RESEARCH ARTICLE

Roady: The Application for Assessing Risk Factors in Driving Activities

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Abstract

Road traffic accidents are a major global cause of mortality. Factors contributing to accidents include exceeding the speed limit, environmental conditions, and vehicle issues. Thailand has the second-highest fatality rate in Asia. The top three causes of accidents in Thailand are driving faster than the legal limit, dangerous lane changes, and driving too close to the vehicle ahead. One way to encourage safe driving is to identify risk factors. In this work, we: (1) propose a framework and develop a mobile application (Roady) to assess risk factors for driving over speed limits, and (2) develop a design prototype that incorporates gamification principles to encourage and motivate users toward safe driving practices. This application was evaluated on a university campus. The evaluation of driving behavior detection regarding overspeeding showed an accuracy of 87.7%. We deployed the Roady application to the App Store and tested it with 53 users. The usability test showed the highest usability level of 4.53 ($\bar{x}$). We then evaluated our gamification design prototype. The results showed mean scores as high as 4.57 ($\bar{x}$). While various technologies are available today to assist in risk detection, we believe that using mobile phones—which are widely used—to identify driving hazards can encourage safe driving and reduce the number of traffic accidents.

1. Introduction

Road traffic accidents are a major cause of death globally, with 1.35 million people dying annually and 50 million injured or disabled (World Health Organization, 2018), making them the leading cause of death among young people aged 15 to 29. In 2015, leaders from various countries joined the UN General Assembly and committed to achieving the Sustainable Development Goals (SDGs) by 2030. SDG 3.6 aims to reduce the number of deaths and injuries from road traffic accidents by half by 2020 (World Health Organization, 2015).

Thailand has the second-highest number of road fatalities globally and ranks first in Asia (Office of Transport and Traffic Policy and Planning (OTP), Ministry of Transport, 2017). In 2015, the death rate was 35.66 per 100,000 people, which is considered high compared to high-income countries. This situation creates social problems for families and children burdened with death and disability. The causes of road accidents in Thailand are attributed to factors such as speeding, environmental conditions like narrow roads, heavy rain, and obstructions, and vehicle issues such as tire blowouts, brake system failures, and engine malfunctions (Royal Thai Police, 2015). The Ministry of Public Health reported that road accidents cost Thailand at least 100 billion baht annually, leading to significant social challenges for affected families and children (Health Information System Development Office, 2013).

From traffic accident statistics reported by the Royal Thai Police from 2006 to 2015, it was found that the top three causes of accidents were driving faster than the legal limit (20%), dangerous lane changes (17%), and driving too close to the vehicle in front (14%) (Royal Thai Police, 2015). Careless driving behaviors, such as exceeding the speed limit, illegal overtaking, running red lights, and neglecting safety equipment such as seat belts and helmets, contribute to most road accidents. In 2015, driving too close to the vehicle in front was found to cause the highest number of accidents, resulting from factors such as risky lane changes at intersections and sudden U-turns. This may stem from drivers' lack of traffic awareness or non-compliance with traffic laws, leading to insufficient information to determine the root causes. This research focuses on reducing risk factors arising from driving faster than the law allows and driving too close to the vehicle in front, primarily caused by sudden acceleration and braking. Therefore, addressing accidents caused by human behavior and promoting safe driving practices are essential to improving road traffic safety.

Considering the gravity of road traffic accidents, especially in Thailand, which holds the unfortunate distinction of having the highest number of road fatalities in Asia, our research seeks to address a key contributor to accidents—speeding—through the development of a mobile application. This application aims to promote safer driving practices across all routes, thereby mitigating accident risks and ultimately reducing road casualties.

In this work, we design a framework and develop a mobile application (the Roady application). This application can be used to report and track human risk factors that are the primary causes of accidents, such as driving speed. The core objective is to create safer driving conditions on all routes and significantly reduce the risk of accidents. In addition to risk tracking, the study applies gamification principles such as rating, promotion, rewards, challenge creation, and rankings within the application to effectively motivate drivers to consistently adopt good driving habits. By incorporating these elements, we aim to make a meaningful contribution to enhancing road traffic safety and fostering a culture of responsible driving behavior.

In summary, the contributions of this work are:

1. A framework and a mobile application (Roady) to assess risk factors for driving over the speed limit.

2. A design prototype that incorporates gamification principles to encourage and motivate users toward safe driving practices; and

3. An empirical evaluation of the application and the design prototype.

Responding to this research, the study endeavors to advance the field of road traffic safety assessment through innovative technological solutions and gamified user interfaces. These contributions have the potential to significantly enhance the detection of critical risk factors, foster responsible driving behavior, and ultimately contribute to the reduction of road accidents and their associated societal burdens.

