Gamified Smartphone App Engagement: Comparative Analysis of Belgian and UK Car Drivers in the i-DREAMS Project

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Abstract. The i-DREAMS project introduced the concept of a 'Safety Tolerance Zone', i.e., a context-aware safety envelope designed to assist drivers in maintaining self-regulated control within the boundaries of safe operations. Using an ecosystem of sensors, i-DREAMS technology continuously monitors factors determining driving task complexity and available coping capacity and calculates risk levels in real-time. Based on this information, both real-time and post-trip interventions are tailored to keep drivers from getting too close to the boundaries of unsafe driving. Real-time interventions are provided via in-vehicle display, while post-trip interventions are delivered via a smartphone app (and web-dashboard) with provisions for gamification. This study focuses on post-trip interventions, specifically user engagement with the i-DREAMS app.

Data from 49 Belgian and 51 UK car drivers over a 10-week period showed a steady decline in drivers' engagement following the first day of app activation. However, when gamification features were activated, user interaction increased, suggesting they re-engaged users. UK drivers exhibited higher engagement than Belgians. Trips, scores and goals were the most visited features in both countries, while the leaderboard was popular among UK drivers only. Analysis showed a dose-response relationship, with intensive app users demonstrating better improvement in driving performance than less frequent users.

Keywords: i-DREAMS · Safety Tolerance Zone · Gamification · Smartphone intervention · User engagement · Dose-response analysis

1 Introduction

Europe has achieved intriguing progress in reducing road fatalities and injuries. The EU member states have, however, faced a slowdown in reducing crash-related fatalities recently [1]. To deal with stagnation in road safety improvement, researchers and

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policymakers are looking for new and innovative solutions, such as smartphone applications with the incorporation of gamification elements [2–4]. The i-DREAMS[1] was a European project funded by the EU's Horizon 2020 research and innovation program. It introduced the 'Safety Tolerance Zone' (STZ) concept, a context-aware safety envelope designed to prevent drivers from getting too close to the boundaries of unsafe driving via both real-time and post-trip interventions. The i-DREAMS platform accounts for driver background factors and real-time risk indicators associated with driving performance as well as driver state and driving task complexity indicators to monitor and determine continuously in real-time if a driver is within acceptable boundaries of safe operation. In-vehicle interventions inform or warn drivers in real-time (nudging), and post-trip interventions inform them after driving through an app-based (and web-based) gamified coaching platform to improve driving behaviour (boosting). More in detail, the smartphone application was developed to provide feedback to drivers about important driving behaviour variables once a trip was completed. Major functionalities included trip-related information, scores, forums/messages, pros-cons, tips, goals and badges, and leaderboard (see Vanrompay et al. [5]). This study focuses on the post-trip interventions.

2 Objectives

The primary aim of this paper is to report on user engagement with the i-DREAMS app. Moreover, this study examines the potential dose-response relationship between the level of engagement with the i-DREAMS app intervention on the one hand and the level of improvement of driving performance on the other hand. We hypothesize that more user engagement leads to better (i.e., safer) driving performance.

3 Methods

Part of the i-DREAMS project was a longitudinal field operational test conducted in a real-world setting, comprising four phases: phase 1: Baseline measurement with no intervention (4 weeks), phase 2: real-time intervention only (4 weeks), phase 3: real-time intervention + post-trip feedback (4 weeks), and phase 4: real-time intervention and post-trip feedback + gamification (6 weeks). The participants were selected based on several inclusion criteria to ensure a diverse and representative group. These criteria included factors like driving experience, road exposure, age (minimum 18 years), balanced representation of gender, vehicle type (to accommodate the i-Dreams technology), smartphone usage, multi-driver access (i.e., one vehicle, many drivers), etc. Data used for this study comes from 49 Belgian and 51 UK private car drivers and covers a 10-week period (i.e., phase 3 and phase 4, where participants were using the app). Data analysis for this study was done in two stages. In the first stage, user engagement data with the app was analysed (1) to determine how frequently drivers used the app, (2) to identify the most popular app functionalities, and (3) to determine how user engagement evolved over 10 weeks, over days in the week, and over hours in the day. In the second stage, we performed a dose-response analysis to check the impact of interventions, specifically

[1] For details, please check i-DREAMS project website: https://idreamsproject.eu.

app engagement, on driving performance. More in detail, participants were divided into low and high-engagement groups based on their app use. Next, a generalised linear mixed effects model (GLMM) was utilised to analyse the impact of app engagement on driving behaviour. The GLMM was chosen because it facilitates the simultaneous analysis of repeated measures in a longitudinal design, and yields more precise estimation of changes in outcomes over time [6]. The dependent variables were the average total number of risky events per 100km observed during four distinct phases, whereas the independent variables were level of engagement (high- and low-engagement group, with low-engagement group as reference) and the four phases of the field trial: phase 1, phase 2, phase 3 and phase 4. Phase 1 served as the reference point for time comparisons.

