Summary

Objectives and Methodology

Road safety is a critical public health and societal issue, as road traffic crashes claim millions of lives and cause severe injuries globally every year. Beyond the tragic loss of life, these incidents impose immense emotional and economic burdens on families and communities. **Research attributes approximately 95% of road crashes to human error**, underscoring the critical role of driver behavior in accident prevention. Understanding and addressing risky driving behaviors—such as distracted driving, speeding, and harsh events—are pivotal to enhancing road safety.

Based on the above, **the primary aim of this dissertation is to investigate the driver telematics feedback mechanism** under the framework of driving behavior and road safety. Despite growing interest from automotive manufacturers and transportation researchers in driver behavior, limited research exists on quantifying the comprehensive impact of driver feedback across its entire lifecycle—encompassing the pre-feedback, feedback, and post-feedback phases. To address this gap, this dissertation adopts a **holistic approach to evaluate the effectiveness of feedback** on modifying driving behavior and ultimately enhancing road safety.

To achieve these objectives, **a series of methodological steps** were carefully implemented. These steps are outlined and visually depicted in Figure I. The methodological framework provides a structured approach to achieving the objectives of this dissertation.

As a first step, a **systematic literature review** was conducted to evaluate the effectiveness of driver feedback within naturalistic driving studies. Feedback methods have evolved from in-vehicle devices and paper-based reports to sophisticated, user-friendly smartphone applications. These advancements enable the collection of high-resolution driving data and the delivery of personalized, data-driven feedback. Systems such as real-time alerts, post-trip summaries, and performance reports have demonstrated potential for improving driver behavior.

However, **significant gaps remain regarding the long-term sustainability of these effects and the differential impacts of feedback features**. While studies highlight the effectiveness of feedback in reducing speeding, harsh braking, and mobile phone use, the influence of feedback type, frequency, and incentives on behavior remains underexplored. Additionally, many studies observe a relapse into risky behaviors once feedback is removed, necessitating further investigation.

Based on the results of the systematic literature review, the following **research questions** were formulated:

1. How does feedback influence driver behavior in terms of speeding and mobile phone use while driving?

2. How does feedback influence driver safety in terms of harsh events, such as harsh accelerations and harsh brakings?

3. Do different feedback features (e.g., scorecards, maps, peer comparisons, motivations, gamification, rewards) have varying effects on driver behavior and safety? Which feature demonstrates the most significant impact?

4. How does the post-feedback effect influence long-term driver behavior and safety, and to what extent are the changes sustained after the feedback is removed?

5. How can advanced statistical techniques be applied to understand the mechanisms of driver feedback and develop more individualized, data-driven approaches for driving behavior change?

To answer the research questions, a **robust methodological framework** was developed, combining theoretical approaches and experimental design principles. This included the application of advanced modeling techniques, such as Generalized Linear Mixed Effects Models (GLMMs), Structural Equation Models (SEMs), and Survival Analysis Models, alongside the design of a naturalistic driving experiment.

A **21-month naturalistic driving experiment involving 230 drivers** was conducted. The participants were divided into three groups (car drivers, professional van drivers, and motorcyclists), and their driving behavior was monitored across **six distinct feedback phases**. These phases were defined as follows:

- Phase 1: Basic trip data and characterization were accessible to drivers.
- Phase 2: Introduction of scorecards with trip-level scoring.
- Phase 3: Addition of maps and highlights for further trip insights.
- Phase 4: Peer comparisons enabled for driver performance benchmarking.
- Phase 5: Competitions and challenges introduced with rewards for safe driving.
- Phase 6: Reversion to Phase 1, removing all additional feedback.

