Summary

Road traffic crashes consist one of the major problems of modern society worldwide and are the **leading cause of death** for individuals aged 5-29. Several factors have a significant impact on road safety. These factors can contribute to the occurrence of road crashes and influence the severity of injuries sustained.

Human behaviour plays a critical role in road safety, accounting for 65-95% of road crashes. Factors such as speeding, distracted driving, impaired or aggressive driving, and non-compliance with traffic regulations can increase the crash risk. In addition, socioeconomic factors, such as income level, education, and access to transportation resources, can indirectly influence road safety. Moreover, the condition and safety features of vehicles also play a critical role in averting crashes and reducing the likelihood of serious. Furthermore, environmental conditions can affect road safety. Factors such as adverse weather conditions, poor visibility, and uneven road surfaces can increase the likelihood of crashes.

This research constitutes **a holistic approach to improve driver safety tolerance zone** through the analysis of road, vehicle and behavioural risk factors. Within the above framework, the aim of the current PhD thesis was to identify the interactions among road, vehicle and driver risk factors for the identification of the Safety Tolerance Zone (STZ). More specifically, the impact of task complexity and coping capacity on crash risk was investigated. Coping capacity was examined in terms of both vehicle and driver state factors.

In order to fulfill these objectives of this PhD dissertation, data from an **on-road and simulator experiment** were exploited, involving a total of 190 drivers. Safety-oriented interventions were developed to prevent drivers from approaching the boundaries of unsafe operation and to guide them back into the STZ. These interventions included both real-time interventions (i.e. in-vehicle while traveling) and post-trip feedback (i.e. aimed at enhancing knowledge, attitudes, perceptions and driving style).

Towards that end, a holistic approach was implemented and an advanced methodology was developed, consisting of **four discrete steps**:

The **first step** concerned the selection of all risk factors for the analysis. This selection exploited the findings of the literature review from environment-vehicle-driver aspects on crash risk. Based on this literature review and in order to meet the PhD thesis objectives, critical parameters and risk factors of task complexity and coping capacity were included.

The **second step** involved the exploitation of data from an on-road and driving simulator experiment, with the largest part of the methodology development consisting of data handling, mining and aggregation. Several aspects were taken into consideration, including the large and representative sample, inclusion criteria, legal and ethical issues,

randomization of trials, adequate practice drives, and data mining, handling, storage, aggregation and cleaning. In this context, data from 190 participants of all age groups from both on-road and simulator experiments were utilized. Following the driving trials, participants filled in a specifically designed questionnaire covering aspects related to their driving habits, attitudes and socio-demographic characteristics.

With regards to the on-road experiment, the **field trials were structured into four phases**, with a total duration of 4 months. Phase 1 served as a reference period where driving behaviour was monitored without any interventions. Phase 2 involved a period of monitoring where only real-time warnings from Advanced Driver Assistance Systems (ADAS) were provided inside the vehicle. In phase 3, these in-vehicle warnings were supplemented with feedback delivered via a smartphone app, while phase 4 introduced gamification features in the app, supported by a web dashboard.

As per the simulator experiment, the **simulator trials consisted of three phases**, with a total duration of 2 months. The experimental scenarios focused on speeding, headway and fatigue as a modifying condition. Risk factors were investigated through a series of risky events tested during the drive-1, drive-2, and drive-3 scenarios. In total, the trials consisted of three 15-minute drives, including a baseline monitoring scenario followed by two intervention scenarios, one with fixed timing warnings and one with variable timing warnings and the inclusion of a condition (i.e. fatigue).

The **third step** concerned the statistical and machine learning analyses. The large dataset collected from the on-road and simulator experiment as well as the relative questionnaires were analysed by means of an innovative methodology, based on the limitations and needs of analysis techniques which were extracted from the respective literature review. Two phases of the analysis methodology were implemented:

- The first phase concerned **statistical analysis** implemented for explanatory purposes to infer the relationships between variables and determine the significance of those relationships.

