations between the level of education and individuals' risk appetite while driving. While a longitudinal design could also create these relationships, a cross-sectional approach would facilitate analysis, as the data would be subject to similar conditions, rather than being influenced by multiple external factors that can impact individuals' risk appetites.

The use of a quantitative method enables effective statistical analysis and objective measurement. Quantitative data allows for unbiased, realistic, and relevant data, providing a solid foundation for relationships and patterns. The variables chosen were identified in collaboration with different experts within the motor insurance industry. The focus on the data, with no tampering or experimental manipulation, ensures this study is valid and ethical.

3.2 Data Source and Sampling

The core data for this study comprises a set of secondary datasets on insurance claims. This dataset includes individual-level records related to motor vehicle insurance claims over three years, 2022 to 2024. Each record contained details such as the level of cover (ie, Fully comprehensive, Third-Party Fire and Theft, Third party only), description of incident, fault, injury, claim severity, and similar claim-related and policyholder information such as age of driver, occupation, vehicle, and engine capacity. These variables, although not all applicable to this study, serve as key indicators for examining risk appetite within a driving context.

The sample was obtained by contacting various insurance companies and requesting their anonymised claims data for this study. The dataset is comprised of a diverse cross-section of drivers, occupations, ages, and even geographical regions (such as the separation of claims and vehicles in Malta and Gozo). Only claims for vehicles that were considered private use cars, and thus, no fleet claims or commercial claims were included. These criteria for inclusion and exclusion were established purposefully to minimize the occurrence of false relationships or links, while also maximizing comparability across cases.

The list contained around 800 self-reported occupations. These occupations were split into ‘Professional’ and ‘Non-Professional’ categories based on the criteria that an individual would need a tertiary education to perform a given occupation. This method has some limitations, such as the ambiguity of certain occupations, including ‘Retired’, ‘Manager’, ‘Assistant Manager’, and ‘Bank Executive’, among others.

The final sample size, after applying all screening criteria, includes approximately 18,000 claims. This volume is considered sufficient for the statistical analysis conducted, allowing for a fair comparison and investigation.

3.3 Variables and Operational Definitions

This section explains the variables used in this study and describes how they were defined based on the data available. The primary focus of the study is to determine whether education is associated with behavioural indicators of driving-related risks, namely risk aversion.

<u>Independent Variable - Education</u>

The primary independent variable was educational attainment. Such information was not available in insurance databases, as they do not request it on their proposal forms. Therefore, occupation was used as a proxy. This approach is supported by established research indicating a strong correlation between occupation type and educational level. (Robst, 2007) Occupations were classified into two categories to facilitate analysis: Professional and Non-Professional. The ‘Professional’ classification contained occupations that require a tertiary education. Lawyers, accountants, architects, doctors, and academics are some of the professions within this classification. The ‘Non-Professional’ classification encompasses occupations that generally don't require a tertiary education to be occupied, with a greater emphasis on experience, such as waiters, clerks, police officers, and builders, to name a few.

Dependent Variables - Proxies for Risk Appetite

Risk appetite is a psychological trait that cannot be directly measured from claims data. However, risk appetite can be inferred from behavioural indicators commonly associated with risk-taking, such as claim severity, injury involvement, and fault status.

Fault status was provided by the insurers themselves, where they indicated whether the person at fault was the 'OI' (Own insured), TP1/2/3/4 (Third party 1,2,3, or 4), or 'BO' (Both at fault). Being deemed at fault was considered an essential indicator of poor judgment or risky driving tendencies. Injury involvement may reflect higher-risk incidents, which may in turn suggest more dangerous driving behaviour. This variable was coded as a binary variable within the data (0 = no injury, and 1 = injury).

Lastly, claims severity was measured in monetary value. This variable was placed into four different buckets, which are also related to injury involvement. Considering that claims involving injuries are generally substantial, they were categorised into claims involving minor injuries and those involving major injuries. As shown in the table below, minor injury claims totalled €5000 or less, while major claims exceeded €5000. The non-injury claims were split similarly, into minor and major claims; however, the claim amount was adjusted to be less than €2500 or more than €2500. Higher claim severity may indicate more aggressive or riskier behaviour.

Claim Category	**Injury Involved**	**Claim Amount (€)**	**Severity Label**
Non-Injury – Minor	No	≤ 2,500	Low
Non-Injury – Major	No	> 2,500	Moderate
Injury – Minor	Yes	≤ 5,000	High
Injury – Major	Yes	> 5,000	Very High

Figure 3: Categorisation of claims severity and amount.

3.4 Data Analysis Techniques

The study employed quantitative statistical methods to examine the relationship between an individual's occupation (and hence level of occupational attainment) and their likelihood and severity of claims. The analysis process was carefully structured to ensure accuracy, reliability, and relevance to the research objectives, while also protecting the interests of both the insurers and the claimants.

Firstly, the data was organised and cleaned using Microsoft Excel, which facilitated preliminary analysis and allowed the researcher to understand the data through descriptive statistics and frequency distributions. During this stage, claims with missing data points were omitted, and professional classifications were assigned. Through descriptive statistics, the researcher determined that the data were not normally distributed, indicating that non-parametric tests would be necessary in the subsequent stages, given the nature of the data.

Next, the true statistical analysis was done using SPSS for its various capabilities and ability to handle complex statistical operations. Here, inferential statistical techniques such as correlation analysis, the Mann-Whitney U test, and the Kruskal-Wallis test were employed, depending on the nature of the variables and the hypotheses being tested. These methods allowed the researcher to determine the presence of any relationships and their strength, understand the levels of statistical significance, and evaluate the predictive abilities of variables. All of these statistical tests were performed with a confidence level of 95% and the results were interpreted in a real-world context. The true details of the statistical analysis will be explained in depth in Chapter 4.

3.5 Ethical Considerations

Given that this study relied on data provided by insurers, the primary concern was the protection of personal information within the insurance claims records. To mitigate any ethical risks associated with the data, the following safeguards were implemented.

1. Firstly, through careful planning, the necessary information was identified. Only this information was requested from the insurer to avoid any potential identification of policyholders and claimants. Furthermore, all of the data used in the study was fully anonymised before being made accessible to the researcher. Any identifiable information, such as names, addresses, contact details, license plate numbers, or ID card numbers, was removed by the insurance companies before the data was provided to the researcher. As a result, no individual could be identified from the data.

2. Secondly, there was the case of data sharing agreements. The participating insurers were informed about the use and handling of the data. It was explicitly stated that the data provided would be strictly limited for the use of the study and that only the researcher and the researcher's supervisor would have access to it.