High-resolution data were collected from 106,776 trips, covering a total of 1,317,573 kilometers and 30,532 hours of driving. Behavioral metrics were captured using non-intrusive smartphone sensors, ensuring a seamless and accurate recording of driving behaviors. This sensor data was complemented by self-reported information from participants, providing a holistic understanding of driver perceptions, habits, and behavioral changes. The **experimental design adhered to strict ethical standards**, having been approved by the Research Ethics and Conduct Committee of NTUA, and ensured full compliance with General Data Protection Regulation (GDPR) guidelines. Continuous communication with participants was maintained throughout the study to address any technical issues, sustain engagement, and monitor the smooth execution of the experiment.

Extensive data processing and cleaning were carried out to ensure the quality and reliability of the dataset. Invalid or incomplete trip data were systematically identified and excluded, while key behavioral metrics such as speeding, mobile phone use while driving, harsh accelerations, and braking events were standardized for analysis. Data preprocessing steps included the conversion of raw sensor outputs into meaningful variables and the integration of self-reported data to enhance the analyses. **This rigorous approach to data management enabled the creation of a robust dataset**, facilitating detailed statistical analyses and ensuring the accuracy of the findings presented in this dissertation.

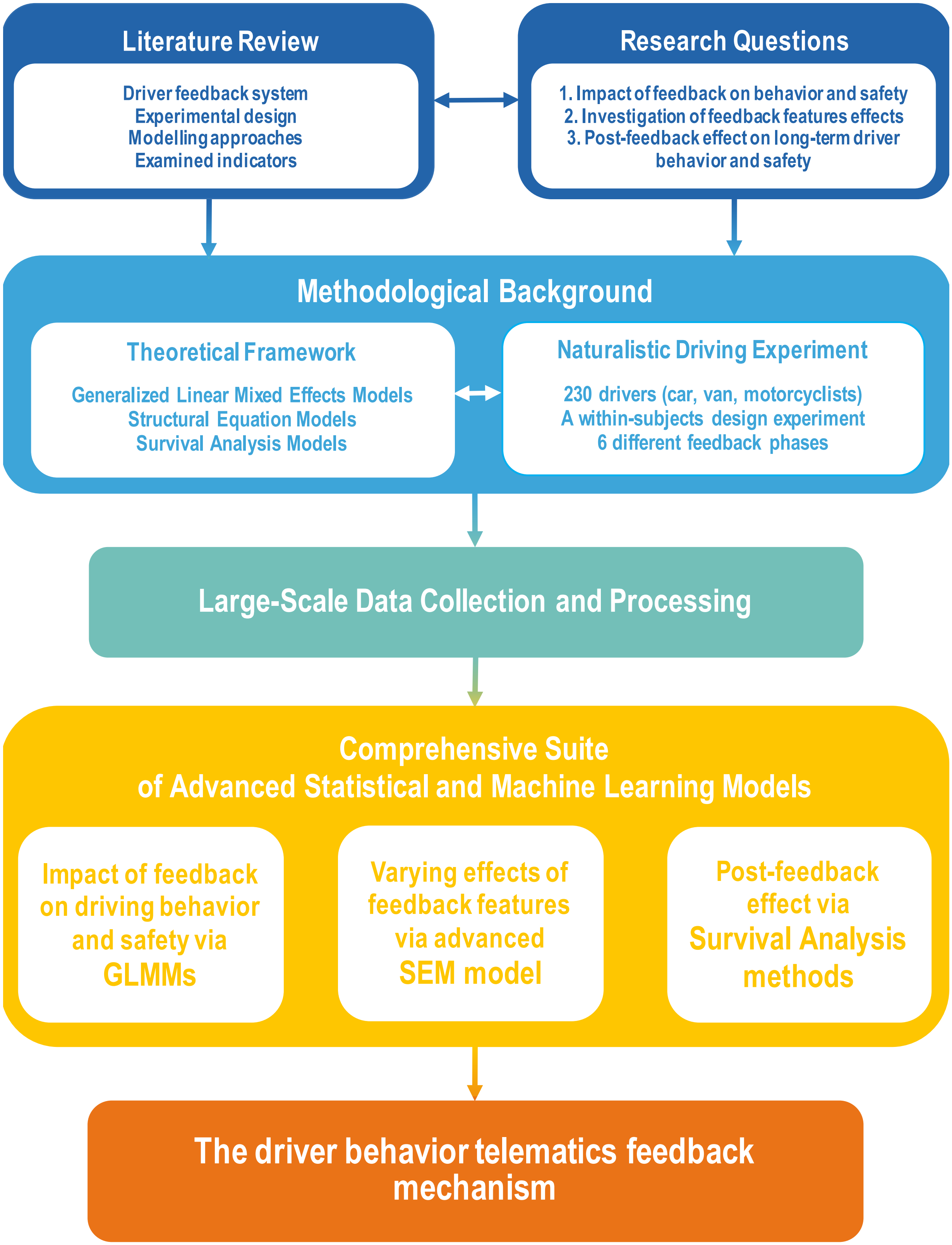

Figure I: Graphical representation of the overall methodological framework of the doctoral dissertation

Advanced statistical techniques were employed to analyze feedback effects on critical driving indicators, such as speeding, mobile phone use, harsh accelerations, and harsh brakings. The analysis unfolded in **three key pillars**:

1. **Impact of Feedback**: This pillar assessed the immediate effects of feedback on i) driver behavior, focusing on speeding among motorcyclists and distraction due to mobile phone use while driving in car drivers, and ii) driver safety, focusing on harsh braking and harsh accelerations among car drivers, and professional drivers on highways. Generalized Linear Mixed-Effects Models (GLMM) were then employed in all cases to evaluate the effects of feedback while accounting for individual differences and contextual factors.

