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## The effectiveness of real-time and post-trip interventions within the i-DREAMS naturalistic driving project: A cross-national analysis

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#### ABSTRACT

The i-DREAMS project set up a platform and system that provides real-time and post-trip interventions (including gamification elements) to keep drivers within safe margins. While the effectiveness of interventions has been widely studied, limited research has explored their interaction. Specifically, it remains unclear how engagement with post-trip interventions influences adherence to real-time interventions and how such engagement and adherence impact individual driving risk. Moreover, the factors contributing to variation in intervention engagement and adherence across drivers remain underexplored. In addition, most existing evaluations of intervention effectiveness have been conducted within a single-country context, with a limited focus on cross-national differences, which are crucial for understanding variation in intervention performance across different national contexts.

This study aims to assess the impact of real-time and post-trip interventions on drivers' individual driving risk across European countries, examine cross-national differences, and explore their underlying causes. The results show that the i-DREAMS interventions significantly reduced traffic offense risk and kinematic driving risk, although cross-national differences were observed between Belgium and the UK. The real-time interventions significantly reduced kinematic driving risk among UK drivers, whereas gamified post-trip interventions were more effective for Belgian drivers. Additionally, the real-time interventions effectively reduced traffic offense risk in both countries. A strong negative association was found between adherence to real-time interventions and traffic offense risk, and engagement with post-trip interventions was negatively associated with kinematic driving risk. Gamification elements enhanced engagement with post-trip interventions. The insights gained from this study help enhance the customization of i-DREAMS interventions and application strategies.

#### 1. Introduction

#### 1.1. Research background

Each year, approximately 1.19 million people die as a result of road traffic crashes. Injuries and deaths due to road crashes pose significant public health concerns that adversely affect economic and social development (WHO, 2023b). Acknowledging the seriousness of this

concern, the United Nations General Assembly has set an ambitious target of halving the global number of deaths and injuries from road traffic crashes by 2030 (WHO, 2023b). Evidence suggests that driver-related factors play a pivotal role in the majority of road crashes, and reducing individual driving risk (IDR) is essential for improving road safety (Bucsuházy et al., 2020; Khan & Lee, 2019; Rahman et al., 2022). Previous studies have uncovered that kinematic driving events such as harsh acceleration, braking, and cornering impair the driver's capacity

Abbreviations: BFPTI, Basic Functionalities in the Post-Trip Interventions; GFPTI, Gamification Functionalities in the Post-Trip Interventions; IDR, Individual Driving Risk; KDR, Kinematic Driving Risk; PTI, Post-Trip Interventions; PTIED, Post-Trip Intervention Engagement Days; PTIMD, Post-Trip Intervention Mean Duration; RTI, Real-Time Interventions; RTIAS, Real-Time Intervention Adherence Score; TOR, Traffic Offense Risk.

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for vehicle control, intensifying the challenges associated with responding to road hazards (af Wåhlberg, 2012; Islam et al., 2023; Simons-Morton et al., 2019; Sun et al., 2021). Traffic offenses such as close-following and speeding also significantly increase crash risk (Job & Brodie, 2022; Kaur et al., 2023; Luo et al., 2022; Möller et al., 2022). Therefore, the emergence of advanced safety systems to assist drivers in reducing or even eliminating these risky driving behaviors plays a critical role in advancing road safety (Furlan et al., 2020; Michelaraki et al., 2021a; Roy et al., 2022).

In recent decades, the development of automotive telematics and driver monitoring systems has created opportunities to provide drivers with real-time and post-trip feedback (Chaovalit et al., 2014; Horrey et al., 2012; Lattanzi & Freschi, 2021). Real-time interventions (RTI) refer to in-vehicle display systems or smartphone applications that are triggered during driving when the driver exhibits aggressive behavior or deviates from normal driving patterns, aiming to maintain and enhance driver safety and comfort (Adell et al., 2011; Bell et al., 2017; Wijnands et al., 2018). Post-trip interventions (PTI) provide drivers with information, guidance, warnings, feedback or notifications through apps or websites after trips. They are based on recognizing specific driving events to help reduce risks (Michelaraki et al., 2021a). Extensive research has shown that RTI and PTI have a significant positive impact on reducing IDR (Michelaraki et al., 2021a; Michelaraki et al., 2021b).

#### 1.2. Real-time interventions

Greenwood et al. (2022) surveyed United States drivers and found that equipping passenger vehicles with Advanced Driver Assistance Systems (ADAS) can improve highway safety. Similarly, a study by Masello et al. (2022) in the UK demonstrated that ADAS could reduce crash frequency by 23.8 %. Mase et al. (2020) investigated the impact of camera monitoring on risky behaviors among heavy vehicle drivers from the UK, claiming that the intervention significantly reduced the frequency of harsh braking and speeding incidents. Yue et al. (2018) reported that Forward Collision Warning (FCW) technology could reduce 35 % of near-crash events under foggy conditions. Birrell et al. (2014) conducted on-road experiments in the UK. They found that drivers using an In-Vehicle Smart Driving Aid (IVSDA) exhibited a 13.7 % increase in mean headway, with an almost threefold reduction in time spent traveling closer than 1.5 s to the vehicle in front. Zhao and Wu (2013), through a driving simulator study in the United States, concluded that the combination of an intelligent speeding prediction (ISPS) system and an intelligent speed adaptation (ISA) system resulted in greater minimum time-to-collision, fewer speeding exceedances, shorter speeding duration, and smaller speeding magnitude.

#### 1.3. Post-trip interventions

Camden et al. (2019) performed on-road experiments in the United States and concluded that web-based instruction programs could significantly reduce harsh braking, harsh cornering, and speeding. A study conducted in the United States by Payyanadan et al. (2017) revealed that trip diary feedback could reduce the estimated route risk of older drivers by 2.9 % and reduce their speeding frequency on average by 0.9 %. Toledo and Shiftan (2016) conducted on-road experiments with drivers in the Israeli army and found that post-trip feedback could lead to a reduction of 8 % in risky incidents. In addition, Mase et al. (2020) conducted on-road experiments with camera-monitoring in heavy vehicle drivers in the UK. They reported that supervisory coaching interventions are more effective in reducing kinematic driving events (e.g., harsh braking and harsh cornering).

In an increasing number of studies, gamification elements have been incorporated into safety interventions. Gamification deals with the application of game-specific design elements, mechanisms, and features in non-game contexts (Deterding et al., 2011). The main purpose of gamification is to trigger the motivation to reinforce, change, or shape a

desired behavior, and to sustain this effect over time by developing socalled intrinsic motivation (Michelaraki et al., 2021a). A review by Hamari et al. (2014) revealed that the effects of gamification (e.g., competition, social pressure, incentives and rewards, and penalties and loss aversion) are generally positive. Musicant and Lotan (2016) found that group incentives positively impacted user retention and sustainable behavioral change among novice drivers in Israel, and Mortimer et al. (2018) found that financial incentives and penalties could reduce risky driving behavior among novice drivers in Australia. Merrikhpour et al. (2014) conducted on-road experiments in Canada and determined that the feedback-reward system substantially improved headway and speed limit compliance. Nicolleau et al. (2022) demonstrated that the adoption of achievement goals was associated with fewer instances of harsh braking and reduced dynamic driving demands, thereby promoting safer driving behavior. Project Drive employed user motivation and retention strategies, such as badges and social networking, as a means to promote safe driving (Bahadoor & Hosein, 2016). The systematic mapping study on gamified applications by El hafidy et al. (2021) suggests that leaderboards can effectively motivate drivers to reduce risky behaviors such as harsh braking and speeding.

#### 1.4. European naturalistic driving projects

There have been several naturalistic driving projects in Europe. The SeMiFOT project (Victor et al., 2010), a Swedish study, served as a pilot to explore data collection technologies and assess driver behavior with limited Advanced Driver Assistance Systems (ADAS) exposure, including some analysis of behavioral changes in response to in-vehicle systems, though not designed as a formal intervention trial. The EuroFOT project conducted European-wide vehicle field tests to evaluate the safety benefit of a range of active safety systems in real traffic conditions (Aust et al., 2011; Benmimoun et al., 2011). The PROLOGUE project (Sagberg et al., 2011), carried out in five countries (Israel, Austria, the Netherlands, Spain, and Greece), was primarily a feasibility study that assessed methods and public acceptability of naturalistic driving data collection, without direct intervention evaluation. The INTERACTION project (Christoph et al., 2013; Haupt et al., 2015), conducted across eight countries (Austria, Czech Republic, France, Germany, Italy, Spain, the Netherlands, and the UK), investigated driver behavior with and without ADAS, and explicitly evaluated the influence of systems such as Lane Departure Warning and Blind Spot Detection on behavior adaptation and risk. The UDRIVE project (Eenink et al., 2014; van Nes et al., 2019), carried out in six countries (Germany, France, Poland, the Netherlands, the UK, and Spain), aimed to build a baseline understanding of driver behavior and traffic safety in natural contexts, without any intervention or system being evaluated.

