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School of Transportation Sciences

Master of Transportation Sciences

Master's thesis

Effects of i-DREAMS interventions on the driving behaviour among Belgian truck drivers

Tsegay Gebru Hagos

Thesis presented in fulfillment of the requirements for the degree of Master of Transportation Sciences, specialization Traffic Safety

SUPERVISOR :
Prof. dr. Tom BRIJS

MENTOR :
De heer Muhammad Wisal KHATTAK

2021
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PREFACE

It is a misery that a road user dies every 23 seconds, and more than 3500 people die every day on the road due to traffic collisions around the world. Human error contributed a lion share for traffic collision. It is booming the application advanced technology to assist drivers in the real-time & post trip to improve their driving behavior and minimizing the risk of involving in traffic collision. The main characteristics that are required for an intervention tool to be successful are its performance (i.e. the effectiveness of the intervention). As a road safety student, I worked on examining the effects of i-DREAMS interventions on driving behavior among Belgian truck drivers. This thesis is submitted in fulfilment of the Master of Science degree in Transportation Sciences at the Hasselt University, Belgium.

Firstly, I would like to express my gratitude to the almighty God for giving me the strength, health, and courage to complete the program in the last two years successfully. Secondly, I gratefully acknowledge the Flemish Inter-University Council (Vlaamse Interuniversitaire Raad/ VLIR-UOS), who awarded me a scholarship to pursue my master's studies. Further, I would like to express my heart felt gratitude my supervisors, Prof. Tom Brijs & Mr. Wisal KHATTAK, for their guidance, support, and encouragement during the course master thesis. Besides, I would like to acknowledge the i-DREAMS project research team (research team led by Hasselt University Transportation Research Institute) , who provided me with the data required for this study. All Hasselt university staff members, my friends, my classmate, and the communities of Diepenbeek and Hasselt deserve special thanks for making my study incredible.

Finally, I want to thanks the people of Tigray, including my whole family, who have been living under complete siege since November 2020, their resilience was an encouragement to complete my study. It was unfortunate that I had to go almost two years without hearing the voices of my entire family in Tigray.

EXECUTIVE SUMMARY

Globally, traffic collisions resulted in yearly estimates of 1.35 million deaths and more than 50 million injuries. Driving safety studies and traffic collision statistics have consistently revealed that driver behavior and error cause the vast majority of road collisions (Musicant et al., 2010; Saiprasert et al., 2017; Uchida et al., 2010). Long-haul trucking has long been considered a high-risk occupation, with drivers facing significantly higher accident and fatality risks than their non-trucking counterparts (Huang et al., 2017; Murphy et al., 2019). Truck drivers are viewed as potential hazards by other traffic vehicle drivers all over the world (Rosenbloom et al., 2009).

The advanced on-board safety monitoring systems have the potential to improve driver safety and reduce crash involvement and related costs by helping address potentially risky driving behaviors before they manifest themselves in a crash (Horrey et al., 2012). Several studies have found on-board safety monitoring (OBM) devices to be extremely effective in increasing driver safety(Bell et al., 2017; Donmez et al., 2007; Mase et al., 2020; Toledo & Lotan, 2006). Further, the in-vehicle data recording devices were also utilized to examine the validity and reliability of self-reported driving data(Marshall et al., 2007; Porter et al., 2015), hence playing a vital role in researching the correspondence between self-reported and objective driving data.

The i-DREAMS is a European Union-funded Horizon 2020 project. The project's goal is to create a platform that provides interventions and automated coaching to keep drivers within safe operating boundaries, which the project refers to as the Safe Tolerance Zone (Brijs et al., 2020). This study seeks to examine the effects of i-DREAMS real-time and post-trip intervention on Belgian truck drivers' risky driving behavior. The i-DREAMS on-road study lasted for 18 weeks and was divided into four phases. Thus, phase 1 (no-intervention) lasted four weeks ,phase 2 (real-time intervention) lasted 4 weeks, phase 3 (real-time intervention plus post-trip intervention (feedback via mobile app)) lasted for four weeks ,and phase 4 (real-time intervention plus post-trip intervention (feedback +gamification via mobile app +dashboard)) lasted for 6 weeks. Besides, the study tries to investigate the correspondence between objective driving data collected through the in-vehicle monitoring system and self-reported data collected via a questionnaire survey.

To examine the effects of the intervention on Belgian truck drivers' risky driving behavior, the i-DREAMS project research team collected naturalistic driving data using the in-vehicle monitoring system from 26 truck drivers. 21 truck drivers who completed all the four phase of the on-road study were used for data analysis. These drivers made around 9500 trips and drove a total of around 692,000 km during all the on-road study phases. The Friedman’s ÁNOVA test showed that there was no statistically significant difference in the total, high, medium, and low risky events among the four phases. However, there was the least proportion of high to total risky events in phase 4; hence this was an indicator of the real-time and post-trip intervention (feedback +gamification via app+ dashboard) produced the best result in minimizing high risky events. Additionally, there was a reduction in mean total speeding and acceleration events per 100 km in all the intervention conditions compared to the non-intervention condition. There was also the highest reduction in the mean high acceleration and speeding events per 100 km in the intervention conditions as compared to the non-intervention conditions. This indicated that the i-DREAMS intervention showed the best result in reducing the high risky events compared to the total, medium, and low risky events. Generally, Mixed results were observed in total risky events per 100 km, primarily due to high traffic variability during the COVID-19 pandemic travel restrictions. The self-reported data obtained from the entry survey showed a good correspondence with the naturalistic driving data obtained from naturalistic driving. What drivers said in the entry survey proved a good corresponds with what was recorded in the i-DREAMS platform.

The on-road study for evaluating the effects of the i-DREAMS intervention was undertaken from September 2021 until April 2022, where there was still traffic volume variability due to COVId-19 pandemic lockdowns and travel restrictions. It is recommended to conduct on-road study with more sample size and when the traffic volume variability due to the pandemic is not existed any more. Conducting a comprehensive driver acceptance to the i-DREAMS intervention based on the unified model of driver acceptance is also important to understand the factors that influenced the performance of the intervention. Working to promote partnership agreements among truck companies and research centers in areas of research and technology transfer is also recommended to increase the sample size of the study.

Keywords: i-DREAMS, Truck drivers, Real-time, Post-trip, Intervention, and STZ

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LIST OF ABBREVIATIONS

ADAS	Advanced Drivers Assistance System
i-DREAMS	Smart Driver, Vehicle & Environment Assessment and Monitoring System
IVMT	In-vehicle Monitoring Technologies
Km	Kilometer
M	Million
STZ	Safety Tolerance Zone
TTC	Time-to-Collision

X

1. INTRODUCTION

1.1 i-DREAMS Project

The i-DREAMS project is a European horizon 2020 project aiming to define, develop, test, and validate a "Safety Tolerance Zone" within a smart Driver, Vehicle & Environment Assessment and Monitoring System (i-DREAMS). It considers the driver background factors, real-time risk-related driving performance as well as driver state and driver complexity indicators, the continuous real-time assessment will be made to monitor and determine if the driver is within a safe driving operation. Furthermore, safety-oriented interventions will be developed to inform or warn the driver in real-time about risky driving events immediately during the trip or after the end of the trip through an- app and web-based coaching platform. Figure 1, demonstrates the conceptual framework of the project that mainly consists of monitoring the driving environment, in-vehicle intervention, and post-trip interventions. The project will be tested using a simulator study and three-stage on-road trials in Belgium, Germany, Greece, Portugal, and the UK, with 600 participants representing car, truck, bus, and train drivers. The key output of the project is to develop in-vehicle interventions and provide coaching feedback to improve future behavior, using a gamified platform for self-determined goal (Kaiser et al., 2020).

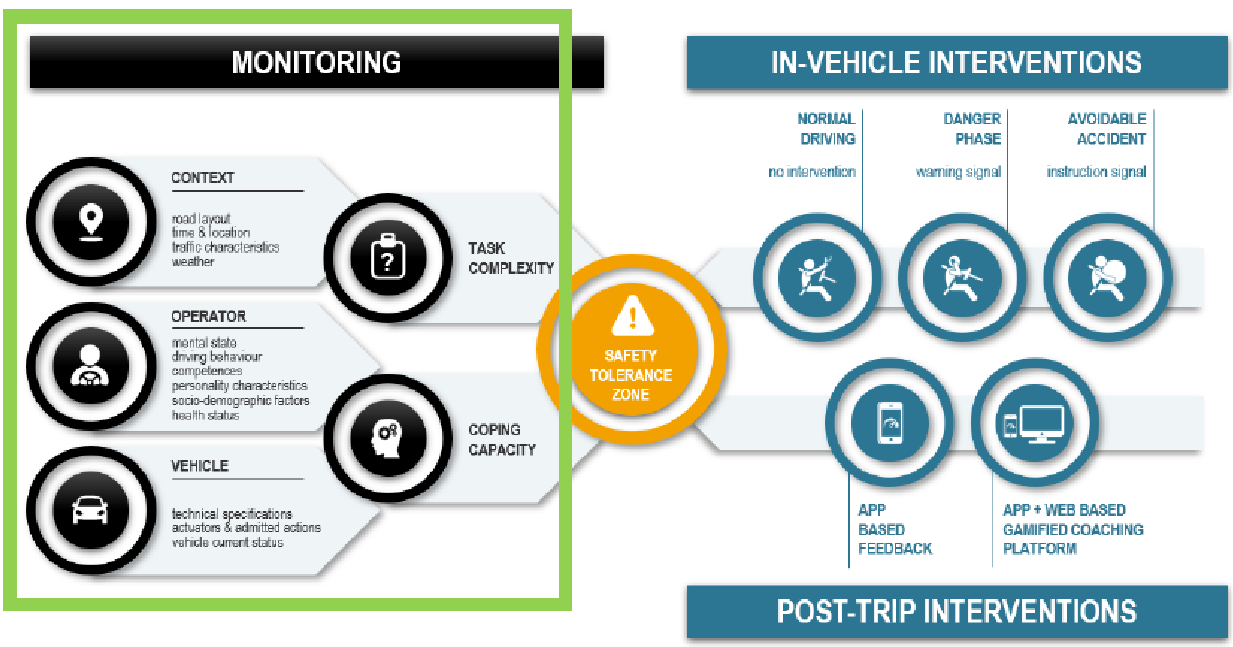


FIGURE 1 Conceptual framework of the i-DREAMS platform (Brijs et al., 2020)

Generally, the i-DREAMS project consists of four stages that took place in five countries with experimental study design. Stage 1 is the simulator trial stage, used to test whether the i-DREAMS technology can detect the safety tolerance zones (STZ) in the field operational trials and the user acceptance/feedback on the i-dreams technology. Stage two (pilot study), stage three (baseline measurement), and stage four (implementing the intervention) are operational field trials done on the road (Hancox et al., 2020). Stages three and four of the field trial operation to measure the effect of the intervention in mitigating risky driving behaviors. In stage 3 (baseline measurement), truck drivers' performance was recorded in the i-DREAMS platform without any intervention for four weeks. Stage four (intervention stage) consists of three different phases of interventions, namely, real-time intervention (4 weeks), real-time plus post-trip interventions (feedback on smart phone)(4 weeks), and real-time plus post-trip interventions (feedback and gamification on smart phone)(6 weeks). Therefore, this study examined the effects of the different i-DREAMS interventions on the risky driving events among Belgian truck drivers. Further, the study also explored the correspondence between self-reported driving data and the naturalistic driving data.

1.2 Problem Statement

In-vehicle monitoring technologies (IVMT) provide extensive & high-quality real-time driving data to identify risky driving events and further analyze the driver behavior in the crash and pre-crash events. The data collected from the system helps identify possible risk indices and evaluate the overall trip safety, giving feedback and corrections for the drivers (Toledo et al., 2008). There is increasing interest in using technology-based solutions to assist drivers in reducing the risk of car crashes. The i-DREAMS project aims to prevent drivers (trucks, buses, personal car, and train) from going to unsafe driving by mitigating risks using real-time and post-trip interventions. The project mainly uses advanced in-vehicle devices to monitor the environment, the vehicle and the driver and to provide the required intervention (Kaiser et al., 2020).

A study on effect of in-vehicle intervention on driving behavior confirmed that the feedback given to drivers enable them to reduce crashes and fuel consumption (Toledo & Shiftan, 2016). Gitelman et al. (2018) also used the in-vehicle data recorders to explore relationships among the risky driving events, road infrastructure characteristics, and crashes. In-vehicle data recorder installations utilized to monitor and provide feedback on driver behavior (Gitelman et al., 2018; Toledo et al., 2008). Toledo and Shiftan (2016) evaluated the effectiveness of the feedback based on in-vehicle data recorders and concluded that it enhanced safe driving behavior(reducing 8% unsafe incidents) and reduced fuel consumption by 3-10%. Some operational field studies evaluated the outcomes of real-time and post-drive feedback, but mainly focused on some risky events like speeding and tailgating (Mazureck & van Hattem, 2006; Merrikhpour et al., 2014; Reagan et al., 2013). Further, a study by (Mase et al., 2020) also unveiled that in-vehicle monitoring and post-trip coaching produced the best outcome in reducing the heavy goods vehicle drivers' risky deriving behaviors.

Self-reporting approaches are relatively inexpensive, can provide detailed information, and reach many people with small effort. The main drawback of self-reporting approaches is that it is uncertain how much they can validly measure the actual behavior. The relationship between self-reported and actual behavior was inconsistent and problematic, even though few studies found a moderately strong relationship (Bailey & Wundersitz, 2019). Despite disagreements about their utility and validity, various self-reporting methodologies have yielded a wealth of information in transportation psychology. Self-reported data collection methods are reliable tools for measuring driving behaviors for research, evaluation, and intervention (Taubman-Ben-Ari & Skvirsky, 2016). (Wang & Xu, 2019) suggested a connection between self-reported driving behavior and driver crashes and near-crash risk events. In contrast, the extent to which self-reporting measures the real driving behavior is uncertain (af Wåhlberg & Dorn, 2015; Helman & Reed, 2015). Studies by

(Agramunt et al., 2017; Marshall et al., 2007; Porter et al., 2015) used in vehicle data recording devices to examine the correspondence between the self-reported and objective driving data.

The safety risks of the transportation industry are disproportionately borne by truck drivers, who are responsible for hauling goods across great distances efficiently and frequently while sharing infrastructure with the travelling public (Douglas et al., 2019). Long-haul trucking has long been considered a high-risk occupation, with drivers facing significantly higher accident and fatality risks than their non-trucking counterparts (Huang et al., 2017; Murphy et al., 2019). Truck drivers are viewed as potential hazards by other traffic vehicle drivers all over the world (Rosenbloom et al., 2009). Considering the impacts of interventions in mitigating drivers' risky driving behavior, this study offers added research done on examining the effects of the i-DREAMS real-time and post-trip interventions on Belgian truck drivers driving behavior. Moreover, the study also presents new research on the connection between the self-reported data obtained from the entry survey and the objective data recorded on the i-DREAMS platform.

1.3 Research Objectives & Questions

1.3.1 Research objective

This research is aimed to investigate the outcome evaluation of i-DREAMS intervention among truck drivers in Belgium based on trip events recorded during the on-road study. intervention and non-intervention conditions. Further, the study also examined how the self-reported data predicts the actual driving behavior by analyzing the relationship between the data collected from the entry survey and the naturalistic driving data recorded in i-DREAMS platform.

1.3.2 Research question

1.Is there a significant difference in the reduction of total risky events between the baseline condition (no intervention) and all the intervention conditions (phases 2,3,and 4) among Belgian truck drivers ?

2.Is there a significant difference in the reduction of high, medium, and low risky events between the baseline condition (no intervention) and all the intervention conditions (phases 2,3,and 4) among Belgian truck drivers' ?

3.Is there a significant difference in the improvement of Belgian truck drivers trip score between the baseline condition (no intervention) and all the intervention conditions (phases 2,3,and 4) ?

4.Is there any relationship between the self-reported measures from the entry survey and objective data (naturalistic driving data) observed in the i-DREAMS platform ?

1.4 Significance Of The Study

Examining the influence of real-time and post-trip interventions in reducing the risky driving among professional truck drivers is important research areas. Truck driving has long been considered a high-risk occupation, with drivers facing significantly higher accident and fatality risks than their non-trucking counterparts (Murphy et al., 2019). The i-DREAMS goal is to create a platform that provides interventions and automated coaching to keep drivers within safe operating boundaries, which the project refers to as the Safe Tolerance Zone. This study will look at the effect evaluation of the i-DREAMS intervention in reducing the undesirable driving behavior of truck drivers. The i-

DREAMS project is an ongoing project , hence it necessary to conduct effect evaluation of the project on trial sample to understand its effectiveness before implementing in large scale in the whole target population. Moreover, this study gives additional insights and further research on the performance of real-time and post-trip intervention in mitigating the risky driving behavior professional truck drivers. Further, the study provides additional research on the correspondence between the objective data and self-reported data. Finally, it provides some basic recommendations to the project team that could be implemented before the end of the project or in the future works.

1.5 Structure Of The Master Thesis

The report of this master thesis structured into six chapter as listed below:

Chapter 1 Introduction: describes introduction about the i-DREAMS project , problem statement ,objectives of the study, research question , study significance and structure of the report.

Chapter 2 Literature review: includes the general overview about road safety , definitions of real time and post trip intervention others aspects in the i- DREAMs project, intervention mapping steps, previous studies on outcome evaluation of real-time and post trip intervention , and self-reported studies.

Chapter 3 Research Methodology :this part mainly focused on the data collection procedure, data processing , data analysis and hypothesis formulation

Chapter 4 Data analysis and result: The naturalistic driving data collected through the i -DREAMS platform and entry survey is analyzed in detail.

Chapter 5 Discussion: This chapter discuss the finding of the study, limitation and areas for future works, and recommendations.

Chapter 6 Conclusion of the study finding

2. LITERATURE REVIEW

2.1 General Overview

Injuries and deaths due to road accidents are major health concerns globally, causing economic and social crises. Road accidents are the eighth leading cause of death worldwide, with 1.35 million deaths and more than 50 million injuries each year (Organization, 2019). Traffic accident statistics confirmed that human error majorly contributed to road crash (Musicant et al., 2010; Uchida et al., 2010). The technology-based solutions are booming to assist the driver in minimizing the risk of involving in road crashes (Musicant & Lotan, 2016). Driver error and behavior are among the three key causes of a road crash, the other two being vehicle capability and infrastructure (Saiprasert et al., 2017). Researchers and experts are working to understand and influence driver behavior and error to improve road safety.

Currently, risky driving practices play a significant role in traffic accidents, and as a result, a variety of instruments have been developed to record and improve driving behavior (Michelaraki et al., 2021).In-vehicle data recorders (IVDRs) have achieved widespread acceptance as a means of monitoring and improving driving behavior, as well as contributing to environmentally friendly driving by lowering fuel consumption and emissions (Toledo & Shiftan, 2016). The IVDR measurements can be used to characterize real-time driving behavior and provide feedback to drivers about their driving, potentially lowering the risk of a car accident, operating costs, and emissions.

Commercial vehicles are exposed to a higher frequency of crashes and severe damages because of long haul distances and transporting heavier loads than other vehicles (Lee & Jang, 2019). The fast expansion of the truck industry and the associated high fatal crash rates of large trucks (large vehicles with a gross vehicle weight rating of more than 10,000 pounds) have raised significant societal concern about traffic safety (Bao et al., 2012). Driver error is still the primary contributing factor in heavy-truck crashes, although heavy-truck drivers are typically more qualified, experienced, and have logged considerably more miles on the road than drivers of passenger cars (Starnes, 2006). Advanced technologies has been utilized to monitor the driving behavior by providing feedback immediately to address the global issue of traffic safety (Hickman & Hanowski, 2011; Horrey et al., 2012; Jones, 2016). Hickman and Hanowski (2011) study showed how the In vehicle monitoring system feedback could reduce risky driving events in long haul trucks drivers. Drivers showed greatest reduction in the risky driving events during IDF period in combination with supervisory coaching, in comparison with the baseline and IDF period only (Bell et al., 2017). Therefore, it is essential to evaluate the different intervention strategies (standalone or combined) to choose the best that positively influences the driving behavior of truck drivers.

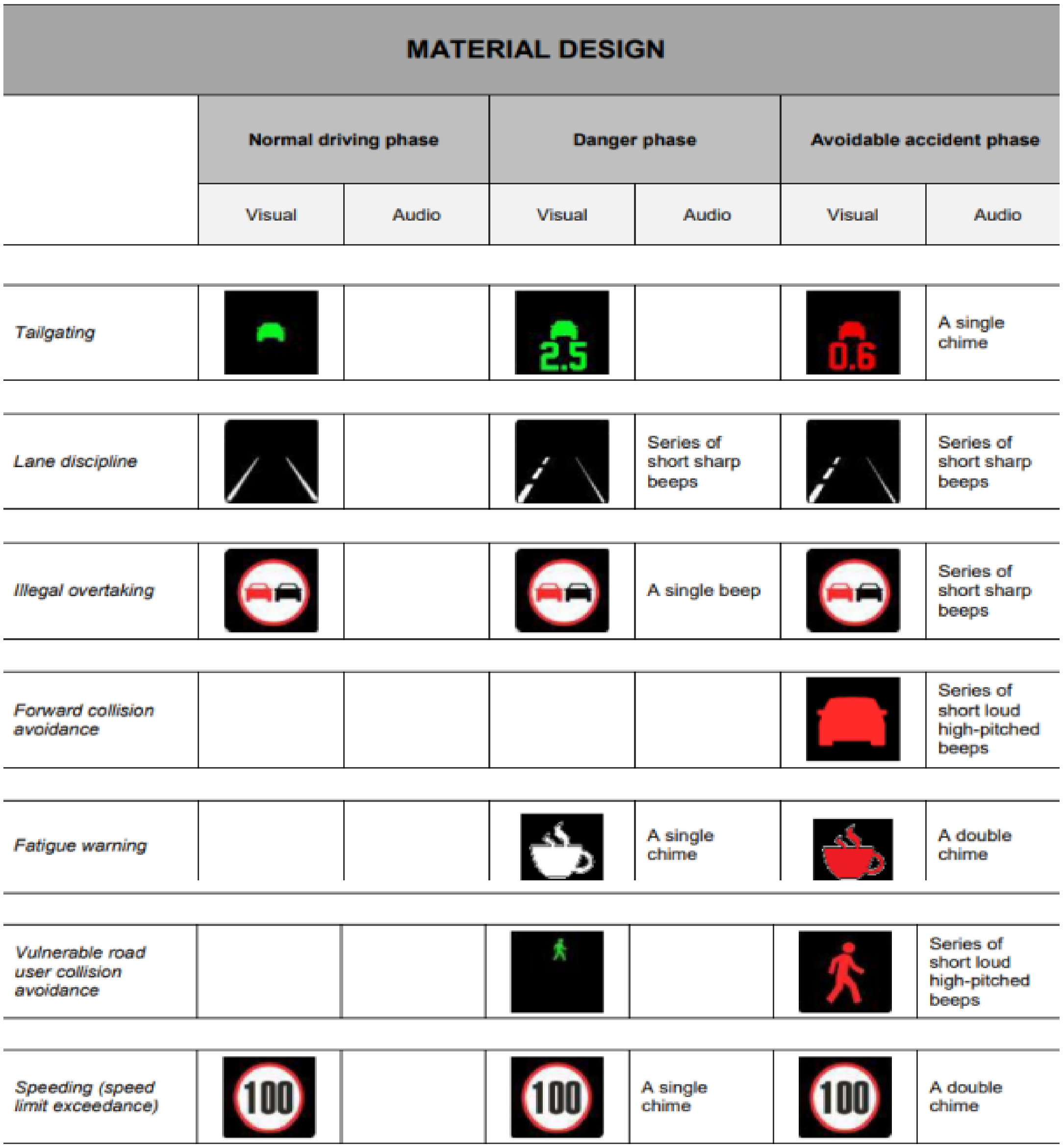
2.2 Real-time(in-vehicle) Interventions

Real-time feedback is a warning to aggressive behavior or drivers who deviate from the normal driving pattern, which can be provided using an in-vehicle display unit or text message (Toledo et al., 2008). In the driving context, feedback is the information provided about the driver's, vehicle's, and environment's state to enhance immediate driving performance or bring long-term behavioral change (Zhao & Wu, 2012). The in-vehicle intervention is a way to assist and support the vehicle operators at the moment of driving. The real-time interventions are provided through the intervention device (visually) and the speaker on the i-DREAMS gateway to keep the drivers in the Safety Tolerance Zone (STZ) (Brijs et al., 2020). Advanced technologies are making it possible to provide immediate feedback to drivers about the driver, the vehicle, and the environment state in real-time, which could help to reduce road fatalities and injuries (Bell et al., 2017).