2. **Varying Effects of Feedback Features**: A Structural Equation Model (SEM) was developed to explore the complex relationships between feedback features (e.g. scorecards, maps, peer comparisons, motivations, gamification, rewards) and driver behavior, exposure metrics and safety outcomes, allowing for the simultaneous analysis of multiple variables and their interactions.

3. **Post-Feedback Effects**: Effects on long-term driver behavior and safety, with a particular emphasis on understanding the relapse of driving behaviors following the withdrawal of feedback telematics during the last phase of the experiment. Survival analysis methods were employed to investigate relapse patterns across various indicators, including harsh accelerations, harsh braking, speeding behavior, and mobile phone use while driving. These analyses leverage Kaplan-Meier curves, Cox-PH models with frailty, Weibull AFT models with clustered heterogeneity, and Random Survival Forests to evaluate and compare the predictive power and insights offered by each model.

Ultimately, the synthesis of all the analyses carried out within the framework of this doctoral dissertation resulted in a driver behavior telematics feedback mechanism with numerous original and interesting results, which are discussed below.

Main findings

Feedback Impact on Driver Behavior and Safety

The investigation of feedback impacts on driver behavior and safety yielded significant findings across different user groups, driving environments, and behavioral metrics. Overall, during the two phases of the experiment a **large dataset of 3,537 trips from a sample of 13 motorcyclists** were recorded and analysed. Using Generalized Linear Mixed-Effects Models with random intercepts and random slopes for total trip duration revealed that providing motorcyclists with feedback about their riding performance during experiment Phase 2 led to a remarkable **decrease in speeding percentage over a trip.** Particularly, in the developed models rider feedback seems to decrease speeding percentage, having a risk ratio of $\exp(\beta=-0.145) = 0.865$ for the overall model (13.5% decrease), and $\exp(\beta=-0.031) = 0.970$ and $\exp(\beta=-0.420) = 0.657$ for urban (3.0% decrease) and rural (34.3%) road types respectively. These results highlight the effectiveness of feedback in targeting high-risk behaviors, offering a foundation for scalable interventions in rider training and policy design.