#### 1.5. i-DREAMS project

Considering the usefulness of RTI and PTI, the overall objective of the European Union's Horizon 2020 i-DREAMS project was to set up a platform that provides timely interventions to keep drivers within safe margins. Specifically, i-DREAMS aimed to set up a framework for the definition, development, and validation of a context-aware 'Safety Tolerance Zone' for driving (Brijs et al., 2020). The RTI within the i-Brijs DREAMS technology consider driver background factors, real-time risky driving performance, as well as driver state and driver complexity indicators. A continuous real-time assessment monitors and determines if the driver is within the boundaries of safe vehicle operation. Furthermore, safety-oriented PTI were developed to inform or warn the driver about risky driving events (immediately) after the trip through a smartphone application, with the inclusion of gamification elements, such as goals, badges, and leaderboards. In the context of the i-DREAMS project, a series of on-road experiments were conducted in Belgium, the UK, Germany, Greece, and Portugal, with these interventions being progressively activated following the same phased approach in all

countries.

#### 1.6. Cross-national analysis

In road safety research, the effectiveness of intervention strategies may be influenced by cultural norms, driving behaviors, infrastructure quality, police enforcement, and legal frameworks, (Auzoult et al., 2015; Goel et al., 2024; Kaye et al., 2024; Labbo et al., 2025; Peiris et al., 2022; Taourarti et al., 2024; Urie et al., 2016), which vary across countries (Brijs et al., 2024b; Calvo-Poyo et al., 2020; Louw et al., 2021; Naci et al., 2009; Nordfjærn et al., 2014; Warner et al., 2009; Briffa, 2024). As a result, cross-national differences in intervention effectiveness may also emerge. Given this potential variability, conducting cross-national analyses becomes essential. Such analyses not only enable the assessment of the applicability of intervention strategies across diverse national contexts, but also help to identify specific factors that shape driver behavior and mediate intervention outcomes (Goel et al., 2024; Huang et al., 2008; Lindgren et al., 2008). These insights are critical for designing more effective, context-sensitive driver interventions.

Although several European naturalistic driving projects have included evaluations of in-vehicle RTI (such as EuroFOT and INTER-ACTION) and others focused on non-intervention contexts have conducted cross-national analyses (such as PROLOGUE and UDRIVE), research that systematically integrates both RTI and PTI assessments within a cross-national framework remains limited. The i-DREAMS project addresses this gap by incorporating RTI and PTI within a cross-national naturalistic driving study design, thus offering a comprehensive approach to evaluating the effectiveness of driver behavior interventions across different national contexts.

#### 1.7. Objectives and research questions

Although extensive research has been conducted on the effectiveness of RTI, PTI, or a combination of both, few studies have thoroughly examined the impact of the extent of drivers' engagement with PTI on their adherence to RTI and how such engagement and adherence affect IDR. Moreover, the reasons for variations in engagement with PTI and adherence to RTI across drivers are also less explored. In addition, most studies in intervention evaluations are conducted within a single country, and too little attention has been paid to cross-national difference analysis.

A preliminary analysis of the i-DREAMS results has previously been conducted. Adnan et al. (2024) assessed the effectiveness of RTI and PTI using the number of events per 100 km as a risk indicator, and Brijs et al. (2024a) focused on PTI, specifically examining user engagement with the i-DREAMS app using visit frequency-based metrics. Addressing the existing research gaps, the present study builds upon these earlier investigations to further extend and deepen the analysis. Specifically, it aims to examine the relationship between RTI adherence and PTI engagement within the i-DREAMS project and their respective impacts on the IDR of drivers from different countries. Furthermore, it explores cross-national differences in the effectiveness of these interventions and investigates their underlying causes. The naturalistic driving data used in this study were collected from participants from Belgium and the UK.

This study is structured around the following research questions to achieve these objectives. First, to assess the effectiveness of RTI and PTI, we investigate differences in IDR across phases among drivers in Belgium and the UK. Second, to explore the cross-national differences in intervention effectiveness, we examine whether there are significant differences in IDR changes between Belgian and UK drivers. Lastly, to explain the observed cross-national differences, we further investigate the variations in drivers' engagement with PTI and adherence to RTI between the two countries, as well as the relationship between drivers' engagement with PTI and their adherence to RTI, and the impact of these factors on intervention effectiveness.

By addressing these questions, this study is expected to make several key contributions. It will provide empirical evidence on the effectiveness and applicability of RTI and PTI within the i-DREAMS technology across different countries, highlight cross-national differences in their impact, and offer insights into the mechanisms by which these interventions reduce IDR. The study will also examine factors influencing drivers' adherence and engagement, and demonstrate the potential of gamification to enhance engagement with PTI. Together, these insights will not only help enhance the customization of i-DREAMS interventions and application strategies, but also contribute to the broader understanding of how RTI and PTI can improve driver safety across contexts. Beyond this platform-specific contribution, the findings will also carry broader implications for road safety practice and policy, such as driver training, fleet safety, insurance practices, enforcement, and legislation.

#### 2. Methodology

#### 2.1. Participant recruitment and sample composition

The naturalistic driving data used in this study was collected during the i-DREAMS H2020 project, funded by the European Union (The i-DREAMS project, 2020). Data from 100 participants, 50 from Belgium and 50 from the UK, was selected for the current study purposes. Participants were recruited based on several inclusion criteria, e.g., balanced representation of gender, age (minimum 18 years old), appropriate driving experience, vehicle type (to ensure the appropriate installation of i-DREAMS technology), and use of a smartphone (to enable the installation of the post-trip intervention application). Each participant held a valid driving license and had been driving for at least one year. The recruitment process followed various steps to ensure a diverse and representative group, such as general advertising, initial screening of interested candidates based on the inclusion criteria, targeted advertisement for specific sub-groups, and provision of detailed enrolment information. Participants were informed of the test protocol, the collected data, and their rights. All participating drivers provided consent before participation, and their personal information was treated strictly confidentially. The study was approved by the Hasselt University Social-Societal Ethics Committee (SSEC) and Loughborough University Ethics Committee and the Ethics Approvals (Human Participants) Sub-Committee (HPSC). Participants received 250 euros upon completion of the experiment.

The sample composition is shown in Table 1. Male and female participants from Belgium accounted for 64 % and 36 % of the Belgian participants, respectively, which is nearly consistent with the 63.5 % male and 36.5 % female proportion of all Belgian car drivers (Belgian Key Indicators Road Safety, 2017). Male and female participants from the UK accounted for 62 % and 38 % of the UK participants, respectively, which is slightly consistent with the 54.3 % male and 45.7 % female proportion of all UK car drivers (GB Driving Licence Data, 2020). The gender ratio of participants was roughly the same in the UK and Belgium, with no significant differences observed in age distributions (U = 1210.500, p = 0.788) and driving experience distributions (U = 1213.000, D = 0.801).

#### 2.2. Real-time and post-trip interventions within the i-DREAMS project

The i-DREAMS technology platform includes RTI and PTI. The interventions were chosen to target immediate behavioral correction and reflective learning. The selection criteria are as follows: (1) Ability to address immediate and long-term behavioral adjustments: The RTI via the in-vehicle display provide instant warnings for unsafe behaviors such as tailgating or speeding, allowing drivers to correct their behavior immediately. The PTI delivered through the mobile app encourage drivers to reflect on overall driving patterns, supporting longer-term behavior change. (2) Alignment with prior literature: Previous studies have demonstrated that both in-vehicle warnings and gamified app-

Table 1
Sample composition.

Country	Gender F	Ratio	Age					Driving	Experience			_
	Male	Female	Min	Max	Median	Mean	SD	Min	Max	Median	Mean	SD
Belgium	64 %	36 %	20	79	43.5	46.7	18.2	2	55	24.0	26.4	17.2
UK	62 %	38 %	19	78	44.0	45.1	13.6	2	60	24.0	25.2	13.9

based feedback can effectively reduce risky driving behaviors, providing empirical support for the chosen interventions. (3) Practical feasibility in naturalistic driving conditions: Both types of interventions can be realistically implemented in everyday driving without causing disruption or requiring excessive participant effort, ensuring high adherence and ecological validity.