3. Lastly, the data were stored on a secure, password-protected computer with restricted access, available only to the researcher. There was no data sharing of any kind to preserve the privacy and security of both the participating insurers and the claimants involved. Adhering to these ethical standards ensures the integrity and confidentiality of the data used, thereby supporting a responsible research process.

3.6 Limitations of the Methodology

While several measures were taken to mitigate limitations, some factors may still limit the interpretation or generalizability of the findings. The primary limitation is the use of occupation as a proxy for educational level. Despite research supporting this correlation, occupation does not perfectly reflect the level of education. Furthermore, this categorisation fails to capture nuances such as informal education or on-the-job training. In some instances, misclassification may be present, such as in underemployed individuals.

The study’s cross-sectional and non-experimental design restricts its ability to establish causality. Statistical associations between occupation and claim characteristics can be identified; it is difficult to conclude without altering the variables and seeing how that would impact the result, as is done in experimental research.

Acknowledging these limitations is crucial to the transparency of this study and provides context for interpreting the findings in the next chapter. While these challenges are substantial, the methodology employed attempts to minimise them as much as possible to explore the relationship between the level of education and risk-related driving behaviour, a field that is relatively unexplored.

3.7 Chapter Summary

This chapter has outlined the methodology adopted to investigate the relationship between education level and risk appetite in driving, using proxies and claims data. The use of a quantitative and cross-sectional research design was ideal due to the large amount of data. As such, the reliability of the findings is ensured. Furthermore, the study's use of real-world data ensures that its findings are grounded in a context relevant to the Maltese insurance sector.

This chapter covered the main variables, data analysis techniques, and the process of identifying patterns and relationships. Along with the constraints, especially those related to the use of proxies and secondary data, it also addressed the ethical considerations involved in the research. When combined, the methodology outlined here provides a solid and moral basis for answering the research questions posed in Chapter 1. The analysis's findings and their interpretation will be presented in the upcoming chapter.

Chapter 4 - Data Analysis and Findings

The chapter presents the analysis and key findings of this study. The purpose of this research was to investigate the relationship between educational attainment and driving behaviour from motor insurance claims data. Insurers did not ask their policyholders for their level of educational attainment; therefore, this was approximated through occupational categories.
The analysis is based on anonymised claims records provided by several motor insurers operating in Malta. The size of the dataset obtained from multiple insurers ensures that the data obtained is robust and representative of the population being studied.

The central hypothesis of this research is that educated drivers with higher educational attainment exhibit greater risk aversion. This results in lower claims amounts, a lower likelihood of being at fault in accidents, and is less likely to create injury claims. To test this hypothesis, several statistical analyses were used to explore patterns between variables.

This chapter is structured as follows. Section 4.2 provides an overview of the dataset, detailing the scope, key characteristics of claims data, and the steps taken to prepare the data for analysis. Section 4.3 will explain the statistical analysis approach, including the statistical methods employed and the rationale behind their selection. Section 4.4 will present the findings of the statistical analysis. The final section, section 4.5, will summarise the key findings and provide an analysis of the results.

4.1 Data overview and preparation

As previously stated, the analysis of this study is based on anonymised claims data provided by multiple Maltese motor insurers. This dataset was comprised of all private motor insurance claims from 2022 to 2024, covering a wide range of policyholders across Malta and Gozo. Commercial motor insurance claims were excluded from the dataset. The use of multiple insurers' claims data was done to ensure that the consolidated dataset reflects a diverse cross-section of policyholders across a broad spectrum of occupations (and thus, educational level), ages, and vehicle types.

4.2 Scope of data and variables

The consolidated claims data contained approximately 30000 claims. Each claims record included information such as:

- The type of cover
- The sum insured of the claimant's vehicle
- The occupation of the claimant was used as a proxy for educational attainment. Occupations were self-declared by the policyholder at the underwriting stage since this was part of the proposal form. The occupations were coded into the database in accordance with standardised occupational classifications. These were then coded as binary variables to be statistically assessed.
- The claim amount was the total cost associated with the claim, in Euro (€), following recoveries through subrogation rights.
- The blame attribution was the insurer's choice in determining who was at fault in the course of the damage or injury occurring. There were four types of blame attribution: own insured (OI), third party (TP), both (BO), and unknown (UN). The 'Unknown' attribution was removed from the dataset since it provided no meaningful insight. The remaining attributions were coded to '0', '1', and '2' for analysis in SPSS.
- The injury presence was a binary variable, ie, '0' or '1'. '0' meant that there were no injuries associated with the claim, and '1' meant that there were.

Further information was included, such as the type of vehicle, engine capacity, sum insured, and date of accident; however, these variables were not the primary focus of this study.

Data cleaning and preparation

The data could not be analysed in the state provided by the insurers; therefore, several cleaning and preparation steps were taken to ensure consistency and reliability:

- Occupational grouping. Occupation data was split into two groups: ‘Professional’ and ‘Non-Professional’. The ‘Professional’ group consisted of occupations that required a tertiary education, such as doctors, accountants, and actuaries, to name a few. On the other hand, the ‘Non-Professional’ group consisted of occupations that did not require any education, required on-the-job training only, or required an educational level lower than tertiary education. These groups were transformed to binary, where ‘0’ and ‘1’ represented ‘Professional’ and ‘Non-Professional’ classifications.
- Missing data. There were various missing variables within the claims data, such as ‘Unknown’ occupations and ‘Unknown’ blame. Excluding these records resulted in a final sample size of ‘26652’ claims.
- Codification of data. In order for the data to be statistically analysed, the raw data must be codified into a set of numbers that represent the data. The occupational groupings, blame attribution, and injury presence were transformed into binary variables.

Descriptive summary

An initial review of the data revealed variations in claim amounts, blame attribution, as well as injury presence among occupational groups. Firstly, non-professionals represented 65% of the total sample, with the remaining 35% being professionals. The average claim amount across all occupations was €1,637. The majority of the claims were the fault of the own-insured for both professionals and non-professionals. 64% of total claims were considered to be caused by the Own insured (ie, OI) while the remaining 36% were comprised of 1% and 35% for both parties (BO) and third parties (TP) respectively.

4.3 Analytical approach

The analysis was conducted using SPSS (Statistical Package for the Social Sciences).