Similarly, **distracted driving, particularly mobile phone use, was examined across urban, rural, and highway** contexts via GLMM models for **65 car drivers over 21,167 trips**. Feedback emerged as a strong restrictive in using the mobile phone while driving overall ($\beta = -0.4276$, $p < 2e{-16}$), particularly in urban settings ($\beta = -0.3687$, $p < 2e{-16}$), while its impact was notably weaker in rural environments ($\beta = -0.1180$, $p < 2e{-16}$) and unexpectedly positive on highways ($\beta = 0.5490$, $p < 2e{-16}$), suggesting compensatory behaviors or a perceived lower risk of distraction on high-speed roads. The substantial variability in random intercepts (SD = 1.4024 overall) highlights **notable individual differences in baseline behavior**, while random slopes for trip duration (SD = 0.2827 overall) show diverse responses to prolonged trips.

In the domain of harsh events such as accelerations and brakings, feedback mechanisms demonstrated significant behavioral improvements, as well. Results from the **analysis of 65 car drivers** during the first two phases of the experiment revealed a **significant reduction in harsh accelerations (12%) and harsh brakings (10%)**, both changes being statistically significant ($p < 0.001$). The GLMM models further reinforce these findings, as feedback was consistently associated with reduced frequencies of harsh events, particularly in urban and rural environments. Notably, the relative risk ratios for speeding duration and trip duration indicate strong positive associations with harsh events, though feedback appears to mitigate these effects to a degree in Phase 2 of the experiment. Importantly, driver-specific variability, captured through random intercepts and slopes, underscores the need for tailored feedback mechanisms to address unique behavioral traits.

Professional drivers, due to their prolonged driving hours and distances, were also a key area of exploration. Using GLMMs calibrated on a dataset of 5,345 trips from 19 professional drivers, the analysis revealed that participation in a **social gamification scheme with incentives led to notable improvements in harsh events of professional drivers**. During the competition phase, the likelihood of harsh accelerations was reduced by a factor of 0.348 ($p < 0.001$), while harsh brakings decreased by a factor of 0.404 ($p < 0.001$), indicating the efficacy of gamification in promoting safer driving practices. Additionally, trip duration showed a positive association with harsh events, with a 1-second increase in driving time raising the odds of harsh accelerations and harsh brakings by factors of 1.558 and 1.564, respectively, highlighting the cumulative effects of extended driving. The inclusion of random intercepts in the models underscored substantial variability in baseline driver behavior, emphasizing the importance of personalized interventions.

<u>Feedback Features Varying Effects on Driver Behavior and Safety</u>

The **Structural Equation Model (SEM) analysis** provided significant insights into the impact of varying effects of feedback features on driver behavior and safety, specifically speeding, harsh braking, and harsh acceleration events. The dataset, comprising **73,869 trips from 175 car drivers over 21 months**, offered a robust basis for modeling. The SEM results identified two latent variables, namely feedback and exposure as critical influences. The model exhibited excellent goodness-of-fit measures, with Comparative Fit Index (CFI) = 0.940, Tucker–Lewis Index (TLI) = 0.944, Root Mean Square Error Approximation (RMSEA) = 0.049, and Standardized Root Mean Square Residual (SRMR) = 0.025, indicating a robust and well-specified structure. The inclusion of covariances among variables, guided by residual correlation analysis, further improved the model fit and highlighted critical relationships, such as those between speeding and harsh braking behaviors.

Among the feedback features analyzed, the **scorecard emerged as the most influential feature**, with the highest positive estimate ($\beta = 2.076$, $p < 0.001$), demonstrating its powerful role in promoting safer driving habits by immediately altering risky behaviors in comparison with the baseline phase. This result can be attributed to the clear, concise, and actionable nature of scorecards, which **provide drivers with straightforward insights into their performance** and specific areas for improvement, making it easier to adjust their behavior. Similarly, the maps feature showed a strong impact ($\beta = 1.646$, $p < 0.001$), emphasizing the importance of spatial awareness in enhancing driving practices. The compare feature allowed drivers to assess their performance relative to peers, positively influencing behavior ($\beta = 1.215$, $p < 0.001$). Additionally, the **competition & challenges feature proved highly effective** ($\beta = 2.053$, $p < 0.001$) by motivating drivers to adopt safer driving behaviors through gamified elements and rewards for safe driving.