Several sensory modalities are used to communicate with the drivers during the time of risky driving behavior. The real-time feedback strategies include visual, auditory, and haptic modalities, either combined or alone (Katrazakas et al., 2020). Real-time feedback is provided at the moment of driving to enhance immediate performance (Donmez et al., 2008). It is usually displayed when drivers tend to drivers improper or create a potential hazard. The limited time allocated for the real-time feedback made it impossible to provide detailed information regarding the event that triggered the feedback. Providing real-time feedback can help avoid further dangerous maneuvers or crashes, but it can't guarantee long-term behavioral change (Donmez et al., 2007).

The Safety Tolerance Zone (STZ) is a self-regulating control over transportation vehicles by human operators (assisted by technology) in order to prevent crashes. One of the key objectives of the i-DREAMS platform is to keep drivers as much as possible in the normal driving state ,with the minimum crash risk occurrence probability. The STZ is comprised of three sub zones ,i.e. normal driving, danger phase, crash avoidable phase (Brijs et al., 2020). Normal driving is the one of the STZ phases where, based on current conditions in the objective state-of-the world, there is no scenario of developing collision, where the vehicle is in the control of the human operators. The danger phase is the second phase in the STZ, and it is during this phase that the possibility for the collision scenario to begin is detected based on the existing circumstances in the objective state of the world. The real-time intervention feature of the i-DREAMS platform sent out the warning signal as the driving task changed from the normal driving to the danger phase. The third subphase of the STZ is the crash avoidable phase. According to the objective status of the world at this time, a collision scenario is actually beginning to form, but the vehicle operator still has a chance to act and prevent the collision. The real-time intervention part of the i-DREAMS component would send an instructional signal in response to the change from the danger phase to the crash avoidable phase (Talbot et al., 2020).

The i-DREAMS platform combines the real time interventions with the post trip interventions approaches. In the real time intervention, the vehicle operators receive support while they are driving under different circumstances in a short time frame and almost automatic response is required to avoid any danger. From a paradigmatic point of view, the real time intervention aligns with the nudging approach. Nudging primarily supports automatic behavior & decision making in a specific situation through the creation of supportive architecture (Karlsson et al., 2017). The real time intervention or on drive monitoring and feedback is an immediate, or real time feedback provided by in vehicle warning and alert systems. Both the real time & post interventions are aimed to influence risky driving behaviors that could result in a crash. For instant and automatic persuasion of the vehicle operator, the real-time intervention employs highly guessable icons and/or symbols in combination with sound, as well as visual and acoustic properties carrying connotative meanings (Brijs et al., 2020). Figure 2 shows how the i- DREAMS in vehicle intervention messages is designed and the content of the message is dependent on the driver's safety tolerance zone(normal driving phase , danger phase and avoidable accident phase).



MATERIAL DESIGN						
	Normal driving phase		Danger phase		Avoidable accident phase	
	Visual	Audio	Visual	Audio	Visual	Audio
Tailgating						A single chime
Lane discipline				Series of short sharp beeps		Series of short sharp beeps
Illegal overtaking				A single beep		Series of short sharp beeps
Forward collision avoidance						Series of short loud high-pitched beeps
Fatigue warning				A single chime		A double chime
Vulnerable road user collision avoidance						Series of short loud high-pitched beeps
Speeding (speed limit exceedance)				A single chime		A double chime

FIGURE 2 Illustrative mock-ups for messages for real-time interventions (Brijs et al., 2020)

2.3 Post Trip Interventions

post-trip safety intervention is defined as follows ‘‘a provided set of information, guidance, warnings, feedback or notifications that drivers receive post-trip, based on a personalized identification of driving episodes with the aim of risk prevention and mitigation” (Katrazakas et al., 2020).These post trip intervention provide the feedback and scores to drivers based on how they personally performed on a number of risk-related behavioral parameters. Drivers are able to identify their behavioral weakness, monitor their driving history , and improve their driving style through post interventions to enhance road safety (Michelaraki et al., 2021). Post trip or retrospective feedback, which is provided at the end of a trip (i.e., post-drive), can include additional information on safety critical situations encountered during the trip and assist the driver in developing safe driving habits. Post-trip feedback can help drivers to assess their weakness and adjust their driving style, hence reducing their estimated risky route and speeding frequency (Payyanadan et al., 2017).

In-vehicle data recorders (IVDR) have made it possible to capture continuous data on real driving behavior, such as unsafe driving behavior, involvement in side tasks, and driver replies (Dingus et al., 2006) to give drivers more objective feedback. Drivers who participated in a behavioral modification intervention in which they received weekly feedback on their speeding performance and goal setting exercises saw a reduction in the frequency of over speeding violations (Newnam et al., 2014).Coaching interventions are more successful in lowering driving errors (e.g., harsh cornering, harsh braking), whose lead to or trigger can be checked in camera monitoring as compared to driving violations (e.g., over speeding) (Mase et al., 2020).

Post-trip interventions have the same end goal as the real time interventions (keep the drivers in normal driving or to prevent the transition from the danger phase to the crash avoiding phase), with much wider operational time. The post trip interventions targets more stable factors that indirectly influence the operators moment to moment decisions and actions during a trip(e.g. safety related attitudes, mastery of safety related driving skills, perceived social norms related to safety etcetera).Changing these more stable factors take more time, ongoing engagements, and follow-up, that coaching is required (Brijs et al., 2020). Coaching is often human to human coaching between people (occasionally aided by technology) to encourage reflective learning, which can affect behavior in a variety of situations (Karlsson et al., 2017). Coaching is mostly provided by people(e.g., safety managers, parents, supervisors, team partners)(Farmer et al., 2010; Hickman & Hanowski, 2011). Study by (Hassan et al., 2015) revealed most of their study participants suggest that drivers turn to accept feedback or coaching from people they respect and trust.

Drivers want specific, constructive, respectful, and individualized feedback. Positive feedback is especially appreciated when accompanied by a sign of appreciation, such as a bonus or an award. Feedback is sought from individuals whom the drivers regard as knowledgeable about their job (Roetting et al., 2003). Previous research has discovered that supervisors play an important role in providing performance feedback to drivers and improving safety outcomes in the context of work-related driving (Newnam et al., 2012). Effective supervisory safety practices have been linked to higher group-level safety climate perceptions (i.e., the priority given to safety over competing for task demands) and lower injury rates (Zohar & Luria, 2003). Supervisors who effectively communicate about safety may have employees who have a better understanding of safe behavior and the potential consequences of unsafe behavior (Michael et al., 2006). Huang et al. (2018) also confirmed the quality of supervisor communication with their respective truck drivers about safety contributes mainly to the safety outcomes above the organizational level safety climate. Moreover, Bell et al. (2017) also confirmed that supervisory coaching plus in-vehicle feedback technologies significantly reduced truck drivers risky driving behavior compared to in-vehicle feedback technologies. Similarly, Hickman and Hanowski (2011) found that driver monitoring and coaching showed greater reduction in driving incidents compared to driver monitoring condition. Mase et al. (2020) also disclosed coaching and monitoring of heavy good vehicle drivers better reduced the harsh corning and harsh braking incidents than monitoring alone. In relation to this finding, the author also confirmed no significant difference in over speeding between the coaching plus monitoring and monitoring only.

2.3.1 Gamification

Gamification is defined as the process of improving services with (motivational) affordances in order to prompt game-like experiences and further behavioral outcomes (Huotari & Hamari, 2012).The use of game design elements (such as competition, badges, leader boards, and rewards) in non-game contexts is known as gamification (Deterding et al., 2011). Gamification's main goal is to elicit motivation to reinforce, change, or shape a desired behavior, and to sustain this effect over time by cultivating so-called intrinsic motivation. Several of gamification mechanisms have been investigated empirically for their effectiveness in the past works of safety and eco-friendly. Scores (Toledo & Lotan, 2006), feedback plus financial incentives (Dijksterhuis et al., 2015), score plus feedback plus group incentive (Musicant & Lotan, 2016), social feedback(McGehee et al., 2007),tips plus recommendations (Sureth et al., 2019),and scores plus ranking plus tips (Magana & Munoz-Organero, 2015) are some previous works on safety and eco driving that used gamification mechanisms. Social factors are strong predictors of how users perceive gamification and whether they intend to continue using the service and/or recommend it to others(Arumugam & Bhargavi, 2019). Recent research has shown that financial incentives can improve driving behavior, but high-value incentives are unlikely to be cost-effective, and attempts to amplify the impact of low-value incentives have so far been ineffective (Mortimer et al., 2018).

External rewards, such as money, can induce behavioral change, but they can also reduce intrinsic interest in completing the incentivized task after the rewards are removed (Ryan & Deci, 2000). Research confirmed monetary incentives do not always result in improved performance (Gneezy & Rustichini, 2000; Goette et al., 2004), For example, because of a poor incentive structure, behavioral "anomalies," or social preferences (Kamenica, 2012). Gamification is important in designing feedback that increases driver motivation by providing a sense of competence, autonomy, and relatedness, which may result in safer driving in the long term (Xie et al., 2016). Drivers who were exposed to safety-related scores calculated based on in-vehicle monitoring and delivered to them via personal web pages significant improves their driving behavior (Toledo & Lotan, 2006). Elvik (2014) conducted a comprehensive review of seven trials designed to reward safe and environmentally sustainable driving found that they were all successful in promoting the rewarded behaviors, with the greatest effects found for rewarding speed limit compliance.

The i-DREAMS post-trip intervention is supported by an app and web-based platform to facilitate and support each stakeholders involved in the driver coaching. The mock-ups are intended to provide a first impression of the 'look and feel' of the front-end of the i-DREAMS post-trip interventions (Brijs et al., 2020) The mock-ups for coping tips in the gamification mechanism menu shown in figure 3 (center) demonstrate the coping tips provided in the form(picture or photo, text, and video fragment) to improve certain performance objectives. The leaderboard in the left side of figure 3 presents the rank orders of the drivers who agree to appear on the leaderboard and is possible to apply to different time periods(day, week, and month). The i-DREAMS post-trip interventions can be qualified as digital- or internet-based interventions, running on a combination of an app and a web-based dashboard and are to be understood as combining e-coaching with virtual coaching (Hancox et al., 2021).

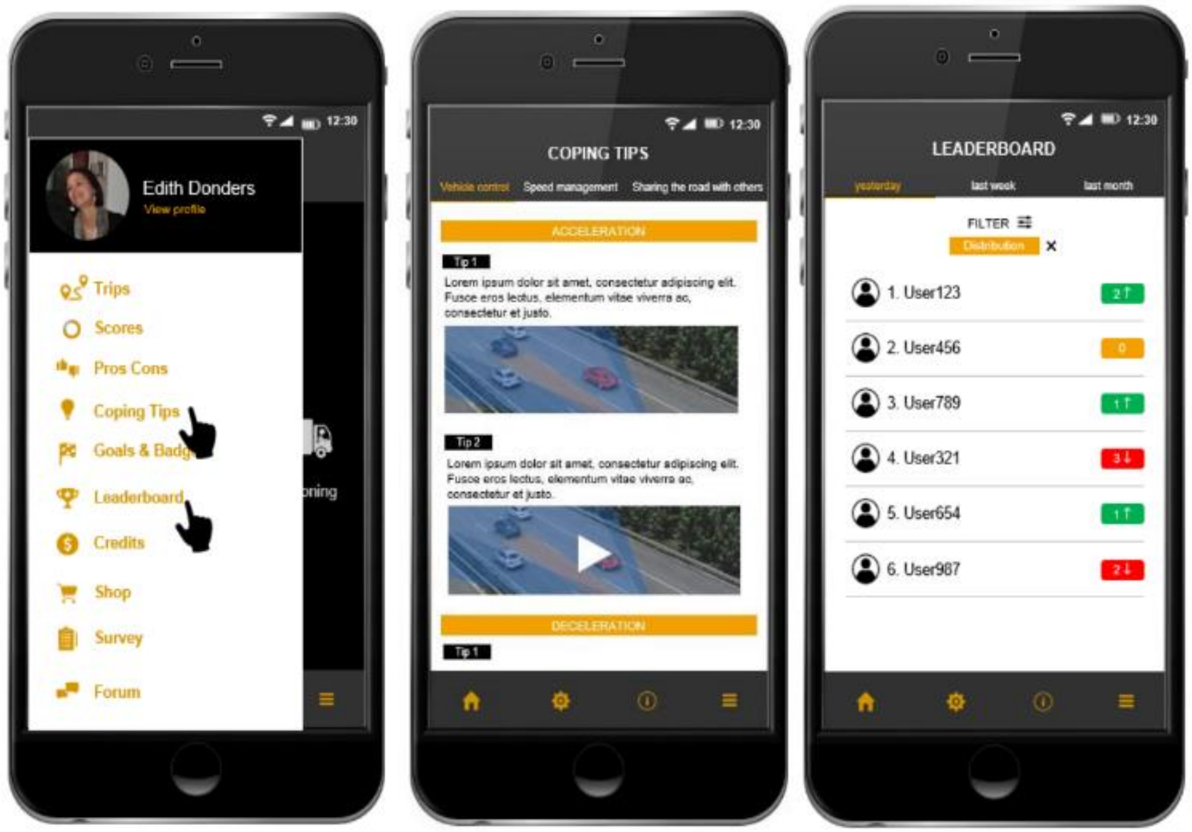


FIGURE 3 Mock-up screens for the i-DREAMS app: coping tips & leaderboard (Brijs et al., 2020)

2.4 Evaluation of Intervention Mapping

The Intervention Mapping (IM) protocol (Eldredge et al., 2016) describes the iterative path from problem identification to problem solving or mitigation. Similarly , Intervention mapping is also defined as a planning strategy that is based on using theory and evidence as the foundation for taking an ecological approach to assessing and intervening in health problems, as well as encouraging community participation. Each step of the Intervention Mapping framework necessitates the completion of several specific tasks that result in a product that serves as the foundation for the subsequent steps. The outcomes of the Intervention Mapping steps are not only the foundation for intervention development but also tools for evaluating the intervention's process and effects. Intervention mapping enables thoughtful formative evaluation to determine the extent to which the intervention map's decisions, assumptions, and expectations have been realized and whether program changes are required. The IM process comprises six steps(see figure 4) and each steps also consists of several tasks which integrate theory and evidence(Eldredge et al., 2016).

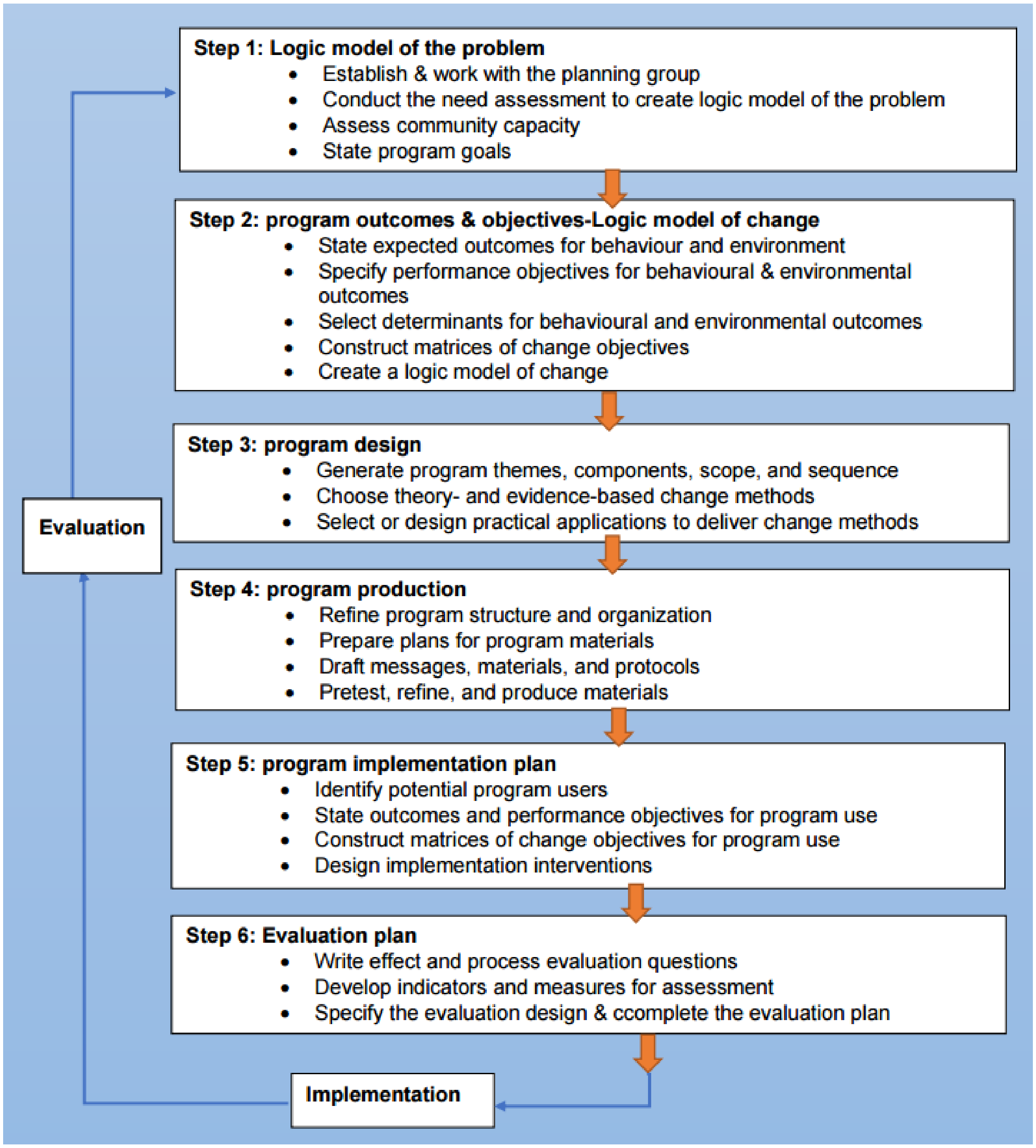


FIGURE 4 Intervention mapping process(Eldredge et al., 2016)

The selection of the appropriate intervention could be critical for improving road safety in everyday life. The real-time (immediate) and post-trip intervention are provided to improve the driving skill of the driver and reinstate in the safe driving field. The main characteristics that are required for an intervention tool to be successful are its performance (i.e. the effectiveness of the intervention) and user acceptance (Yardley et al., 2015).Therefore, it is vital to conduct the effectiveness of the interventions to examine the potential effects in achieving the desire behaviors or quality of life outcomes.

Evaluation is the final step of the intervention mapping protocol, which consists of outcome and process evaluation used to assess both effectiveness or efficacy and implementation program. Outcome evaluation involves measuring whether the road safety intervention objective is reached or not (Delhomme et al., 2009).The efficacy of an intervention or its effectiveness in achieving the targeted cognitive, belief, skill, or behavioral outcomes in a given group is determined through outcome evaluation (Dragutinovic & Twisk, 2006).The outcome evaluation of road safety could vary with the program's objective. The effect of a road safety intervention should be directly related to the number or severity of a crash, the number of violations, the frequency of safe or dangerous behavior, knowledge about safe behavior, beliefs supporting safe behavior, and self-reported behavior (Delhomme et al., 2009). It is essential to compare the data obtained before the program to that of the data obtained during and /or after the program to fully understand its outcome. Outcome evaluation measures the effectiveness of a program in terms of the targeted outcome within a specific population, and outcome evaluations are conducted (Raftery & Wundersitz, 2011).

According to the literature, the outcome evaluation was carried out in terms of the outcomes proposed in the logic model of change, and it was discovered that safety-promoting goals and performance objectives had the greatest impact on intervention evaluation (Michelaraki et al., 2021). It is also possible to detect a significant effect of intervention in the safety outcomes(e.g. crash occurrence, conflict, other critical events). Safety outcome was less examined in previous works of outcome evaluation as accidents are rare events, and the total duration the field experiment covered was a few months. Speeding, harsh acceleration, harsh braking, lane deviation, and left turns had the greatest impact on intervention evaluation, while distraction, stress, fatigue, drowsiness, attentions, concentration, and blind spot appeared to have a lesser impact.

Adoption of a new intervention to address a specific road safety problem may be successful if the intervention is effective in reducing risk behavior and is used efficiently by the driver. The outcome evaluation of the i-DREAMS intervention is evaluated based on the impact of the intervention on the safety promoting goals and performance objectives (Christos Katrakazas et al., 2020). User acceptance and user acceptability should be addressed in the domain of outcome evaluation, as these are essential factors for the effectiveness and adoption of the intervention. The unified model of driver acceptance (Rahman et al., 2018) is a good conceptual frame work to identify the key parameters to identify user acceptance. The model consists of attitude, perceived usefulness, perceived ease of use, subjective norm, perceived behavioral control, compatibility, trust, endorsement, and affordability. The effectiveness of an intervention are heavily dependent on the driver's acceptance of the system (Michelaraki et al., 2021).