The statistical analysis was structured around 3 variables. Firstly, it is the claim amount - a continuous and descriptive variable that represents the cost of settling the claim. Secondly, it is the blame attribution - a categorical variable that indicates whether the insured, a third party, or both parties were considered to be at fault by the insurer. Lastly, it is injury presence - a binary categorical value that indicates whether the claim involved any injuries or not.
Professional status is the main variable. It is also a categorical variable with 2 variations being 'Professional' and 'Non-Professional'. Both of these groups represent different levels of education as well as socioeconomic status.

Descriptive statistics were used to analyse the categorical variables. Categorical variables refer to nominal variables that can be distinctly placed in non-ordered categories. In the case of injury involvement and professional status, this was done through a binary where 'No injury' and 'Professional' were coded as '0' and 'Injury' and 'Non-Professional' were coded as '1'. Similarly, blame status was coded as '1' for 'BO' (Both parties), '2' for 'OI' (Own insured), and '3' for 'TP' (Third party). Categorical variables were analysed through descriptive statistics since counts and percentages allowed for the initial assessment of patterns and relationships through the use of counts and percentages across professional and non-professional groups.

As a continuous numerical variable, claim data requires descriptive statistics such as the mean, median, and standard deviation. As such, the following steps were testing whether claims were normally distributed. Determining if it is normally distributed is a crucial part of the statistical analysis since it determines which tests and methods can be used. A normality test - The Kolmogorov-Smirnov test was done to check if the data were normally distributed.

The objective of the Kolmogorov-Smirnov test is to check whether a sample's distribution differs significantly from a specified theoretical distribution, in this case, the normal distribution. The test statistic refers to the maximum distance between one sample's cumulative distribution function (CDF) and the CDF of a normal distribution. The significance refers to the probability of observing a difference at least as large as the one measured, assuming that the data is normally distributed. The idea behind this test is a goodness-of-fit whereby the claims data's cumulative distribution function is compared to the CDF of a normal distribution and compared to see how similar they are.

As can be seen from the results below, the test resulted in a test statistic of 0.378 and a significance of less than 0.001. This suggests that there is a significant difference between the data and a normal distribution. It is highly unlikely that the claim amounts are normally distributed, less than 0.1% in fact, as can be seen from the probability of observing such a deviation from normality (0.378).

Tests of Normality

	Kolmogorov-Smirnov[a]		
	Statistic	df	Sig.
Claim Amount	.378	17284	<.001

a. Lilliefors Significance Correction

(Sean Borda, SPSS- IBM Corp., 2023)

Figure 4: Test of Normality

This is confirmed by the skewness and kurtosis found in the descriptives below. Skewness refers to the asymmetry of the probability distribution of a real-valued random variable about its mean. Kurtosis refers to how light or heavy the tails of the distribution are. The high skewness of 61.50 and kurtosis of 5784.60 support the conclusion that the sample is not normally distributed.

Descriptives

			Statistic	Std. Error
Claim Amount	Mean		1637.1370	40.55010
	95% Confidence Interval for Mean	Lower Bound	1557.6547	
		Upper Bound	1716.6193	
	5% Trimmed Mean		1171.7923	
	Median		884.1800	
	Variance		28420262.231	
	Std. Deviation		5331.06577	
	Minimum		-588.76	
	Maximum		532779.46	
	Range		533368.22	
	Interquartile Range		1862.49	
	Skewness		61.501	.019
	Kurtosis		5784.599	.037

(Sean Borda, SPSS - IBM Corp., 2023)

Figure 5: Descriptive statistics

The use of descriptive analysis was an important first step in understanding the data and establishing an appropriate analytical approach. Had the data been normally distributed, parametric tests such as an independent samples t-test or ANOVA would have been used. However, due to the significant deviation from normality observed by the Kolmogorov-Smirnov test, non-parametric alternatives such as the Mann-Whitney U test and Kruskal-Wallis test were used.

4.4 Findings

This section presents the findings of the statistical analyses explained in the previous section. The analysis undertaken was to examine the relationship between the professional classification variable (used as a proxy for educational attainment) and claim amount, blame attribution, and injury presence. An additional analysis also explored whether vehicle value and cover type resulted in any difference in claim amounts between the different professional classifications.

4.4.1 - Descriptive statistics

Figure 2 shows the characteristics of the distribution of claim amounts. The figure shows the results of descriptive statistics. This was informative since it allowed the researcher to understand the shape of the distribution and decide upon an appropriate analysis approach. The mean claim amount was €1,637.14, while the median was €884.18. The notable disparity between the mean and median provided an early indication of substantial positive skew, reflecting the influence of a small number of very large claims that pulled the mean to the right. The standard deviation was €5,331.07, indicating wide dispersion in claim amounts. Skewness and kurtosis were observed to be at 61.50 and 5784.80, respectively. Both values significantly exceed thresholds indicative of normal distribution (typically ±2 for skewness, and ±7 for kurtosis). Thus, these statistics confirmed the presence of extreme asymmetry and heavy tails within the dataset.

The minimum claim amount was -€ 588.76, likely due to recoveries, while the maximum claim amount was € 532,779.46. The wide range further reinforced the non-normal nature of the distribution. The Kolmogorov-Smirnov test was performed to test whether the claim amount data conformed to a normal distribution. Figure 1 shows the test statistic result of 0.378 with a significance value of less than 0.001, indicating a statistically significant deviation from normality. As a result, non-parametric tests were used in the subsequent analyses, since parametric tests would not have produced accurate results due to the sample's characteristics deviating significantly from a normal distribution.

4.4.2 - Claim amount by professional classification

The Mann-Whitney U test (results shown below in Figure 3) was applied to assess for differences in claim amounts among professional and non-professional groups. This test evaluates whether the distributions of two independent groups differ significantly by comparing the ranks of values rather than the values themselves. The U statistic reflects the number of instances where a value from one group ranks higher than one from the other. ‘P’ or the ‘asymptotic significance’ indicates the probability of obtaining a test statistic at least as extreme as the one observed, assuming the null hypothesis is true. In this case, the 'U' result was 33,177,215.5, and 'p' was 0.009. Such results indicate a statistically significant difference between the populations. From descriptive statistics shown in Figure 4, it was observed that the professional population had a higher mean claim amount of €1,753 with a standard deviation of €4207. Conversely, the non-professional population had a mean claim amount of €1573.55 with a standard deviation of €5847.26. While the difference in mean claim amount is substantial, the large variance in claim amounts observed in the non-professional population suggests that the practical significance of this difference may be limited.