In terms of driving behavior metrics, driver telematics feedback significantly **reduced the percentage of speeding time** ($\beta = -0.214$, $p < 0.001$) **and harsh braking events per 100km** ($\beta = -0.027$, $p < 0.001$). However, an **increase in harsh accelerations** per 100km ($\beta = 0.026$, $p < 0.001$) suggests the need for further refinement of feedback systems to address unintended consequences. Exposure factors also played a key role in shaping driver behavior, with morning peak exposure correlating with increased risk-taking ($\beta = 2.473$, $p < 0.001$), likely driven by time pressure during commuting hours. Conversely, afternoon peak exposure was associated with less aggressive behavior ($\beta = -1.360$, $p < 0.001$), providing insights into temporal variations in driving patterns.

Regression analysis confirmed these findings, highlighting the **interplay between exposure and feedback features**. While exposure positively influenced speeding ($\beta = 0.326$, $p < 0.001$), feedback features effectively mitigated this behavior. The competition & challenges feature, in particular, showed promise in moderating harsh accelerations ($\beta = -0.001$, $p < 0.001$). Harsh braking incidents were also significantly reduced by feedback, reinforcing the role of feedback in promoting safer driving practices. Covariance analysis further revealed strong interrelationships between risky behaviors, such as speeding and harsh braking, **underscoring the complexity of driver behavior patterns**. These findings suggest that speeding often necessitates sudden corrections, like harsh braking, and both behaviors may stem from underlying traits such as risk-taking tendencies or aggressive driving habits.

The practical implications of these findings are substantial. Feedback features, particularly those leveraging personalized scorecards, spatial tools, and gamification elements, hold great promise for improving driver safety. Tailored interventions targeting specific behaviors and times of day could further enhance the efficacy of these systems. However, limitations such as the exclusion of mobile phone use from the final model and potential selection biases due to the voluntary nature of participation should be addressed in future research.

Post-Feedback Effect on Long-Term Driver Behavior and Safety

Survival analysis techniques were applied to a dataset of 24,904 trips from 31 car drivers, each contributing at least 20 trips in the post-feedback phase, to investigate the long-term effects of driver telematics feedback on driving behavior. The analysis focused on relapse patterns in mobile phone use, speeding, harsh braking, and harsh accelerations. The methods utilized included Kaplan-Meier curves, Cox-PH models with frailty, Weibull Accelerated Failure Time (AFT) models incorporating clustered heterogeneity, and Random Survival Forests. The findings demonstrate the effectiveness of feedback interventions in achieving significant short-term behavioral improvements during the feedback phase. However, the **post-feedback phase reveals varied relapse tendencies**, emphasizing the need for sustained interventions to maintain these improvements over time.

The Kaplan-Meier survival analysis emphasized **relapse trends**, showing a steady decline in improved behavior over successive trips in the post-feedback phase. For harsh accelerations, **survival probabilities dropped from 84.8% at 50 trips to 49.2% by 150 trips**. Similar trends were observed for harsh braking and speeding, with survival probabilities declining to approximately 40.3% and 46.8%, respectively, by the 150-trip mark. These patterns underscore the **transient nature of feedback effects** and the need for continuous reinforcement mechanisms. Mobile phone use showed slightly greater resilience, with survival probabilities remaining above 80% at 100 trips, but the gradual relapse was evident over time.