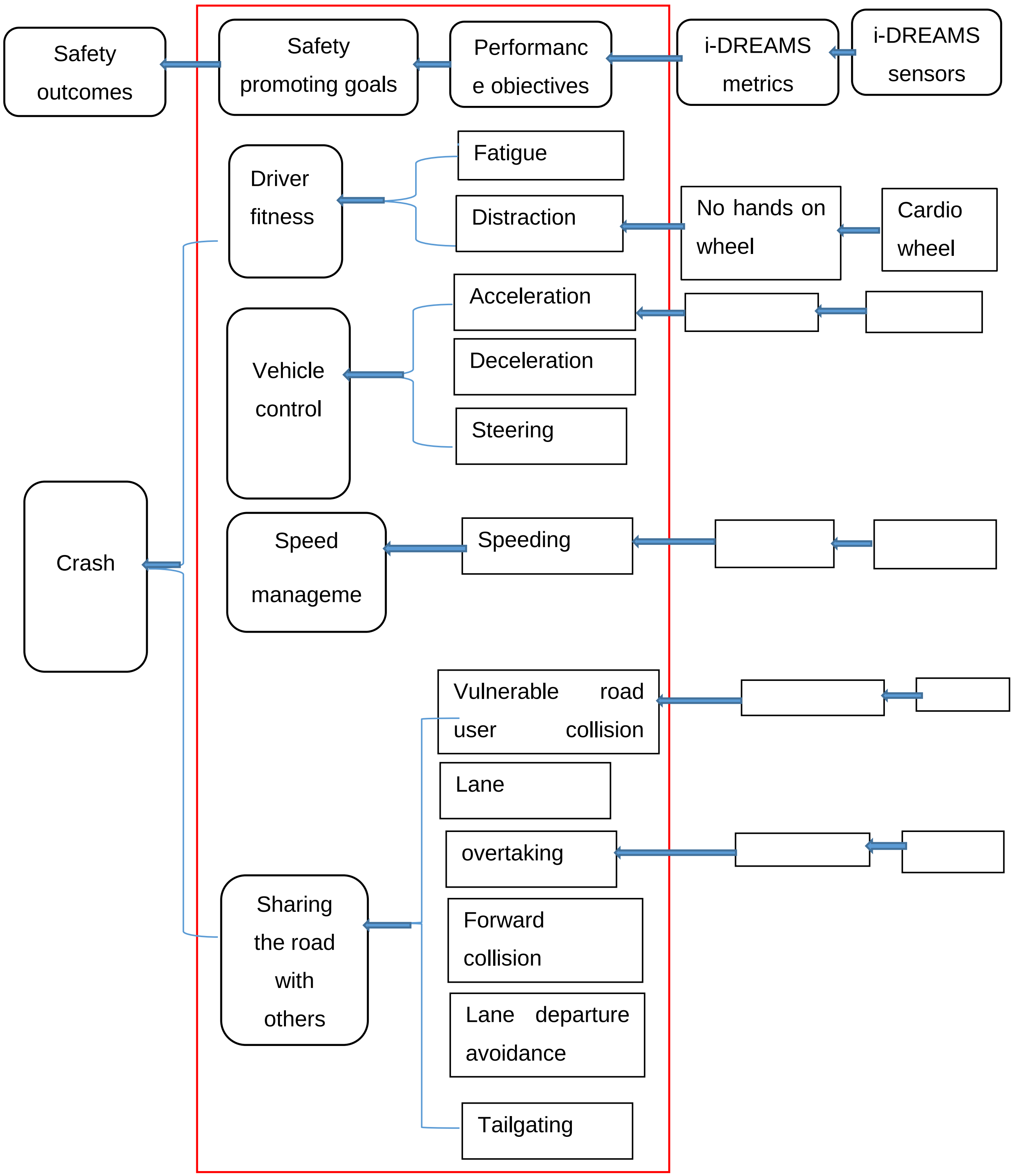


FIGURE 5 Safety promoting goals and performance of objective in the i-DREAMS intervention (Brijs et al., 2020)

2.5 Previous Works

One way to mitigate risky driving behavior is by providing real-time warnings to enhance immediate performance and feedback to promote behavioral change. Drivers receive concurrent feedback (in the form of auditory and/vision warnings) at the moment when the risky event happens. Retrospective feedback, in other words, is given after the end of the trip that consists of all the trip information to show how drivers were driving to improve their long-term behavior (Donmez et al., 2008). The onboard safety monitoring (OBSM) system uses in-vehicle recorders to record the driver's driving behavior. The behavioral approach to safety in conjunction with the OBSM system, can reduce risky behaviors largely (Hickman & Hanowski, 2011).

A simulator study conducted by (Donmez et al., 2008) involving 48 study participants and under three conditions: retrospective feedback, retrospective and concurrent feedback(combined feedback), and no feedback confirmed that the combined feedback produced the best result in terms of faster reaction time and longer glance on the road. In this study, the combined feedback resulted in 0.41 seconds and the retrospective feedback 0.34 seconds faster reaction time than with no feedback condition. There was no significant difference in the driving performance between the combined and retrospective conditions. Another study was conducted using a video monitor approach to reduce at-risk driving behaviors among commercial vehicle operators in two conditions: base case (no intervention) and intervention case (real-time warning + feedback from safety managers). The study result confirmed the drivers significantly reduced their mean risky driving events per 10,000 miles traveled due to the in-vehicle warning and the feedback received from the safety managers(Hickman & Hanowski, 2011).

Speeding is a crucial threat to traffic safety in the United States, with 31% of fatalities related to speeding in 2008 (Ascone et al., 2009). The study on the effect of external motivation and real-time automated feedback on speeding behavior revealed that the incentive system resulted in a higher reduction of speeding; In contrast, the automatic feedback exhibited a medium decrease in speeding(Reagan et al., 2013). This study also found drivers showed similar speed reduction in the incentive only and combined (incentive automated feedback). Afield operational study conducted to evaluate the effect of feedback-reward system on the speeding and tailgating behavior in Canada confirmed the best compliance to speed and headway recorded during the feedback-reward stage (Merrikhpour et al., 2014).The trial comprised three different stages: baseline(2 weeks), intervention(12 weeks), and post-intervention(2 weeks). During the intervention phase, drivers received real-time in-vehicle feedback on the in-vehicle display based on the speed limit and headway compliance and collected reward points.

A simulator study conducted in Canada to examine the feedback gamification for mitigating driver distraction among 29 young drivers. Xie et al. (2016) compared the off-road glance behavior under four conditions: no feedback, real-time feedback, post-drive feedback (real-time feedback +post drive feedback), and gamification feedback system (real-time feedback +post drive feedback game design elements). The post-drive feedback condition showed shorter average glance duration and less frequent risky glance than no feedback and real-time feedback conditions. In this study, no improvement was obtained on the driver distraction from the gamification over the post-drive. The Netherland department of transportation conducted a study to explore the influence of reward and feedback on speeding and following distance. The “Belonitor trial” focused on speeding and headway in three phases: pre measurements (4 weeks), feedback and reward (16 weeks), and post-measurement for four weeks (Mazureck & van Hattem, 2006). If all Dutch drivers had the Belonitor system and the results obtained in the trial times were constant over a long time, then progress on traffic safety would be significant. Therefore, reward and feedback could reduce fatalities, injuries, and fuel consumption by approximately 15%, 9%, and 5.5%, respectively.

Evaluating an in-vehicle monitoring system (IVMS) to reduce risky driving among commercial drivers through immediate driver feedback (IDF) and supervisory coaching indicates positive outcomes. Drivers showed greatest reduction in the risky driving events during IDF period in combination with supervisory coaching, in comparison with the baseline and IDF period only (Bell et al., 2017). The study also confirmed the immediate driver feedback does not show significant reduction in comparison with the baseline data. Farmer et al. (2010) also confirmed that the in vehicle monitoring system positively influences the driving behavior of teenagers, especially the use of seat belts. Monitoring the teenage drivers electronically from the vehicle is not sufficient to change the risky driving without continuous and close follow-up from parents.

A study by (Mase et al., 2020) to investigate the influence of camera monitoring on heavy vehicle driver's risky behaviors, claimed that the intervention showed a significant reduction in the frequency of harsh braking and over speeding incidents from the baseline. Further, this study also examined that coaching significantly differs in reducing the frequency of harsh braking and cornering compared to just camera monitoring. An integrated, in vehicle warning system enhances the heavy truck driver's ability to maintain headway and shorter reaction time to potential ahead traffic conflicts The presence of the in vehicle warning system enabled heavy truck drivers to increase their mean time headway by 0.28 seconds and faster their reaction time by 0.26 seconds to respond forward conflict (Bao et al., 2012).

Bao et al. (2012) conducted a field evaluation study on the effect of an in-vehicle crash warning system as a real-time intervention on the following behavior of heavy truck drivers by considering mean & minimum headway time and brake reaction time as critical evaluation parameters. Eighteen heavy truck drivers have participated in the naturalistic experiment for ten months (i.e., two months as a baseline and eight months for treatment). Results show that, even if the difference was not statistically significant at 95% confidence level, drivers generally kept longer mean time headway during the intervention condition (2.89 s) than in the baseline condition (2.78 s). In the case of minimum headway time, no significant difference was observed between the two conditions (i.e., 0.98s in the treatment condition and 0.96 in the baseline condition). However, a significant positive effect was observed in headway time feedback during difficult driving situations such as dense traffic and slippery road surface condition. Further, the intervention significantly impacted average brake reaction time as a shorter break reaction time was observed (1.62 s) than the baseline condition (1.88 sec). Table1 demonstrates a summary of some previous works on effectiveness of real-time and post-trip intervention to improve driving behavior that are believed the causal of traffic collision.

TABLE 1 Summary of some previous intervention evaluation studies and their finding

Studies	variables	Analysis method	Finding/result
Toledo and Lotan (2006)	Crash, speed, position, and acceleration	Regression and direct comparison of average risk indices	Feedback provided by the system significantly improve driving performance
Camden et al. (2019)	Hard braking, hard acceleration, hard cornering, and speeding	Paired sample t-test	Statistically significant reduction in speeding hard braking and hard cornering
Mase et al. (2020)	Hard braking, hard cornering and over speeding	Repeated measures of ANOVA	Monitoring produce Significant reduction in mean hard braking & speeding Monitoring plus Coaching also produce significance difference in hard braking and hard cornering than monitoring only
Bell et al. (2017)	Risking driving behaviors	Paired t-test	Coaching plus instant feedback with light produce the best effect in reducing the risky events
Donmez et al. (2007)	Braking and steering	Mixed linear model	The real time feedback didn't produce significant result in braking and steering, but it alter the engagement with distracting activities
Hickman and Hanowski (2011)	Risky events per 10000 miles	Paired sample t-test	Coaching and video monitoring significantly reduce the risky events per 10000 miles of travel compared to the baseline condition
Merrikhpour et al. (2014)	Safe headway and speed limit	Mixed linear model	In vehicle feedback and reward system produce promising result for less speed and head way compliant drivers
Toledo et al. (2008)	Crash rates and risk indices	Regression analysis and crash rate per 10,000 driving hours	In vehicle monitoring and feedback produce in reduction in crash rates and risk indices
Reagan et al. (2013)	Speeding	Mixed ANCOVA	Incentive systems produce significant reduction in speeding, while in vehicle feedback show modest reduction in speeding compared to the baseline condition. The speeding reduction found combined

			incentive & feedback was similar to the speed reduction by incentive only
McGehee et al. (2007)	Exceeded Lateral and forward acceleration	Paired t-test and frequency per 1000 miles travel	Combining the in vehicle warning with weekly parental feedback resulted a significant reduction of events for at risk teen drivers
Roberts et al. (2012)	Driver distraction	Paired t-test	The real-time auditory or visual warning is more obtrusive and less easy than post drive feedback. Informing drivers with detail information about their driving was more acceptable than warning while driving
Donmez et al. (2008)	Driver performance and distraction	MANOVA analysis	Combined retrospective and concurrent feedback resulted faster response to lead vehicle braking and longer glance to the road
Boodlal and Chiang (2014)	Safe driving and eco driving	Paired t-test	The telematic system improved safe driving (reduce harsh braking, sudden acceleration, and speeding) also reduce the fuel consumption
Carney et al. (2010)	Coachable risky events	Coachable risky events per 1000 miles of travel and t-test	Event triggered video intervention for newly licensed adolescent drivers reduced the coachable risky event by 60 % compared to the baseline condition
Dotzauer et al. (2013)	Driving behavior and driving performance at intersection	Friedman's ANOVA	Drivers equipped with ADAS gave more attention toward the center of the road, crossed the intersection in short time, engaged in high speeding ,and crossed with critical TTC value

2.6 Self-Reported Driving Data

Self-reported driving data are commonly used in traffic safety research and evaluation of road safety intervention measures. Questionnaires, interviews, focus groups, and driver diaries are used in the self-report approach. The self-reports approach is less expensive, provides more detail information than observation, can reach a significant portion of the study population and easy to establish representative sample (Bailey & Wundersitz, 2019). Even though self-report measures have been used to gather much of the knowledge in transportation psychology, there is still disagreement over the value and validity of such tools (Taubman–Ben-Ari et al., 2016). The self-reported measures limitations, however, include the potential for self-serving biases, recall biases, and shared residual variance with other self-report measures, which can result in less than optimal and reliable reporting on a person's driving behavior and crash involvement (Nesbit et al., 2007).

The advance in technology has made it possible to explore naturalistic driving behavior using the data collected from the in vehicle monitoring device, hence possible to compensate for the weakness of self-reported data in the field. Studies have been conducted by (Agramunt et al., 2017; Blanchard et al., 2010; Thompson et al., 2016) to examine the validity and the reliability of the self-reported driving data in comparison to the objective (driver monitor) data. Agramunt et al. (2017) draw the conclusion that self-reported diary data may not be reliable for assessing driving outcomes, particularly for estimating the duration and distance of journeys for elderly drivers. Similar to this, a study by (Blanchard et al., 2010) to examine the accuracy of self-reported data on elderly drivers was found to be inaccurate (missing a significant number of trips and stops), and they concluded that in order to fully understand the driving behavior of elderly drivers, it is crucial to use data from in-vehicle monitoring devices in combination with self-reported data. In contrast, a study by (Taubman-Ben-Ari & Skvirsky, 2016) on the importance of self-reported measures as indicators of driving behavior among young drivers noted that self-reported data are trustworthy methods for measuring driving behavior for the purpose of research, assessment, and interventions.

Traffic safety researchers have ignored or dismissed the possibility that self-reported crashes and violations may be systematically biased, as with common method variance, because their properties have not been tested (af Wåhlberg & Dorn, 2015). The reliability of self-reported data could be influenced by the actual change of the parameter over time, reporting bias, and random error. Self-report measures of driving behavior may be subject to participant biases such as social desirability effects, and participants may fail to complete all or portions of self-report driving diaries (Kaye et al., 2018). On the other hand, objective driving data are susceptible to technological malfunctions and, in the case of in-vehicle devices, it may be difficult to accurately determine who drove the vehicle at the time of data collection.

Boufous et al. (2010) discovered positive correlations between self-reports of traffic accidents and offenses on the one hand and official police records on the other. Taubman–Ben-Ari et al. (2016) found positive correlations between high Multidimensional Driving Style Inventory (MDSI) scores on risky and hostile driving styles and risky behaviors measured by the in-vehicle data recorder (IVDR), as well as inverse correlations between the latter and high MDSI scores on anxious and cautious driving styles. Similarly, associations were discovered between self-reported frequency of reckless driving habits and several risky behaviors as measured by the driving simulator

(Taubman–Ben-Ari et al., 2016). In contrast, another study found only one significant correlation between Manchester Driver Behavior Questionnaire (DBQ) scores and simulated driving: drivers with more violations tended to brake less heavily (Stephens & Groeger, 2009). Study by(Helman & Reed, 2015) ,found correlations between DBQ violations and naturalistic driving speed only during the day, not at night, and no correlations with the other DBQ scales.

It is important to understand the correspondence between what drivers do they say and what the actually do to further impact their driving behavior and traffic safety (Blanchard et al., 2010).The fact that self-reported driving data have several limitation (WÅhlberg, 2017), it is possible to observe in the naturalistic driving setting to validate the reported behavior with the increased functionality of the in vehicle data recorders(Helman & Reed, 2015). The speed violation obtained from driver behavior questionnaire is a valid measures of the observed driving behavior in the naturalistic driving condition (Helman & Reed, 2015).To ensure that the techniques utilized provide the most accurate assessment measures on various driving behavior measurements, a variety of objective and self-report measuring tools should be incorporated into the research (Blanchard et al., 2010; Kaye et al., 2018). Further researches has been recommended by author that did their previous study on the relationship between the self-reported and objective driving behavior (Blanchard et al., 2010; Helman & Reed, 2015; Kaye et al., 2018).

3. METHODOLOGY

3.1 Data Collection Instruments

The data used in this study is collected via an entry survey questionnaire and a naturalistic driving study of the i-DREAMS project conducted by a consortium of a research team led by Hasselt University Transportation Research Institute (IMOB).Socio-demographic data, the drivers' company's safety culture, traffic accident & offense history, and other driving-related data are collected via an entry survey questionnaire. In the i-DREAMS project, a new in-vehicle monitoring system is developed to collect continuous naturalistic data. Under usual driving (without intervention) and different intervention types meant to guide vehicle drivers depending on how the driver is within the safety Tolerance Zone (STZ) while driving. Data on the number of risky events in each trip, trip starting data, the distance and duration of each trip, and trip score are gathered from the i-DREAMS platform, as shown in figure 6.

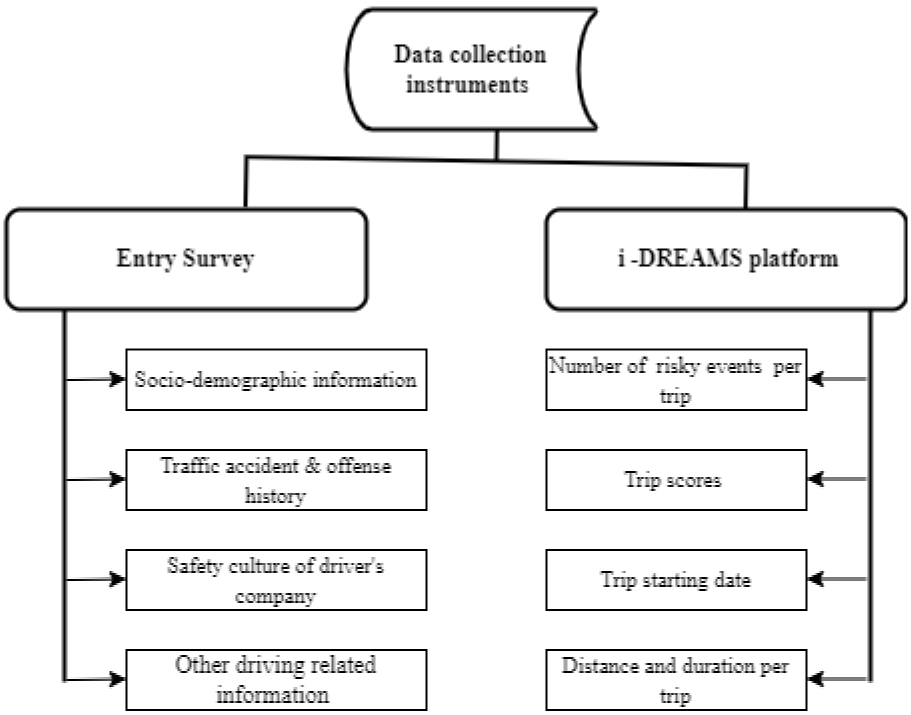


FIGURE 6 Data collection instruments

The first four weeks served as a baseline period in which the i-DREAMS platform functionalities will not be open to the participant drivers but running in the background. After the baseline period, the first real-time intervention functioned and spanned for four weeks. The second intervention is the i-DREAMS in-vehicle platform, plus drivers also received their driving performance(score) via the mobile app. Finally, the final intervention, the in-vehicle intervention coupled with a mobile app and a web-based gamified coaching dashboard, spanned six weeks, and the end of the intervention experiment.

3.2 Participants and data collection procedure

Participants were asked to fill out the entry survey questionnaire before entering the major on-road study. All truck drivers participated in all four phases of the on-road field operational test were used for analysis. The major on-road test is divided into four phases (see figure 7). The first phase of the on-road test was monitoring, where the in-vehicle monitoring systems collected unsafe driving behavior/situations without providing intervention to the drivers. During the second phase, the in-vehicle monitoring system gave real-time warning and collected the information for the unsafe driving behaviors. The third phase drivers received both in-vehicle waring and post-trip feedback via smartphone apps about their driving and also the unsafe driving evets were collected into the system. During the final phase drivers received in-vehicle waring and post-trip feedback plus gamifications features.

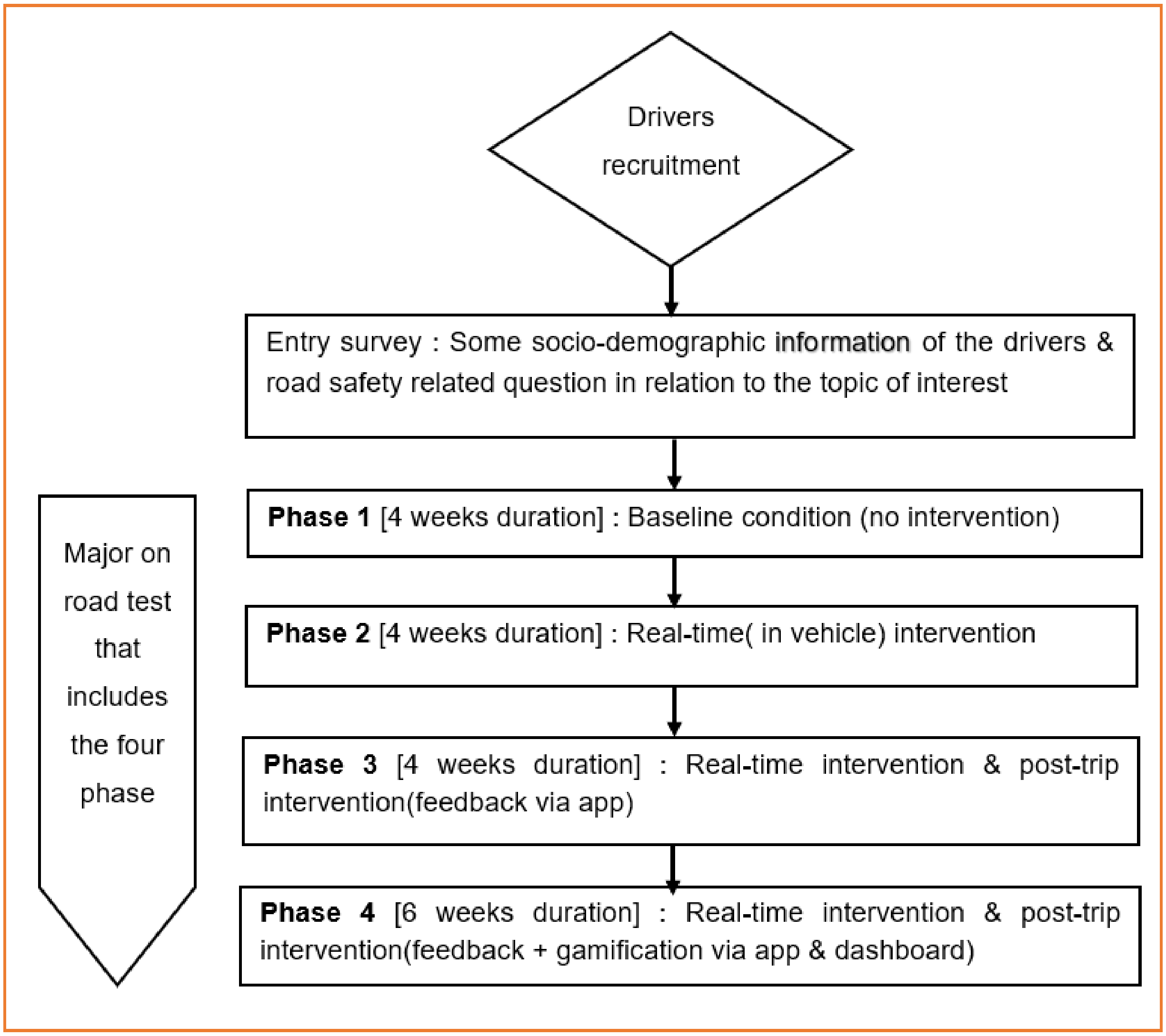


FIGURE 7 Data collection procedure (Hancox et al., 2021)

A total of twenty six truck drivers from two companies(Company X and Company Y) participated in this study. Among the drivers who participated in the study, seventeen filled out the entry survey questionnaires. The naturalistic driving data through the i-DREAMS platform is collected from 18 truck drivers employed at company X and 8 employed at company Y.