  Firstly, the development of the **descriptive analysis** allowed for a first understanding of the large number of parameters examined. More precisely, an overview of all risk factors provided by the on-road and driving simulator experiment was given, investigating the effect of specific driving characteristics of task complexity and coping capacity on crash risk.

  Secondly, regression analysis (e.g. **Generalized Linear Models**) was implemented regarding key performance parameters, such as speeding and headway. Such models were often used in driver behaviour analysis in order to examine the key correlations among observed metrics and identify the effect of task complexity and coping capacity on specific driving performance parameters. Explanatory variables of risk and the most reliable indicators of task complexity (e.g. time of the day, weather conditions), coping capacity - vehicle state (e.g. fuel type, vehicle age, gearbox) and coping capacity - driver state (e.g. speeding, headway, overtaking, fatigue, harsh events, forward collision or distraction) were assessed. GLMs are appropriate for the purpose of this PhD, as they provide a flexible framework for modelling relationships between multiple explanatory variables and driving performance outcomes (e.g. speeding/headway events). GLMs are particularly well-suited for handling non-normally distributed data, which is common in behavioural and traffic-related datasets, allowing for accurate examination of how task complexity and coping capacity affect key performance parameters, such as speeding and headway. Additionally, their ability to incorporate different link functions makes them ideal for analysing a wide range of response variables, ensuring robust and interpretable results.

Thirdly, latent analysis (e.g. **Structural Equation Models**) was performed in order to identify the effect between latent and observable variables of task complexity and coping capacity with complex relationships (i.e. crash risk). It should be mentioned that SEM constitutes the fundamental aspect of this PhD thesis as it can be used to explore how the model variables are inter-related, allowing for both direct and indirect relationships to be modelled. SEM analysis is the most widely used and appropriate for modelling complex and multi-layered relationships between observed (e.g. number of speeding and headway events) and unobserved variables (e.g. crash risk). It should be noted that observed variables are measurable, whereas unobserved variables are latent constructs. This type of analysis is designed to deal with several difficult modelling challenges, including cases in which some variables of interest are unobservable or latent and are measured using one or more exogenous variables. In the present analysis, task complexity, coping capacity and risk were the unobserved variables which were estimated from specific parameters. The main goal of this attempt was to estimate directly the effect of road, vehicle and driver risk factors for the STZ identification.

- In the second step, **machine learning analysis** was conducted for predictive purposes to make the most accurate and repeatable predictions possible.

Firstly, feature importance analysis (e.g. **XGBoost**) was implemented in order to evaluate the significance of various variables in forecasting STZ levels in terms of speeding and headway. This approach allowed for the selection of the most appropriate independent variables, ensuring that the most influential factors were identified and prioritized in the analysis.

Secondly, machine learning analysis (e.g. **Neural Networks**) was applied in order to make accurate and data-driven predictions by identifying complex patterns between task complexity and coping capacity on crash risk. Neural Networks are particularly appropriate due to their ability to model non-linear relationships and capture hidden patterns in high-dimensional data, offering superior predictive accuracy compared to traditional statistical methods. Their adaptability makes them ideal for understanding the complicated interactions between task complexity, coping capacity and crash risk, leading to more robust and data-driven insights.