Claim Amount

Professional Status	Mean	N	Std. Deviation
Professional	1753.2267	6054	4207.13134
Non-Professional	1574.554	11230	5847.25573
Total	1637.137	17284	5331.06577

Total N	17284
Mann-Whitney U	33177215.5
Wilcoxon W	96239280.5
Test Statistic	33177215.5
Standard Error	311743.987
Standardized Test Statistic	-2.618
Asymptotic Sig.(2-sided test)	0.009

(Sean Borda, SPSS - *IBM Corp., 2023)*

Figures 6 and 7: Mann-Whitney and Kruskal-Wallis output

Further analysis using the Kruskal-Wallis test was done to test differences in claim amounts across combinations of occupational status and blame groups. The purpose of this test is to determine whether multiple independent groups come from the same distribution. Six groups were created: three for the professional category, own insured to blame, third party to blame, and both to blame, and three for the non-professional category with corresponding blame categories. The test revealed a statistically significant difference between groups with an 'H' or 'test statistic' of 6,242.37, 5 degrees of freedom, and a 'p' or 'asymptotic significance' of < 0.001. Mean claim amounts ranged from €2,415.02 for professionals at fault to €576.88 for non-professionals not at fault. Pairwise comparisons confirmed that most group differences were statistically significant, particularly between at-fault and non-fault groups within both occupational categories.

4.4.3 - Blame attribution and professional classification

Descriptive statistics were used to determine the distribution of blame attribution. 63.6% of claims were attributed to the insured driver, 35.2% were attributed to the third parties, and 1.2% involved shared blame. A chi-square test was conducted to reveal associations between occupational status and blame attribution. The purpose of a chi-square test is to determine whether two categorical variables, in this case, blame attribution and professional classification, are related or independent of each other. A larger χ^2 indicates a greater difference between the observed and expected counts, ie, a statistically significant association.

Thus, a test statistic of 9.839 indicates that the observed frequencies differ from the frequencies expected if independence is assumed. The degrees of freedom relate to the number of categories in each variable; in this case, 2 degrees of freedom, using the following formula: $df = (rows - 1)(columns - 1)$. The p-value is the probability of obtaining a test statistic as large or larger than the one calculated if there is no relationship between variables. It indicates the probability of observing a test statistic as extreme as the one calculated, assuming that the null hypothesis is true (i.e. that blame attribution and professional classification are independent). A p-value of 0.007 ($p < 0.05$) indicates a statistically significant association between occupational classification and blame attribution.

4.4.4 - Injury presence and occupational status

Injury-related claims were relatively rare in the dataset, representing only 1.1% of all claims. When analysed by professional status, only 0.9% of claims from professionals involved injury, compared to 1.2% for non-professionals. While the difference appears small in absolute terms, a chi-square test revealed that the difference between professional status and injury presence was statistically significant.

The purpose of this test is to determine whether or not there is an association between two categorical variables. This is done by comparing frequencies in each category combination with the frequencies that would be expected if the variables were independent. In other words, it compares the observed frequencies with those expected under the assumption of independence between variables.

The result of the test was a chi-square statistic of 4.129 with 1 degree of freedom. The degrees of freedom represent the number of independent comparisons that can be made. In this case, since the variables are binary, the degree of freedom was 1. The p-value result was 0.042, which is below the common alpha threshold of 0.05. This value represents the probability of observing a chi-square statistic as extreme or more extreme than the one calculated from the data if the null hypothesis is true. The null hypothesis is that the two variables are independent. As a result, the null hypothesis is rejected, meaning that there is a statistically significant association between occupational status and injury presence.

4.4.5 - Cover type and professional classification

A crosstab analysis was used to summarise and examine the relationship between cover type and professional classification. This type of analysis is often used to display the frequency distribution of the two categorical variables in the form of a matrix. This allows the relationship of the variables to be examined and analysed. Such a test is used in preparation for a chi-square test to determine whether an association between the variables exists, as was done in the previous analysis. The crosstabs analysis showed that professionals were significantly more likely to have comprehensive cover (81.9% vs. 76.1% for non-professionals). In contrast, non-professionals were more likely to hold third-party or third-party fire and theft policies. A chi-square test was conducted to examine potential associations between occupational status and cover type. The result of the chi-square test was ($\chi^2 = 94.046$, $df = 2$, $p < 0.001$). This indicated statistical significance. In other words, cover type and occupational status were not independent.

4.4.6 Vehicle Value by Professional Classification

A Mann-Whitney U test was done to assess whether professionals drove higher-value vehicles when compared to non-professionals. This test compares the rank values in two independent groups rather than their raw values. This means that rather than comparing the raw data individually, the vehicles were ranked by means of vehicle value. These ranks are then compared between the professional and non-professional classifications. The U statistic is based on the number of times values from one group rank higher than values from the other group. A small U value typically suggests more differences between groups. However, given the size of this data set, the mean ranks need to be analysed to provide the full picture of the analysis. The mean ranks were 8300 for professionals and 6847 for non-professionals, meaning that vehicle value was generally higher among professionals since they ranked higher in the rankings. Lastly, the p-value of 0.001 means that the probability of observing such a difference in rankings purely out of luck is small. Thus, this resulted in a statistically significant difference, meaning that professionals tended to drive higher-value vehicles.

4.4.7 Claim Amount by Profession within Cover Types

To further investigate whether the difference in claim amounts between professionals and non-professionals was influenced by the type of insurance cover held, three separate Mann-Whitney U tests were conducted for each category type. This was done to target specific groups of policyholders and their cover types.

The first test was done with a comprehensive cover. A statistically significant difference in claim amounts was found between occupational groups, with a higher mean rank for professionals (6926 vs 6655). The U statistic was 20344980.5 with a p-value of less than 0.001. This suggests that professionals with comprehensive cover tend to file higher-value claims than their non-professional counterparts. The tests for third-party and third-party fire and theft cover showed no statistically significant differences between the two groups. These results indicate that the difference in claim amounts between professionals and non-professionals was limited to those holding comprehensive cover. Other levels of cover had similar claim amount distributions between professional classifications.

4.4.8 Correlation Between Vehicle Value and Claim Amount

To explore whether the value of the vehicle influenced the amount claimed, a Spearman's rank-order correlation was conducted between vehicle value (sum insured) and claim amount. Spearman's correlation is a non-parametric measure of association that evaluates the strength and direction of a monotonic relationship between two continuous or ordinal variables. It is particularly appropriate when the data are not normally distributed, as was the case here.

The test produced a correlation coefficient (rho) of 0.006, with a p-value of 0.434. The correlation coefficient ranges from -1 to +1, where values close to ±1 indicate a strong relationship, while values near 0 indicate no association. A rho of 0.006 suggests an extremely weak, almost nonexistent relationship between the two variables. The p-value further indicates that this result is not statistically significant. The non-significant p-value provides insufficient evidence to reject the null hypothesis of no association.