The RTI utilize 2.4-inch in-vehicle displays (see Fig. 1, left panel) to provide warning messages to drivers concerning traffic offenses such as tailgating and speeding. The triggering strategy is based on the Safety Tolerance Zone concept. The Safety Tolerance Zone takes into account driver background factors, real-time risky driving performance as well as driver state and driver task complexity indicators. A continuous realtime assessment is conducted to monitor and determine whether the driver remains within a safe driving operation. According to the Safety Tolerance Zone, a driver can be in one of three different driving stages, i. e., normal driving stage, dangerous driving stage, and avoidable crash stage (Brijs et al., 2023). Correspondingly, the RTI can be in three states, i.e., reminder, warning, and intrusive warning (see Table 2). The variable thresholds for RTI of tailgating and speeding in Table 2 are calculated in real-time based on indicators that estimate task complexity (e.g., weather conditions and time of day) and the driver's coping capacity (e. g., fatigue, distraction, and trip duration) (Yang et al., 2024), Each RTI state for tailgating and speeding had its own specific symbol and sound that changes in sensory intrusiveness (size, sound level, intensity) according to the safety tolerance zone stage. The level of sensory intrusiveness had to increase in function of event severity of traffic offenses, with more intrusive warnings for more severe events, and less intrusive warnings for less severe events. For the participants, the warning volume could be adjusted. The icon style and duration were fixed features in the RTI and could not be adjusted by them.

The normal driving stage refers to conditions under which a crash is unlikely, and the operator is successfully adjusting driving behavior to maintain safe driving. In this driving stage, no RTI are required, and only reminders, such as vehicle detected ahead and speed limit information, are provided (see Table 3). The dangerous driving stage is characterized by changes to the normal driving stage that indicate a crash is more

**Table 2**Overview of the safety tolerance zone for tailgating and speeding.

			<u> </u>
Behavior	Safety Tolerance Zone	Condition	RTI State
Tailgating	Normal driving stage	Time headway $\geq$ variable threshold 1 (1.0 s $-$ 2.2 s)	Reminder
	Dangerous driving stage	Time headway $<$ variable threshold 1 (1.0 s $-$ 2.2 s) & Time headway $>$ variable threshold 2 (0.6 s $-$ 1.2 s)	Warning
	Avoidable crash stage	Time headway $\leq$ variable threshold 2 (0.6 s $-$ 1.2 s)	Intrusive warning
Speeding	Normal driving stage	Speed $\leq$ variable threshold 1 (3.25 % $-$ 10 % above the speed limit)	Reminder
	Dangerous driving stage	Speed $>$ variable threshold 1 (3.25 % $-$ 10 % above the speed limit) & Speed $<$ variable threshold 2 (4.75 % $-$ 15 % above the speed limit)	Warning
	Avoidable crash stage	Speed $\geq$ variable threshold 2 (4.75 % $-$ 15 % above the speed limit)	Intrusive warning

likely to occur but is not yet inevitable. In this driving stage, warnings are provided. Lastly, the avoidable crash stage occurs when a collision scenario is developing, but the operator still has time to intervene and avoid the crash. In this driving stage, the need for action is urgent, as the absence of corrective action or evasive maneuvers would likely result in a crash. Therefore, more intrusive warnings are provided. The RTI were triggered by a single event such as a time headway below one second. Each time an offense exceeded a specific threshold corresponding to different stages of the safety tolerance zone, as listed in Table 2, a warning of the corresponding level was issued, with distinct design features such as symbols and sounds. The warning persisted until the event fell below the threshold for that level.



Fig. 1. Real-time and post-trip interventions.

**Table 3**Overview of the messaging strategy in RTI for tailgating and speeding.

Behavior	RTI State	Display	Symbol
Tailgating	Reminder	Vehicle detected ahead. Time headway is displayed in seconds when lower or equal to 2.5 sec and at speeds above 20 km/h	
	Warning	Vehicle ahead is too close. Time headway is displayed in seconds and only shown at speeds above 20 km/h	1.3
	Intrusive warning	Vehicle ahead is too close. Immediately increase headway distance! Time headway is displayed in seconds and only shown at speeds above 20 km/h. Flashing icon, accompanied by auditory signal	
Speeding *	Reminder	The smart camera has detected a new speed limit sign. Displayed in large for 1 sec, then shown as small icon	130
	Warning	Vehicle speed is above the detected speed limit, requested to reduce speed. Displayed in large for 1 sec, then shown as small icon	130
	Intrusive warning	Vehicle speed is dangerously above the detected speed limit, reduce speed immediately! Displayed as a flashing icon in large for 1.5 sec, accompanied by auditory signal, then shown as small icon	130

 $<sup>\</sup>star$ : The speed limit displayed on the screen is shown in kilometers per hour in Belgium and miles per hour in the UK.

The PTI provide feedback to drivers through the i-DREAMS app, which consists of basic functionalities and gamification functionalities. The basic functionalities in the post-trip interventions (BFPTI) consist of two elements (i.e., scores and trips) and provide feedback on drivers' driving performance for each trip (see Fig. 1, central panel). The driving performance includes traffic offenses (e.g., tailgating and speeding) and kinematic driving behaviors (i.e., acceleration, braking, and cornering). The scores functionality provides an overview of performance scores in

traffic offenses and kinematic driving behaviors. The performance scores were calculated based on the number and duration of driving events at each severity level during a trip. The performance scores range from 0 to 100, with higher values indicating better driving performance. A higher number of driving events, longer duration, and greater severity result in a larger performance score deduction. For example, the score deduction for tailgating in the avoidable crash stage was greater than that for tailgating in the dangerous driving stage, and the score deduction for high-level harsh acceleration was greater than that for low-level harsh acceleration. Since the RTI were generated for traffic offenses such as tailgating and speeding, drivers' performance scores for traffic offenses can be used to measure adherence to RTI. Therefore, higher performance scores of tailgating and speeding indicated better adherence to RTI. These scores are aggregated according to the time interval the driver can choose on top of the screen. In the trips functionality, the user sees a list of the trips that were performed for the chosen date interval (yesterday is the default choice). Clicking on a trip shows basic information about the trip (date, time, duration, distance), and the scores the driver obtained in the selected trip for their driving performance objectives. A trip can also be visualized on a map, showing the GPS trace and the events that happened during the trip. By clicking on an event, more information about the event is shown, including time, intensity, and a video if

The gamification functionalities in the post-trip interventions (GFPTI) consist of two gamification elements, i.e., goals & badges, and leaderboards (see Fig. 1, right panel). In the i-DREAMS platform, goals are set for specific parameters (e.g., tailgating, speeding, acceleration, braking, and cornering), and based on a methodology aimed at progressive substitution of undesired behaviors by desired behaviors, and stepwise reversal of bad habits into good ones. In order to do that, challenges are defined that gradually increase in terms of difficulty, and are achievable but attractive enough for drivers. The driver can list the goals that were completed, are open, or are new in the goals & badges functionality. Goals are grouped according to driving performance objectives and require the driver to obtain a minimal score for a specified distance on the driving performance objective. The driver can check the progress made on open goals and take up new goals. Each challenge consisted of four consecutive goals with gradually increasing difficulty. The interface of goals & badges functionality shown in Fig. 1 illustrates a challenge for acceleration, consisting of four consecutive goals. If a driver succeeds in a challenge, i.e., four consecutive goals, he receives a badge. There are four categories of badges in increasing order of difficulty: bronze, silver, gold, and platinum. These corresponded to the consecutive completion of 1, 2, 3, and 4 challenges, respectively, or equivalently, 4, 8, 12, and 16 goals.

Drivers obtained points in function of how they scored in terms of performance on a desired behavioral parameter (e.g., keeping a safe headway distance, respecting speed limits) at the end of a trip. The leaderboards functionality shows a ranking of the drivers who are part of a group in a project, based on drivers' points related to their performance scores, and includes daily, weekly, and lifetime rankings. An indication of change in ranking is also given. The i-DREAMS gamification backend platform allows users to make the leaderboards visible either to all participants or to smaller subgroups (e.g., within specific challenges or competitions). In the i-DREAMS field trial, all users chose to make the leaderboards public to all participants.

Additionally, push notifications are sent to users to help enhance engagement with the i-DREAMS app. For instance, if a tip related to a new goal had not yet been read, users could receive a message such as: "Don't forget to check tips with respect to your current goal." Similarly, drivers who received a very low score might be sent the message: "Unfortunate that you obtained a lower score. Tomorrow is a new day, don't give up." More details on RTI, BFPTI, and GFPTI within the i-DREAMS technology can be found in the project's technical reports (Lourenço et al., 2020; Vanrompay et al., 2020).

#### 2.3. Study design of the i-DREAMS naturalistic field trial

This study is based on real driving data collected under naturalistic driving conditions in Belgium and the UK. The same i-DREAMS technology platform was implemented, ensuring that the interventions, data collection methods, and behavioral measures were consistent across sites. This approach allows for a valid and meaningful comparison between Belgium and the UK. The naturalistic field trial lasted 18 weeks and was divided into four phases. Table 4 presents the interventions and their duration for each phase. During these periods, the respective peaks of the COVID-19 pandemic in each country, along with changing traffic restrictions, may have influenced participants' travel behavior. Table 5 provides an overview of trips and the proportion of travel distance by road types and trip purposes for Belgian and UK drivers, with a difference analysis between the two countries. The UK drivers had a significantly higher proportion of travel distance on motorways compared to Belgian drivers, whereas Belgian drivers had significantly higher proportions of travel distance on roads both outside and inside built-up areas. In addition, Belgian drivers had a significantly higher proportion of travel distance for medical purposes than UK drivers, while no significant differences were observed for other trip purposes such as commuting or leisure.