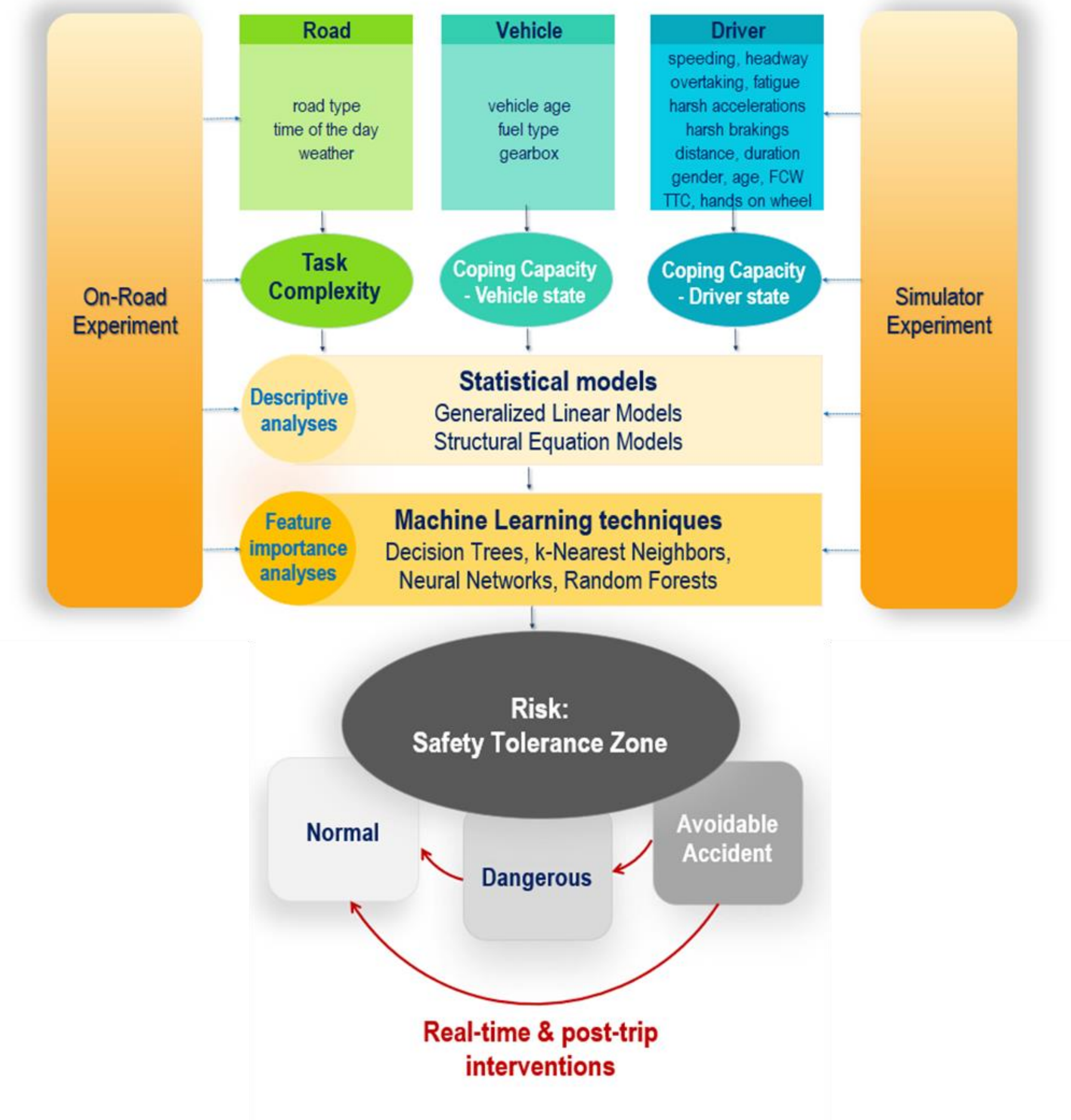
Thirdly, to achieve the objectives of this PhD, (i.e. the identification of STZ levels), three classification models were proposed due to their **strong performance and widespread use** in the literature for identifying unsafe driving behaviour, real-time collision prediction and other real-world challenges. The selected algorithms were Decision Trees (DT), k-Nearest Neighbors (kNN) and Random Forest (RF). The predictive nature of these models is emphasized by their ability to anticipate dangerous driving behaviours before they occur, utilizing real-time data to forecast the likelihood of speeding and headway events. The results were evaluated based on several metrics, such as accuracy, precision, recall, false alarm rate and F1-score.