This finding implies that higher vehicle values do not correspond to higher claim amounts, at least not in a consistent or predictable way. Thus, vehicle value does not consistently predict claim amount. Despite professionals tending to drive higher-value vehicles, this does not appear to account for their higher average claim costs. Therefore, other factors—potentially behavioural or circumstantial—may be influencing the differences in claim amounts between occupational groups.

4.4.9 - Summary of findings

The findings above clearly show that the professional classification had higher mean claim amounts. An initial interpretation of this finding suggested it might be explained by a tendency to drive higher-value vehicles and a higher likelihood of having comprehensive cover. While it was statistically true that the professional group had higher-value vehicles and more comprehensive coverage, the results from the Chi-square and Mann-Whitney tests were not sufficient to account for the higher claim amounts observed. The difference in claim amount between professional and non-professional claimants was evident when assessing comprehensive cover; however, no statistically significant difference was observed concerning third-party or third-party fire and theft coverage. Furthermore, vehicle value was not meaningfully correlated with claim amount.

In summary, the analyses revealed several statistically significant relationships between occupational status, claim amount, blame attribution, and injury presence. Professionals were more likely to purchase comprehensive cover and drive higher-value vehicles. Claim amounts were also higher for professionals; however, this difference was not explained by higher vehicle values. Blame attribution and injury presence showed some statistically significant associations with professional status. These findings set the stage for a deeper interpretation of the results, their implications, and the potential factors that may underlie the observed patterns, as discussed in the following section.

4.5 Interpretation of results

The primary objective of this study was to investigate whether occupational status, used as a proxy for educational attainment, is associated with indicators of driving behaviour, as reflected in motor insurance claims data. Claim amount, blame attribution, and injury presence were used as proxies for driving behaviour, while vehicle value (sum insured) and level of cover were examined as possible explanatory factors for any observed occupational differences. These results provide important insights into the relationships between these variables and bring to light important considerations regarding the use of socioeconomic proxies in insurance risk assessment.

The analysis revealed that professionals had higher mean claim amounts compared to non-professionals. While this difference was statistically significant, the absolute difference in mean claim amounts between the two groups was quite modest when the high variance and skewness were taken into consideration. It was evident that the distribution of claim amounts was heavily influenced by a small number of very large claims, as evidenced by the extreme skewness and kurtosis values. This means that while professionals on average had higher claim amounts, the median claim cost and spread of claims values suggest that the difference in risk profile may not be as pronounced as the means alone might suggest. In other words, the major outliers in claims have a major impact on the averages. Relying solely on the mean claim amount could lead to misleading results. The use of median and spread of claims costs serves as a way to mitigate the large impact of the outliers on the mean claim cost.

When claim amounts were examined within specific insurance cover types, a clearer picture emerged. The higher claim amounts among professionals were found predominantly in comprehensive cover policies. For third-party and third-party fire and theft (TPFT) policies, there was no significant difference in claim amounts between professional and non-professional drivers. This finding suggests the possibility that the relationship between occupational status and claim amount is influenced by the type of insurance product selected. Therefore, there might be external factors foreign to the professional category that may influence the rationale behind choosing one level of cover over another. The higher mean claim costs for professionals may reflect the nature of the claims under comprehensive policies, often including own damage cover, rather than the inherent differences in driving behaviour or risk propensity.

Further analysis examined if vehicle value was a factor in professional classification and claim amounts, ie, why professionals had a higher mean claim amount compared to non-professionals. Professionals were more likely to drive higher-value vehicles, as was shown by the claims data. This makes sense with the idea that professionals likely have greater disposable income or preferences for more expensive vehicles. Despite this logic, the correlation between vehicle value and claims amount, while present, was negligible. Regression analysis also confirmed that vehicle value was not a substantial predictor of claims cost. Moreover, when both vehicle value and occupational status were included in the regression model (with log-transformed claim amount as the dependent variable), neither emerged as a meaningful predictor, and the model as a whole explained only a tiny fraction of the variance in claim costs ($R^2 = 0.001$). This indicates that neither occupation nor vehicle value, at least in isolation, is sufficient to account for differences in claim outcomes.

In relation to blame attribution, the findings showed that professionals were slightly less likely to be deemed at fault compared to non-professionals. Although this difference was statistically significant, the absolute difference was small (around two percentage points) and therefore unlikely to represent a meaningful difference in driving behaviour. A similar pattern was observed for injury presence: while non-professionals were slightly more likely to have injury-related claims, the difference in proportions was minimal, and the low overall injury rate suggests that occupational status is not a strong determinant of injury risk in motor claims.

Collectively, these results suggest that occupational status, while associated with certain policyholder characteristics (such as cover type and vehicle value), does not provide substantial explanatory power in relation to claim outcomes once these factors are accounted for. The tendency for professionals to have higher claim amounts within comprehensive cover may reflect differences in claims reporting behaviour, the types of incidents leading to claims, or even variations in repair and replacement costs that are not directly tied to vehicle value. It is possible that external factors not considered in this study, such as geographical location, driving areas (such as commuting patterns or general errand routes, or annual mileage, play a role in claims amount and frequency.

An important implication of these findings is that occupation acting as a proxy for educational attainment may have limited utility as a standalone predictor of insurance claims risk. While this variable may capture some underlying socio-economic differences that correlate with certain behaviours or preferences, its ability to meaningfully predict claims outcomes appears constrained in this context. Given the legal scrutiny around indirect discrimination and the need for risk models to accurately reflect actual variations in risk exposure, there are potential concerns for insurers regarding the fairness and predictive validity of using occupation as a rating factor. This is particularly important under EU and UK regulations, where socio-economic variables are likely to be scrutinised for fairness.

These results underscore just how complex insurance risk modelling can be and highlight the importance of having richer, more detailed datasets to truly grasp what drives claim costs. Incorporating information on exposure factors—such as how far people drive, the kinds of journeys they take, or the conditions under which they typically drive—would allow insurers to build more accurate risk models. In addition, data drawn from behavioural sources like telematics could significantly sharpen predictions of claim outcomes. It's also worth considering that qualitative aspects—such as drivers' attitudes towards making claims, their preferences when it comes to repairs, or what they expect in terms of service—might shape claim costs. These factors are likely to vary across different socio-economic groups.

In summary, while this study did find some links between occupational status and how claims play out, the differences were generally small and couldn't be accounted for simply by looking at the value of the vehicle or the level of cover. This suggests that other factors outside of this study are at play and have an influence on the cost of claims. Overall, the findings highlight the limitations of using education proxies like occupation in isolation for insurance risk assessment and underscore the value of richer behavioural and exposure data.