Phase 1 served as a baseline measurement and lasted from Week 1 to Week 4. Phase 2 spanned from Week 5 to Week 8. Phase 3 covered Week 9 to Week 12. Phase 4 extended from Week 13 to Week 18. Specifically, Phase 1 corresponds to an initial reference monitoring period after installing the i-DREAMS technology when no intervention was active. Phase 2 corresponds to the monitoring period when only RTI were active within a vehicle. Phase 3 corresponds to the monitoring period when RTI were active, and drivers also received post-trip feedback (scores and events per trip) on their driving performance through the i-DREAMS app. Phase 4 corresponds to the monitoring period when RTI were active along with post-trip feedback, but at the same time, gamification elements were also active. The timing and duration of drivers' visits to the i-DREAMS app were recorded during Phase 3 and Phase 4. Throughout the field trial period where the i-DREAMS interventions were activated, various driving behaviors and performance scores for each trip were recorded in the i-DREAMS Data Back-office. However, the feedback was not provided to drivers through the i-DREAMS app during Phase 1 and Phase 2, in which PTI were not yet activated. Additionally, since RTI were not activated in Phase 1, the performance scores during this phase actually reflected drivers' baseline performance without interventions.

#### 2.4. Data analysis

This study analyzes the effectiveness of RTI and PTI in reducing IDR and examines any eventual cross-national differences in intervention effectiveness and their underlying causes. The data analytical framework (see Fig. 2) serving these aims will be outlined in more detail below.

## 2.4.1. Assessment of individual driving risk, RTI adherence, and PTI engagement

In this study, the IDR for each driver in each phase was assessed based on the assessment method we previously developed and described (Song et al., 2025). Rather than relying on the number of events per 100 km, the IDR was measured by the weighted probability of multithreshold events (WPMTE) in risky driving scenarios. WPMTE considers multi-levels for driving events and uses the probability of driving events to indicate driving risk instead of frequency (Camden et al., 2019; Mase et al., 2020; Masello et al., 2022), thereby more accurately capturing the drivers' propensity to engage in risky driving behaviors in risky driving scenarios. The IDR comprised kinematic driving risk (KDR) and traffic offense risk (TOR). The KDR reflects the risk associated with vehicle maneuvering behaviors, measured by the average of the acceleration risk, braking risk, and cornering risk, while TOR reflects the risk

Activation time for each type of intervention

Intervention	Phase 1				Phase 2				Phase 3				Phase 4					
	Week 1	Week 2	Week 2 Week 3 Week 4	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 9 Week 10 Week 11 Week 12	Week 11	Week 12	Week 13	Week 14	Week 13 Week 14 Week 15 Week 16	Week 16	Week 17	Week 18
(a). RTI	N	N	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
(b). BFPTI	z	z	z	z	z	z	z	z	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
(c). GFPTI	Z	Z	Z	Z	Z	Z	z	Z	z	z	Z	Z	Y	X	Y	Y	Y	Y

**Table 5**Overview of trips and the proportion of travel distance by road types and trip purposes for Belgian and UK drivers, with a difference analysis between the two countries.

		Belgian Dr	ivers		UK Drivers			Mann-Whitn	ey U Test
		Median	Mean	SD	Median	Mean	SD	U	Sig.
Trips	Number of trips	360	367	165	278	313	173	996.000	0.080
	Total distance (km)	4371	5123	3369	3881	3746	1816	997.000	0.081
	Average trip distance (km)	12.2	14.6	8.1	12.2	13.7	7.2	1150.000	0.491
	Average daily distance (km)	45.9	51.9	26.1	50.6	49.1	18.2	1241.000	0.951
Road types	Motorways	17.1 %	20.5 %	14.6 %	36.6 %	36.0 %	17.8 %	627.000	<0.001 ***
	Roads outside built-up areas	48.6 %	49.6 %	13.1 %	37.9 %	40.3 %	12.6 %	797.000	0.002 **
	Roads inside built-up areas	28.5 %	29.9 %	12.6 %	23.8 %	23.7 %	9.8 %	887.000	0.012 *
Trip purposes	Commuting	19.0 %	26.8 %	27.5 %	26.7 %	31.6 %	29.9 %	1154.000	0.502
	Visiting	22.7 %	23.7 %	16.9 %	28.1 %	29.3 %	22.5 %	1098.000	0.295
	Shopping	10.0 %	14.4 %	13.0 %	14.6 %	16.3 %	12.8 %	1129.500	0.406
	Leisure	7.6 %	12.5 %	14.4 %	5.3 %	11.8 %	14.7 %	1165.000	0.557
	Errands	5.5 %	8.7 %	10.1 %	4.0 %	6.8 %	9.1 %	1051.000	0.169
	Medical	1.4 %	5.5 %	10.3 %	0.0 %	1.8 %	3.7 %	931.000	0.017 *

<sup>\*:</sup> p < 0.05, \*\*: p < 0.01, \*\*\*: p < 0.001.

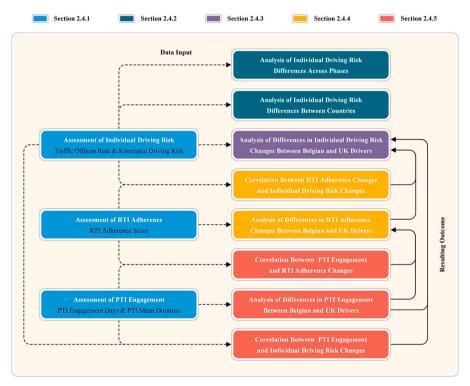


Fig. 2. Data analytical framework.

related to traffic offenses, determined based on the average of the tailgating risk and speeding risk. The detailed formulas for calculating TOR and KDR can be found in the work by Song et al. (2025). The values of TOR and KDR ranged between 0 and 1, with higher values indicating greater risk.

The RTI adherence for each driver was assessed through RTI adherence score (RTIAS) in each phase (see Eq. (1)). The RTIAS was calculated as the average of the tailgating score and speeding score (see Eq. (2)). The RTIAS ranged from 0 to 100, with higher values indicating better RTI adherence.

$$PS_{xik} = \sum_{j=1}^{n} \frac{TS_{xijk}TD_{xij}}{TD_{xi}}$$
 (1)

$$RTIAS_{xi} = \frac{PS_{xit} + PS_{xis}}{2} \tag{2}$$

where x represents the participant's serial number, from 1 to 100,

corresponding to the 100 participants in the study; i represents the phase of naturalistic field trial, which can be 1, 2, 3, or 4; n represents the total number of trips taken by driver x during Phase i; j represents the trip serial number, from 1 to n; k represents the type of driving performance, which can be t (tailgating) or s (speeding);  $PS_{xik}$  represents the weighted average of the performance scores corresponding to driving performance k for all trips taken by driver x during Phase i;  $TS_{xijk}$  represents the performance scores corresponding to driving performance k for trip j taken by driver k during Phase k; k0 represents the travel distance for trip k1 taken by driver k2 during Phase k3. The k4 represents the total travel distance for trips taken by driver k3 during Phase k4; k5 represents the RTIAS of driver k6 in Phase k5 represents the performance scores of driver k6 in Phase k6 represents the performance scores of driver k6 in Phase k6 represents the performance scores of driver k6 in Phase k6 represents the performance scores of driver k6 in Phase k6 represents the performance scores of driver k7 in Phase k8 represents the performance scores of driver k8 in Phase k9 represents the performance scores of driver k8 in Phase k9 represents the performance scores of driver k8 in Phase k9 represents the performance scores of driver k8 in Phase k9 represents the performance scores of driver k9 represents the performance scores

In previous work related to the i-DREAMS project, PTI engagement was examined using visit frequency-based metrics (Brijs et al., 2024a). In the present study, it was further assessed through PTI engagement

days (PTIED) and PTI mean duration (PTIMD) per visit on the i-DREAMS app in each phase, providing a more comprehensive understanding of both the frequency and intensity of app usage over time.

## 2.4.2. Analysis of individual driving risk differences across phases and between countries

The 25th, 50th, and 75th percentiles of TOR and KDR for drivers in Belgium and the UK across the four phases were calculated, providing an initial understanding of the risk distribution among drivers in each country in each phase. To demonstrate the effectiveness of the interventions, a series of two-way repeated measures ANOVA tests were conducted to investigate the differences in IDR between intervention phases for drivers in Belgium and the UK. Since two factors were involved, i.e., country (Belgium, UK) and phase (Phase 1, 2, 3, 4), we first assessed whether an interaction effect existed. In case a significant interaction effect was present, we analyzed the simple effects of country and phase while in case no interaction effect was found, we examined the main effects of country and phase. For the multi-group phase, we performed pairwise comparisons to examine which phases showed significant differences in IDR.