Among the survival analysis models applied, **the Weibull Accelerated Failure Time (AFT) model consistently emerged as a robust performer** across the examined indicators, balancing predictive accuracy and interpretability. The **concordance index (**C-index) values ranged between 0.677 and 0.773, with the model achieving the highest predictive ability for mobile phone use relapse (C-index = 0.773), indicating strong discriminative capacity in identifying drivers most at risk of relapse. Key predictors such as age group [35-54] ($\beta = 0.165$, $p = 0.041$), trip duration ($\beta = -0.022$, $p < 0.001$), and self-reported aggressiveness (approaching significance at $p = 0.089$) were highlighted, providing actionable insights into relapse behavior. The model also **captured heterogeneity across drivers by incorporating random effects**, with frailty effects showing significant variability in survival times.

For speeding relapse, the Weibull AFT model achieved a C-index = 0.700 with significant predictors including trip duration ($\beta = -0.022$, $p < 0.001$) and morning peak hours ($\beta = -0.096$, $p = 0.004$). **Trip duration, in particular, emerged as the dominant predictor, consistently reducing survival time across all relapse indicators**, underscoring the role of prolonged driving in behavioral regression. Similarly, in the analysis of harsh braking relapse, the model achieved a moderate predictive accuracy (C-index = 0.724) with significant contributions from variables such as age group [35-54] ($\beta = 0.360$, $p = 0.010$) and vehicle engine capacity (>1400cc) ($\beta = -0.508$, $p = 0.012$). These findings highlight that younger age groups and drivers of larger-engine vehicles are more prone to relapse.

The **Random Survival Forest (RSF) model demonstrated superior predictive performance in some examined indicators**, excelling in capturing non-linear interactions and complex relationships between predictors. With Root Mean Squared Error (RMSE) values as low as 85.87

and out-of-bag (OOB) prediction errors of 24.3% for mobile phone use relapse, RSF identified critical predictors such as trip duration, aggressive driving tendencies, and vehicle engine size. Its **flexibility in handling diverse predictors** and uncovering nuanced dynamics makes RSF an invaluable tool for predictive analyses. However, the model's "black box" nature and reliance on larger datasets limit its interpretability and applicability for explanatory purposes.

Overall, comparing the models**, the Weibull AFT model stands out for balancing interpretability and predictive accuracy**, making it particularly suited for contexts requiring actionable insights into survival dynamics. The Cox model offers a useful compromise with its interpretability and ability to handle frailty, however repeatedly failed to meet model assumptions. The RSF model is most appropriate for predictive tasks where capturing non-linear relationships and complex interactions is critical, though its lack of transparency limits its utility in understanding the underlying behavioral mechanisms. These findings emphasize the **importance of aligning model selection with research objectives**. For studies focused on understanding behavioral dynamics and guiding intervention design, the Weibull AFT model provides robust insights. Conversely, when predictive accuracy is paramount, RSF offers a superior alternative.

While this study offers valuable insights into the dynamics of driver feedback and relapse, limitations such as the relatively small sample size, exclusion of traffic conditions, and macroscopic focus should be noted. Future research could incorporate more granular data, such as traffic dynamics and moment-to-moment driver decisions, to provide a deeper understanding of behavioral patterns. Employing advanced modeling techniques, such as random parameters with heterogeneity-in-means, could further enhance the analysis by accounting for driver-specific variability.

Innovative Scientific Contributions

The innovative contributions of this doctoral dissertation consist of five original scientific contributions, as described below, and illustrated in Figure II.