In this PhD thesis, the aforementioned classifiers were selected to predict the three STZ levels. Firstly, Decision Trees were used due to their **simplicity and ability to handle categorical data**, such as vehicle features and road conditions. Secondly, Random Forests, being an ensemble method, provided enhanced stability and accuracy by aggregating multiple Decision Trees, which **mitigated overfitting and improved generalization to new data**. Thirdly, k-Nearest Neighbors were selected for their **proficiency in identifying non-linear relationships** that might be overlooked by tree-based methods. It should be noted that kNN is a non-parametric method that excels in capturing local patterns within the data, offering flexibility when predicting STZ levels in both on-road and simulator contexts, where relationships may vary. Together, these classifiers allowed for a robust comparison of performance and suitability across different driving environments.

In the **fourth step**, a conceptual framework for the identification of the Safety Tolerance Zone (STZ) is developed. According to this framework, the STZ is influenced by a combination of risk factors, including road, vehicle and driver. A direct consequence of crash risk is the alteration of STZ levels. This change in STZ levels is reflected in both task complexity and coping capacity, which includes both vehicle and driver state. To keep the driver within safe boundaries, real-time and post-trip interventions are implemented.

The concept of the STZ attempted to describe the point at which self-regulated control is considered safe. It is the zone where the demands of the driving task (task complexity) are balanced with the ability of the driver to cope with them (coping capacity). The **STZ comprises three phases**: normal driving, danger and avoidable accident phase. The normal driving refers to the phase where conditions at that point in time suggest that a crash is unlikely to occur and therefore the crash risk is low and the driver is successfully adjusting their behaviour to meet task demands. The danger phase is characterised by changes to the normal driving that suggest a crash may occur and therefore, there is an increased crash risk. At this stage a crash is not inevitable but becomes more likely. The STZ switches to the danger phase whenever instantaneous measurements detect changes that imply an increased crash risk. Lastly, the switch to avoidable accident phase occurs when a collision scenario is developing but there is still time for the driver to intervene in order to avoid the crash. In this phase, the need for action is more urgent as if there are no changes or corrections in the road or rail traffic system or an evasive manoeuvre is performed by the driver, a crash is very likely to occur.

The following Figure illustrates the conceptual framework of the current PhD thesis.



Within the framework of the statistical modelling, regression analysis was employed to examine the explanatory variables and their interactions within the driver-vehicle-environment framework. Interestingly, the GLMs applied revealed **consistent results across both experiments**, suggesting that despite the differing conditions, the fundamental relationships among the variables remained stable. This comparison highlighted the critical elements that influenced the outcomes and reliability of the analysis models, particularly indicators of task complexity and coping capacity, and their effect on crash risk, offering insights into their respective contributions to the STZ identification.

Through the application of SEM models, the analyses revealed that **task complexity was positively correlated with risk**, which means that as task complexity increases, the crash risk increases. Firstly, crucial indicators such as the time of day and weather conditions significantly affect crash risk. Driving during night-time or in adverse weather conditions, such as rain or fog can exacerbate the challenges posed by complex tasks, further increasing the likelihood of crashes. Secondly, drivers could become overwhelmed by the demands of complex tasks, leading to reduced attention to the road and other traffic participants. This can result in delayed detection of critical events and inadequate responses. Additionally, complex tasks may require drivers to allocate more mental resources, causing them to divert attention from essential driving activities. For instance, interacting with in-vehicle technology or navigation systems can increase cognitive workload and lead to decreased focus on the primary task of driving.

On the other hand, **coping capacity was negatively correlated with risk**, which means that as coping capacity increases, the crash risk decreases. This relationship can be explained by the fact that drivers with higher coping capacity are better equipped to handle complex and challenging driving situations. They can manage stress, make quicker and more accurate decisions and maintain better control over their vehicles, all of which contribute to safer driving. Consequently, their enhanced ability to cope with driving demands reduces the likelihood of crashes and other risky incidents, leading to a lower overall risk. Conversely, drivers with limited coping capacity may struggle to effectively manage complex tasks, leading to higher crash risk. Reduced coping capacity can manifest as slower reaction times, impaired judgment, and difficulties in prioritizing information. In situations where the demands of the driving task exceed a driver's coping capacity, there is an increased likelihood of errors, misjudgements, and collisions.