#### 2.4.3. Cross-national differences in intervention effectiveness

To examine the cross-national differences in intervention effectiveness, we calculated the changes in TOR and KDR between adjacent phases for drivers in Belgium and the UK, and further examined whether there were significant differences in TOR changes and KDR changes between Belgian and UK drivers through statistical difference analyses. If the data for the grouped variables followed a normal (or approximately normal) distribution, independent samples t-tests were used. Otherwise, non-parametric independent samples Wilcoxon rank-sum tests were applied. If there were significant differences in IDR changes between Belgian and UK drivers, this also implied significant differences in intervention effectiveness.

#### 2.4.4. The role of RTI adherence in cross-national differences

The study investigated whether and how variations in drivers' RTI adherence between the two countries contribute to the cross-national differences in intervention effectiveness. The changes in RTIAS between phases reflected the variations in RTI adherence. We analyzed the correlation between RTIAS changes and IDR changes, as well as the differences in RTIAS changes between Belgian and UK drivers. Specifically, we calculated Spearman's rank correlation coefficients between RTIAS changes and IDR changes to examine their relationship. We plotted scatter plots of RTIAS changes against IDR changes for drivers from both countries to find out the distribution of RTIAS changes and IDR changes for Belgian and UK drivers. Next, we further examined the differences in RTIAS changes between Belgian and UK drivers. More in particular, we assessed whether significant differences in RTIAS changes between Belgian and UK drivers resulted in significant differences in IDR changes. Similarly, if the data for the grouped variables followed a normal (or approximately normal) distribution, independent samples ttests were used. Otherwise, non-parametric independent samples Wilcoxon rank-sum tests were applied.

#### 2.4.5. The role of PTI engagement in cross-national differences

The study investigated whether and how variations in drivers' PTI engagement between the two countries contribute to the cross-national differences in RTI adherence and intervention effectiveness. The PTI engagement was assessed through PTIED and PTIMD. We analyzed the correlation between PTIED, PTIMD and the changes of RTIAS, TOR, KDR, as well as the differences in PTIED and PTIMD between Belgian and UK drivers. Specifically, we calculated Spearman's rank correlation coefficients between PTIED, PTIMD and the changes of RTIAS, TOR, KDR to examine their associations. We plotted scatter plots of PTIED, PTIMD against the changes of RTIAS, TOR, KDR for drivers from both countries to find out the distribution of PTIED, PTIMD, and the changes

of RTIAS, TOR, KDR for Belgian and UK drivers. We further examined the differences between Belgian and UK drivers in PTIED and PTIMD during Phase 3 and Phase 4. More precisely, we investigated whether significant differences in PTIED and PTIMD between Belgian and UK drivers were accompanied by significant differences in the changes of RTIAS, TOR, KDR. Similarly, if the data for the grouped variables followed a normal (or approximately normal) distribution, independent samples t-tests were used. Otherwise, non-parametric independent samples Wilcoxon rank-sum tests were applied.

#### 3. Results

### 3.1. Analysis of individual driving risk differences across phases and between countries

Fig. 3 illustrates the distribution of TOR and KDR for Belgian and UK drivers in each phase, with the 25th, 50th, and 75th percentiles of risks marked. This provides a clear understanding of the variations in TOR and KDR across the phases for Belgian and UK drivers.

The results from the two-way repeated measures ANOVA tests (Table 6) indicated a significant interaction between country and phase for KDR. Therefore, we further analyzed the simple effects of country for each phase and the simple effects of phase for Belgian and UK drivers.

We found significant differences in KDR between Belgian and UK drivers in each phase, as well as significant differences in KDR between the phases for both Belgian and UK drivers. For TOR, no interaction between country and phase was observed. Thus, we analyzed the main effects of country and phase separately, finding significant differences in TOR between Belgian and UK drivers, as well as significant differences in TOR across the phases (see Table 6).

The pairwise comparison results in Table 7 show a significant difference in KDR between Phase 1 (no intervention) and Phase 2 (RTI) for UK drivers, as well as a significant difference in TOR between Phase 1 (no intervention) and Phase 2 (RTI) for both Belgian and UK drivers. This indicates that the activation of RTI can significantly reduce the overall KDR of UK drivers and the overall TOR of both Belgian and UK drivers. However, there were no significant differences in KDR or TOR between Phase 2 (RTI) and Phase 3 (RTI and BFPTI) for Belgian and UK drivers, suggesting that the activation of BFPTI did not have a significant effect on further reducing overall TOR and KDR of Belgian and UK drivers. In contrast, a significant difference in KDR was observed between Phase 3 (RTI and BFPTI) and Phase 4 (RTI, BFPTI, and GFPTI) for Belgian drivers, indicating that the activation of GFPTI significantly further reduced the overall KDR of Belgian drivers.

#### 3.2. Cross-national differences in intervention effectiveness

The IDR differences between adjacent phases reflected the effectiveness of various interventions. Fig. 4 shows the differences in TOR and KDR between adjacent phases for Belgian and UK drivers. In Belgium and the UK, significant risk differences between adjacent phases were observed (as found in Table 7), with more than 70 % of drivers (i.e., over 35 out of 50 in one country) experiencing a risk reduction across these phases, indicating that the majority of drivers experienced a risk reduction between these two phases. Due to the non-normal distribution of the IDR changes, we used the non-parametric independent samples Wilcoxon rank-sum tests to analyze whether there were significant differences in IDR changes between Belgian and UK drivers (see Table 8).

Table 8 shows that there were no significant differences between Belgian and UK drivers in TOR changes between adjacent phases. However, there were significant differences between Belgian and UK drivers in KDR changes from Phase 1 to Phase 2 and from Phase 3 to Phase 4, indicating that the effectiveness of RTI and GFPTI in reducing KDR exhibited cross-national differences. This is consistent with the results in Table 7, where the activation of RTI significantly reduced the

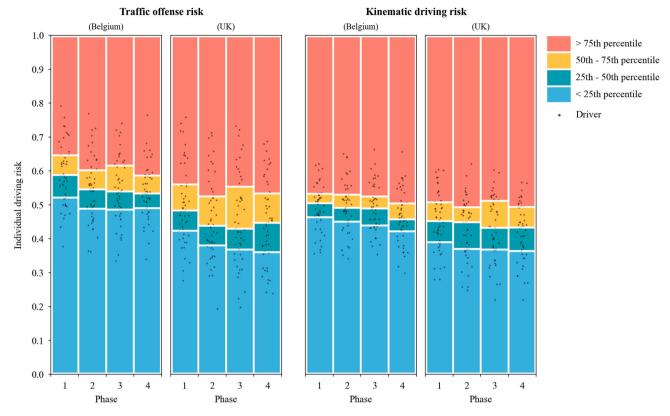


Fig. 3. Risk distributions.

**Table 6**Results of the two-way repeated-measures ANOVA.

Risk	Interaction	Effect	Main Effect	of Country		Main Effect of	Phase	
	F	Sig.	F	Sig.		F	Sig.	
TOR	0.049	0.986	18.599 Simple Effec	<0.001 *** t of Country		28.505 Simple Effect	<0.001 *** of Phase	
			Phase	F	Sig.	Country	F	Sig.
KDR	5.107	0.002 **	1	7.705	0.007 **	Belgium	17.138	<0.001 ***
			2	16.497	<0.001 ***	UK	12.948	< 0.001 ***
			3	13.523	< 0.001 ***			
			4	6.787	0.011 *			

<sup>\*:</sup> p < 0.05, \*\*: p < 0.01, \*\*\*: p < 0.001.

overall KDR for UK drivers, while the activation of GFPTI significantly reduced the overall KDR for Belgian drivers.

To assess whether the cross-national differences in intervention effectiveness (i.e., KDR<sub>2-1</sub> and KDR<sub>4-3</sub>) were associated with the triprelated factors that showed significant differences between the two countries (Table 5), we conducted Spearman's rank correlation analyses. None of the factors were significantly correlated with KDR<sub>2-1</sub> or KDR<sub>4-3</sub>: the proportion of travel distance on motorways ( $r_s = 0.000, p = 0.998$ ;  $r_s = 0.030, p = 0.768$ ), roads outside built-up areas ( $r_s = 0.028, p = 0.779$ ;  $r_s = 0.072, p = 0.478$ ), roads inside built-up areas ( $r_s = -0.047, p = 0.640$ ;  $r_s = -0.113, p = 0.263$ ), or for medical trips ( $r_s = -0.109, p = 0.281$ ;  $r_s = -0.036, p = 0.725$ ). In sum, although these trip-related factors differed significantly between the two countries, they do not account for the observed cross-national differences in intervention effectiveness.