The naturalistic driving data is categorized into total, high, medium , and low risk events based on their relative zone of the driver in the STZ(normal driving, danger phase and crash avoidable phase).The total risk events is the summation of all the three(high, medium & low) risk events. The categorizations of the risk events as low, medium, and high directly relate to the Safety Tolerance Zone(STZ) concept.

The low-risky events are directly associated with the normal driving phase of the STZ, in which there is no indication that a collision scenario is likely to happen at that time. At the normal driving stage, drivers receive information messages or reminders about the possible occurrence of a specific risky event; hence the number of these messages that a driver gets from the real-time interventions are considered low risky events. The danger phase of the STZ is where the possibility for the beginning of the collision scenario is observed, and is also directly associated with medium risky events. The number of warning signals a driver received from the real time intervention during the danger phase are considered the medium risky events. While, the avoidable crash phase of the STZ is where, ”a collision scenario is actually starting to develop, but the vehicle operator still has the potential to intervene and avoid a crash”(Brijs et al., 2020). The number of instructional signals a driver received from the real time intervention during the avoidable crash phase are considered as high risky events.

3.3 Data processing

The data collected from the twenty-six truck drivers needs processing before proceeding to the next stage, that is, the data analysis. The data processing includes removal of trips which are collected before the starting date of phase 1 and after the ending date of phase 4 for all the truck drivers. Trips with less than 2 km are also excluded from the analysis as these trips are usually considered maneuver trips or logistical loading and unloading between warehouses . After removing all the unnecessary data , all the trips are then categorized into their respective phases using initial and ending dates for each phase. Then, the total number of risky events for each driver in each phase is found by adding the risky events in all the trips and divided by the total distance travelled per their respective phase. Five among the twenty six truck drivers have incomplete trip information for some of their phases, hence not included for further analysis unless it is found applicable.

For comparing the number of risky events between each phase and among the truck drivers it is important to normalize the data to the same standard as there is variation in the total time & distance travelled. It is possible to normalize the data by converting the number of risky events per the same standard unit of distance(Wang & Xu, 2019) or time(Mase et al., 2020). For this study , the data is normalized based on standard unit of distance using equation 3.1 ,which is the number of risky events per 100 km.

$$N\text{umber of risky events per 100 km} = \frac{\text{total number of risky events per phase} * 100\text{ km}}{\text{total distance travelled per phase}} \qquad \text{equation[3.1]}$$

3.4 Data Analysis

In total, the data used in this study is collected from 21 drivers over an 18 weeks period with a total of around 9500 trips, 14,000 hrs. travel time , and 692,000 kms distance. The core data analysis, including descriptive analysis and hypothesis testing, is done in SPSS after the data has been exported from Microsoft Excel where the data processing is done. Friedman's ANOVA was selected for hypothesis testing and to determine the effect of the intervention. Friedman's ANOVA is a non-parametric equivalent of one way repeated measures of ANOVA employed when the assumptions to conduct parametric tests are violated(Field, 2009).

3.4.1 Friedman's ANOVA

Friedman's ANOVA is a non-parametric test used when the same participants are participating in all conditions of the experiment (Field, 2009; Hazra & Gogtay, 2016). Batool and Carsten (2018) used Friedman's ANOVA to measure the impact of performing cognitive tasks on measures of driver's visual behavior, vehicle control , and subjective rating where the data did not meet assumptions to conduct parametric tests. The effect of intersection Advanced Driver Assistance Systems (ADAS) on the driving performance and driving behavior of older drivers (Dotzauer et al., 2013) also used Friedman's ANOVA as the data violated basic assumptions to conduct parametric tests. Therefore, Friedman's ANOVA in IBM SPSS 28 software was used to test for the significance difference between the number of risky events in the baseline period and compared to the intervention period as the data didn't follow the normal distribution & violated the sphericity assumption.

The naturalistic data collected using i-DREAMS platforms mainly follows non normal distribution and thus Friedman's ANOVA is suitable for the analysis. Friedman's ANOVA is used to test the following hypotheses. The hypothesis testing is done based on the total, high, medium, and low number of risky events recorded per 100 kms as well as the trip score recorded by the i-DREAMS platform.

Total risky events

H_0: There is no significant difference in the frequency of *total risky* events between the baseline (no intervention) and interventions (real-time intervention, real-time intervention plus post-trip intervention score with smartphone, and real-time intervention plus post-trip intervention score and gamification with smartphone)

H_1: There is a significant difference in the frequency of *total risky* events between the baseline(no intervention) and interventions(real-time intervention, real-time intervention plus post-trip intervention score with smartphone , and real-time intervention plus post -trip intervention score and gamification with smartphone)

High risky events

H_0: There is no significant difference in the frequency of *high risky* events between the baseline (no intervention) and interventions (real-time intervention, real-time intervention plus post-trip intervention score with smartphone, and real-time intervention plus post-trip intervention score and gamification with smartphone)

H_1: There is a significant difference in the frequency of *high risky* events between the baseline condition (no intervention) and interventions(real-time intervention, real-time intervention plus post -trip intervention score with smartphone , and real-time intervention plus post-trip intervention score and gamification with smartphone)

Medium risky events

H_0: There is no significant difference in the frequency of *medium risky* events between the baseline condition (no intervention) and interventions (real-time intervention, real-time intervention plus post-trip intervention score with smartphone, and real-time intervention plus post-trip intervention score and gamification with smartphone)

H_1: There is a significant difference in the frequency of *medium risky* events between the baseline(no intervention) and interventions(real-time intervention, real-time intervention plus post-trip intervention score with smartphone , and real-time intervention plus post-trip intervention score and gamification with smartphone)

Low risky events

H_0: There is no significant difference in the frequency of *low risky* events between the baseline condition (no intervention) and interventions (real-time intervention, real-time intervention plus post-trip intervention score with smartphone, and real-time intervention plus post-trip intervention score and gamification with smartphone)

H_1: There is a significant difference in the frequency of *low risky* events between the baseline condition (no intervention) and interventions(real-time intervention, real-time intervention plus post-trip intervention score with smartphone , and real-time intervention plus post-trip intervention score and gamification with smartphone

Trip score

H_0: There is no significant difference in the trip scores between the baseline condition (no intervention) and interventions (real-time intervention, real-time intervention plus post-trip intervention score with smartphone, and real-time intervention plus post-trip intervention score and gamification with smartphone).

H_1: There is a significant difference in trip scores between the baseline condition(no intervention) and interventions(real-time intervention, real-time intervention plus post-trip intervention score with smartphone , and real-time intervention plus post-trip intervention score and gamification with smartphone).

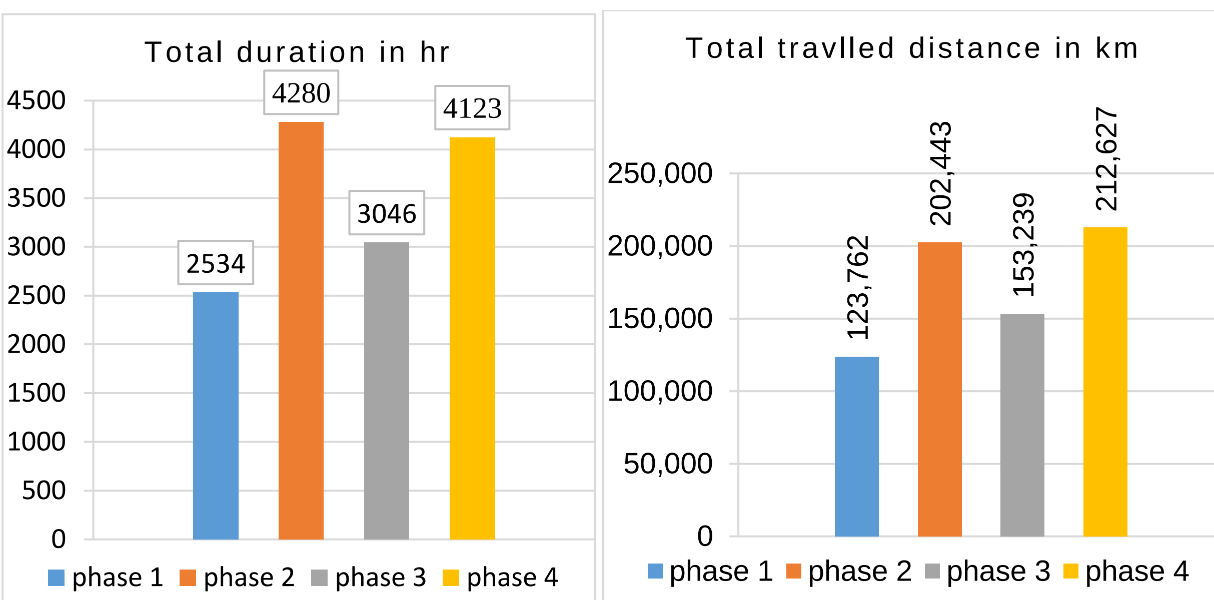
4. DATA ANALYSIS AND RESULTS

4.1 Descriptive Analysis of Study Participants

Belgian truck drivers between 66 and 24 years were among the oldest and youngest (M=49, SD=10.17), with driving experience ranging from 7 to 47 years (M=25.88, SD=11.27) participated in the study. All are professional truck drivers who did full-time driving jobs, and more than 83 percent completed secondary education.

4.1.1 Total Distance and Duration of The On-Road Study

A total of twenty-one (N=21) all male truck drivers completed all four phases of the on-road study experiment in 18 weeks. The drivers travelled a total distance of around 124,000 km(M=5665.75, SD=2704.83) and around 2500 hours travel time (M=114.87, SD=59.56) in base case condition(phase 1). Similarly , in phase 2(real-time intervention) ,they travelled a total distance of around 202,000 km (M=9167.34,SD=3742.38) and around 4200 hours travel time (M=191.68,SD=96.6). Further, in the third phase (real-time intervention and post-trip intervention (feedback with smartphone)), the drivers traveled a total distance of around 153,000km (M=7117.48, SD=3705.91) and for around 3000 hours of travel time (M=141.21, SD=67.81). Finally, they traveled a total distance of around 212,000 km (M=10125.09, SD=4318.44) and around 4100 hours of travel time (M=196.31, SD=73.43) in phase 4 (real-time intervention and post-trip intervention (feedback and gamification with smartphone)). Drivers traveled less distance & duration in phase 1, while almost equally highest in phases two and four. Figure 6 demonstrates the total distance and travel time covered by the drivers during the whole on-road study calculated to the nearest zero decimal place.



a. total travel time in hour b. total distance in km

FIGURE 8 Total travel time (a) and total distance (b) per phase

4.1.2 The Proportion of High, Medium, and Low Risky Events

The total risk events was the summation of high, medium, and low events recorded by the i-DREAMS platform for each trip. The classification of the risky events into high, medium, and low was based on the concept of a safety tolerance zone, which comprises the normal driving, danger phase, and avoidable crash phase. In this study, the low, medium, and high risky events are the events detected by the i-DREAMS platform in the normal driving, danger phase, and crash avoidable phase, respectively. As demonstrated in figure 7, low risky events have the highest proportion(60 to 63 percent of the total) followed by medium, and high risky events ,respectively. Averagely, drivers showed from a minimum 247 to maximum of 275 total risk events per 100 km trip. Furthermore, there was the highest proportion of high risky events in phase 1(8.30%), preceded by phases 2,3, and 4 by 7.57%, 7.12%, and 7.07% of the total, respectively.

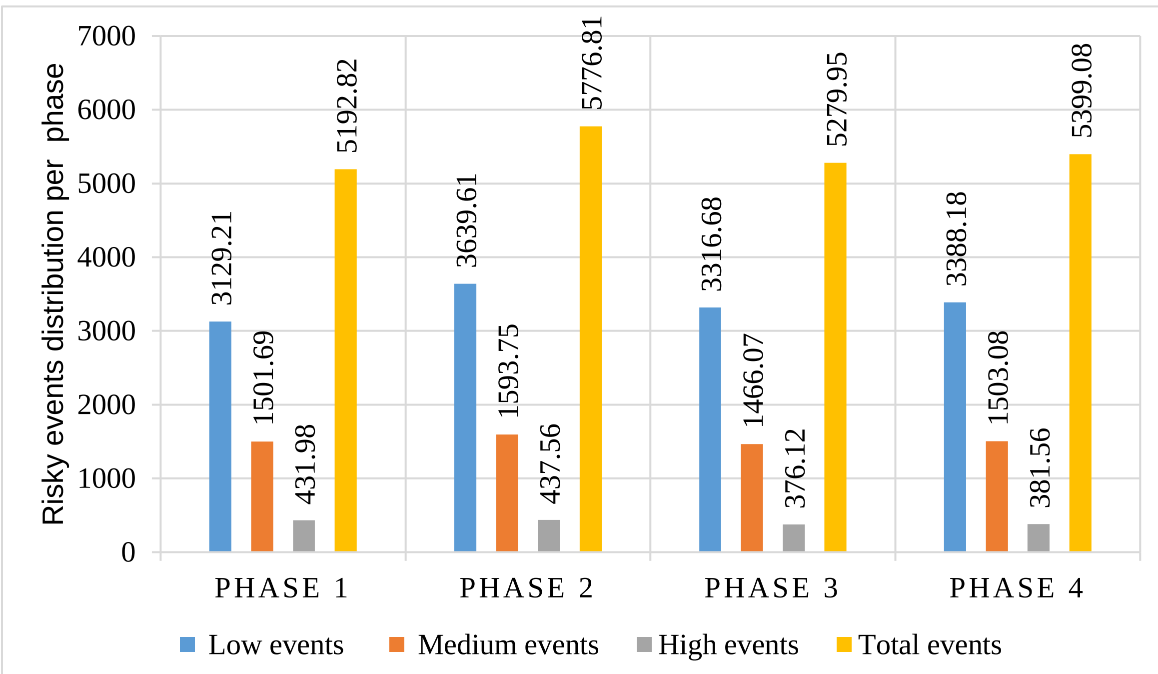


FIGURE 9 Low, medium, high, & total risky events distribution

4.1.3 Proportion of Risky Events

Among the 11 risky events examined in the study, tailgating and steering the top most events together represents more than 60 percent of all the events captured. Speeding , deceleration, and acceleration events were also in the top five events that make up more than 35 percent of all the events. Figure 8 demonstrated the top five risky events, tailgating, steering, speeding, deceleration, and acceleration events represent more than 85 percent of the events observed in the study. The remaining six risky events (overtaking, lane discipline, forward collision avoidance, vulnerable road users collision avoidance, distraction, and fatigue) only represents 15 percent of the total events recorded during the on-road study.

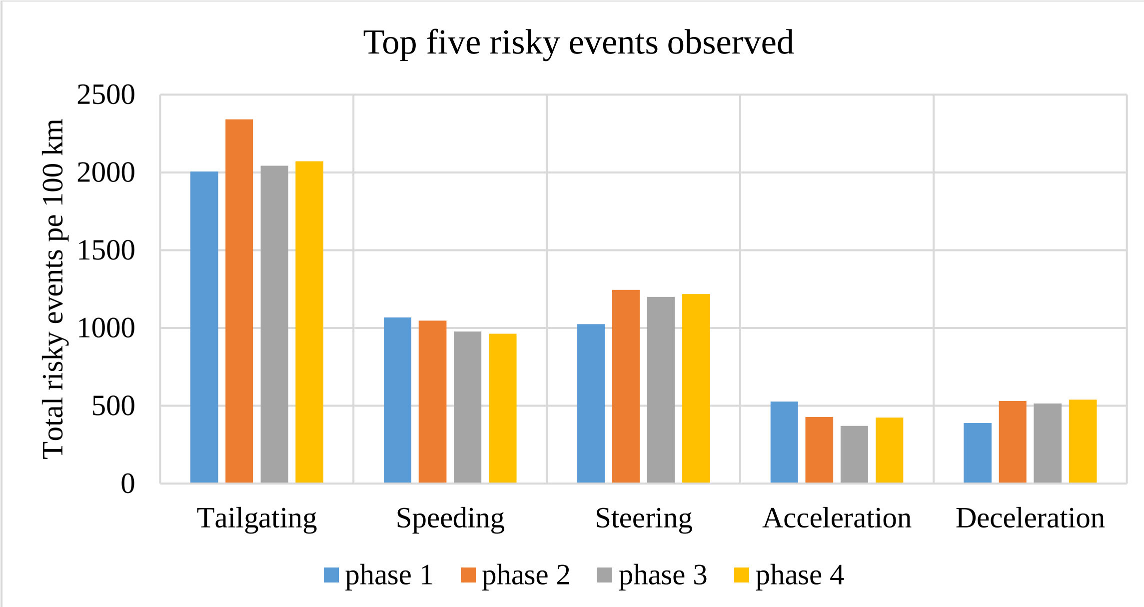


FIGURE 10 Top five most observed risk events

4.2 Total risky events

The total risky events were the summation of the high, medium, and low-risk events a driver recorded while driving. One of the key objectives of this study is to evaluate the outcomes of the real time and post trip intervention in reducing the occurrence of total risky events that lead into traffic collisions. The performance objectives (e.g. speeding, tailgating, distraction) are among the key risky events that resulted in traffic collisions. Friedman's ANOVA was performed on the total speeding events if there is a significant difference between the baseline (phase 1) and interventions (phase2,phase 3 and phase4).

TABLE 2 Friedman's ANOVA (Hypothesis test summary)

Null hypothesis	test	Sig.[a,b]	decision
The distribution of speeding 1, speeding 2, speeding 3, and speeding 4 are the same	Related-Samples Kendall's Coefficient of Concordance	0.235	Retain the null hypothesis.

A Friedman's ANOVA test showed that there was no significant difference in the total speeding events between the baseline(no intervention) and interventions, X^2 (3)= 4.257,p=0.235,w=0.068. Since the p= 0.235 is greater than 0.05, the null hypothesis that no significant difference in total speeding events between the non-intervention and intervention need to be retained. As shown in Table 3 the summary Friedman's test result for all total events ,there was no significance difference between the baseline case and interventions in all parameters except for total deceleration (p=0.002) and total steering (p=0.02) events as their p value is less than 0.05.

TABLE 3 Friedman's test statistics summary result for all total events

Variables	N	Kendall's W	Test Statistic	Degree Of Freedom	Asymptotic Sig.(2-sided test)
Speeding	21	0.068	4.257	3	0.235
Acceleration	21	0.040	2.543	3	0.468
Deceleration	21	0.238	15.000	3	*0.002*
Steering	21	0.156	9.857	3	*0.020*
Tailgating	21	0.041	2.580	3	0.461
Overtaking	21	0.119	7.500	3	0.058
Lane discipline	21	0.010	0.600	3	0.896
Forward collision avoidance	21	0.036	2.246	3	0.523
Vulnerable road user collision avoidance	21	0.009	0.579	3	0.901
Fatigue	21	0.049	3.057	3	0.383
Distraction	21	0.095	6.000	3	0.112
Speed managemen t	21	0.068	4.257	3	0.235
Vehicle control	21	0.099	6.257	3	0.100
Road sharing	21	0.081	5.100	3	0.165
Health	21	0.036	2.254	3	0.521

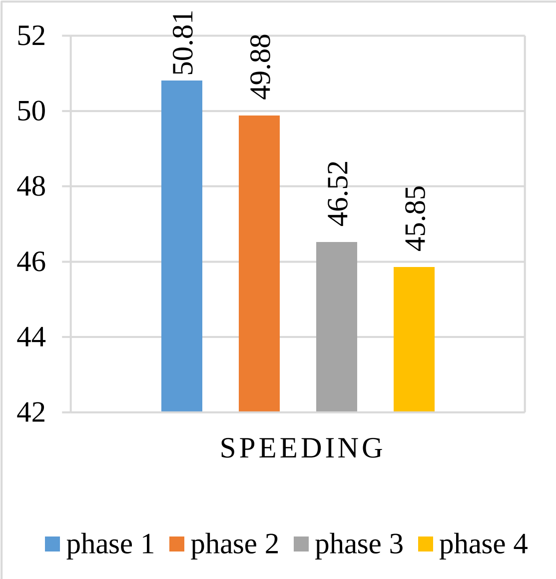
Even though there was no significant differences in most of the total risky events between the base case and interventions, deceleration & steering showed a difference. A Friedman's ANOVA test showed that there was a significant difference in the total deceleration between the baseline(no intervention) and interventions, X^2 (3)= 15,p=0.002,w=0.238.For a post hoc analysis, Wilcoxon tests have been administered with an adjusted level of significance set to .05**.**The test result is demonstrated in table 4, drivers showed less deceleration events in the baseline condition (phase 1) as compared to the real time intervention condition (phase2)(p=0.031). drivers also showed less deceleration events in the phase 1 as compared to the real time intervention & post trip intervention (score with smart phone application) condition (phase 3)(p=0.001), and showed less deceleration events in phase 1 as compared to real time intervention & post trip intervention (score & gamification with smart phone application) condition (phase 4) (p=0.001). Meanwhile, the result of the pairwise comparison didn't show a significant difference in the deceleration event between phase 2, phase 3, and phase 4.