The latent analyses also demonstrated a **positive correlation of task complexity and coping capacity** which implied that drivers' coping capacity increased as the complexity of driving task increases. It was revealed that when drivers encountered complex tasks, such as driving during risky hours (22:00-05:00) or adverse weather conditions, they were compelled to engage more deeply with the driving process and tended to regulate well their capacity to react to potential difficulties, while driving. This heightened engagement fostered the development of advanced driving skills and strategies, enabling drivers to manage difficult situations more effectively. Consequently, the experience gained from handling complex tasks translated into improved overall driving competence and a greater ability to cope with unexpected challenges on the road.

The inter-relationship between task complexity and coping capacity significantly impacts driver's ability to remain within the STZ level. High task complexity, such as navigating through heavy traffic, adverse weather conditions or unfamiliar routes, demands increased cognitive resources, quick decision-making and heightened alertness. When drivers have a high coping capacity, they can manage these challenges more effectively, maintaining their actions within a safe tolerance zone. However, if the coping capacity is low, the driver may struggle to handle these complexities, leading to elevated stress and tension levels that push their actions outside the safety tolerance zone. Thus, the balance between task complexity and coping capacity is crucial in determining overall safety. High task complexity combined with low coping capacity **results in significantly higher risks**, as the driver is more likely to operate outside the STZ, potentially compromising driving performance and safety.

Safety interventions were evaluated in terms of their effectiveness in keeping the driver within safe boundaries (i.e. STZ) by monitoring and collecting data on driving behaviour. Findings from the current PhD thesis revealed that both real-time and post-trip **interventions positively influenced risk compensation**, increased drivers' coping capacity, and reduced dangerous driving behaviour. When safety interventions were introduced during different phases of the experiments, drivers improved their performance, became more aware and compliant with speed regulations, which led to a noticeable reduction in average speed, greater headways, and fewer harsh events. Additionally, drivers experienced fewer avoidable accident events and spent less time in dangerous phases.

Within the framework of the machine learning analysis, NNs proved to be the best approach for capturing complex relationships among various driving parameters and predicting the likelihood of potential risks or crashes. The results of predictive analyses revealed **high accuracy for the NN models** in both on-road and simulator experiments. Simulator experiments showed exceptional performance, especially in predicting STZ headway, with strong precision and recall, indicating the model's effectiveness in identifying positive samples and safety-critical classes. In contrast, the on-road experiments, while still robust, showed slightly lower accuracy due to the unpredictability and variability of real-world conditions. The models performed best in normal driving phases, likely because these conditions were more consistent and made up the majority of the training data. Moreover, normal driving features were more distinct and less ambiguous compared to risk conditions, reducing misclassification risks. Overall, both experiments demonstrated good model performance, but the controlled environment of simulator experiments allowed for higher accuracy and better predictive capability.

In the **on-road experiment** with regards to STZ speeding, the NN exhibited an overall accuracy of 80%. The precision rate of 82% and recall rate of 79.9% indicated a robust ability to identify positive samples and detect safety-critical classes (i.e. “dangerous” and “avoidable accident”) effectively. Regarding the on-road experiment with regards to STZ headway, similar trends were observed. In particular, the model was 81.7% accurate in making correct predictions.