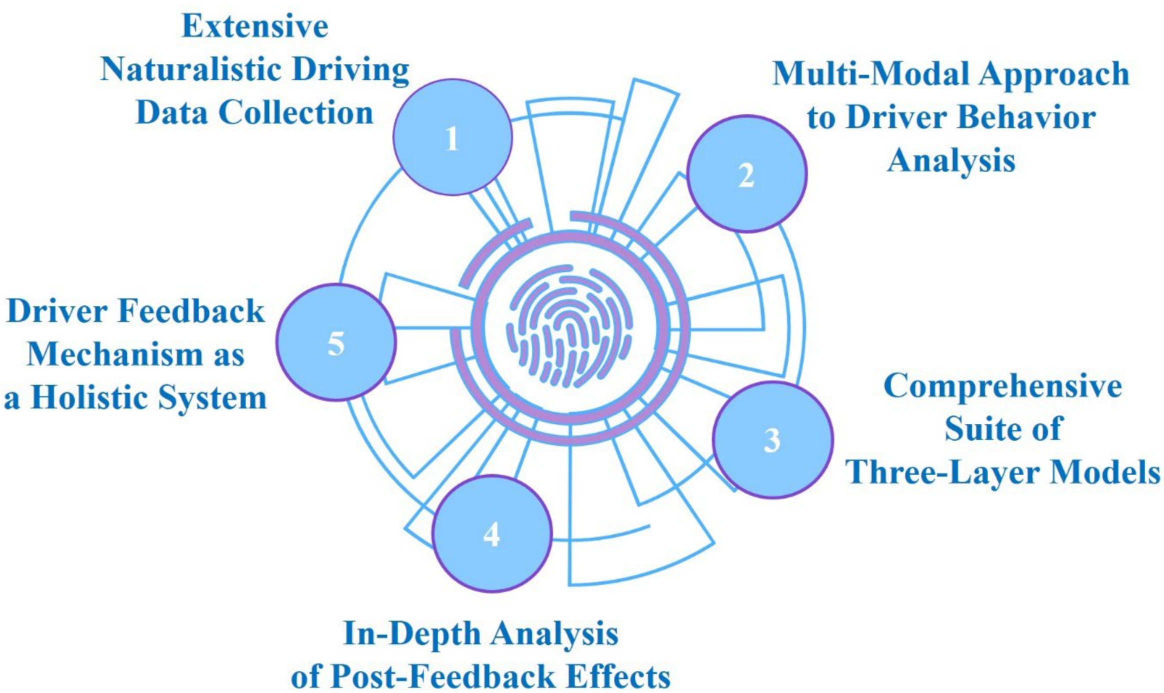

Figure II: Innovative contributions of the doctoral dissertation

Extensive Naturalistic Driving Data Collection

The present dissertation represents a **significant step forward in naturalistic driving (ND) research** by leveraging **non-intrusive data collection methods** that rely on smartphone sensors. Unlike traditional approaches, this methodology minimizes disruption to participants, enabling the unobtrusive capture of real-world driving behaviors. **The data spans a large sample size of drivers (230) across diverse road environments and vehicle types**, including car drivers, motorcyclists, and professional van drivers. This inclusivity ensures that findings are not only representative but also account for variations across driver demographics and vehicle categories. The dataset's rich temporal resolution provides detailed insights into driving behaviors at the trip level, offering a granular perspective on driver behavior dynamics.

Moreover, the **long-term data collection 21-month period**, spanning multiple feedback phases and covering various road environments, adds unique value. By capturing behavior changes over time, **the study bridges a critical gap in existing ND research**, which often relies on short-term observations. This long-term perspective enables the assessment of sustained behavior modifications and relapse tendencies, providing a robust foundation for developing adaptive and sustainable interventions to improve road safety. The **methodology sets a new benchmark for ND experiments**, paving the way for more scalable, cost-effective, and technologically advanced driving behavior studies.

Multi-Modal Approach to Driver Behavior Analysis

This dissertation takes a multi-modal approach, emphasizing the importance of understanding driving behaviors across diverse road user groups and environments. By including **car drivers, motorcyclists, and professional van drivers**, the research recognizes the critical need to study vulnerable road users, such as motorcyclists, who face heightened risks, and professional drivers, who spend extended hours on the road. This i**nclusive focus ensures a comprehensive evaluation of driver telematics feedback**, highlighting their relevance across varying risk profiles and exposure levels.