The following sections present the background and related work. Driving behavior detection and the gamification design prototype are described in Section 3. The evaluation results are presented in Section 4. Finally, the conclusions are discussed in Section 5.

2. Related Work

In this section, we discuss driving behavior and the main factors contributing to road accidents. Then, we present the potential of mobile sensors on mobile devices for detecting risk factors. There are many mobile applications that can track driving behavior. We provide a comparison of the features of these applications and discuss their limitations. Finally, we discuss gamification design in terms of promoting road safety and enhancing driver awareness.

2.1 Driving Behavior

Driving behavior is influenced by various factors. Personal driving behavior is a complex issue shaped by psychological factors, social constructs, cultural attitudes, technological interventions, and environmental conditions. These factors can lead to risky driving, non-compliance with traffic regulations, and environmental damage (Zaidan et al., 2022).

Several research studies have shown that driving behaviors such as exceeding the speed limit are significant contributors to road accidents (Etika et al., 2023; Malyshkina and Mannering, 2008; Summala, 2000). When drivers surpass the designated speed limit, they compromise their ability to maintain control of their vehicles, reducing their capacity to respond effectively to unexpected situations (Mahmood et al., 2024). This combination of speeding disrupts traffic flow, increases the likelihood of collisions, and jeopardizes road safety (Florence School of Regulation (FSR), European University Institute, 2020). Therefore, addressing and mitigating these driving behaviors through targeted interventions, such as awareness campaigns and stricter enforcement measures, is crucial for enhancing road safety and reducing the incidence of accidents (Desjardins and Lavallière, 2023; Wilmot and Khanal, 1999).

2.2 Driving Behavior Detection on Mobile Applications

A mobile application, commonly referred to as a mobile app, is software designed to run on mobile devices such as smartphones and tablets. Mobile applications offer a wide range of functionalities and can be developed for various purposes, including detecting driving behavior. These applications utilize sensors embedded in mobile devices, such as Global Positioning System (GPS), accelerometers, and gyroscopes, to collect data on driving-related parameters such as speed, acceleration, braking, and lane positioning (Freidlin et al., 2018; Mantouka et al., 2021; Sawant and Pande, 2015). The collected data are then analyzed using machine learning algorithms and data analytics techniques to determine driving behavior patterns and assess driver performance (Lindow and Kashevnik, 2019; Mantouka et al., 2021). By leveraging the capabilities of mobile devices, these applications provide a convenient and accessible means to monitor and evaluate driving behavior, contributing to efforts aimed at promoting road safety and enhancing driver awareness.

2.3 Gamification and Road Safety

Gamification refers to the application of game design elements and principles in non-game contexts to engage and motivate individuals. In the context of driving behavior and mobile applications, gamification techniques can be employed to incentivize safe driving practices and promote road safety. By integrating elements such as points, levels, badges, and leaderboards into mobile applications that detect driving behavior, gamification can provide drivers with immediate feedback, rewards, and a sense of achievement for exhibiting safe driving habits (Magaña and Organero, 2014; El hafidy et al., 2021). These game-inspired features can enhance driver engagement, encourage self-reflection, and reinforce positive behavioral changes (Ciceri and Ruscio, 2014; Steinberger et al., 2017). Furthermore, gamification has the potential to create a social aspect by allowing drivers to compete with friends or participate in virtual communities, fostering a sense of camaraderie and promoting friendly competition toward safer driving practices (Alyamani et al., 2023). The game mechanics that can be used in game design to fulfill human desires (gamification dynamics) are shown in Table 1. An example of game design is the use of points as rewards to encourage behavioral change.

Table 1. The relationship between basic human desires and game mechanics (Bunchball, Inc., 2010).

Game Mechanics	Reward	Status	Achievement	Self-Expression	Competition	Altruism
Points	•	○	○		○	○
Levels		•	○		○	
Challenges	○	○	•	○	○	○
Virtual Goods	○	○	○	•	○	
Leaderboards		○	○		•	○
Gifting and Charity		○	○		○	•

• Primary ○ Secondary

However, the design and implementation of gamification strategies need to consider individual differences, avoid potential distractions, and ensure a balance between entertainment and road safety objectives (Steinberger et al., 2017; Morschheuser et al., 2018).

This study reviews the literature on mobile applications for assessing driving risk factors and identifies significant gaps. Existing research has focused on driving behavior detection, but no studies have been able to detect overspeeding, which is the leading cause of road accidents. In our work, we compare driving speed with the speed limit of the road to detect overspeeding. Additionally, our application integrates gamification to encourage safer driving through rewards and challenges.