#### 3.3. The role of RTI adherence in cross-national differences

Table 9 presents Spearman's rank correlation coefficients between RTIAS changes and IDR changes, between adjacent phases. RTIAS

changes and TOR changes exhibited a significant negative correlation, whereas no significant correlation was observed with KDR changes. As illustrated in Fig. 5, greater increases in RTIAS corresponded to larger reductions in TOR, but no comparable relationship was observed with KDR. The non-parametric independent samples Wilcoxon rank-sum tests indicate no significant differences in RTIAS changes between Belgian and UK drivers, as displayed in Table 10, which aligns with the pattern found in TOR changes observed in Table 8.

Significant differences between Belgian and UK drivers in  $KDR_{2-1}$  (i. e., KDR changes from Phase 1 to Phase 2) were observed. To explore the role of RTI in these cross-national differences, we further examined the correlation between  $KDR_{2-1}$  and  $TOR_2$  and  $TOR_{2-1}$  (i.e., TOR in Phase 2 and TOR changes from Phase 1 to Phase 2, both of which may reflect the impact of RTI in Phase 2), as well as the differences between Belgian and UK drivers in  $TOR_2$  and  $TOR_{2-1}$ . A significant positive correlation was found between  $TOR_2$  and  $KDR_{2-1}$  ( $r_s = 0.204$ , p = 0.041), indicating that a lower  $TOR_2$  was associated with greater KDR decrements. A significant positive correlation was also found between  $TOR_{2-1}$  and  $KDR_{2-1}$  ( $r_s = 0.211$ , p = 0.035), confirming that greater TOR decrements were

**Table 7**Pairwise comparisons.

Risk	Country	Phase (I)	Phase (J)	Mean Difference (I-J)	Sig.
TOR	Belgium & UK	1	2	0.043	<0.001 ***
		2	3	0.002	1.000
		3	4	0.006	1.000
		2	4	0.008	1.000
		1	3	0.045	<0.001 ***
		1	4	0.051	<0.001 ***
KDR	Belgium	1	2	< 0.001	1.000
		2	3	0.003	1.000
		3	4	0.028	<0.001 ***
		2	4	0.031	<0.001 ***
		1	3	0.004	1.000
		1	4	0.031	<0.001 ***
	UK	1	2	0.021	<0.001 ***
		2	3	< 0.001	1.000
		3	4	0.009	0.405
		2	4	0.009	0.619
		1	3	0.021	0.001 **
		1	4	0.030	<0.001

<sup>\*:</sup> p < 0.05, \*\*: p < 0.01, \*\*\*: p < 0.001.

associated with more substantial KDR decrements. Moreover, although there was no significant difference in  $TOR_{2\cdot 1}$  between Belgian and UK drivers ( $U=1210.000,\,p=0.783$ ), UK drivers had significantly lower  $TOR_2$  than Belgian drivers ( $U=687.000,\,p<0.001$ ). Notably, UK drivers had significantly lower baseline  $TOR_1$  than Belgian drivers ( $U=665.000,\,p<0.001$ ), and  $TOR_1$  and  $TOR_2$  were significantly positively correlated ( $r_s=0.879,\,p<0.001$ ).

There were no significant differences in  $KDR_{3\cdot2}$  between Belgian and UK drivers, whereas significant differences were observed in  $KDR_{4\cdot3}$  between the two groups. As no significant changes in overall TOR were observed for Belgian and UK drivers across Phases 2 to 4, we did not conduct an exploratory analysis similar to that described above to account for these cross-national differences. Instead, in the following section, we examined the role of PTI engagement in these cross-national differences.

#### 3.4. The role of PTI engagement in cross-national differences

From Table 11, we found that neither PTIED nor PTIMD in Phase 3 and Phase 4 was significantly correlated with the changes of RTIAS and TOR. The PTIED were not significantly correlated with KDR changes, while PTIMD was significantly negatively correlated with KDR changes. We plotted scatter diagrams of PTIMD and KDR changes (see Fig. 6), showing that higher PTIMD was associated with greater reductions in KDR. Next, we further examined the differences in PTIMD3 and PTIMD4 between Belgian and UK drivers. As shown in Table 12, the nonparametric independent samples Wilcoxon rank-sum tests indicate no significant differences in PTIMD3 between Belgian and UK drivers, whereas Belgian drivers had significantly higher PTIMD4 than UK drivers. Additionally, the non-parametric paired samples Wilcoxon signed-rank tests reveal a significant increase in PTIMD from Phase 3 to Phase 4 for Belgian drivers (Z = -2.573, p = 0.010), whereas no significant difference was observed for UK drivers (Z = -0.507, p = 0.612). Notably, Belgian drivers had significantly higher KDR3 than UK drivers (U = 800.000, p = 0.002), and KDR<sub>3</sub> and PTIMD<sub>4</sub> were significantly positively correlated ( $r_s = 0.339$ , p < 0.001).

To assess whether the cross-national difference in intervention use (i.

e., PTIMD<sub>4</sub>) was associated with the trip-related factors that showed significant differences between the two countries (Table 5), we conducted Spearman's rank correlation analyses. None of the factors were significantly correlated with PTIMD<sub>4</sub>: the proportion of travel distance on motorways ( $r_s = -0.178, p = 0.077$ ), roads outside built-up areas ( $r_s = 0.130, p = 0.197$ ), roads inside built-up areas ( $r_s = 0.089, p = 0.381$ ), or for medical trips ( $r_s = 0.092, p = 0.362$ ). In sum, although these trip-related factors differed significantly between the two countries, they do not account for the observed cross-national difference in intervention use.

#### 4. Discussion

The results of this study show that, by comparing the risks between Phase 1 (no intervention) and Phase 4 (RTI, BFPTI, and GFPTI within the i-DREAMS interventions) for Belgian and UK drivers, both TOR and KDR significantly decreased after the field trial, indicating that the i-DREAMS interventions are effective in reducing IDR. This is consistent with the findings of Adnan et al. (2024), who observed a reduction in events per 100 km after exposure to the i-DREAMS technology. These results are also in line with those of previous studies regarding the positive effect of RTI and PTI on kinematic driving events and traffic offenses (Donmez et al., 2008; Hickman & Hanowski, 2011; Mase et al., 2020; Merrikhpour et al., 2014).

## 4.1. The effectiveness of real-time interventions in reducing individual driving risk

In Phase 2, the activation of RTI significantly reduced the TOR for both Belgian and UK drivers. This finding aligns with previous studies indicating that RTI can effectively reduce the occurrence of traffic offense events by providing warning messages for traffic offense events such as close-following and speeding, thereby lowering drivers' TOR (Birrell et al., 2014; Yue et al., 2018; Zhao & Wu, 2013).

Since traffic offenses have been widely recognized as major contributors to road crashes (WHO, 2023a), and kinematic driving events are frequently employed as surrogate safety measures for assessing crash risk (Feng et al., 2017; Simons-Morton et al., 2019), a positive correlation between TOR and KDR is theoretically expected, as also evidenced in our previous study (Song et al., 2025). Therefore, although RTI does not directly provide warning messages for kinematic driving events, it may contribute to their reduction by lowering traffic offense events. For example, reducing close-following behavior often leads to fewer instances of harsh braking (Feng et al., 2017; Karim et al., 2014).

One interesting finding is that the effectiveness of RTI in reducing KDR showed cross-national differences, with a significant reduction observed in KDR for UK drivers, while no such effect was found for Belgian drivers. A possible explanation for this might be that, compared to Belgian drivers, UK drivers exhibited a significantly lower baseline TOR<sub>1</sub> under no intervention, which could be attributed to differences in national traffic safety climate, including traffic safety attitudes, safety skills, values, and road safety culture (Antov et al., 2012; Gehlert et al., 2014; Kaçan et al., 2019; Nævestad et al., 2019; Özkan et al., 2006; Quimby et al., 2005). For example, Özkan et al. (2006) assessed drivers from the UK, the Netherlands, Finland, Greece, Iran, and Turkey using the Driver Skill Inventory (DSI), revealing that UK drivers scored higher in safety skills. The third SARTRE (Social Attitudes to Road Traffic Risk in Europe) survey investigated drivers' attitudes toward speed and speeding in 23 European countries (including Belgium and the UK). It indicated that UK drivers perceived themselves as safer than other drivers and reported speeding less than Belgian drivers and the average European driver (Quimby et al., 2005). The fourth SARTRE survey (Antov et al., 2012), conducted across 19 European countries, including Belgium but excluding the UK, revealed that 39 % of Belgian drivers reported following the vehicle in front too closely at least sometimes—an increase of 5.6 % compared to the third SARTRE survey. Only

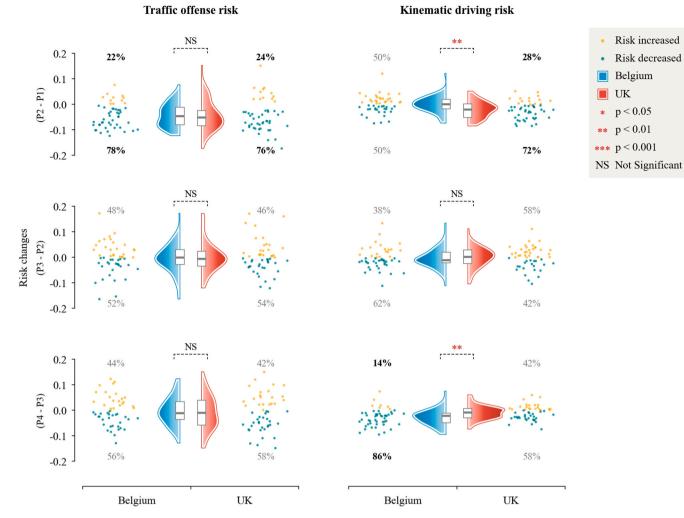


Fig. 4. Risk changes between adjacent phases and their half violin plots.