In the **simulator experiment** with regards to STZ speeding, the NN exhibited an overall accuracy of 85.1%, with a precision of 83.9% and recall of 80.4%. These metrics illustrated the model's strong performance in predicting the normal phase but revealed challenges in accurately identifying the dangerous and avoidable accident phases. Despite this, the model maintained a balanced trade-off between precision, recall, and false alarm rates, indicating a well-rounded performance. The best results were found in the simulator experiment with regards to STZ headway. The overall model metrics were impressive, with an accuracy of 89.8%, precision of 91.2% and recall of 90.6%. These metrics indicated that the model is highly accurate in making correct predictions and excels in identifying positive samples. The model's ability to detect safety-critical classes effectively was also demonstrated by its high recall. This performance suggested a well-rounded and effective predictive capability for headway in the simulator environment.

In the context of machine learning analysis, the performance of three machine learning classifiers (i.e. DT, RF, kNN) across two distinct datasets (i.e. on-road experiment dataset and simulator experiment dataset) was thoroughly assessed in order to provide insights into the complex relationship between risk and the interdependence of task complexity and coping capacity. It is worth noting that these classification models were selected due to their **strong performance and widespread use** in the literature for identifying unsafe driving patterns and real-time risk prediction.

The evaluation of the three machine learning classifiers (DT, RF, kNN) revealed varying performance across the two datasets. In the **on-road experiment** for STZ speeding, RF achieved an adequate accuracy of 85.7% and a high precision (85.2%) and recall (89.8%) demonstrating a robust performance in classifying real-world driving behaviour. Moreover, the DT model also performed admirably with an accuracy of 83.2%, balancing precision (82.1%) and recall (87.7%) effectively. While the kNN showed a strong recall of 79.4%, indicating its ability to effectively capture true positive instances, it appeared to have the lowest accuracy (75.8%) and precision (73.6%) compared to RF and DT models. As per STZ headway, RF exhibited higher performance, leading in satisfactory accuracy (86.9%) and precision (88.7%), while showing competitive recall scores (90.7%). DT and kNN showed similar performance, though kNN tended to lag slightly behind in precision.

The results from the simulator were similar to those observed in the on-road experiment. In particular, in the **simulator experiment** for STZ speeding, RF maintained its strong performance with a high accuracy of 89.1%, balancing precision (90.8%) effectively, achieving a competitive recall (87.5%). The DT model also performed admirably with an accuracy of 85.2%, highlighting its capability in this simulator framework, balancing precision (85.3%) and recall (83.1%) effectively. Furthermore, the kNN model achieved a reasonable accuracy (81.5%) but had lower precision (78.3%) and recall (79.6%) compared to RF and DT. With regards to STZ headway, RF emerged as the top-performing model with an accuracy of 90.1%, demonstrating its ability to accurately classify driving behaviour in a controlled environment. Following the DT model which also performed well scoring a notable 87.1% accuracy. Regarding kNN model, they underperformed compared to the other two, displaying a lower weighted accuracy (85%) and recall (82.6%). Among the different algorithms, RF stranded out with the highest accuracy of 90% in STZ headway, indicating its ability to accurately classify driving behaviours in a controlled environment. RF also achieved a well-balanced precision (87.2%) and recall (84.1%), demonstrating its robustness and versatility.

In summary, the three algorithms had insightful results in terms of accuracy, precision and recall. The performance variations observed underscored the importance of selecting the right model based on data characteristics and precision-recall trade-offs, essential for real-world applications. Since, in the context of the current study, it was more dangerous to misidentify driving behaviour as less dangerous, the recall metric was the most significant metric to consider. Thus, evaluating the results of both approaches (i.e. on-road and simulator experiment), the RF model emerged as the most efficient one. Overall, the **RF model outperformed the DT and kNN** models across all metrics, making it the most effective for predicting headway. The DT model showed satisfactory performance, while the kNN model consistently had the lowest but moderate scores, indicating that it is the least effective for this task. These findings are essential for advancing the understanding of driving behaviour across various contexts, ultimately contributing to the development of safer and more efficient transportation systems.