4 Results

4.1 User Engagement

Table 1 provides details of app visits of i-DREAMS participants in Belgium and the UK. The average daily visits were higher in the UK (51.3) than in Belgium (39.5). However, the average daily users were higher in Belgium (18.4) than in the UK (17.6).

Table 1. Total app users, total visits, and average daily app users and visits

	Belgium	UK
Total # of users	49	51
Total # app visits	2768	3594
Av. # visits per day	39.5	51.3
Av. # users per day	18.4	17.6
Av. # visits per user per day	2.1	2.6

A more detailed frequency analysis indicated that ‘trip’ was the most intensively visited functionality in both countries. For Belgium, following the ‘trip’ menu, users often visited the ‘scores,’ ‘goals,’ and ‘fact’ menus, while in the UK, the ‘leaderboard’ and ‘scores’ were particularly popular. As for the evolution of app engagement over time, Fig. 1 shows the total daily app visits, and demonstrates how app use varied during the trial period. The app was not active for the initial eight weeks and only commenced on day 57.

In both Belgium and the UK, drivers exhibited increased app usage during Phase 4, following the introduction of gamification features. However, the level of app engagement differed between the two countries. During Phase 3, Belgian drivers had higher usage, while in Phase 4, UK drivers showed higher use. In both countries, there was a notable spike in app usage at the beginning of each phase, gradually decreasing as the phase continued. Further analysis showed that, in Belgium, app usage was higher during midweek days, whereas in the UK, the proportion of visits remained relatively consistent throughout the week, with minor variations. Regardless of the country, there

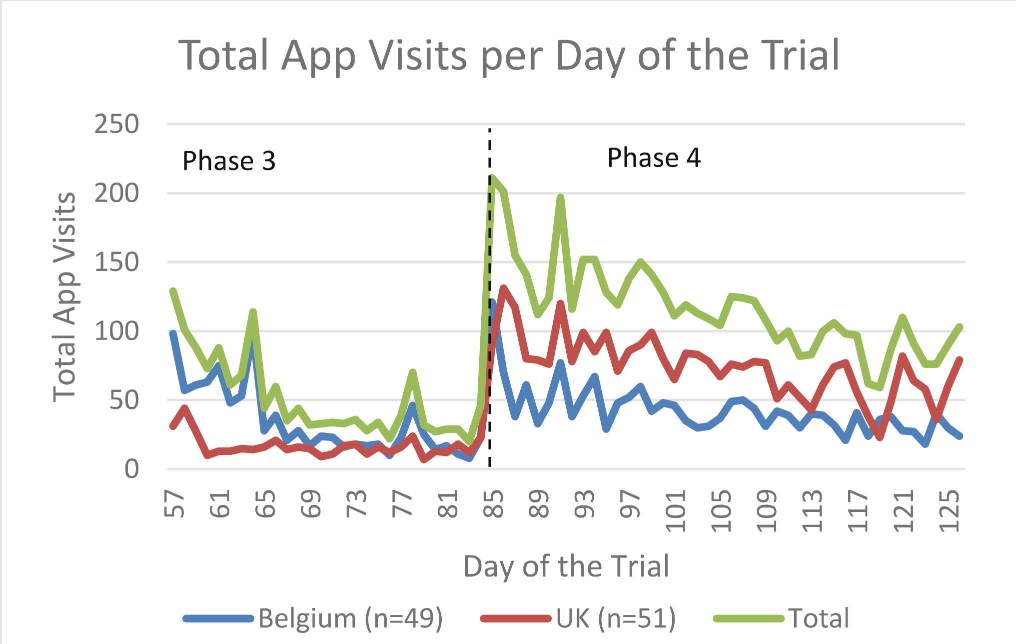

Fig. 1. Total app visits per day of trial by country and for combined sample

were three distinct peaks in app usage at 7 AM, noon, and 9 PM. Interestingly, these peaks coincided with the times when participants received push notifications aimed at encouraging app use.