Table 8
Difference analysis of IDR changes between Belgian and UK drivers.

Intervention Difference	Risk Change	Country	Count	Mean Rank	Sum of Ranks	U	Sig.
RTI	TOR <sub>2-1</sub>	Belgium	50	51.30	2565.00	1210.000	0.783
		UK	50	49.70	2485.00		
		Total	100				
	$KDR_{2-1}$	Belgium	50	58.82	2941.00	834.000	0.004 **
		UK	50	42.18	2109.00		
		Total	100				
BFPTI	TOR <sub>3-2</sub>	Belgium	50	50.80	2540.00	1235.000	0.918
		UK	50	50.20	2510.00		
		Total	100				
	KDR <sub>3-2</sub>	Belgium	50	47.92	2396.00	1121.000	0.374
		UK	50	53.08	2654.00		
		Total	100				
GFPTI	TOR <sub>4-3</sub>	Belgium	50	52.00	2600.00	1175.000	0.605
		UK	50	49.00	2450.00		
		Total	100				
	KDR <sub>4-3</sub>	Belgium	50	42.88	2144.00	869.000	0.009 **
		UK	50	58.12	2906.00		
		Total	100				

<sup>\*:</sup> p < 0.05, \*\*: p < 0.01, \*\*\*: p < 0.001.

38 % of Belgian drivers strongly agreed or agreed that penalties for speeding should be more severe—a figure significantly lower than the European average of 52 %, and 22 percentage points lower than Belgium's result in the third SARTRE survey.

Consequently, compared to Belgian drivers, UK drivers with a lower

baseline  $TOR_1$  exhibited a lower  $TOR_2$  under the effect of RTI, which can be explained by the significant positive correlation observed between  $TOR_2$  and  $TOR_1$ , and the absence of a significant difference in  $TOR_{2-1}$  between the two countries. This lower  $TOR_2$  subsequently contributed to a more significant reduction in KDR for UK drivers (McDonald et al.,

Table 9
Spearman's rank correlations between RTIAS changes and IDR changes.

Score Change	Risk Change	Spearman	Sig.
RTIAS <sub>2-1</sub>	TOR <sub>2-1</sub>	-0.428	<0.001 ***
	$KDR_{2-1}$	-0.110	0.276
RTIAS <sub>3-2</sub>	TOR <sub>3-2</sub>	-0.276	0.005 **
	KDR <sub>3-2</sub>	-0.131	0.195
RTIAS <sub>4-3</sub>	TOR <sub>4-3</sub>	-0.426	< 0.001 ***
	KDR <sub>4-3</sub>	-0.146	0.146

<sup>\*:</sup> p < 0.05, \*\*: p < 0.01, \*\*\*: p < 0.001.

2024; Xu et al., 2022), given the significant positive correlation observed between  $KDR_{2-1}$  and  $TOR_2$ . These findings suggest that for drivers who achieve lower TOR through the use of RTI, both their TOR and KDR may be significantly reduced.

## 4.2. The effectiveness of post-trip interventions in reducing individual driving risk

In Phase 3, the BFPTI provided drivers with performance scores and event details for each trip. The BFPTI were found not to make significant contributions to reducing drivers' IDR in this study. This finding might be explained by the fact that BFPTI provide information alone without appropriate motives or penalties, leading drivers to disregard or insufficiently attend to post-trip feedback, which in turn fails to help them adjust risky driving behaviors and ultimately fails to reduce their IDR (Michelaraki et al., 2021a; Picco et al., 2023). It is consistent with previous findings (Mullen et al., 2015; Reagan et al., 2013; Stevenson et al., 2021) that feedback alone does not significantly reduce risky driving behaviors, whereas the combination of feedback and incentives proves effective.

In Phase 4, gamification functionalities (i.e., goals & badges, and leaderboards) were added to BFPTI to facilitate drivers' motivation for self-comparison and social comparison (Hamari et al., 2014; Mekler et al., 2017). Brijs et al. (2024a) revealed that when these gamification functionalities were activated, user interaction increased, suggesting they re-engaged users. This study further found that, compared to the BFPTI, gamification elements encouraged drivers with higher KDR<sub>3</sub> before the activation of GFPTI to exhibit longer PTIMD<sub>4</sub>, since PTIMD<sub>4</sub> and KDR<sub>3</sub> were found to be significantly positively correlated. A possible explanation for this might be that drivers with higher KDR<sub>3</sub>, driven by motivation for self-comparison and social comparison, tended to spend more time reviewing their kinematic driving event details more carefully through the i-DREAMS app. This may have contributed to significant KDR decrements in Phase 4, since KDR<sub>4-3</sub> and PTIMD<sub>4</sub> were found to be significantly negatively correlated.

Our findings align with those of Mase et al. (2020), who demonstrated that PTI are more effective in reducing kinematic driving events compared to traffic offenses. The GFPTI appear to be more effective for Belgian drivers with higher KDR $_3$  compared to UK drivers, as the former typically performed poorly on goals and leaderboards at the onset of the GFPTI activation and were therefore more responsive to the gamification elements. In contrast, UK drivers with lower KDR $_3$  tended to receive more positive post-trip feedback, potentially reducing the need for long PTIMD $_4$  to carefully review event details. Consequently, it is unsurprising that their KDR did not decrease significantly from Phase 3 to Phase 4.

Taken together, these findings suggest that the BFPTI in the current study did not significantly reduce drivers' IDR. However, incorporating gamification elements led to a significant reduction in KDR, particularly among drivers with initially high KDR levels. Therefore, the customization of i-DREAMS interventions and application strategies can be enhanced based on the baseline risk levels of individuals or groups.

#### 4.3. Implications of the study

The most direct implication of this study is that it helps enhance the customization of i-DREAMS interventions and application strategies and contributes to the broader understanding of how RTI and PTI can improve driver safety across contexts. Beyond this platform-specific contribution, the findings also carry broader implications for road safety practice and policy.

First, the demonstrated effectiveness of RTI and PTI in reducing both TOR and KDR suggests that driver training programs could integrate similar feedback-based tools. Incorporating real-time warnings and post-trip feedback, particularly with gamification elements, may strengthen drivers' awareness of unsafe behaviors and promote sustained behavioral change beyond conventional training approaches (Klauer et al., 2016; Lavallière et al., 2012).

Second, the results highlight opportunities for fleet safety management. Organizations with professional drivers may adopt customized RTI and PTI to monitor and reduce risky driving behaviors within their fleets. Tailoring interventions to specific risk profiles, as evidenced by the cross-national differences observed in this study, could enhance the effectiveness of corporate road safety programs (Bell et al., 2017; Fitzharris et al., 2017; Pradhan et al., 2024).

Third, intervention engagement and adherence are strongly associated with reductions in driving risk, which has important implications for the insurance industry. Insurers could incentivize drivers to engage with intervention platforms by offering usage-based insurance models that reward safe driving behavior, thereby aligning individual incentives with broader road safety goals (Ebert et al., 2025; Li et al., 2023).

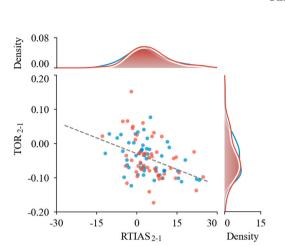
Fourth, the evidence that RTI can reduce TOR has direct relevance for traffic law enforcement. By complementing traditional enforcement strategies with behavioral feedback systems, traffic police could promote self-regulation among drivers, reducing the need for punitive measures (Karimpour et al., 2021).