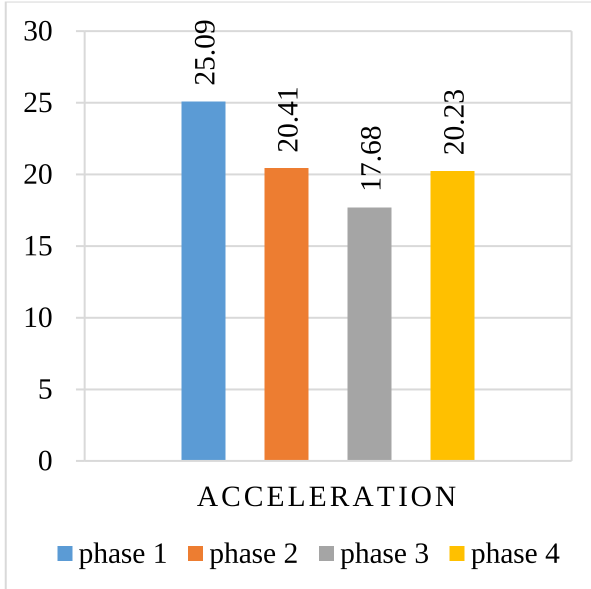
A Friedman's ANOVA test also showed that there was a significant difference in the total steering events between the baseline (no intervention) and interventions, X^2 (3)= 9.857,p=0.02,w=0.156. For a post hoc analysis, Wilcoxon tests have been administered with an adjusted level of significance set to .05.The test result was drivers showed less steering events in phase 1 as compared to phase 3 (p=0.012), similarly less steering events in phase 1 as compared to phase 4(p=0.004). On the other hand, the pairwise comparison test indicates no significant difference between phase 2, phase3, and phase4.

TABLE 4 Pairwise comparisons for total deceleration and steering

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.a
deceleration_1-deceleration_2	-0.857	0.398	-2.151	0.031	0.189
deceleration_1-deceleration_3	-1.286	0.398	-3.227	0.001	0.008
deceleration_1-deceleration_4	-1.381	0.398	-3.466	0.001	0.003
deceleration_2-deceleration_3	-0.429	0.398	-1.076	0.282	1.000
deceleration_2-deceleration_4	-0.524	0.398	-1.315	0.189	1.000
deceleration_3-deceleration_4	-0.095	0.398	-0.239	0.811	1.000
steering_1-steering_2	-0.619	0.398	-1.554	0.120	0.721
steering_1-steering_3	-1.000	0.398	-2.510	0.012	0.072
steering_1-steering_4	-1.143	0.398	-2.869	0.004	0.025
steering_2-steering_3	-0.381	0.398	-0.956	0.339	1.000
steering_2-steering_4	-0.524	0.398	-1.315	0.189	1.000
steering_3-steering_4	-0.143	0.398	-0.359	0.720	1.000

Even though there is no statistically significant reduction of the risky events due to the intervention, some risky events showed a reduction in their mean per 100 km in the intervention condition compared to the base case condition as shown in figure 9. Results showed there was a reduction in the mean total speeding event per 100 km from phase 1 to phase 2 by 1.8%, from phase 1 to phase 3 by 8.4% , and from phase 1 to phase 4 by 9.7 %. Furthermore, there was also a reduction in the mean total acceleration event per 100 km from phase 1 to phase2 , from phase 1 to phase 3 , and from phase 1 to phase 4 by 18.6%, 29.5% ,and 19.3% , respectively. Additionally, there was also a reduction in the mean of total distraction event per 100 km from phase 1 (0.41) to phase 2(0.025) by 9.4% and from phase 1 (0.41) to both phase 3 & 4 (0).





(a) speeding (b) acceleration

FIGURE 11 Mean total (a) speeding and (b) acceleration per 100 km in the four phases

4.2.1 High risky events

High risky events are counted /recorded based on the number of instructional signals given by the real-time intervention platform to the drivers in each trip. It is also important to evaluate the outcomes of the real-time and post-trip intervention in reducing the occurrence of high risky events that could result in traffic collisions unless the driver intervenes shortly. Friedman's ANOVA was performed on the high events if there was a significant difference between the baseline (phase 1) and interventions(phase2,phase 3 and phase4).

TABLE 5 Friedman's test statistics summary result for all high events

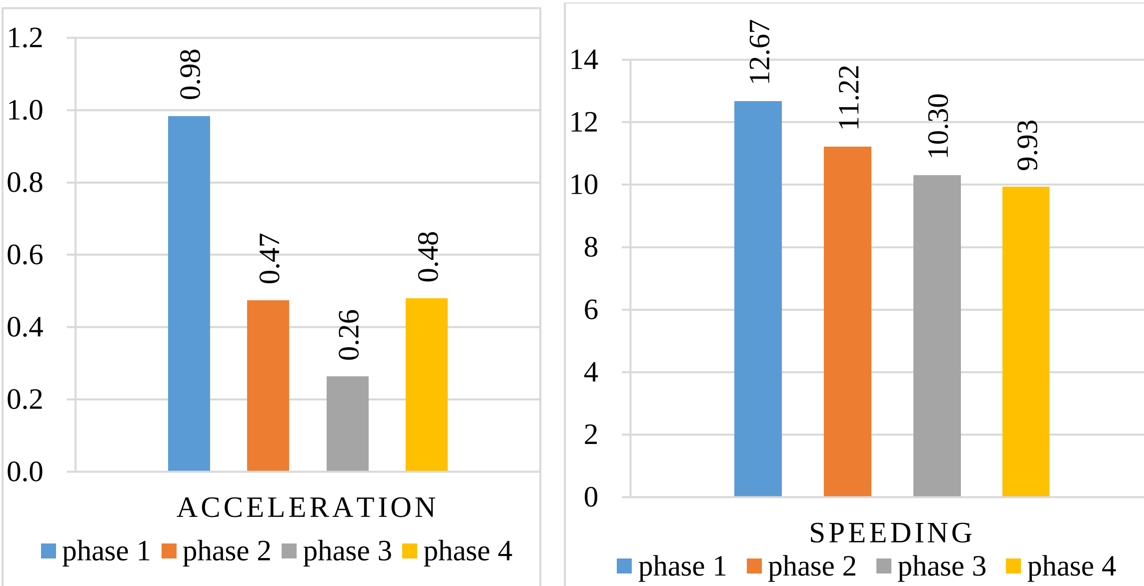
Variables	N	Kendall's W	Test Statistic	Degree Of Freedom	Asymptotic Sig.(2-sided test)
Speeding	21	0.060	3.780	3	0.286
Acceleration	21	0.024	1.543	3	0.672
Deceleration	21	0.050	3.149	3	0.369
Steering	21	0.171	10.748	3	*0.013*
Tailgating	21	0.007	0.420	3	0.936
Overtaking	21	0.024	1.500	3	0.682
Fatigue	21	0.035	2.202	3	0.532
Speed management	21	0.06	3.78	3	0.286
Vehicle control	21	0.053	3.343	3	0.342
Road sharing	21	0.007	0.420	3	0.936
Health	21	0.035	2.202	3	0.532

As shown in table 5, the summary of Friedman's test result for all high risky events ,there was no significance difference between the baseline condition and intervention conditions in all parameters except for High steering(p=0.013) as the significance value is less than 0.05. A Friedman’s ANOVA test showed that there was a significant difference in the high steering events between the baseline (no intervention) and interventions, X^2 (3)= 10.748,p=0.013,w=0.171. For a post hoc analysis, Wilcoxon tests have been administered with an adjusted level of significance set to .05. This was the result that drivers showed less high steering events in phase 1 as compared to phase 3 (p=0.012), similarly less steering events in phase 1 as compared to phase 4(p=0.012). Moreover, the result also indicated drivers showed less high steering events in phase 2 as compared to phase 3 (p=0.042), as well as less steering events in phase 2 as compared to phase 4 (p=0.004). As shown in table 6, the pairwise comparison test indicates no significant difference between phase 1 and 2,and correspondingly between phase 3 and phase 4.

TABLE 6 Pairwise comparisons for high steering events

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
steering_1-steering_2	-0.190	0.398	-0.478	0.633	1.000
steering_1-steering_3	-1.000	0.398	-2.510	0.012	0.072
steering_1-steering_4	-1.000	0.398	-2.510	0.012	0.072
steering_2-steering_3	-0.810	0.398	-2.032	0.042	0.253
steering_2-steering_4	-0.810	0.398	-2.032	0.042	0.253
steering_3-steering_4	0.000	0.398	0.000	1.000	1.000

Although the intervention did not produce statistically significant output in reducing the high risk events occurrences, two risky events (speeding and acceleration) did exhibit a decrease in their mean per 100 km when compared to the base case condition, as shown in figure 10. Results show there is a decrease in the mean high acceleration event per 100 km from phase 1 to phase 2 by 52%, from phase 1 to phase 3 by 73.4% , and from phase 1 to phase 4 by 51%. Likewise , there is also a reduction in the mean high speeding event per 100 km from phase 1 to phase2 by 11.4%, from phase 1 to phase 3 by 18.7% , and from phase 1 to phase 4 by 21.6%.



(a) acceleration (b) speeding

FIGURE 12 Mean high (a) acceleration and (b) speeding events per 100 km in the four phases

4.2.1 Medium Risky Events

Medium risky events are counted /registered based on the number of warning signals given by the real-time intervention platform to the drivers in each trip. Moreover, it is also vital to conduct the outcome evaluation of the real-time and post-trip intervention in reducing the occurrence of medium risky events that could turn into high risky events unless avoided by taking necessary reactions. Friedman's ANOVA was performed on the medium events if there is a significant difference between the baseline (phase1) and interventions (phase 2,phase 3 and phase 4).

Table 7 Friedman's test statistics summary result for all medium events

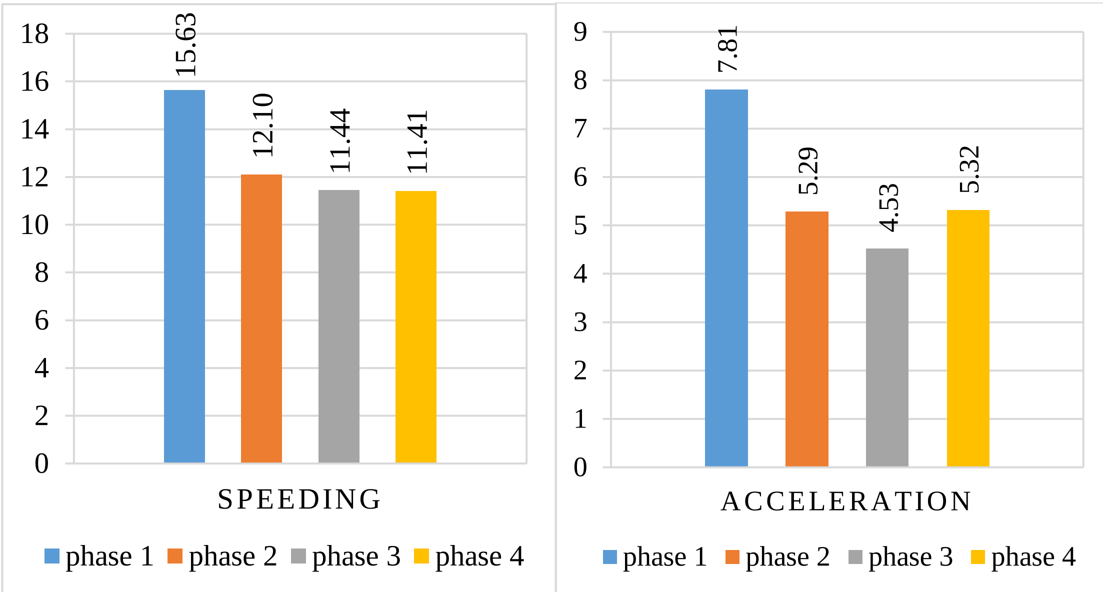
Variables	N	Kendall's W	Test Statistic	Degree Of Freedom	Asymptotic Sig.(2-sided test)
Speeding	21	0.012	0.761	3	0.859
Acceleration	21	0.028	1.743	3	0.627
Deceleration	21	0.105	6.646	3	0.084
Steering	21	0.176	11.114	3	0.011
Tailgating	21	0.058	3.660	3	0.301
Overtaking	21	0.025	1.588	3	0.662
Fatigue	21	0.049	3.057	3	0.383
Speed management	21	0.012	0.761	3	0.859
Vehicle control	21	0.093	5.857	3	0.119
Road sharing	21	0.058	3.660	3	0.301
Health	21	0.049	3.057	3	0.383

As shown in Table 7, the summary of Friedman's test result for all medium risky events ,there was no significant difference between the baseline condition and intervention conditions in all parameters except for medium steering (p=0.011) as the significance value is less than 0.05.For a post hoc analysis, Wilcoxon tests have been administered with an adjusted level of significance set to .05. The pairwise comparison test summarized in table 8, indicates drivers showed less medium steering events in phase 1 as compared to phase 3 (p=0.009) , and also showed less steering events in phase 1 as compared to phase 4 (p=0.003). In contrast, the pairwise comparison shows there was no significant difference in medium steering between the other phases.

TABLE 8 Pairwise comparisons for medium steering events

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
steering_1-steering_2	-0.524	0.398	-1.315	0.189	1.000
steering_1-steering_3	-1.048	0.398	-2.630	0.009	0.051
steering_1-steering_4	-1.190	0.398	-2.988	0.003	0.017
steering_2-steering_3	-0.524	0.398	-1.315	0.189	1.000
steering_2-steering_4	-0.667	0.398	-1.673	0.094	0.566
steering_3-steering_4	-0.143	0.398	-0.359	0.720	1.000

Although the intervention did not produce statistically significantly output in reducing the medium risk events occasions, two risky events (speeding and acceleration) did exhibit a decrease in their mean per 100 km when compared to the base case condition as shown in figure 11. Results show there is a decrease in the mean medium acceleration event per 100 km from phase 1 to phase 2 by 22.6 %, from phase 1 to phase 3 by 26.8% , and from phase 1 to phase 4 by 27%. Similarly , there is also a reduction in the mean Medium acceleration event per 100 km from phase 1 to phase2 by 32.2 %, from phase 1 to phase 3 by 42% , and from phase 1 to phase 4 by 31.9%.



(a) (b)

FIGURE 13 Mean medium (a) speeding and (b) acceleration per 100 kms in the four phases

4.2.3 Low Risky Events

Low risky events are counted based on the number of information messages or reminders that drivers received about the possible occurrence of a specific risky event from the real time intervention platform. As one component of the total events, it is useful to conduct the outcome evaluation of the real-time and post-trip intervention in reducing the occurrence of low risky events that could transfer into medium risky events unless avoided by taking necessary action.

TABLE 9 Friedman's test statistics summary result for all low events

Variables	N	Kendall's W	Test Statistic	Degree Of Freedom	Asymptotic Sig.(2-sided test)
Speeding	21	0.092	5.800	3	0.122
Acceleration	21	0.029	1.857	3	0.603
Deceleration	21	0.205	12.886	3	0.005
Steering	21	0.122	7.686	3	0.053
Tailgating	21	0.011	0.720	3	0.868
Overtaking	21	0.131	8.280	3	0.041
Fatigue	21	0.078	4.923	3	0.177
Speed management	21	0.092	5.800	3	0.122
Vehicle control	21	0.137	8.600	3	0.035
Road sharing	21	0.026	1.620	3	0.655
Health	21	0.078	4.923	3	0.177

Friedman’s ANOVA was performed on the low events if there was a significant difference between the baseline (phase1) and interventions (phase2,phase 3 and phase4).Firstly, a Friedman’s ANOVA test as demonstrated in table 9 that there was a significant difference in the low deceleration events between the baseline (no intervention) and interventions, X^2 (3)= 12.886,p=0.005,w=0.205. For a post hoc analysis, Wilcoxon tests have been administered with an adjusted level of significance set to .05 and the result was drivers showed fewer low deceleration events in phase 1 as compared to phase 2 (p=0.031), fewer deceleration events in phase 1 as compared to phase 3 (p=0.002), and fewer deceleration events in phase 1 as compared to phase 4 (p=0.002).Further, a Friedman’s ANOVA test showed that there was a significant difference in the low overtaking events between the baseline(no intervention) and interventions, X^2 (3)= 8.28,p=0.041,w=0.131. As shown in table 10 ,drivers showed fewer low overtaking events in phase 1 as compared to phase 4 (p=0.023), and also fewer low overtaking events in phase 1 as compared to phase 3 (p=0.009). Finally, Friedman's ANOVA test showed that there was a significant difference in the low vehicle control between the baseline (no intervention) and interventions, X^2 (3)= 8.6,p=0.035,w=0.137.

TABLE 10 Pairwise comparisons for low deceleration, overtaking, & vehicle control

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
deceleration1-deceleration 2	-0.857	0.398	-2.151	0.031	0.189
deceleration1-deceleration 3	-1.238	0.398	-3.108	0.002	0.011
deceleration1-deceleration4	-1.238	0.398	-3.108	0.002	0.011
deceleration2-deceleration3	-0.381	0.398	-0.956	0.339	1.000
deceleration2-deceleration4	-0.381	0.398	-0.956	0.339	1.000
deceleration3-deceleration 4	0.000	0.398	0.000	1.000	1.000
overtaking1-overtaking3	-0.286	0.398	-0.717	0.473	1.000
overtaking1-overtaking4	-0.857	0.398	-2.151	0.031	0.189
overtaking1-overtaking2	-0.952	0.398	-2.390	0.017	0.101
overtaking3-overtaking4	-0.571	0.398	-1.434	0.151	0.909
overtaking3-overtaking2	0.667	0.398	1.673	0.094	0.566
overtaking4-overtaking2	0.095	0.398	0.239	0.811	1.000
vehicle control1-vehicle control 2	-0.429	0.398	-1.076	0.282	1.000
vehicle control 1-vehicle control 4	-0.905	0.398	-2.271	0.023	0.139
vehicle control 1-vehicle control 3	-1.048	0.398	-2.630	0.009	0.051
vehicle control 2-vehicle control 4	-0.476	0.398	-1.195	0.232	1.000
vehicle control 2-vehicle control 3	-0.619	0.398	-1.554	0.120	0.721
vehicle control 4-vehicle control 3	0.143	0.398	0.359	0.720	1.000

This was the result that drivers showed fewer low vehicle control in phase 1 as compared to phase 4 (p=0.023),and similarly fewer low vehicle control in phase 1 as compared to phase 3 (p=0.009).

Although the intervention did not produce statistically significant output in reducing the low risk events , acceleration did exhibit a decrease in its mean per 100 km when compared to the base case condition as shown in figure 14. Results show there is a decrease in the mean low acceleration event per 100 km from phase 1 to phase 2 by 10 %, from phase 1 to phase 3 by 20.9% , and from phase 1 to phase 4 by 11.4 %.

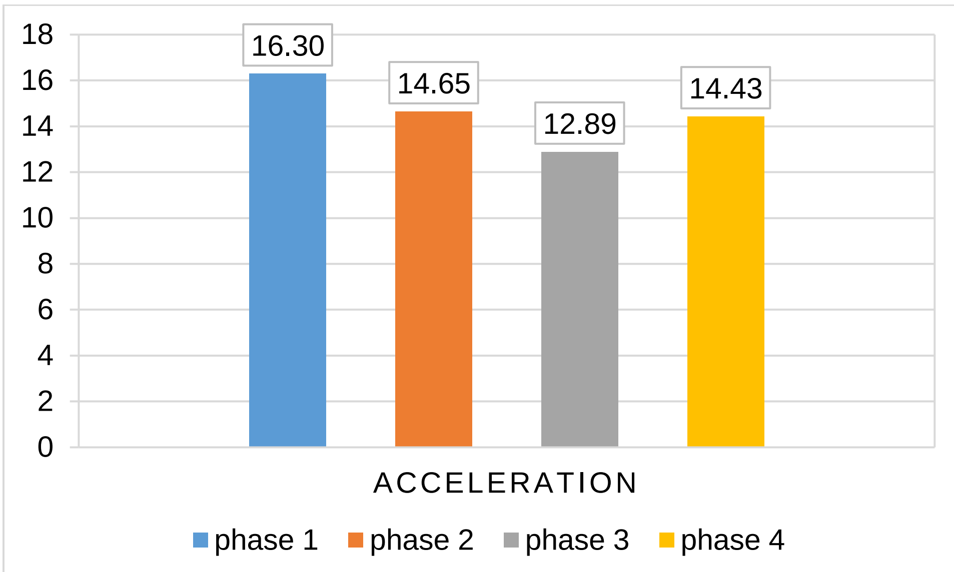


FIGURE 14 Mean acceleration per 100 kms in the four phases

4.2.4 Trip Score

Scores is time evolution of project-average and driver-specific scores for performance objectives and safety promoting goals. A trip score is a performance indicator number given, usually from a hundred in a trip, based on the occurrence of risky driving behavior. It is the score given to drivers based on the frequency of the risky events in their driving. Drivers who showed less risky events in their driving got a higher score, while drivers who showed more risky events in their trip obtained lower value. As the study's key objective is to evaluate the real-time and post-trip intervention outcome, it is essential to examine whether the interventions also produce better successes in terms of trip score than the base case condition. Friedman's ANOVA was performed on the trip scores of the different events to estimate whether there is a significant difference in score between the baseline and the intervention conditions. Firstly, as demonstrated in table 11 ,the summary Friedman's test for all the trip scores ,there was no significance difference between the baseline condition and interventions conditions for fitness, fatigue, distraction, vehicle control, acceleration, deceleration, road sharing, tailgating, overtaking, forward collision avoidance, and Vulnerable road user collision avoidance as their significance(p) value is greater than 0.05.

TABLE 11 Friedman's test statistics summary result for all trip scores

Parameters	N	Kendall's W	Test Statistic	Degree Of Freedom	Asymptotic Sig.(2-sided test)
Fitness	21	0.095	5.957	3	0.114
Fatigue	21	0.095	5.957	3	0.114
Distraction	21	0.067	4.250	3	0.236
Vehicle control	21	0.016	1.000	3	0.801
Acceleration	21	0.037	2.314	3	0.510
Deceleration	21	0.081	5.096	3	0.165
Steering	21	0.171	10.771	3	0.013
Road sharing	21	0.034	2.122	3	0.547
Tailgating	21	0.012	0.786	3	0.853
Lane discipline	21	0.170	10.733	3	0.013
Overtaking	21	0.070	4.430	3	0.219
Forward collision avoidance	21	0.023	1.449	3	0.694
Vulnerable road user	21	0.018	1.162	3	0.762
Speeding	21	0.213	13.450	3	0.004

Whereas, the Friedman's ANOVA test also showed that there was a significant difference in the steering trip score between the baseline (no intervention) and interventions, X^2 (3)= 10.771,p=0.013,w=0.171. For a post hoc analysis, Wilcoxon tests have been administered with an adjusted level of significance set to .05 and the result presented in table 12, drivers have a higher steering score in phase 1 as compared to phase 3 (p=0.003) , and higher steering score in phase 1 as compared to phase 4 (p=0.017). To mention another point from the Friedman's ANOVA test, there was also a significant difference in the speeding trip score between the baseline (no intervention) and interventions, X^2 (3)= 13.45, p=0.004,w=0.213. This was the result in drivers have a higher speeding score in phase 1 as compared to phase 4 (p=0.006), higher speeding score in phase 1 as compared to phase 3 (p=0.02),higher speeding score in phase 2 as compared to phase 4 (p=0.005) , and higher speeding score in phase 2 as compared to phase 3 (p=0.017). Furthermore, there was also a significant difference in the lane discipline score between the non -intervention and intervention conditions, X^2(3)=10.733,p=0.013, w=0.170. Even though the Friedmans ANOVA test showed a significant difference between the intervention and non-intervention lane discipline score, the follow-up post hoc analysis didn't show a statistically significant difference between all the possible pair combinations.