4.2 Dose-Response Relationship

Tables 2 and 3 present findings of the GLMM examining the impact of the real-time interventions alone (i.e., phase 2), and of app engagement (i.e., phases 3 and 4), on the average frequency of total events per 100km for the entire sample and the UK sample. There were no significant results for the Belgian sample, most likely because Belgian trials started when some COVID-19 restrictions were still in effect. These restrictions eased during the trials for some users, resulting in fluctuated traffic density, which would have caused a more complex environment than experienced in the initial phases.

For the combined sample, the high-engagement group demonstrated a notable improvement in driving performance compared to the low-engagement group. On average, the high-engagement group had 0.458 fewer risky events per 100 km ($\beta = -0.458$; $p < 0.001$) than the low-engagement group. The difference in event rates per 100km between the high- and low-engagement groups increased from phase 1 to phase 4 with the former showing more reduction in event rates per 100km than the latter, which indicates better driving performance in the high-engagement group[2]. There were reductions of 1.41%, 2.54%, and 3.16% in event rates per 100km within the high-engagement group compared to the low-engagement group during phases 2, 3, and 4, respectively[3]. This underscores the positive impact of higher app engagement on driving performance.

[2] Analysis results not provided due to page limit constraints.

[3] **Total users**: percentage decrease in risky events per 100km for high engagement vs. low engagement groups (P_{2-1}: 4.70% vs. 3.29%, P_{3-2}: 4.67% vs. 2.13%, and P_{4-3}:5.94% vs.

Table 2. GLMM results for both countries

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	5.481	0.086	63.498	<2e−16	***
Phase 2 vs Phase 1	−0.039	0.023	−1.687	0.09162	
Phase 3 vs Phase 1	−0.074	0.023	−3.170	0.00152	**
Phase 4 vs Phase 1	−0.129	0.022	−5.529	3.23E−08	***
Cluster 2 vs Cluster 1	−0.458	0.115	−3.968	7.25E−05	***

For UK drivers (Table 3), both high- and low-engagement groups consistently exhibited better driving performance. However, on average, the high-engagement group had 0.498 fewer risky events per 100km ($\beta = -0.498$; $p < 0.001$) than the low-engagement group. Regarding within-group differences, the high-engagement group saw reductions of 2.48%, 0.91%, and 2.19% in event rates per 100km compared to the low-engagement group during phases 2, 3, and 4, respectively[4].

Table 3. GLMM results for the UK

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	5.605	0.104	54.057	< 2e−16	***
Phase 2 vs Phase 1	−0.086	0.031	−2.798	0.00514	**
Phase 3 vs Phase 1	−0.135	0.031	−4.394	1.11E−05	***
Phase 4 vs Phase 1	−0.184	0.031	−5.979	2.25E−09	***
Cluster 2 vs Cluster 1	−0.498	0.15593	−3.193	0.00141	**

5 Discussion

Considering the positive impact of app engagement on driving performance, enhancing driver intervention adherence and engagement can be considered as critical. Several recommended approaches to achieve this are outlined in the existing literature. Firstly, tailoring the intervention content to participants' individual preferences is essential. Secondly, priority should go to usability and user experience. Previous studies in other fields, such as mHealth, have underscored the importance of perceived usefulness and a user-friendly experience in enhancing engagement, e.g., see [6, 7]. Another strategy to boost driver engagement could be to offer timely and personalized feedback.

2.77%), where P_{21} means the difference (%) between phase 2 and phase 1 and so on for P_{32} and P_{43}.

[4] **UK users**: percentage decrease in risky events per 100km for high engagement vs. low engagement groups (P_{2-1}: 9.35% vs. 6.86%, P_{3-2}: 4.79% vs. 3.88%, and P_{4-3}: 5.57% vs. 3.38%).

Unavoidably, this study was subject to certain limitations. First, the study sample predominantly consisted of men who were highly educated, employed, and experienced drivers. Therefore, caution should be exercised when generalising the results to a broader population. Secondly, it is essential to acknowledge the presence of potential measurement biases in assessing driver engagement. Moreover, the app functionality was considered visited when clicked, but there was no verification of the actual engagement with the functionality. This merits further research.

6 Conclusion

This study reported on user engagement with the i-DREAMS app, how it evolved during the field trial period and how it impacted the driving behaviour. It also informed about the most popular app functionalities and the differences between Belgian and UK car drivers regarding app use. Results indicated that app use increased when gamification features were unlocked. App engagement was highest during the mid-week days than on Monday, Friday and the weekend. The provision of push notifications influenced app use positively. Most importantly, findings revealed a positive dose–response relationship between user engagement with the smartphone app and safe driving behaviour.

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