Results demonstrated that while both on-road and simulator data provided valuable insights, **simulator experiments proved to be the most suitable for predicting STZ levels**. This is probably due to the fact that the controlled environment of the simulator allows for the manipulation of specific variables, which is difficult to achieve in naturalistic on-road settings. Without the validation and flexibility offered by simulators, relying solely on naturalistic data may lead to incomplete or less accurate conclusions, as real-world conditions are often unpredictable and harder to control for critical factors like task complexity and coping capacity. Therefore, simulator validation is essential for robust and reliable findings.

The relevant contributions of this work collectively represent a significant advancement in the field of road safety research, offering innovative methodologies and insights which has not been examined in the past. The innovative scientific outcomes of this PhD thesis consist of **five original scientific contributions**, as described below:

The first contribution of this research is the **comprehensive analysis of all risk factors,** including road environment, vehicle state and driver behaviour. This multifaceted examination includes an in-depth exploration of how these elements interact and affect road safety. By doing so, it addresses the complex interplay among these elements, which is often overlooked in conventional research that tends to isolate each factor. By integrating data from diverse sources and considering a wide range of variables, this PhD thesis provides a more holistic and nuanced understanding of the precursors to road crashes, which has not been examined in the past. Particular emphasis was given to speeding and headway which found to be the most crucial risk factors among all the examined parameters. Thus, the need for investigation and comparative assessment of the impact of the aforementioned variables on risk became a high priority in order to accurately assess and mitigate their influence on road safety outcomes.

A significant advancement presented in this PhD thesis is the dual exploitation of data from **both on-road and driving simulator experiments**. This innovative combination allows for a detailed and controlled analysis of driver behaviour under different conditions, providing valuable insights that cannot be obtained from either method alone. On-road experiments provide real-world validity, while simulator experiments offer the ability to manipulate and control specific variables without risk. The use of these complementary experimental setups enhances the robustness and applicability of the research findings, contributing valuable methodological insights that advance the understanding of risky driving behaviour and its prevention. It also offers a more comprehensive perspective on how drivers respond to various driving environments and scenarios.

The third contribution involves the **development of an integrated methodology that combines statistical models and machine learning techniques**. This methodological framework is designed to handle and analyse large datasets, identifying complex patterns and relationships within the data. The inclusion of advanced methods, such as regression and latent analyses, neural networks and machine learning algorithms, facilitates a deeper understanding of the factors contributing to road safety. Furthermore, the most effective models to describe the STZ were rigorously selected and incorporated into the framework. This methodological innovation is essential for generating accurate, data-driven insights that can inform effective safety interventions.

This PhD dissertation makes a ground-breaking contribution to driver safety technology through the implementation of both **real-time in-vehicle interventions and post-trip feedback**. These interventions are specifically tailored to individual driver risk profiles, thereby enhancing their effectiveness in preventing road crashes. Real-time interventions help prevent drivers from approaching unsafe operational boundaries, while post-trip feedback educates drivers and promotes long-term behavioural changes. This dual approach not only mitigates immediate risks but also fosters ongoing improvements in driver safety and awareness.

One of the most novel contributions of this research is the **introduction of the STZ concept**. This innovative framework offers a new way of understanding and managing road safety by considering how drivers perceive and respond to their driving environment. The STZ theory integrates insights into driver behaviour and risk factors, providing a more comprehensive understanding of road safety dynamics. This holistic perspective is unique and significantly enhances the ability to predict and prevent unsafe (e.g. danger and avoidable accident) driving conditions.

Overall, this PhD thesis **pioneers a holistic approach** to road safety by treating the environment, vehicle, and driver as an interconnected system. This integrative perspective addresses the complex interactions among these elements, which are often overlooked in conventional research that isolates each factor. By adopting this holistic approach, the research improves the accuracy of risk assessments and facilitates the development of more effective safety interventions. This comprehensive understanding of road safety includes all the fundamental building blocks (i.e. all risk factors, on-road and simulator experiments, statistical and machine learning methodology, real-time and post-trip interventions, and the STZ) representing a significant scientific advancement and underscoring the holistic and interdisciplinary nature of this research.