TABLE 12 Pairwise comparisons of steering and speeding scores

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
steering_3-steering_4	-0.238	0.398	-0.598	0.55	1.000
steering_3-steering_2	0.762	0.398	1.912	0.056	0.335
steering_3-steering_1	1.19	0.398	2.988	0.003	0.017
steering_4-steering_2	0.524	0.398	1.315	0.189	1.000
steering_4-steering_1	0.952	0.398	2.39	0.017	0.101
steering_2-steering_1	0.429	0.398	1.076	0.282	1.000
speeding_4-speeding_3	0.167	0.398	0.418	0.676	1.000
speeding_4-speeding_1	1.095	0.398	2.749	0.006	0.036
speeding_4-speeding_2	1.119	0.398	2.809	0.005	0.030
speeding_3-speeding_1	0.929	0.398	2.331	0.02	0.119
speeding_3-speeding_2	0.952	0.398	2.39	0.017	0.101
speeding_1-speeding_2	-0.024	0.398	-0.06	0.952	1.000
lane_discipline_3-lane_discipline_4	-0.143	0.398	-0.359	0.720	1.000
lane_discipline_3-lane_discipline_2	0.524	0.398	1.315	0.189	1.000
lane_discipline_3-lane_discipline_1	0.762	0.398	1.912	0.056	0.335
lane_discipline_4-lane_discipline_2	0.381	0.398	0.956	0.339	1.000
lane_discipline_4-lane_discipline_1	0.619	0.398	1.554	0.120	0.721
lane_discipline_2-lane_discipline_1	0.238	0.398	0.598	0.550	1.000

Even though the intervention didn't not show statistically significant improvement in the trip score , acceleration and distraction did reveal improvement in their trips scores when compared to the base case condition, as shown in figure 15. Results show there is an increase in the distraction trip score from phase 1 to phase 2 by 2.66 %, similarly from phase 1 to phases 3 and 4 by 2.79 % ,equally. Moreover , there is also an increase in acceleration trip score from phase 1 to phase2 by 7.44% , from phase 1 to phase 3 by 8.06%, and from phase 1 to phase 4 by 6.47%.

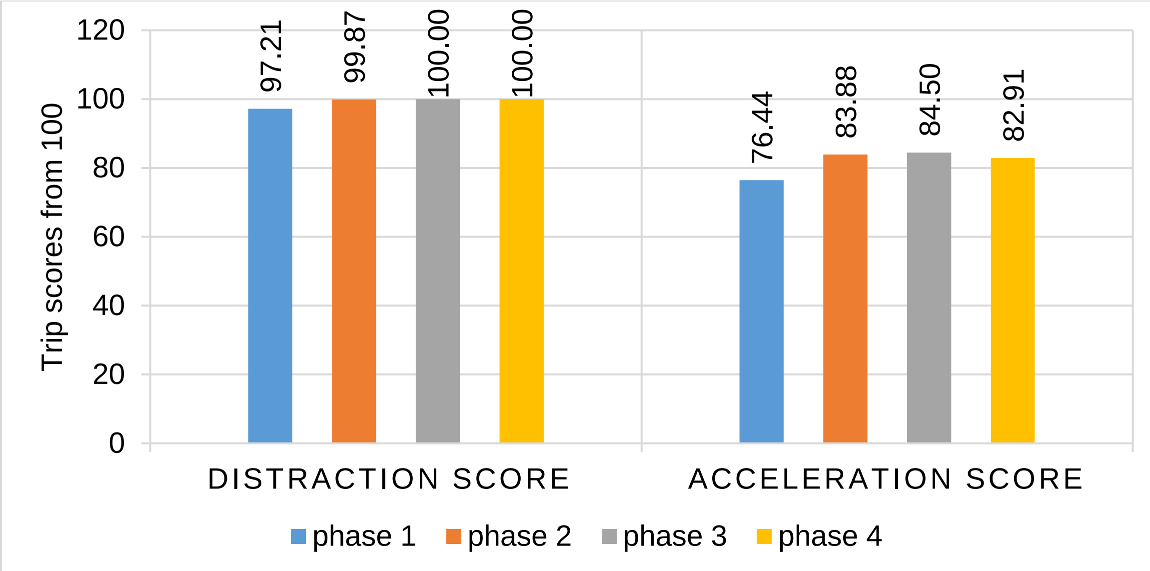


FIGURE 15 Mean distraction and acceleration trip scores

As shown in figure 16, the speeding score and the mean speeding events per 100 kms shows some contradicting results. While, the speeding event is decreasing from mean total speeding of 50.81 to 45.85 per 100 km, the speeding score is diminishing from 98.49 to 89.79 percent. The trip score is based on the occurrence of the risky events in a trip, hence as the number of risky events increase the trip score should decrease and vice versa.

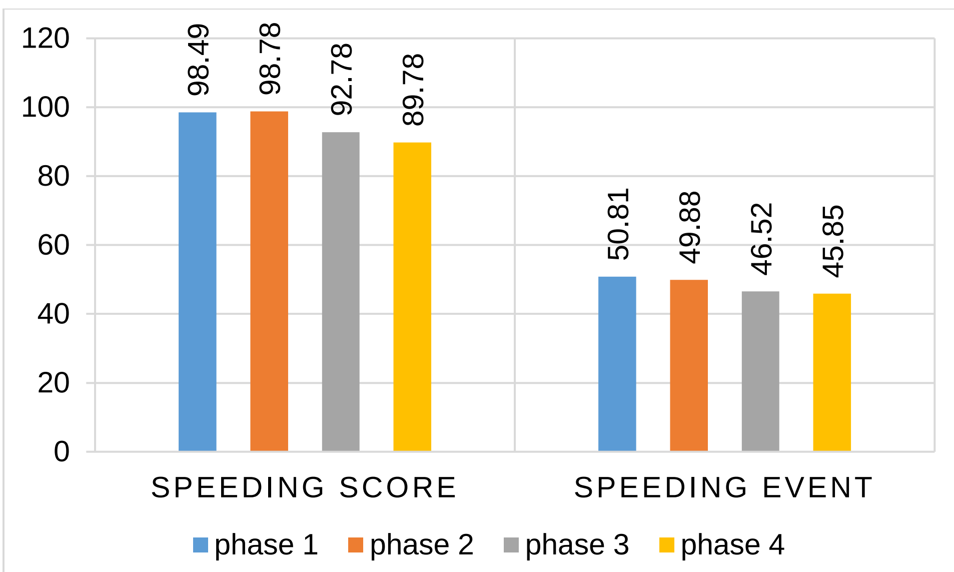


FIGURE 16 Mean speeding score and total speeding event per 100 Kms

4.2.5 Comparison Based On Trip Score & Total Events Per 100 Km

Besides comparing drivers based on their mean value or rank for non-parametric data, it is also possible to compare based on their total number of events per 100 km and overall trip score in each phase. Among the 21 drivers who participated in the study, eight drivers showed improvement in their overall trip score or decline in the number of risky events per 100 km in the intervention condition as compared to baseline (no intervention) condition. As shown in figure 17 left, the trip score of the drivers is enhanced in the intervention condition (phases 2,3 and 4) as compared to no intervention condition(phase 1).

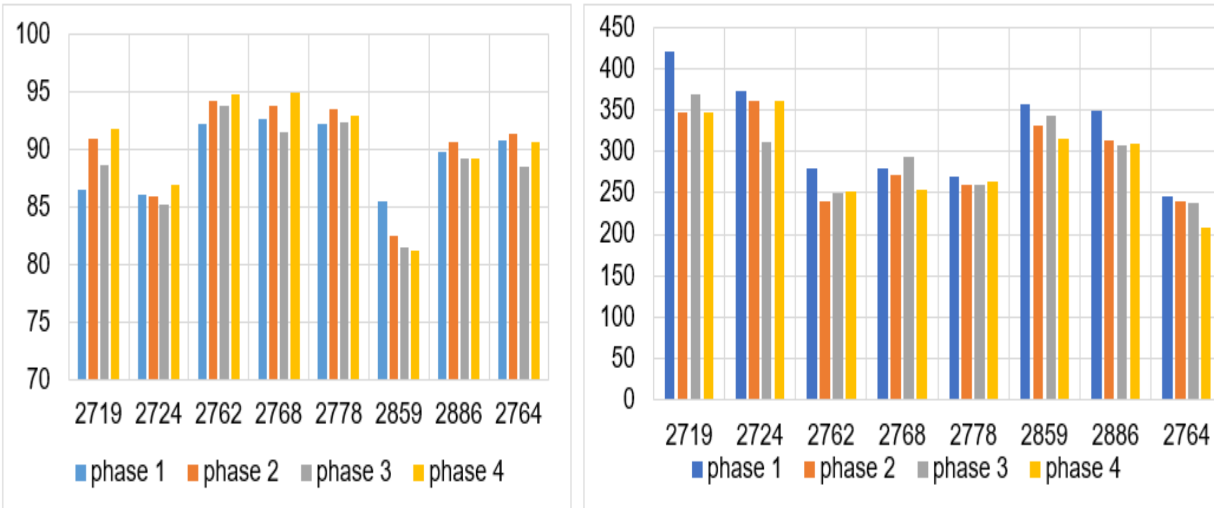


FIGURE 17 Trip score and total risky events for drivers who showed improvement in the intervention

Moreover, in right of the figure also demonstrated the decrease in the number of risky events in the intervention conditions as compared to the non-intervention condition. Despite the fact that 8 drivers showed an improvement in their driving performance, the other 13 drivers diminished their driving performance in the intervention condition as compared to the non-intervention condition. As shown in figure 18 left, the number of risky events observed in the phase 1(no-intervention condition) is less than those observed in the intervention conditions. The right side of the figure also indicated, the trip score of the drivers decreased in the intervention condition (phases 2,3 and 4) as compared to no intervention condition (phase 1).

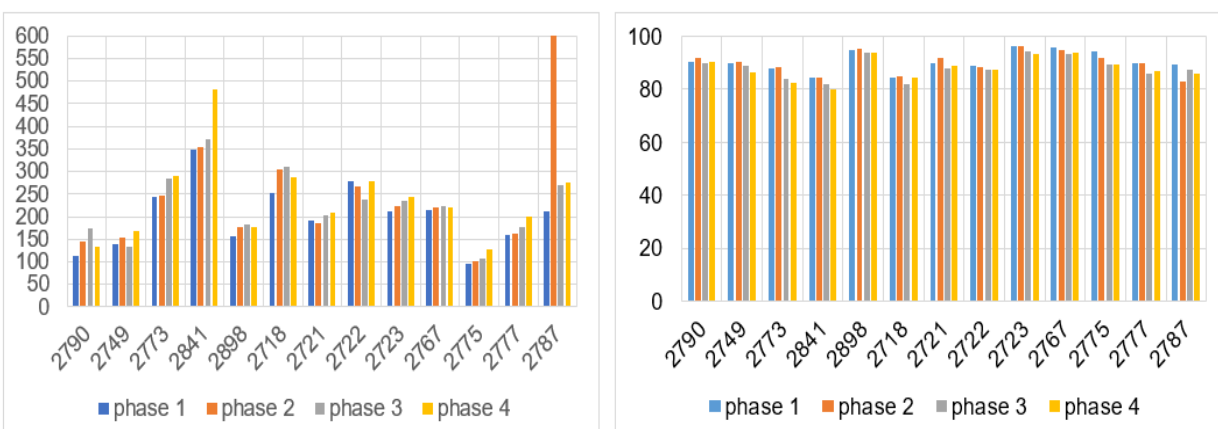
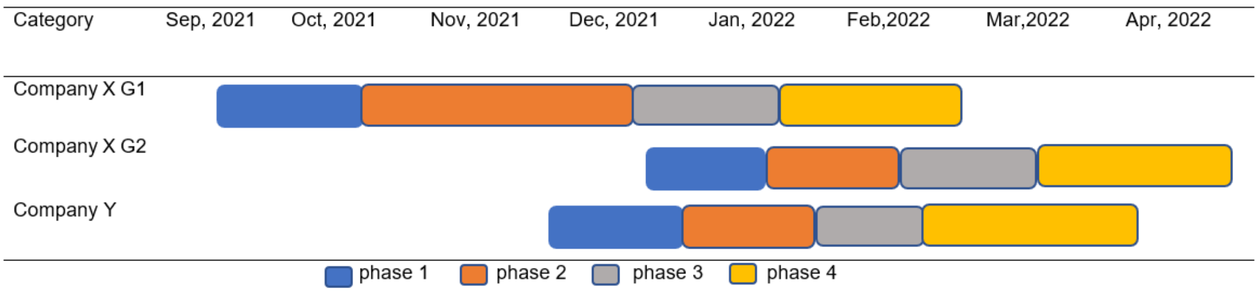


FIGURE 18 Trip score and total risky events for drivers who didn’t show improvement in the intervention

4.2.6 Comparison Based on Traffic Exposure

The coronavirus pandemic had changed the traffic exposure during the different waves everywhere around the world. The on-road study experiment was conducted for 18 weeks in 4 different phases, while they had started at different times. There were three categories of truck drivers based on the starting time of the on road study experiment (see table 13). Company X had 13 truck drivers in total of which 6 drivers in group one (G1) started the experiment in late September and completed the experiment in late February, while 7 drivers in group two (G2) started the experiment in late December and completed the experiment in late April. The third category, company Y had 8 truck drivers started the on road experiment in late November and completed in late March.

TABLE 13 Timeline for the four phases of on-road study experiment



As shown in figure 19 , the total kilometers traveled in Flanders region motorways during the four phases for company XG1 was decreased in the intervention condition (phases 2, 3, &4) compared to the non-intervention condition (phase1).

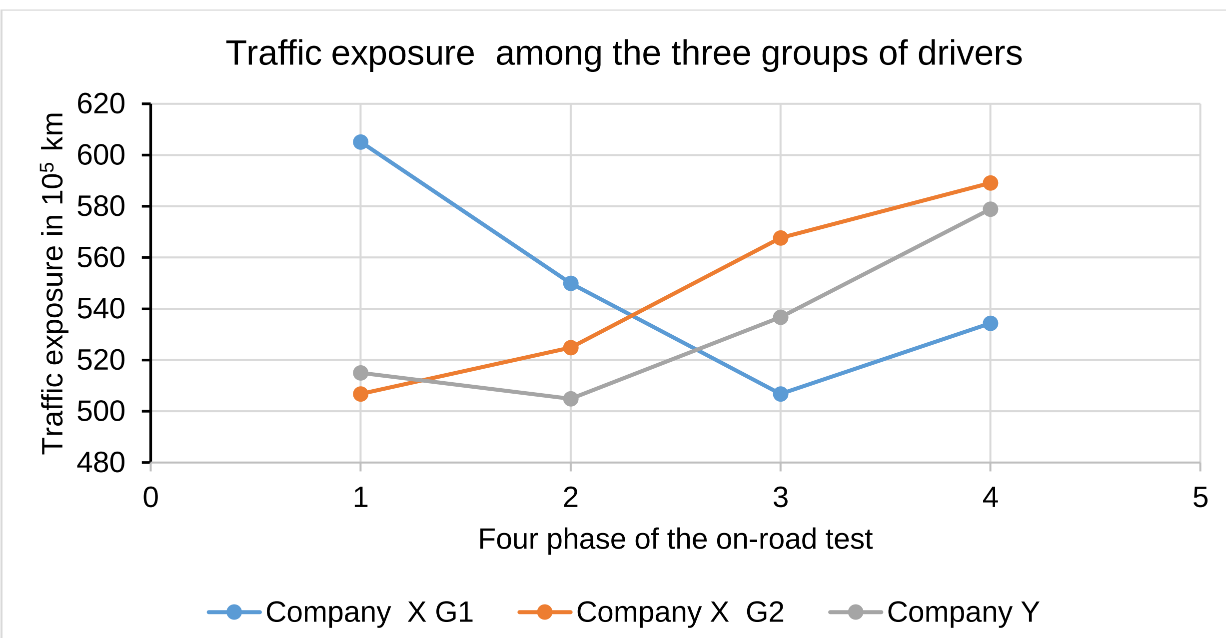


FIGURE 19 Total kilometers traveled in Flanders region motorways during the on road experiment

However, the total kilometers traveled in Flanders region motorways during the four phases for company XG 2 and company Y was increased in the intervention conditions compared to the non-intervention condition. Among the drivers who participated in this on road experiment 15 drivers conducted their experiment when the total kilometers travel was increasing from phase 1 to phase 4, while 6 drivers undertaken their test when the total kilometer travel was decreasing from phase 1 to phase 4.Therefore, this on road experiment was conducted under increasing total kilometers of travel in the Flanders regions motorways.

Among the six drivers in the company X G1, five drivers showed decline in the total number of risky events per 100 km travel. These drivers were those who conducted their on road experiment , where the traffic exposure was declining in the intervention condition as compared to non-intervention condition. As shown in figure 20, there is almost a linear relationship between the traffic exposure and number of the risky events per 100km in all phases; hence when there was higher traffic exposure there could be higher probability occurrence of risky events and vice versa.

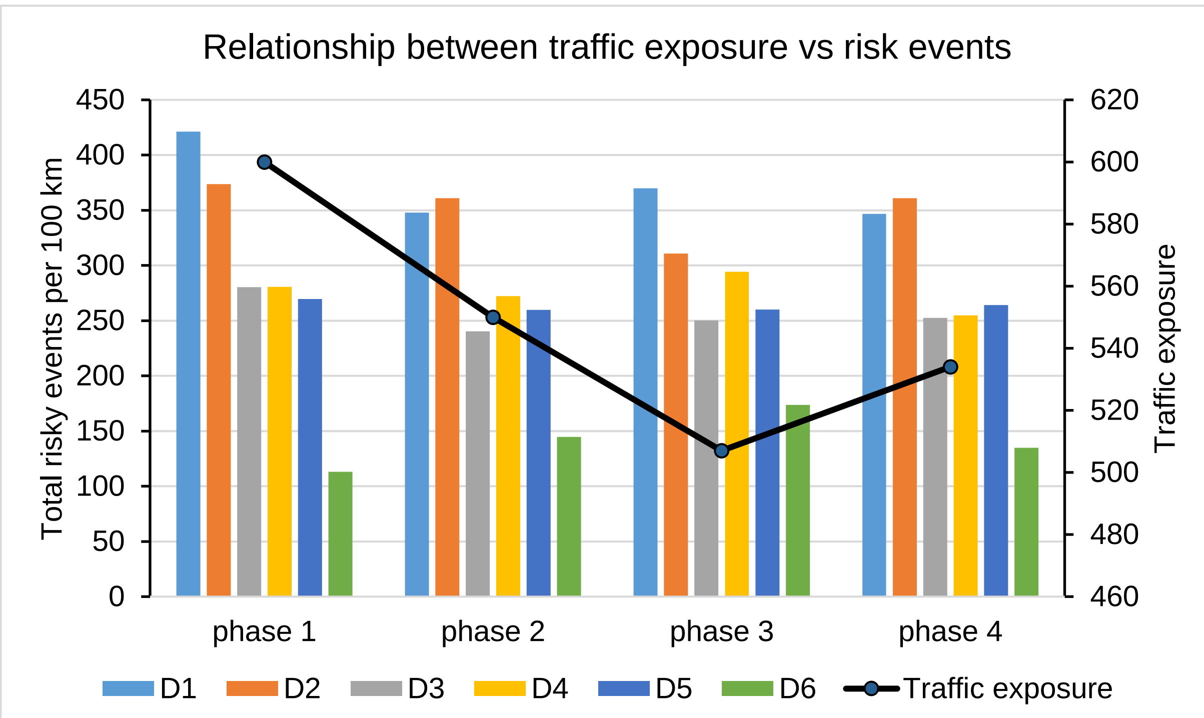


Figure 20 Relationship between total risky events per 100 km vs total kilometers traveled in Flanders motorways for Company X G1 drivers

Among the eight drivers in the company X G2, seven drivers showed an increase in the total number of risky events per 100 km of travel. These drivers were those who conducted their on road experiment , where the traffic exposure was increasing in the intervention condition as compared to non-intervention condition. As shown in figure 21, there is almost a linear relationship between the traffic exposure and number of the risky events per 100km in all phases; hence when there was higher traffic exposure there could be higher probability occurrence of risky events and vice versa.

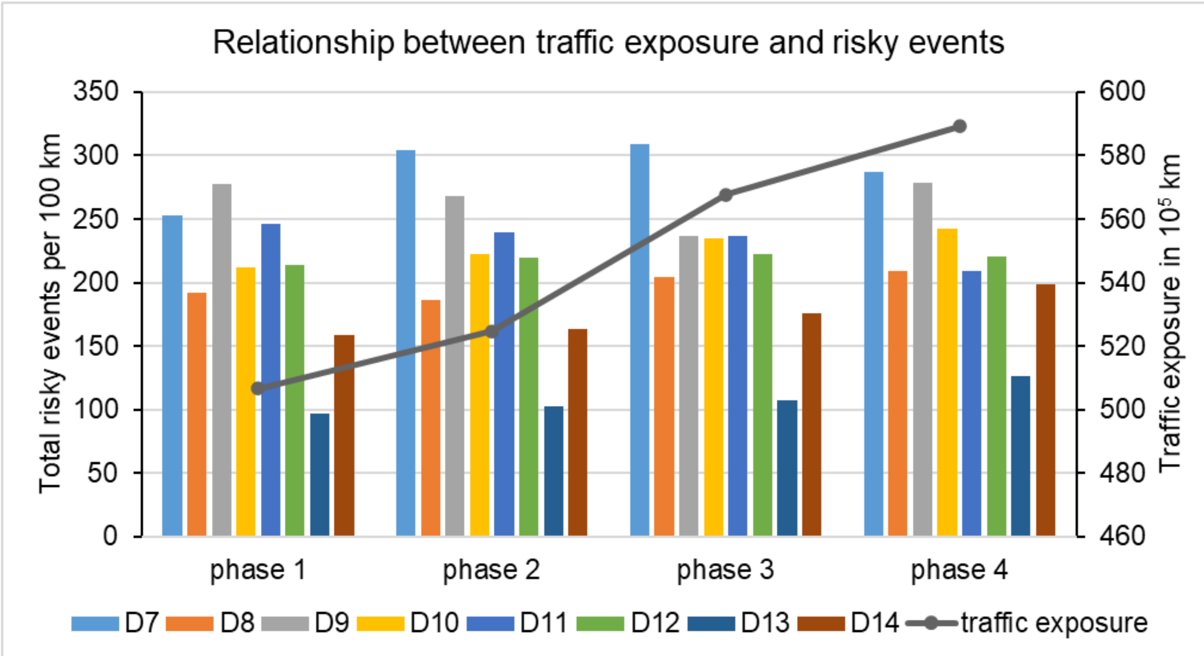


FIGURE 21 Relationship between total risky events per 100 km vs total kilometers traveled in Flanders motorways for Company X G2 drivers

Among the seven drivers in the company Y, two drivers showed an increase in the total number of risky events per 100 km travel. These drivers were those who performed their on road experiment , where the traffic exposure was increasing in the intervention condition as compared to non-intervention condition. As shown in figure 22, there is almost a linear relationship between the traffic exposure and number of the risky events per 100km in all phases; hence when there was higher traffic exposure there could be higher probability occurrence of risky events and vice versal.