Chapter 5 - Conclusion

5.1 - Summary of Key Findings

This study aimed to examine whether occupational status, used as a proxy for educational attainment, was associated with motor insurance claim outcomes. The chosen indicators of driving behaviour were claim amount, blame attribution, and injury presence. Apart from these variables, the study also explored whether the relationships observed between professional status and claims outcome were due to differences in vehicle value and level of insurance cover. The analysis was based on anonymised claims data obtained from local motor insurers. This data was analysed using a variety of non-parametric methods due to the characteristics of the claim amount and vehicle value distributions.

<u>Claim amount and occupational status</u>

A key finding was that professionals exhibited higher average claim amounts compared to non-professionals. This difference was identified using the Mann-Whitney U test ($U = 33{,}177{,}215.5$, $p = 0.009$). This result indicates a statistically significant difference between statistically significant difference in mean claim amounts of the professional population compared to the non-professional population. The observed discrepancy is relatively modest when observed in absolute terms. The mean claim amount for the professional population was €1,753.23, while the non-professional population had a mean claim amount of €1,573.55. It was evident that the mean differences were heavily influenced by a small number of very large claims. This is evidenced by examining the standard deviations and skewness of the claims data. As such, the practical significance of this observed difference in claim amounts between the two groups is somewhat limited.

Analysis of claim amounts within specific insurance cover types revealed clear patterns. The higher claim amounts among professionals were primarily observed within comprehensive cover policies. Among policyholders with third-party or third-party fire and theft (TPFT) cover, there was no statistically significant difference in claim amounts between professionals and non-professionals. This suggested that the differences identified between occupation and claims cost were linked to cover type. Interestingly, an analysis of the relationship between professional classification and cover type revealed a statistically significant correlation between the two. The professional population was significantly more likely to opt for comprehensive cover over TPFT and TP options compared to the non-professional population (81.9% vs. 76.1%). This, combined with the wider coverage and therefore, higher claims cost offered by comprehensive policies, justifies this relationship.

Blame attribution and injury presence.

The study also examined the relationship between blame attribution and professional classification. Overall, 63.6% of claims were attributed to the insured driver, 35.2% to the third party, and 1.2% involved shared blame. A chi-square test revealed a statistically significant association between occupational status and blame attribution ($\chi^2 = 9.839$, df = 2, $p = 0.007$). This revealed that the professional classification drivers were less likely to be found at fault than non-professional classification drivers. 62.2% of professionals were deemed to be at fault, while 64.4% of non-professionals were deemed to be at fault. This difference was found to be statistically significant using a chi-square test. While the difference is quite small in this sample, this could be even more significant when the entire population is considered. A similar outcome was discovered for injury-related claims, with professionals having fewer injury-related claims (0.9%) compared to non-professionals (1.2%). Once again, the difference may seem small; however, it was observed to be statistically significant ($\chi^2 = 4.129$, df = 1, $p = 0.042$) and may be even more significant in the context of the entire population.

Vehicle value, cover type, and their explanatory power

As previously stated, professionals were significantly more likely to hold comprehensive cover. It was also discovered that they drove higher-value vehicles, as indicated by the sums insured. A Mann-Whitney U test confirmed that vehicles owned by professionals had significantly higher insured values ($U = 18,702,043.5$, $p < 0.001$). However, no significant correlation was found between vehicle value and claim amount (Spearman's rho = 0.006, $p = 0.434$).

5.2 - Implications

The findings of this study have several important implications for insurers, risk modelling, and the use of occupational status as a factor in insurance underwriting. Occupational status was associated with certain policyholder choices, such as the selection of cover type and vehicle value. Professional classification was found to be statistically significant in relation to injury claims and blame attribution. However, professional classification was found not to be a meaningful predictor of claim amount.

For insurers, the result highlights the limitations of relying on socio-economic proxies like occupation to differentiate risk. The use of the level of educational attainment directly may alleviate some of the limitations and distortions brought about by the inaccuracies of using proxies. The differences observed in the claim amounts between professionals and non-professionals appeared to be driven more by cover type than intrinsic differences in risk behaviour. These findings support a move towards more data-driven approaches that focus on direct indicators of risk, such as telematics data, driving behaviour, commuting patterns, and annual mileage.

From a risk modelling perspective, these results illustrate the importance of incorporating a rich set of variables when assessing driver risk. The combination of telematics data and socioeconomic factors may allow for better relationships and comparisons to be drawn.

5.3 - Limitations

While this study provided valuable insights into the relationship between occupational status and insurance claim outcomes, several limitations must be acknowledged. Consideration of these limitations is crucial when interpreting the findings and drawing broader conclusions about the role of occupational status in motor insurance risk.

<u>Measurement of educational attainment</u>

The most significant limitation is the use of occupational status as a proxy for educational attainment and socioeconomic status. Insurers do not ask for information such as the level of education; therefore, such a proxy was employed. Unfortunately, it is not a perfect measure and may not fully capture the complexities of an individual's socioeconomic position or associated risk factors.

<u>Available data</u>

Insurers either don't have access to data such as annual mileage, commuting distance and patterns, or driving behaviour. The absence of such variables somewhat limits the ability to control for confounding variables and makes it difficult to isolate the impact of professional classification on claim outcomes. Driving behaviour could only be approximated through proxies such as claim amount, blame attribution, and injury presence. It may not fully capture the nuances of an individual's socioeconomic position or driving behaviour.

5.4 Recommendations for future research

The results of this study suggest several potential directions for future research in the field of motor insurance and driver risk analysis. First, future studies should seek access to more robust datasets that include behavioural variables such as annual mileage, commuting patterns, vehicle usage, and telematics data. Having access to such data would provide a more accurate and comprehensive understanding of risk factors.

The use of longitudinal data would allow researchers to track changes in policyholder behaviour and claim outcomes over time. This would enable a better understanding of how changes in socioeconomic factors such as employment, vehicle ownership, and driving patterns evolve in changing economic and sociological conditions.

5.5 Final Conclusion

In conclusion, this study found that while occupational status correlates with certain insurance-related choices, namely, cover type and vehicle value, it does not serve as a sufficient predictor of actual claim behaviour. Crucially, these findings support an industry-wide shift towards personalised, data-driven risk models that prioritise real-world behaviour over the traditional socio-demographic approximations. This shift is underscored by the popularity of telematics technology, enhancing pricing fairness, improving risk prediction, and better aligning premiums with true driving behaviour.