The investigation also considers the influence of urban, rural, and highway environments, acknowledging the distinct challenges posed by each road type. This contextual approach reveals that **feedback effectiveness is not uniform**; behaviors like mobile phone use or speeding respond differently to interventions **depending on the driving environment**. For instance, motorcyclists may benefit more from feedback targeting situational awareness, while professional drivers might require tailored interventions addressing fatigue and repetitive exposure to high-risk scenarios.

By integrating this diversity of user groups and contexts, the dissertation provides **actionable insights for policymakers**, road safety advocates, and technology developers. It emphasizes the importance of developing tailored feedback systems that cater to the unique needs of vulnerable road users, such as motorcyclists, and professional drivers, who contribute significantly to road traffic activity. This comprehensive approach supports the creation of adaptive, context-sensitive interventions, ultimately improving road safety for all users.

<u>Comprehensive Suite of Three-Layer Models</u>

This dissertation employs a **comprehensive suite of advanced statistical and machine learning models,** tailored to address the multifaceted nature of driving behavior analysis. By incorporating Generalized Linear Mixed-Effects Models, Structural Equation Models, and Survival Analysis techniques (e.g., Weibull AFT, Cox-PH with frailty, and Random Survival Forest), the study provides a rigorous analytical framework capable of uncovering both linear and non-linear relationships between variables. Each model is carefully selected to align with the research objectives, balancing predictive accuracy with interpretability to ensure actionable insights.

This model suite also enables the **exploration of complex phenomena**, such as the interplay between feedback features, driving behaviors, and contextual factors like time of day or road type. For example, survival models uniquely capture relapse dynamics, offering novel insights into post-feedback behavioral tendencies. Machine learning techniques further enhance the study by capturing nuanced, non-linear interactions, ensuring that the models are equipped to handle the complexity of real-world driving data. This **innovative analytical framework** not only elevates the scientific rigor of the research but also demonstrates the potential of combining traditional statistical methods with state-of-the-art machine learning approaches for driver behavior studies.

<u>In-Depth Analysis of Post-Feedback Effects</u>

This dissertation is **among the first to analyze thoroughly post-feedback effects** on driver behavior using advanced statistical and machine learning techniques, addressing a critical gap in existing research. Through survival analysis methods, such as Weibull AFT and Random Survival Forest, the study evaluates long-term behavior changes and relapse patterns after feedback withdrawal. These techniques enable a detailed exploration of the factors influencing relapse in risky behaviors like speeding, harsh events, and mobile phone use, providing actionable insights for the design of sustained intervention strategies.

The findings reveal the importance of adaptive feedback systems that can maintain behavior improvements over time. For example, survival analysis showed that trip duration and time of day significantly influence relapse dynamics, emphasizing the need for context-aware feedback mechanisms. This innovative focus on the post-feedback phase provides a **novel framework for understanding the longevity of feedback-induced improvements**, allowing for more durable and impactful road safety interventions. It also sets a precedent for future research to integrate long-term perspectives into the evaluation of driving behavior modification strategies.

Feedback Mechanism as a Holistic System

This dissertation uniquely approaches the **feedback mechanism as a holistic system, examining its full lifecycle through a multiparametric analytical framework**. By systematically analyzing the pre-feedback, feedback, and post-feedback phases, the study offers a comprehensive understanding of how feedback influences driver behavior across time. The integration of diverse feedback features, such as scorecards, maps, comparison tools, and competition elements, enables the evaluation of their individual and combined impacts on behavior modification. This multi-phase perspective not only captures immediate behavior changes but also sheds light on long-term patterns and relapse tendencies.

Furthermore, the holistic framework provides valuable insights into the synergies and trade-offs between different feedback features. For instance, while scorecards and competition elements are highly effective in reducing speeding, their impact on other behaviors like harsh accelerations requires further refinement. This systemic approach advances the field by moving beyond isolated feedback evaluations, offering a **scalable, data-driven framework for designing and implementing telematics-based interventions**. The findings emphasize the potential of adaptive feedback systems to improve driving behavior sustainably, ultimately contributing to safer road environments.