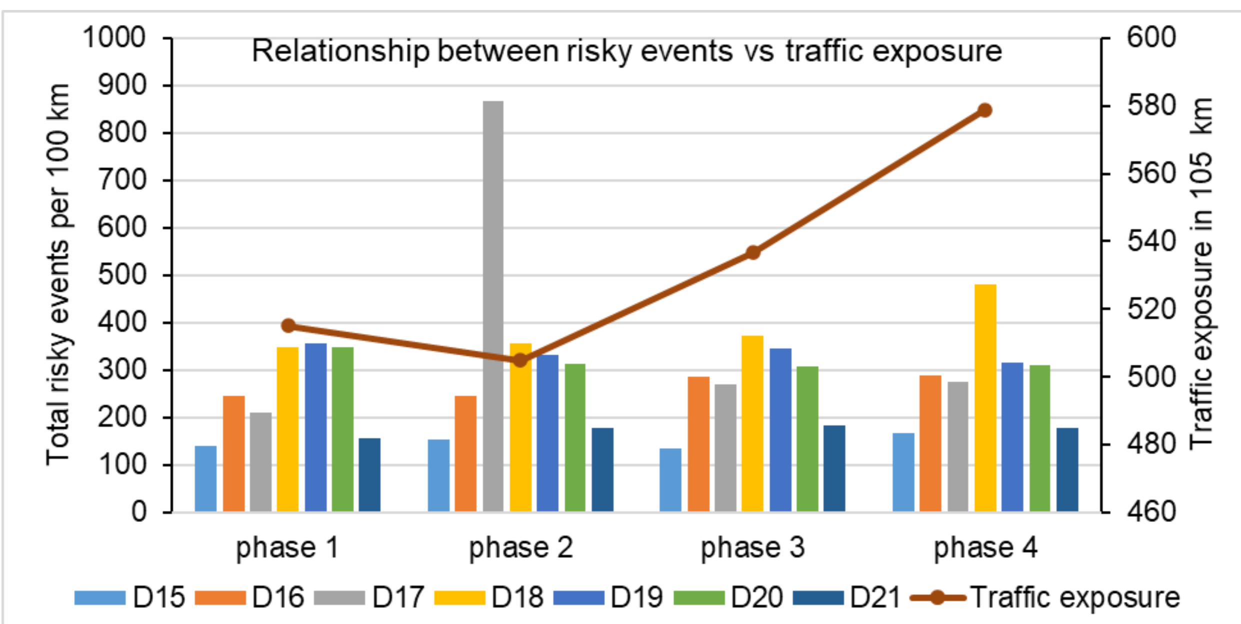


FIGURE 22 Relationship between total risky events per 100 km vs total kilometers traveled in Flanders motorways for Company Y drivers

4.4 Relationship Between Self-Reported Data & Naturalistic Data

The drivers filled an entry survey questionnaire that comprised some socio demographic information and their driving behavior in relation to the risky events investigated in the field experiment. This portion of the paper contains mainly some descriptive information on the relationship between the data collected from the entry survey and objective data collected via the i-DREAMS platform. The objective data (naturalistic data) is based on the risky events collected through the i-DREAMS in vehicle data recorder system.

Five drivers responded either they regularly or often drove faster than the indicated speed limit, while eleven drivers answered sometime or never drove faster than the speed limit. As shown in figure 23, drivers who respond in the survey as they often/regularly drive above the speed limit also showed higher average speeding events than those who never /sometimes drive above the speed limit. Drivers who answered in the entry survey as they often /regularly drive above the speed limit had an average speeding 63.7 per 100km, while those who responded as they never/sometimes drove above the speed limit had an average speeding 47.05 per 100km. Another descriptive information from the correspondence between the self-reported data and objective data was older and more experienced drivers tend to show more speeding events.

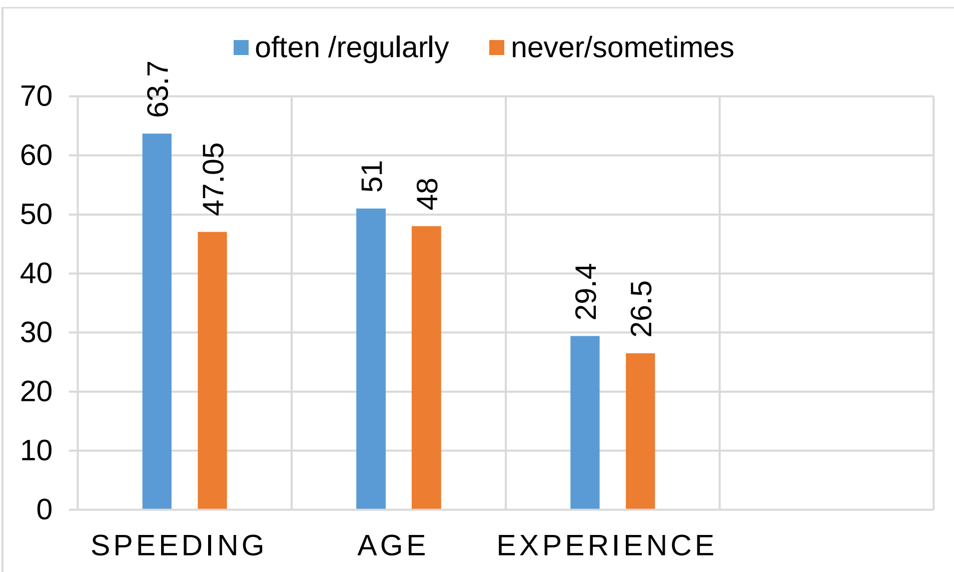


FIGURE 23 Comparisons of speeding event , age ,and experience between drivers who often/regularly and sometimes/ never drives faster than speed limit

One driver answered in the entry survey, he regularly drove without maintaining a safe following distance from the vehicle that was driving in his front and the others responded that they sometimes/never follow too close for the car in front. The one who said the front driven car was too close showed 159.55 tailgating events per 100 km, while the average tailgating of all the drivers is 81.24 per 100 km. Furthermore , seven drivers responded neutral or disagreed on the compliance to the posted speed limit, where eleven answered agree/strongly agree on their compliance to the posted speed limit. The average speeding events per 100 km for those drivers who responded neutral or below to their compliance to the speed limit was 71.86 and for those who agree or strongly agree they drive equal or below the speed limit was 41.08.Another, interesting finding is shown in figure 24 was all the seven drivers who neutrally or below compliant to the speed limit have been fined for a traffic violation one time or more than one times in the past three years, and five out of the seven drivers have been involved in a traffic accident in the past three years.

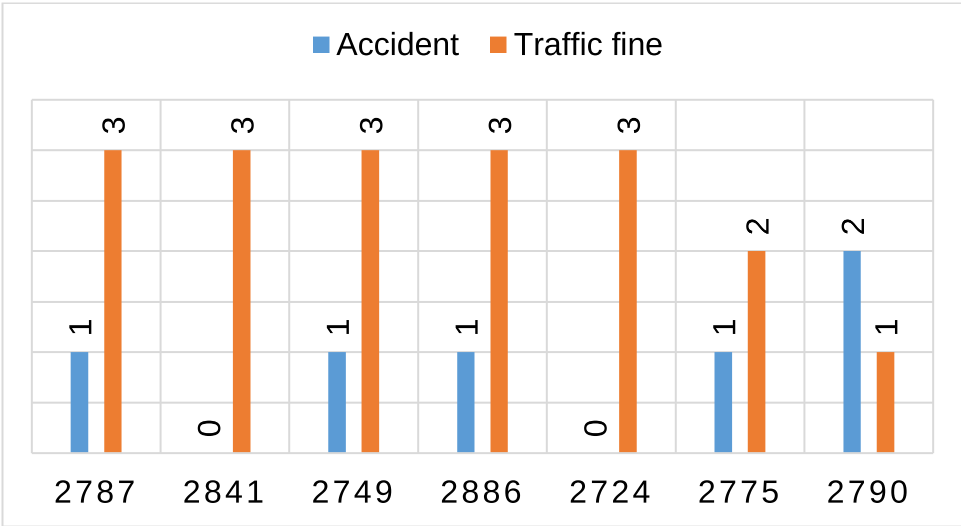


FIGURE 24 Number of accidents involved and traffic fines received speed limit non-compliant drivers

Moreover, figure 25 also demonstrated the trending of the top five most risky events (Tailgating, steering, speeding, acceleration, and deceleration) among the drivers who are non-compliant to the posted speed limit.

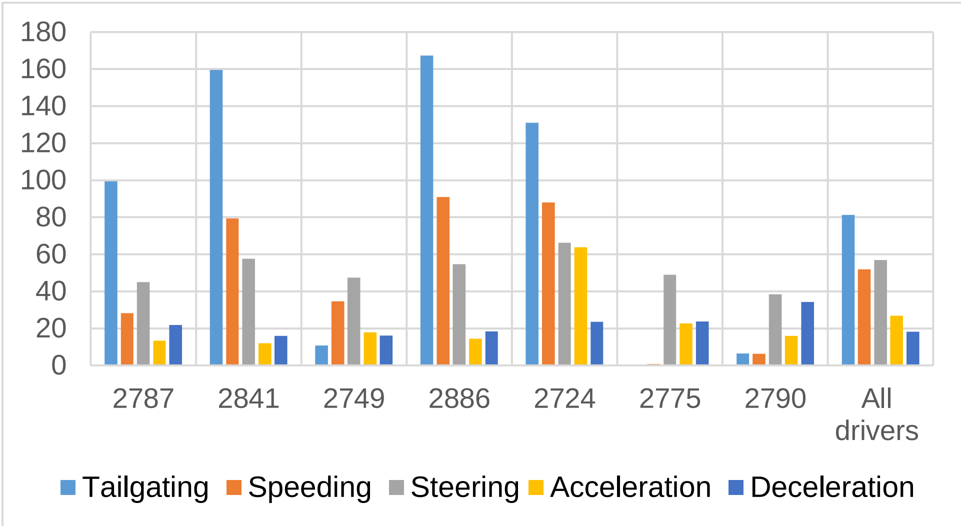


FIGURE 25 Top five risky events for speed non-compliant drivers as compared to all drivers average

Four from seven drivers recorded higher tailgating events as compared to the average tailgating of all the drivers .Five from 7 drivers also observed a higher deceleration event than the average of all the drivers. While three drivers recorded a higher speeding event than the average only one driver showed a higher acceleration event above the average. Finally, 8 drivers as shown in figure 26 observed a reduction of their risky events (improved their driving behavior) in the intervention conditions as compared to the nonintervention condition. Those drivers have common agreement on the advanced driver assistance system (ADAS) ease of use ,and are clear and easy to understand. In addition, those drivers also disagree that ADAS is distracting while driving. Two third of those drivers haven’t been involved in a traffic accident in the past 3 years.

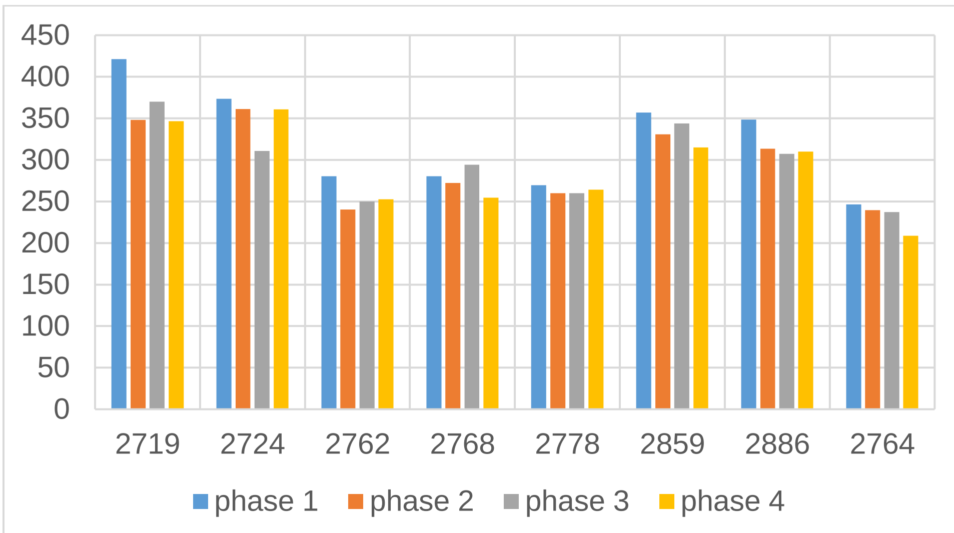


FIGURE 26 Total risky events observed for the drivers   who showed improvement through intervention

5. DISCUSSION

This study aimed to evaluate the effectiveness of the i-DREAMS intervention in reducing the occurrence of risky events among Belgian truck drivers. The i-DREAMS platform's real-time and post-trip interventions are expected to reduce the likelihood of a crash occurring at the highest level (Brijs et al., 2020). The performance objectives and the safety-promoting goals were utilized to evaluate the effectiveness of the i-DREAMS intervention as the on-road experiment was conducted for a few months. This chapter discusses the results of the study.

5.1 Risky Events

Risky events are specific action or behavioral parameters that need to change for the safety-promoting goals to be achievable and have been used in many previous works to evaluate the performance of an intervention (Arumugam & Bhargavi, 2019; Bell et al., 2017; Musicant & Lotan, 2016; Newnam et al., 2014). The result of the study showed that no statistically significant difference in the total , high, medium, and low risky events between the intervention condition and non -intervention condition. Further, the result of the study also revealed that there no significant difference in the trip score between the intervention and non-intervention conditions. The finding contrasts with the earlier findings on the positive outcomes on the real-time intervention and post-trip intervention on speeding (Bell et al., 2017; Farmer et al., 2010; Mase et al., 2020; Mazureck & van Hattem, 2006; Merrikhpour et al., 2014; Newnam et al., 2014; Reagan et al., 2013),tailgating (Bao et al., 2012; Mazureck & van Hattem, 2006; Merrikhpour et al., 2014), coachable events (Carney et al., 2010),safety-related events (Hickman & Hanowski, 2011; McGehee et al., 2007), and crash rates (Toledo & Lotan, 2006).

Due to the expense and feasibility of many driving studies, small samples have been cited as a consistent and significant barrier in driving research (Hird et al., 2016). In a smaller sample size, the results on the difference between groups are expected to be non-statistically significant (Babulal et al., 2019) and this could be the reason non statistically significant difference in total speeding and total acceleration events per 100 km in this study. The study result disclosed there was a reduction in the mean total speeding and acceleration events per 100 km in the intervention conditions compared to the non-intervention condition. There was a reduction in the mean total speeding event per 100 km from phase 1 to phase 2 by 1.8%, from phase 1 to phase 3 by 8.4% , and from phase 1 to phase 4 by 9.7 %. Furthermore, there was also a reduction in the mean total acceleration event per 100 km from phase 1 to phase2 , from phase 1 to phase 3 , and from phase 1 to phase 4 by 18.6%, 29.5% ,and 19.3% , respectively. This indicates the combination of real-time and post trip intervention (feedback and gamification via app +dashboard) resulted best outcome in reducing the total speeding and acceleration events. The result was complementary with previous findings by (Bell et al., 2017; Hickman & Hanowski, 2011; Mase et al., 2020),where real-time and post-trip feedback has been suggested more effective in reducing the rate of risky events compared to real time feedback only.

There was a decrease in the mean high acceleration event per 100 km from phase 1 to phase 2 by 52%, from phase 1 to phase 3 by 73.4% , and from phase 1 to phase 4 by 51%. Similarly , there was also a reduction in the mean high speeding event per 100 km from phase 1 to phase2 by 11.4%, from phase 1 to phase 3 by 18.7% , and from phase 1 to phase 4 by 21.6%. This shows the i-DREAMS intervention resulted in higher reduction of high speeding and acceleration events per 100 km. Reducing high risky events is directly associated with the reducing avoidable crash phase in the STZ sub zone in which collision scenario is actually developing unless the operator intervene. The decrease in high speeding and acceleration events could be the result of the i-DREAMS intervention that drivers take action when they receive informing message (normal driving phase) or warning signal (danger phase) before they reached the crash avoidable phase (Talbot et al., 2020).

There was a slight decrease in the proportion of total high risk to the total risk events in the intervention condition as compared to the non-intervention condition. There was the highest proportion of high risky events in phase 1 (8.30%), preceded by phases 2,3, and 4 by 7.57%, 7.12%, and 7.07% of the total, respectively. This was an indication that the real-time intervention and post-trip intervention (feedback plus gamification via app) produced the best result in terms of minimizing the high risky events proportion. Furthermore, the result matched the finding that the real-time and post-trip interventions showed the most successful behavioral achievement compared to real-time and without intervention conditions (Bell et al., 2017; Carney et al., 2010; Donmez et al., 2008; Farmer et al., 2010; Hickman & Hanowski, 2011).The use of gamification elements (e.g., scores, incentives, self-interest) also produced positive impact on safe and eco-friendly driving (Newnam et al., 2014).High risky events have a higher probability of resulting in traffic collision unless the driver intervenes compared to low and medium risky events.

Tailgating, steering, speeding, deceleration, and acceleration were the top five risky events observed during the on-road study and represented around 85 % of all the risky events recorded by the i-DERAMS platform. Speeding and tailgating were listed among major contributing factors to road fatalities and injuries (Ascone et al., 2009; Singh, 2003). The effectiveness of intervention to reduce these risky events has been investigated in many naturalistic studies, Speeding (Bell et al., 2017; Farmer et al., 2010; Mase et al., 2020; Mazureck & van Hattem, 2006; Merrikhpour et al., 2014; Newnam et al., 2014; Reagan et al., 2013), tailgating (Bao et al., 2012; Kovaceva et al., 2020; Mazureck & van Hattem, 2006; Merrikhpour et al., 2014), deceleration (Bergasa et al., 2019; Mase et al., 2020; Toledo et al., 2008) ,and acceleration (Bergasa et al., 2019; Toledo et al., 2008).The remaining six risky events (overtaking, lane discipline, vulnerable road user collision avoidance, forward collision, distraction, and fatigue) only represented a round 15 % of the risky events observed during the on-road study.

5.2 Influence Of Traffic Exposure On Effectiveness of the Intervention

The on-road study was started in September 2021 and finished in April 2022; hence some phases of the experiment could be influenced by traffic variability on the roads due to the Covid-19 pandemic lockdown (Christos Katrakazas et al., 2020). Because the drivers had conducted their on-road experiment at different times, the studies tried to examine the influence of traffic exposure on the effectiveness of the intervention. During the on-road study for the first six drivers , the total kilometers traveled in Flanders motorways was around 60 million km in phase 1 and decreased to the lowest, approximately 50 million km in phase 3. The result showed that five drivers in this group decreased the total frequency of risky events per 100 km in the intervention condition compared to the non-intervention condition. It is difficult to conclude the reduction in the frequency of risky events was influenced by the intervention or not, as the study was quasi-experimental with no control group for comparison. Studies by (Cadar et al., 2017; Dickerson et al., 2000; Retallack

& Ostendorf, 2020) confirmed that the decrease in traffic exposure lowered the frequency of traffic crash and risky events.

In contrast to the first group of drivers, the second and third group of drivers (15) was undertaken their on road test when traffic exposure was increasing. During the on-road study for the second group of 8 drivers , the total kilometers traveled in Flanders motorways was around 50 million km in phase 1 and increased to approximately 59 million in phase 4. The result showed that a single drivers in this second group decreased the total frequency of risky events per 100 km in the intervention condition compared to the non-intervention condition. The third group of 7 drivers also undertaken their on road test when the traffic exposure was increasing from approximately 51 to 58 million km. The result of the third group drivers indicated two drivers showed decreased the total frequency of risky events per 100 km in the intervention condition compared to the non-intervention condition. Generally, 12 from 15 drivers increased their frequency of their total risky events in the intervention condition as compared to the non-intervention condition.it is ambitious to conclude drivers were not improving their performance due to ineffective intervention as the increase in traffic exposure could contribute to increase the frequency of risky events. Previous road safety researches confirmed presence more traffic on the road resulted in more risky taking behavior. The presence of higher traffic volume caused in more frequent tailgating and overtaking events (Emo et al., 2016), and more risky lane changes (Qi et al., 2017).

5.3 Relationship Between Self-Reported Data And Naturalistic Driving Data

Self-reported driving data are commonly used in traffic safety research and road safety measures because it is less expensive, provide more detailed information in a shorter time, and can reach a significant portion of the population (Wang & Xu, 2019). This study also sought to examine the relationship between the self-reported data obtained from the entry survey and the naturalistic driving data collected through the i-DREAMS platform. The result of the study confirmed that drivers who responded in the survey as they either regularly or often drove above the speed limit also observed higher average speed events (63.70) per 100km. while, those drivers travel who answered they never/ sometime drove above speed limit recorded lower average speeding event (47.05) per 100 km. Furthermore, drivers who answered regularly drove without maintaining a safe following distance from the vehicle that was driving in front pointed a higher tailgating events (159.55) per 100km. Drivers who replied they disagree/ neutral on their compliance to the posted speed limit were also registered higher average speeding events 71.86 per 100 km as compared to those who answered who answered they agree/strongly agree on their compliance to the posted speed limit observed average speeding events 41.08 per 100 km. These results indicated the self-reported driving data could be used in combination with naturalistic driving data in field of road safety and also showed correspondence with previous studies on the relationship between self-reported data and naturalistic driving data (Helman & Reed, 2015; Reimer et al., 2006; Taubman–Ben-Ari et al., 2016)

Among the seven drivers who answered they neutral or disagree compliant to the posted speed limit have been fined for a traffic violation one time or more than one times in the past three years, and five out of the seven drivers have been involved in a traffic accident in the past three years. Moreover, 8 drivers observed a reduction of their risky events (improved their driving behavior) in the intervention conditions as compared to the nonintervention condition. Two third of those drivers haven't been involved in a traffic accident in the past 3 years. Those drivers have common agreement on the advanced driver assistance system (ADAS) ease of use ,and are clear and easy to understand. In addition, those drivers also disagree that ADAS was distracting while driving. Perceived ease of use and compatibility are among key parameters that determines user acceptance in the unified model of driver acceptance (Rahman et al., 2018), hence user acceptance is important for the adoption and effectiveness of intervention.