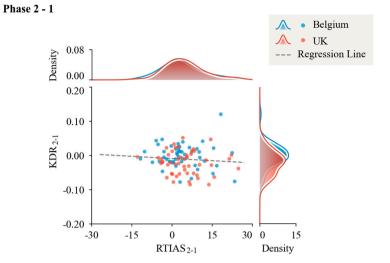
Finally, the observed cross-national differences underscore the importance of considering cultural and contextual factors in road traffic legislation. Policymakers may use these insights to design adaptive regulatory frameworks that support the integration of RTI and PTI into national road safety strategies (Van den Berghe et al., 2020).

Together, these implications not only inform the customization of i-DREAMS interventions and application strategies but also contribute to the broader field by demonstrating how behavioral feedback technologies can be leveraged across driver training, fleet safety, insurance practices, enforcement, and legislation to advance road safety.

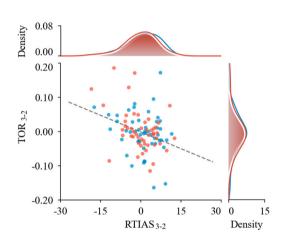
#### 4.4. Limitations and future work

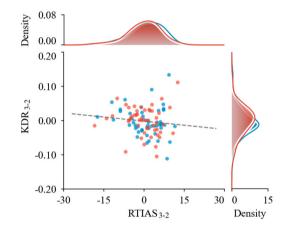
There are several limitations to this work. First, although the differences in the impact of BFPTI and GFPTI activation on drivers' PTI engagement have been analyzed, the relationships among the four functionalities (i.e., scores, trips, goals & badges, and leaderboards) within the i-DREAMS app remain unclear. Therefore, further work might examine the extent of visits to each functionality and explore their interactions. This will contribute to a deeper understanding of the PTI mechanisms and facilitate the optimization of PTI design. Second, drivers' usage and feedback on the i-DREAMS technology may also be influenced by other driver-related factors, such as RTI technology acceptance (Al Haddad et al., 2024; Ghazizadeh et al., 2012; Voinea et al., 2020; Xu et al., 2021) and personality traits (Günthner & Proff, 2021; Li et al., 2020; Nordhoff & Lehtonen, 2025; Qu et al., 2021). Therefore, further work might explore the influence of drivers' RTI technology acceptance (e.g., perceived ease of use, perceived usefulness, attitude toward using, and intention to use) on RTI adherence, as well as the impact of drivers' safe driving attitudes and personality traits (e.g., anger and adventure) on the usage of RTI and PTI. This will contribute to optimizing the design of i-DREAMS technology, facilitating its acceptance and promotion, and enabling precise user segmentation, which in



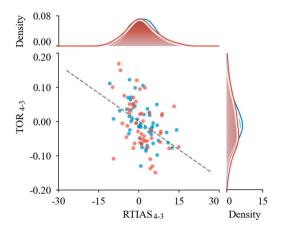


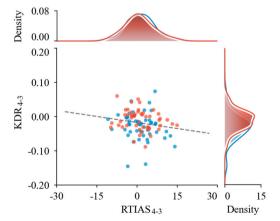
Phase 3 - 2





Phase 4 - 3





 $\textbf{Fig. 5.} \ \ \textbf{Scatter diagrams and density distributions of RTIAS changes and IDR changes.}$ 

Table 10
Difference analysis of RTIAS changes between Belgian and UK drivers.

Intervention Difference	Score Change	Country	Count	Mean Rank	Sum of Ranks	U	Sig.
RTI	RTIAS <sub>2-1</sub>	Belgium UK	50 50	48.76 52.24	2438.00 2612.00	1163.000	0.549
		Total	100				
BFPTI	RTIAS <sub>3-2</sub>	Belgium	50	53.00	2650.00	1125.000	0.389
		UK	50	48.00	2400.00		
		Total	100				
GFPTI	RTIAS <sub>4-3</sub>	Belgium	50	51.56	2578.00	1197.000	0.715
		UK	50	49.44	2472.00		
		Total	100				

**Table 11**Spearman's rank correlations between PTIED, PTIMD and the changes of RTIAS, TOR, KDR.

PTI Engagement	Score/Risk Change	Spearman	Sig.
PTIED <sub>3</sub>	RTIAS <sub>3-2</sub>	0.145	0.151
	TOR <sub>3-2</sub>	0.060	0.552
	KDR <sub>3-2</sub>	-0.145	0.150
$PTIMD_3$	RTIAS <sub>3-2</sub>	-0.041	0.688
	TOR <sub>3-2</sub>	-0.118	0.244
	KDR <sub>3-2</sub>	-0.239	0.017 *
$PTIED_4$	RTIAS <sub>4-3</sub>	0.072	0.475
	TOR <sub>4-3</sub>	-0.083	0.409
	KDR <sub>4-3</sub>	0.077	0.444
$PTIMD_4$	RTIAS <sub>4-3</sub>	0.095	0.346
	TOR <sub>4-3</sub>	0.037	0.711
	KDR <sub>4-3</sub>	-0.250	0.012 *

<sup>\*:</sup> p < 0.05, \*\*: p < 0.01, \*\*\*: p < 0.001.

turn supports personalized technology application strategies and customized training programs.

#### 5. Conclusion

This study enhanced understanding of the effectiveness and applicability of RTI and PTI within the i-DREAMS technology across different countries, as well as the mechanisms of these interventions in reducing IDR.

This study confirmed that the i-DREAMS interventions were effective in reducing IDR and that the effectiveness of the interventions exhibited cross-national differences. In Phase 2, with the support of the RTI, both Belgian and UK drivers demonstrated a significant reduction in TOR. Moreover, UK drivers, who had a significantly lower baseline TOR compared to Belgian drivers, also showed a significant reduction in KDR. In Phase 3, the BFPTI were found to have no significant impact on reducing drivers' IDR. In Phase 4, the GFPTI provided gamification elements, i.e., goals & badges, and leaderboards, which enhanced drivers' motivation for self-comparison and social comparison. This encouraged drivers, particularly Belgian drivers who exhibited significantly higher

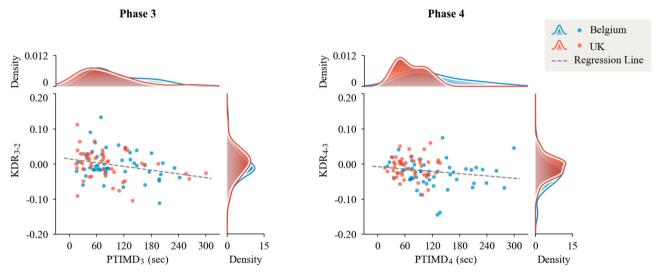


Fig. 6. Scatter diagrams and density distributions of PTIMD and KDR changes.

**Table 12**Difference analysis of PTIMD between Belgian and UK drivers.

Intervention	PTI Engagement	Country	Count	Mean Rank	Sum of Ranks	U	Sig.
BFPTI	PTIMD <sub>3</sub>	Belgium	50	55.98	2799.00	976.000	0.059
		UK	50	45.02	2251.00		
		Total	100				
BFPTI + GFPTI	$PTIMD_4$	Belgium	50	62.16	3108.00	667.000	<0.001 ***
		UK	50	38.84	1942.00		
		Total	100				

<sup>\*:</sup> p < 0.05, \*\*: p < 0.01, \*\*\*: p < 0.001.

KDR compared to UK drivers before the activation of GFPTI, to engage in significantly longer PTIMD on the i-DREAMS app and to examine their kinematic driving event details more thoroughly, which in turn contributed to a reduction in risky kinematic driving events and a corresponding decrease in KDR.

This study found that greater increases in RTIAS were associated with larger reductions in TOR, indicating a strong negative correlation between RTI adherence and TOR. Moreover, the findings showed that the extent of PTI engagement impacted KDR. Specifically, drivers with significantly longer PTIMD tended to show significantly larger reductions in KDR. The insights gained from this study help enhance the customization of i-DREAMS interventions and application strategies and contribute to the broader understanding of how RTI and PTI can improve driver safety across contexts. Beyond this platform-specific contribution, the findings also carry broader implications for road safety practice and policy, such as driver training, fleet safety, insurance practices, enforcement, and legislation.

#### CRediT authorship contribution statement

Yanchao Song: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. Kris Brijs: Writing – review & editing, Supervision, Project administration, Funding acquisition, Data curation. Robert A.C. Ruiter: Writing – review & editing, Supervision. Tom Brijs: Supervision, Project administration, Funding acquisition, Data curation. Muhammad Adnan: Writing – review & editing, Funding acquisition, Data curation. Muhammad Wisal Khattak: Writing – review & editing, Funding acquisition, Data curation. Yongjun Shen: Writing – review & editing. Geert Wets: Writing – review & editing, Supervision. Veerle Ross: Writing – review & editing, Supervision, Data curation.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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#### Data availability

The data that has been used is confidential.

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