The purpose of this study was to explore whether a person's level of educational attainment, in this case proxied by occupation, had an impact on driving behaviour and insurance claims. Using anonymised claims data from Maltese insurers, occupations were split into 'professional' and 'non-professional' classifications. They were then assessed for differences in the size of claims, who was at fault, and whether there were injuries involved.

Interestingly, professionals tended to have higher claim amounts and were more likely to hold comprehensive insurance policies. They also drove higher-value vehicles. However, occupational classification was found not to be a reliable predictor of risk. This means that while occupation may be linked to certain choices that drivers make, such as the type of cover they buy, it may not be linked to driving behaviour.

These findings highlight the move forward towards detailed and personalised premiums and data, which tells us how individuals behave rather than who they are on paper. This is accelerated through the rapid advancements in technology, with telematics becoming increasingly nuanced. As the industry continues to embrace data-driven information, findings such as these reinforce the importance of aligning pricing models with real-world behaviour, fairness, and transparency.

References

- Barsky, R.B., Juster, F.T., Kimball, M.S. and Shapiro, M.D., 1997. Preference parameters and behavioural heterogeneity: An experimental approach in the Health and Retirement Study. Quarterly Journal of Economics, 112(2), pp.537–579.
- Bourdieu, P., 1986. The forms of capital. In: J. Richardson, ed. Handbook of Theory and Research for the Sociology of Education. New York: Greenwood Press, pp.241–258.
- Cutler, D.M. and Lleras-Muney, A., 2010. Understanding differences in health behaviors by education. Journal of Health Economics, 29(1), pp.1–28.
- Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J. and Wagner, G.G., 2011. Individual risk attitudes: Measurement, determinants, and behavioral consequences. Journal of the European Economic Association, 9(3), pp.522–550.
- Kahneman, D. and Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica, 47(2), pp.263–291.
- Le Fur, E. and Outreville, J.F., 2022. Financial literacy, education and risk aversion: A survey of French students. Managerial Finance, 48(9/10), pp.1530–1543.
- Sivak, M., Schoettle, B. and Kelley, D.H., 2007. Driver characteristics associated with fatality risk per vehicle crash. UMTRI Research Review, 38(5), pp.1–3. [online] University of Michigan Transportation Research Institute. Available at: https://deepblue.lib.umich.edu
- O'Donoghue, T. and Somerville, J., 2018. Modeling Risk Aversion in Economics. [online] Available at: https://people.orie.cornell.edu/tdo1/RiskAversionModeling.pdf
- ScienceDirect, 2014. Prospect Theory - an Overview. [online] Available at: https://www.sciencedirect.com/topics/neuroscience/prospect-theory
- Mansfield, E. and Yohe, G.W., 2000. Microeconomics: Theory, Applications. New York: W.W. Norton.
- Varian, H.R., 1993. Intermediate Microeconomics: A Modern Approach. 1st ed. New York: Norton.
- Slovic, P., 1987. Perception of risk. Science, 236(4799), pp.280–285.
- Von Neumann, J. and Morgenstern, O., 1944. Theory of Games and Economic Behavior. Princeton: Princeton University Press.

- Arrow, K.J., 2001. Uncertainty and the welfare economics of medical care. Journal of Health Politics, Policy and Law, 26(5), pp.851–883.
- van der Heijden, K., et al., 2020. A token as a ticket to smarter financial decision-making. Advances in Consumer Research, 48, pp.400–401.
- Peltzman, S., 1975. The effects of automobile safety regulation. The Journal of Political Economy, 83(4), pp.677–725.
- Peltzman, S., 1986. Accident risk and risk-taking behaviour among young drivers. Accident Analysis & Prevention, 18(4), pp.255–271.
- Rhodes, N. and Pivik, K., n.d. Age and gender differences in risky driving: The roles of positive affect and risk perception. Accident Analysis & Prevention, 43(3), pp.923–931.
- Fuller, R., n.d. Towards a general theory of driver behaviour. Accident Analysis & Prevention, 37(3), pp.461–472.
- Lonero, L. and Mayhew, D.R., 2010. Large-scale evaluation of driver education: Review of the literature on driver education evaluation 2010 update. Traffic Injury Research Foundation.
- Greaves, S.P. and Ellison, A.B., 2011. Personality, risk aversion and speeding: An empirical investigation. Accident Analysis & Prevention, 43(5), pp.1828–1836. https://doi.org/10.1016/j.aap.2011.04.018
- Obermeier, V. and Schneider, T., 2015. Educational choice and risk preferences: How important is relative vs. individual risk preference? [online] Available at: https://www.pedocs.de/volltexte/2015/11492/pdf/JERO_2015_2_Obermeier_Schneider_Educational_choice_and_risk.pdf
- Hu, Y., et al., 2024. Traffic violations and economic preferences: Evidence from full-time drivers of a large transportation network company in China. China Economic Review, 87, p.102255. [online] Available at: https://www.acem.sjtu.edu.cn/ueditor/jsp/upload/file/20240830/1725007456064025744.pdf
- Vaughn, M.G., et al., 2011. Sociodemographic, behavioral, and substance use correlates of reckless driving in the United States: Findings from a national sample. Journal of Psychiatric Research, 45(3), pp.347–353. https://doi.org/10.1016/j.jpsychires.2010.06.016

- Ma, M., et al., 2010. Safety of public transportation occupational drivers: Risk perception, attitudes, and driving behavior. Transportation Research Record, 2145(1), pp.72–79. https://doi.org/10.3141/2145-09
- Danciu, B., et al., 2012. Psychological risk factors for road safety. Procedia - Social and Behavioral Sciences, 33, pp.363–367. https://doi.org/10.1016/j.sbspro.2012.01.144
- Abdul Aziz Sabri, A., 2015. Awareness and education are the most significant elements for safe driving behavior and better life quality. Journal of Local and Global Health Science, 2015(2). https://doi.org/10.5339/jlghs.2015.itma.1
- Simply Psychology, 2024. Impression Management: Erving Goffman Theory. [online] Available at: https://www.simplypsychology.org/impression-management.html
- Hartlaub, V. and Schneider, T., 2012. Educational choice and risk aversion: How important is structural vs. individual risk aversion? ResearchGate. [online] Available at: https://www.researchgate.net/publication/254405986_Educational_Choice_and_Risk_Aversion_How_Important_Is_Structural_vs_Individual_Risk_Aversion
- Kahneman, D., Knetsch, J.L. and Thaler, R.H., 1990. Experimental tests of the endowment effect and the Coase theorem. Journal of Political Economy, 98(6), pp.1325–1348. https://doi.org/10.1086/261737
- Karakuş, İ., 2024. University students' cognitive flexibility and critical thinking dispositions. Frontiers in Psychology, 15. https://doi.org/10.3389/fpsyg.2024.1420272
- Wang, Y., Qu, W., Ge, Y., Sun, X. and Zhang, K. (2018). Effect of personality traits on driving style: Psychometric adaption of the multidimensional driving style inventory in a Chinese sample. *PLOS ONE*, 13(9), p.e0202126. doi:https://doi.org/10.1371/journal.pone.0202126.
- Robst, J. (2007). Education and job match: The relatedness of college major and work. Economics of Education Review, [online] 26(4), pp.397–407. doi:https://doi.org/10.1016/j.econedurev.2006.08.003.
- Sciencedirect.com. (2014). *Prospect Theory - an overview | ScienceDirect Topics*. [online] Available at: https://www.sciencedirect.com/topics/neuroscience/prospect-theory.
- Peter Philips. Researchgate.com. (2021). A Regular Shaped Concave Utility Function. [online]