5.4 Limitations and Areas for Further Research

The study has a number of limitations that need to be acknowledged. Limitations to this study are:

- The study followed quasi experimental design with no control group for comparison and it was difficult to confirm the behavioral change the intervention could be over stated or under stated (Carney et al., 2010; McGehee et al., 2007; Newnam et al., 2014). Further research in this area by including a true control group to control the seasonal effects, traffic exposure, road type and weather condition (Merrikhpour et al., 2014)
- Only 21 male truck drivers from two companies participated in this study, hence it is recommended to include wide range/ varieties of participants as their behavior is influenced by organizational safety culture. The organizations of the safety culture directly associate with the frequency and severity of accident (Gillen et al., 2002; Zohar, 1980). Gender difference also associated with involvement in risky driving behavior (Özkan & Lajunen, 2005; Rhodes & Pivik, 2011).Therefore, further studies is recommended by including female drivers and truck drivers from more companies with larger sample size.
- The naturalistic data was collected in three different seasons started in summer and finished in the spring. Weather difference among the different seasons and the traffic exposure difference changes the frequency of risky events (Carney et al., 2010). Further study is important by controlling the effect of seasonal variation on the frequency of the risky events to evaluate the performance of the intervention.
- The study design didn't incorporate post-intervention baseline to examine whether the intervention have a lasting effect. Previous studies on evaluation of intervention incorporated the post-intervention baseline (second baseline) to examine the long-term effects of the intervention (Bell et al., 2017; Carney et al., 2010; Merrikhpour et al., 2014). Further, other studies (Farmer et al., 2010; Toledo et al., 2008) recommended further research by including post-intervention baseline to examine the long-term effects of the interventions on reducing the undesired driving behavior. Donmez et al. (2008) also mentioned the lack of post-intervention baseline in their study as limitations to evaluate the lasting effects of real-time and post-trip intervention on distraction. Therefore, it is recommended to further research the long term effects of the i-DREAMS intervention in reducing the risky driving events.

5.5 Recommendations

Recommendations to the i- DREAMS project team , policy makers, and other who are concerned in area of road safety are suggested below.

Previous works on the performance of real-time and post-trip intervention showed positive outcome in creating a safer and eco-friendly road environment (Bell et al., 2017; Mase et al., 2020; Toledo & Shiftan, 2016; Toledo & Lotan, 2006). The i-DREAMS intervention effect showed mixed result in reducing the total risky events per 100 km. However, the on-road study to evaluate the effectiveness of the i-DREAMS interventions was started in September 2021 and finished in April 2022; hence there was high traffic flow variability in this period due to COVID -19 pandemic travel restrictions and other related factors. Studies by (Cadar et al., 2017; Retallack & Ostendorf, 2020) disclosed the variation in traffic volume affects the occurrence road crashes and risky events. Therefore, further study in the coming years is recommended when the traffic on the road is back to normal and with more participants over an extended period.

The study only covered the effect evaluation of the i-DREAMS intervention based on the impacts on the performance objective and safety-promoting goals. In the domain of outcome evaluation, evaluating the user acceptability and user acceptance of i-DREAMS intervention is necessary as these two factors are essential for the adoption and effectiveness of the intervention (Christos Katrakazas et al., 2020). Evaluating the user acceptance is recommended to include all the drivers who started the on-road study for comprehensive understanding about i-DREAMS intervention, including drivers who dropped out from the study, if any, to examine their reason for not completing their participation. Using the Unified Model of Driver Acceptance (UMDA) (Rahman et al., 2018) parameters , the level of driver acceptance of the i-DREAMS intervention can be evaluated. Drivers' acceptance of the driver support systems plays a vital role in achieving their intended goals of reducing road collisions (Adell, 2010). Therefore, conducting thorough drivers acceptance toward the i-DREAMS intervention is recommended to get better understanding on the performance of the intervention.

Tailgating, steering, speeding, deceleration, and acceleration were the top five risky events observed during the on-road study and represented around 85 % of all the risky events recorded by the i-DERAMS platform. This indicates focusing the intervention design and implementation in a way that prioritize to mitigate these five risky events could produce the better outcome. Therefore, it is recommended to design an intervention focusing on the frequently observed risky events to get better result and make intervention sustainable.

The study used the naturalistic data collected from 21 truck drivers from two companies. Small samples have been cited as a consistent and significant barrier in driving research (Hird et al., 2016). Therefore, policy and decision maker in the transportation sector, road safety planner, and other concerned bodies in the area of road safety should work to promote good cooperation between truck companies and research center in the field of research, technology transfer and other mutually beneficial areas. The research and development centers (e.g., Universities) should prepare some awareness raising campaign or seminars to the truck company owners/representatives to motivate their employee drivers to voluntarily participate on different studies to create safer and eco-friendly world.

6. CONCLUSION

Many road safety research proved that real-time and post-trip interventions in combined or standalone produced effective outcomes in safe and eco- friendly driving (Bell et al., 2017; Boodlal & Chiang, 2014; Carney et al., 2010; Mase et al., 2020; Merrikhpour et al., 2014; Toledo & Lotan, 2006). Studies by (Boodlal & Chiang, 2014; Donmez et al., 2007; Dotzauer et al., 2013) revealed that real-time intervention were able to reduce safety related events compared to the non-intervention conditions. The combination of the real-time and post-trip intervention showed the most successful behavioral achievement compared to real-time intervention and without intervention conditions (Bell et al., 2017; Carney et al., 2010; Donmez et al., 2008; Farmer et al., 2010; Hickman & Hanowski, 2011). Hassan et al. (2015) also confirmed that the post-trip feedback given to drivers produces better driving behavior as compared to baseline condition.

Based on the results of the study, there was no statistically significant difference in the mean rank of the risky events and trip scores among Belgian truck drivers in no-intervention, real-time intervention, and real-time intervention plus post-trip intervention conditions. The non-statistically significant result could be due to the small sample size (N=21) as (Hird et al., 2016; Mase et al., 2020) suggested smaller sample size is barrier to obtain a significant result. The traffic volume (Due to COVID-19 travel restrictions) difference between the starting and ending of the on-road study could be another factor to the result of the intervention. Further, the seasonal effects, and the traffic exposure could also change the result of the intervention (Merrikhpour et al., 2014). There was higher reduction in the mean high speeding and acceleration events in the intervention condition compared to the non -intervention conditions. A maximum of 73.4% and 21.6% reduction in mean high acceleration and speeding events, respectively, was observed in the intervention phase. Additionally, there was lowest high risky events in proportion to the total risky events in phase four of the on-road study. This could be an indication that the real-time and post-trip intervention (feedback plus gamification) produced best result in reducing high risky events. The lowest proportion of high risky events in phase 4 is an another indicator of the real-time intervention and post-trip intervention (feedback plus gamification features) could be effective in minimizing the high risky events occurrence. Overall, Eight drivers showed a decrease in the total risky events per 100 km in the intervention conditions compared to the non-intervention conditions. However, it is difficult to conclude the reduction of the risky events was due the intervention only or combined with other factors.

The self-reported data obtained from the entry survey showed a good correspondence with the naturalistic driving data obtained from naturalistic driving. What drivers say in the entry survey corresponds with what was recorded in the i-DREAMS platform. The finding is complementary to the study (Taubman–Ben-Ari et al., 2016) ,self-reported measures as indicators of driving behavior trustworthy methods for measuring driving behavior for the purpose of research, assessment, and interventions. Combining the self-reported data with the objective data in road safety researches and drivers intervention mapping could produce efficient output. Socio-demographic data, historical driving data, and other road safety related data could better collected using properly designed self-reported data mechanisms.

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8. ANNEXES

8.1 Normality Test

TABLE 14 Normality test for low risky events

Normality Test						
	Kolmogorov-Smirnova			Shapiro-Wilk		
Parameters	Statistic	N	Sig.	Statistic	N	Sig.
speeding_1	0.248	21	0.002	0.851	21	0.004
acceleration_1	0.272	21	<,001	0.573	21	<,001
deceleration_1	0.099	21	.200*	0.97	21	0.735
steering_1	0.322	21	<,001	0.658	21	<,001
tailgating_1	0.246	21	0.002	0.823	21	0.002
overtaking_1	0.125	21	.200*	0.954	21	0.41
fatigue_1	0.2	21	0.027	0.824	21	0.002
speeding_2	0.328	21	<,001	0.569	21	<,001
acceleration_2	0.189	21	0.048	0.871	21	0.01
deceleration_2	0.232	21	0.005	0.82	21	0.001
steering_2	0.303	21	<,001	0.679	21	<,001
tailgating_2	0.272	21	<,001	0.778	21	<,001
overtaking_2	0.157	21	0.19	0.926	21	0.116
fatigue_2	0.318	21	<,001	0.516	21	<,001
speeding_3	0.148	21	.200*	0.921	21	0.091
acceleration_3	0.191	21	0.044	0.88	21	0.015
deceleration_3	0.185	21	0.06	0.823	21	0.001
steering_3	0.238	21	0.003	0.728	21	<,001
tailgating_3	0.25	21	0.001	0.81	21	<,001
overtaking_3	0.117	21	.200*	0.949	21	0.329
fatigue_3	0.14	21	.200*	0.935	21	0.176
speeding_4	0.235	21	0.004	0.889	21	0.021
acceleration_4	0.104	21	.200*	0.967	21	0.664
deceleration_4	0.136	21	.200*	0.855	21	0.005
steering_4	0.28	21	<,001	0.725	21	<,001
tailgating_4	0.193	21	0.04	0.851	21	0.004
overtaking_4	0.178	21	0.08	0.925	21	0.111
fatigue_4	0.163	21	0.149	0.827	21	0.002

Note: If the significance (p value) is greater than 0.05 normal distribution is assumed.
If the significance (p value) is less than 0.05 normal distribution is not assumed.

TABLE 15 Normality test for medium risky events

Normality Test						
	Kolmogorov-Smirnova			Shapiro-Wilk		
Parameters	**Statistics**	**N**	**Sig.**	**Statistics**	**N**	**Sig.**
speeding_1	0.208	21	0.018	0.9	21	0.034
acceleration_1	0.338	21	<,001	0.699	21	<,001
deceleration_1	0.172	21	0.107	0.857	21	0.006
steering_1	0.189	21	0.048	0.74	21	<,001
tailgating_1	0.181	21	0.07	0.893	21	0.026
overtaking_1	0.417	21	<,001	0.614	21	<,001
fatigue_1	0.144	21	.200*	0.958	21	0.474
speeding_2	0.259	21	<,001	0.833	21	0.002
acceleration_2	0.109	21	.200*	0.962	21	0.547
deceleration_2	0.221	21	0.009	0.734	21	<,001
steering_2	0.328	21	<,001	0.69	21	<,001
tailgating_2	0.212	21	0.014	0.828	21	0.002
overtaking_2	0.404	21	<,001	0.583	21	<,001
fatigue_2	0.319	21	<,001	0.562	21	<,001
speeding_3	0.28	21	<,001	0.781	21	<,001
acceleration_3	0.131	21	.200*	0.942	21	0.237
deceleration_3	0.158	21	0.186	0.918	21	0.081
steering_3	0.21	21	0.016	0.724	21	<,001
tailgating_3	0.173	21	0.103	0.931	21	0.146
overtaking_3	0.419	21	<,001	0.618	21	<,001
fatigue_3	0.256	21	<,001	0.743	21	<,001
speeding_4	0.27	21	<,001	0.757	21	<,001
acceleration_4	0.177	21	0.086	0.898	21	0.033
deceleration_4	0.213	21	0.014	0.854	21	0.005
steering_4	0.191	21	0.043	0.834	21	0.002
tailgating_4	0.144	21	.200*	0.946	21	0.289
overtaking_4	0.385	21	<,001	0.657	21	<,001
fatigue_4	0.134	21	.200*	0.921	21	0.09

TABLE 16 Normality test for high risky events

	Normality Test					
	Kolmogorov-Smirnova			**Shapiro-Wilk**		
Parameters	**Statistic**	**N**	**Sig.**	**Statistic**	**N**	**Sig.**
speeding_1	0.176	21	0.089	0.878	21	0.013
acceleration_1	0.402	21	<0.001	0.412	21	< 0.001
deceleration_1	0.246	21	0.002	0.693	21	<0.001
steering_1	0.225	21	0.007	0.877	21	0.013
tailgating_1	0.165	21	0.138	0.91	21	0.054
overtaking_1	0.51	21	<0.001	0.44	21	<0.001
fatigue_1	0.155	21	.200*	0.879	21	0.014
speeding_2	0.299	21	<,001	0.749	21	<,001
acceleration_2	0.241	21	0.002	0.754	21	<,001
deceleration_2	0.246	21	0.002	0.689	21	<,001
steering_2	0.334	21	<,001	0.596	21	<,001
tailgating_2	0.19	21	0.047	0.759	21	<,001
overtaking_2	0.474	21	<,001	0.5	21	<,001
fatigue_2	0.29	21	<,001	0.493	21	<,001
speeding_3	0.304	21	<,001	0.712	21	<,001
acceleration_3	0.167	21	0.129	0.916	21	0.072
deceleration_3	0.206	21	0.02	0.704	21	<,001
steering_3	0.2	21	0.027	0.86	21	0.006
tailgating_3	0.183	21	0.065	0.861	21	0.007
overtaking_3	0.484	21	<,001	0.375	21	<,001
fatigue_3	0.201	21	0.027	0.803	21	<,001
speeding_4	0.302	21	<,001	0.696	21	<,001
acceleration_4	0.251	21	0.001	0.76	21	<,001
deceleration_4	0.187	21	0.054	0.868	21	0.009
steering_4	0.232	21	0.004	0.772	21	<,001
tailgating_4	0.176	21	0.09	0.884	21	0.018
overtaking_4	0.463	21	<,001	0.472	21	<,001
fatigue_4	0.268	21	<,001	0.667	21	<,001

TABLE 17 Normality test for total risky events

Normality Test						
	Kolmogorov-Smirnova			Shapiro-Wilk		
Parameters	**Statistics**	**N**	**Sig.**	**Statistics**	**N**	**Sig.**
speeding_1	0.138	21	.200*	0.965	21	0.616
acceleration_1	0.349	21	<,001	0.647	21	<,001
deceleration_1	0.107	21	.200*	0.96	21	0.521
steering_1	0.249	21	0.001	0.663	21	<,001
tailgating_1	0.214	21	0.013	0.863	21	0.007
overtaking_1	0.121	21	.200*	0.956	21	0.438
lane discipline_1	0.323	21	<,001	0.736	21	<,001
forward collision avoidance_1	0.255	21	<,001	0.728	21	<,001
vulnerable road user collision avoidance_1	0.385	21	<,001	0.715	21	<,001
fatigue_1	0.247	21	0.002	0.84	21	0.003
distraction_1	0.511	21	<,001	0.305	21	<,001
speeding_2	0.237	21	0.003	0.844	21	0.003
acceleration_2	0.146	21	.200*	0.9	21	0.035
deceleration_2	0.247	21	0.002	0.821	21	0.001
steering_2	0.377	21	<,001	0.667	21	<,001
tailgating_2	0.211	21	0.015	0.804	21	<,001
overtaking_2	0.153	21	.200*	0.93	21	0.139
lane discipline_2	0.335	21	<,001	0.743	21	<,001
forward collision avoidance_2	0.264	21	<,001	0.733	21	<,001
vulnerable road user collision avoidance_2	0.262	21	<,001	0.699	21	<,001
fatigue_2	0.318	21	<,001	0.511	21	<,001
distraction_2	0.505	21	<,001	0.282	21	<,001
speeding_3	0.177	21	0.083	0.909	21	0.052
acceleration_3	0.162	21	0.154	0.932	21	0.148
deceleration_3	0.169	21	0.122	0.845	21	0.003
steering_3	0.218	21	0.011	0.718	21	<,001
tailgating_3	0.222	21	0.008	0.872	21	0.01
overtaking_3	0.118	21	.200*	0.95	21	0.335
lane discipline_3	0.337	21	<,001	0.743	21	<,001
forward collision avoidance_3	0.295	21	<,001	0.728	21	<,001
vulnerable road user collision avoidance_3	0.338	21	<,001	0.468	21	<,001
fatigue_3	0.278	21	<,001	0.784	21	<,001
distraction_3	.	21	.	.	21	.
speeding_4	0.183	21	0.063	0.898	21	0.032
acceleration_4	0.128	21	.200*	0.962	21	0.564
deceleration_4	0.121	21	.200*	0.895	21	0.028
steering_4	0.249	21	0.001	0.779	21	<,001
tailgating_4	0.169	21	0.118	0.905	21	0.043

overtaking_4	0.173	21	0.1	0.927	21	0.12
Lane discipline_4	0.342	21	<,001	0.756	21	<,001
forward collision avoidance_4	0.238	21	0.003	0.736	21	<,001
vulnerable road user collision avoidance_4	0.232	21	0.004	0.789	21	<,001
fatigue_4	0.183	21	0.065	0.839	21	0.003
distraction_4	.	21	.	.	21	.

TABLE 18 Normality test for trip scores

Normality Test						
	Kolmogorov-Smirnova			**Shapiro-Wilk**		
Parameters	**Statistic**	**N**	**Sig.**	**Statistic**	**N**	**Sig.**
fatigue_1	0.294	21	<,001	0.736	21	<,001
distraction_1	0.513	21	<,001	0.311	21	<,001
acceleration_1	0.2	21	0.027	0.856	21	0.005
deceleration_1	0.193	21	0.04	0.862	21	0.007
steering_1	0.085	21	.200*	0.981	21	0.933
tailgating_1	0.218	21	0.01	0.852	21	0.005
lane discipline_1	0.333	21	<,001	0.749	21	<,001
overtaking_1	0.423	21	<,001	0.626	21	<,001
forward collision avoidance_1	0.229	21	0.005	0.746	21	<,001
vulnerable road user collision avoidance_1	0.384	21	<,001	0.716	21	<,001
speeding_1	0.234	21	0.004	0.847	21	0.004
fatigue_2	0.302	21	<,001	0.776	21	<,001
distraction_2	0.462	21	<,001	0.538	21	<,001
acceleration_2	0.097	21	.200*	0.983	21	0.963
deceleration_2	0.249	21	0.001	0.802	21	<,001
steering_2	0.12	21	.200*	0.978	21	0.892
tailgating_2	0.194	21	0.039	0.838	21	0.003
Lane discipline_2	0.339	21	<,001	0.76	21	<,001
overtaking_2	0.401	21	<,001	0.663	21	<,001
forward collision avoidance_2	0.211	21	0.015	0.867	21	0.008
vulnerable road user collision avoidance_2	0.313	21	<,001	0.705	21	<,001
speeding_2	0.181	21	0.07	0.852	21	0.005
fatigue_3	0.214	21	0.013	0.795	21	<,001
distraction_3	.	21	.	.	21	.
acceleration_3	0.152	21	.200*	0.93	21	0.137
deceleration_3	0.144	21	.200*	0.935	21	0.175
steering_3	0.118	21	.200*	0.96	21	0.507
tailgating_3	0.167	21	0.13	0.869	21	0.009
Lane discipline_3	0.342	21	<,001	0.757	21	<,001
overtaking_3	0.429	21	<,001	0.622	21	<,001
forward collision avoidance_3	0.291	21	<,001	0.682	21	<,001
speeding_3	0.137	21	.200*	0.927	21	0.122
fatigue_4	0.261	21	<,001	0.812	21	<,001
distraction_4	.	21	.	.	21	.
acceleration_4	0.187	21	0.053	0.933	21	0.155
deceleration_4	0.287	21	<,001	0.832	21	0.002

steering_4	0.118	21	.200*	0.962	21	0.568
tailgating_4	0.198	21	0.03	0.881	21	0.016
Lane discipline_4	0.342	21	<,001	0.759	21	<,001
overtaking_4	0.345	21	<,001	0.667	21	<,001
forward collision avoidance_4	0.24	21	0.003	0.765	21	<,001
vulnerable road user collision avoidance_4	0.245	21	0.002	0.849	21	0.004
speeding_4	0.188	21	0.051	0.873	21	0.011

8.2 Sphericity Test

TABLE 19 Sphericity test for low risky events

Mauchly's Test of Sphericity				
parameters	**Mauchly's W**	**Approx. Chi-Square**	**df**	**sig**
speeding	0.029	66.059	3	<,001
acceleration	0.098	43.557	3	<,001
deceleration	0.466	14.312	3	0.014
steering	0.191	30.953	3	<,001
tailgating	0.016	77.287	3	<,001
overtaking	0.676	7.34	3	0.197
fatigue	0.049	56.63	3	<,001

TABLE 20 Sphericity test for medium risky events

Mauchly's Test of Sphericity				
parameters	**Mauchly's W**	**Approx. Chi-Square**	**df**	**sig**
speeding	0.097	43.599	3	<,001
acceleration	0.035	63.003	3	<,001
deceleration	0.543	11.424	3	0.044
steering	0.324	21.096	3	<,001
tailgating	0.047	57.417	3	<,001
overtaking	0.319	21.403	3	<,001
fatigue	0.056	53.883	3	<,001

TABLE 21 Sphericity test for high risky events

Mauchly's Test of Sphericity				
parameters	**Mauchly's W**	**Approx. Chi-Square**	**df**	**sig**
speeding	0.119	39.792	3	<,001
acceleration	0.005	99.882	3	<,001
deceleration	0.894	2.108	3	0.834
steering	0.219	28.416	3	<,001
tailgating	0.022	71.365	3	<,001
overtaking	0.447	15.089	3	0.01
fatigue	0.031	64.795	3	<,001

Note: If the significance (p value) is less than 0.05 sphericity assumption is violated.
If the significance (p value) is greater than 0.05 sphericity assumptions is met.

TABLE 22 Sphericity test for total risky events

Mauchly's Test of Sphericity				
parameters	**Mauchly's W**	**Approx. Chi-Square**	**df**	**sig**
speeding	0.146	36.023	3	<,001
acceleration	0.059	53.112	3	<,001
steering	0.204	29.743	3	<,001
tailgating	0.023	70.962	3	<,001
deceleration	0.493	13.235	3	0.021
overtaking	0.672	7.43	3	0.191
lane discipline	0.146	36.016	3	<,001
vulnerable road user collision avoidance	0.418	16.33	3	0.006
forward collision avoidance	0.658	7.842	3	0.166
distraction	0	.	3	.
fatigue	0.05	55.971	3	<,001

TABLE 23 Sphericity test for trip scores

Mauchly's Test of Sphericity				
parameters	**Mauchly's W**	**Approx. Chi-Square**	**df**	**sig**
distraction	0	.	3	.
acceleration	0.022	71.677	3	<,001
deceleration	0.653	7.967	3	0.159
steering	0.503	12.862	3	0.025
tailgating	0.52	12.253	3	0.032
overtaking	0.409	16.719	3	0.005
lane discipline	0.646	8.167	3	0.148
forward collision avoidance	0.564	10.728	3	0.057
vulnerable road user collision avoidance	0.644	8.25	3	0.143
speeding	0.065	51.11	3	<,001