https://www.researchgate.net/figure/A-Regular-Shaped-Concave-Utility-Function_fig1_349515129

- MFSA (2025) *Motor Insurance*. Malta Financial Services Authority. Available at: https://www.mfsa.mt/service-detail/motor-insurance/
- legislation.mt. (n.d.). *LEĠIŻLAZZJONI MALTA*. [online] Available at: https://legislation.mt/eli/cap/104/eng/pdf.
- Espinoza, I. and Johnston, A. (2025). *The Luminaries Interview Series: How InsurTech, AI and Modern Telematics are Revolutionizing Motor Insurance Practices*. [online] Ajg.com. Available at: https://www.ajg.com/gallagherre/news-and-insights/the-luminaries-interview-series-insurtech-ai-and-how-modern-telematics-are-revolutionizing-motor-insurance/
- Kouabenan, Dongo Rémi. "Occupation, Driving Experience, and Risk and Accident Perception." *Journal of Risk Research*, vol. 5, no. 1, Jan. 2002, pp. 49–68, https://doi.org/10.1080/13669870110036577.
- Deary, I. J., and W. Johnson. "Intelligence and Education: Causal Perceptions Drive Analytic Processes and Therefore Conclusions." *International Journal of Epidemiology*, vol. 39, no. 5, 26 May 2010, pp. 1362–1369, https://doi.org/10.1093/ije/dyq072.
- Koekemoer, Zandri. "The Influence of the Level of Education on Investors Risk Tolerance Level." *Ideas.repec.org*, 1 Oct. 2019, ideas.repec.org/p/sek/iefpro/9511449.html
- Law, Advocate. "Does Education Level Impact Accident Rates?" *Advocate Law Firm Professional Law Corporation*, 13 May 2022, www.advocatelawfirm.org/blog/2022/05/does-education-level-impact-accident-rates/.
- migliore, sharon. "Road Traffic Accidents: Q4/2023 - NSO Malta." *NSO Malta*, 14 Feb. 2024, nso.gov.mt/road-traffic-accidents-q4-2023 /.
- Steinberg, L. "APA PsycNet." *Apa.org*, 2025, psycnet.apa.org/record/2011-27217-003.
- Stephens, Mobolaji S., and Wilfred I. Ukpere. "Accidents and Level of Intelligence: A View from the Nigerian Experience." *Journal of Human Ecology*, vol. 35, no. 2, Aug. 2011, pp. 75–84, https://doi.org/10.1080/09709274.2011.11906393.
- Topolšek, Darja, et al. "The Effect of Road Safety Education on the Relationship between Driver's Errors, Violations and Accidents: Slovenian Case Study." *European Transport*

Research Review, vol. 11, no. 1, 12 Mar. 2019, https://doi.org/10.1186/s12544-019-0351-y.

- Williams, A.F. "Williams, A.F. (2003) Teenage Drivers Patterns of Risk. Journal of Safety Research, 34, 5-15. - References - Scientific Research Publishing." *Scirp.org*, 2015, www.scirp.org/reference/referencespapers?referenceid=1384057.
- Borrell, C., Plasència, A., Huisman, M., Costa, G., Kunst, A., Andersen, O., Bopp, M., Borgan, J., Deboosere, P., Glickman, M., Gadeyne, S., Minder, C., Regidor, E., Spadea, T., Valkonen, T. & Mackenbach, J.P. 2005, "Education level inequalities and transportation injury mortality in the middle aged and elderly in European settings", Injury Prevention, vol. 11, no. 3, pp. 138.
- Abay, K.A. and Mannering, F.L. (2016). An empirical analysis of risk-taking in car driving and other aspects of life. *Accident Analysis & Prevention*, 97, pp.57–68. doi:https://doi.org/10.1016/j.aap.2016.08.022.
- Chung, E.K., Park, S.Y. and Sohn, Y.W. (2021). Effects of Occupational Drivers' Traffic Accident History on Risk Perception, Work Attitudes, and Unstable Driving. *Transportation Research Record: Journal of the Transportation Research Board*, 2675(10), pp.734–744. doi:https://doi.org/10.1177/03611981211012695.
- Hartog, J., Ferrer‐i‐Carbonell, A. and Jonker, N. (2002). Linking Measured Risk Aversion to Individual Characteristics. *Kyklos*, 55(1), pp.3–26. doi:https://doi.org/10.1111/1467-6435.00175.
- Kouabenan, D.R. (2002). Occupation, driving experience, and risk and accident perception. *Journal of Risk Research*, 5(1), pp.49–68. doi:https://doi.org/10.1080/13669870110036577.
- Piccardi, L., Palmiero, M., Guariglia, P., Dacquino, C., Pierluigi Cordellieri and Anna Maria Giannini (2021). Is the Risk Behaviour Related to the Ordinary Driving Violations? *Psychological Studies*, 66(1), pp.26–35. doi:https://doi.org/10.1007/s12646-020-00593-5.
- Sümer, N. (2003). Personality and behavioral predictors of traffic accidents: testing a contextual mediated model. *Accident Analysis & Prevention*, 35(6), pp.949–964. doi:https://doi.org/10.1016/s0001-4575(02)00103-3.

- Harris, C. and Wu, C. (2014). Using tri-reference point theory to evaluate risk attitude and the effects of financial incentives in a gamified crowdsourcing task. *Journal of Business Economics*, 84(3), pp.281–302. doi:https://doi.org/10.1007/s11573-014-0718-4.