3. Materials and Methods

We designed and developed a framework and a mobile application for assessing driving risk factors. The framework consists of four parts: *(1)* mobile devices equipped with GPS and acceleration sensors for collecting coordinates and speed data. We designed the mobile application to require minimal attention from the driver, allowing for passive behavior tracking without any interaction during driving. *(2)* A real-time driving information section that obtains time, distance, speed, coordinates, and events of driving over the speed limit. *(3)* A road speed limit database from the OSM system for overspeed detection. *(4)* A database for collecting user information, driving data, and events related to excessive speed. The application targets school personnel and university students categorized as experienced and intermediate drivers. We used the GOMS Design Model (Goals, Operators, Methods, and Selection Rules) and Figma for our UX/UI design. We built a native iOS application and deployed it to the App Store for real-life testing on a university campus. The accelerometer sensors and GPS capabilities of mobile devices were used to collect information for driving behavior analysis. The Roady Application Framework is shown in Figure 1.

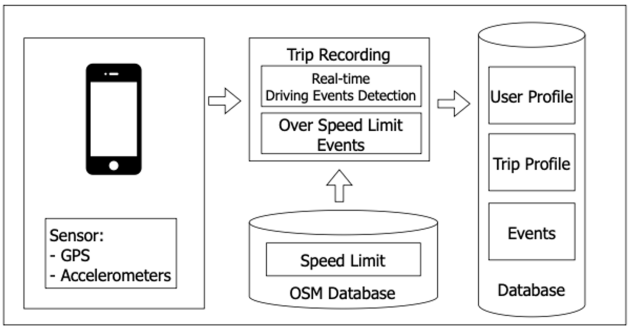


Figure 1. Roady application framework.

3.1 Road Speed Limits in OpenStreetMap (OSM)

To detect whether a motorist is driving over the speed limit, speed limit data associated with each part of the road are required. OSM is a free, collaborative mapping project with editable maps. In this research, OSM is utilized as a road speed limit database. It supports database connections and stores data in the form of SQL, allowing the application to collect and display data immediately. In this work, we updated the speed limit data in OSM according to the traffic signs indicating the speed limits for the study area—a university campus. An example of the speed limit information in OSM is shown in Figure 2.

Figure 2. OSM map with the speed limit.

In Figure 2, the speed limits for each road are annotated as 60 km/h, 40 km/h, 30 km/h, and 25 km/h in red, orange, yellow, and green, respectively.

3.2 Overspeed Detection

Detecting driving over the speed limit in a mobile application involves the use of various techniques and technologies to monitor and analyze vehicle speed in real time. One common approach is to utilize the GPS to track the location and speed of the vehicle. Comparing the current vehicle speed with the designated speed limit of the road can indicate whether the vehicle is overspeeding.

In this research, to identify instances where a driver is exceeding the speed limit, GPS data are collected at regular intervals (every second), providing latitude and longitude coordinates for each event. The speed limit database from OSM contains information about speed limits for different road segments. By referencing the data from OSM, the application can determine the designated speed limit for the driver's current location and compare it with the vehicle's speed.

3.3 Gamification Design Prototype

In this work, we developed a gamification design prototype for a mobile application that integrates elements such as points, levels, badges, and leaderboards in the driving behavior context. We focus on user engagement, particularly using points to create incentives for participation and interaction. We developed an application model based on gamification principles, utilizing game mechanics, dynamics, and responses to human needs to enhance driver engagement, encourage self-reflection, and reinforce positive behavioral changes. The game mechanics are incorporated as follows:

1. The game mechanics involve points targeting gamification dynamics that focus on rewards. Drivers earn one point for continuously exhibiting good driving behavior for every kilometer driven. The design of this mechanic is shown in Figure 3a.

2. The game mechanics involve levels targeting gamification dynamics that focus on status, using a policy applied to individuals who score up to 200 points. Drivers start at the bronze level with 0 points. The silver, gold, and platinum levels are achieved when drivers reach 50, 100, and 200 points, respectively. The design of this mechanic is shown in Figure 3b.

3. The game mechanics involve Challenges targeting gamification dynamics that focus on Achievement, using various policies that promote safe driving. Drivers can earn more points when they meet certain conditions. For example, they will earn 10 additional points per trip when they never drive over the speed limit. The design of this mechanic is shown in Figure 3c.

4. The game mechanics involve Virtual Goods targeting gamification dynamics that focus on Self-Expression, using a policy where users can view their profile picture and driving score. They may redeem their scores for physical or virtual goods. This mechanic helps motivate drivers to maintain good driving habits. The design of this mechanic is shown in Figure 3d.

5. The game mechanics involve Leaderboards targeting gamification dynamics that focus on Competition, using a policy where users can see their ranking on the leaderboard. This mechanic encourages drivers to maintain good driving habits to improve their rank. The design of this mechanic is shown in Figure 3e.

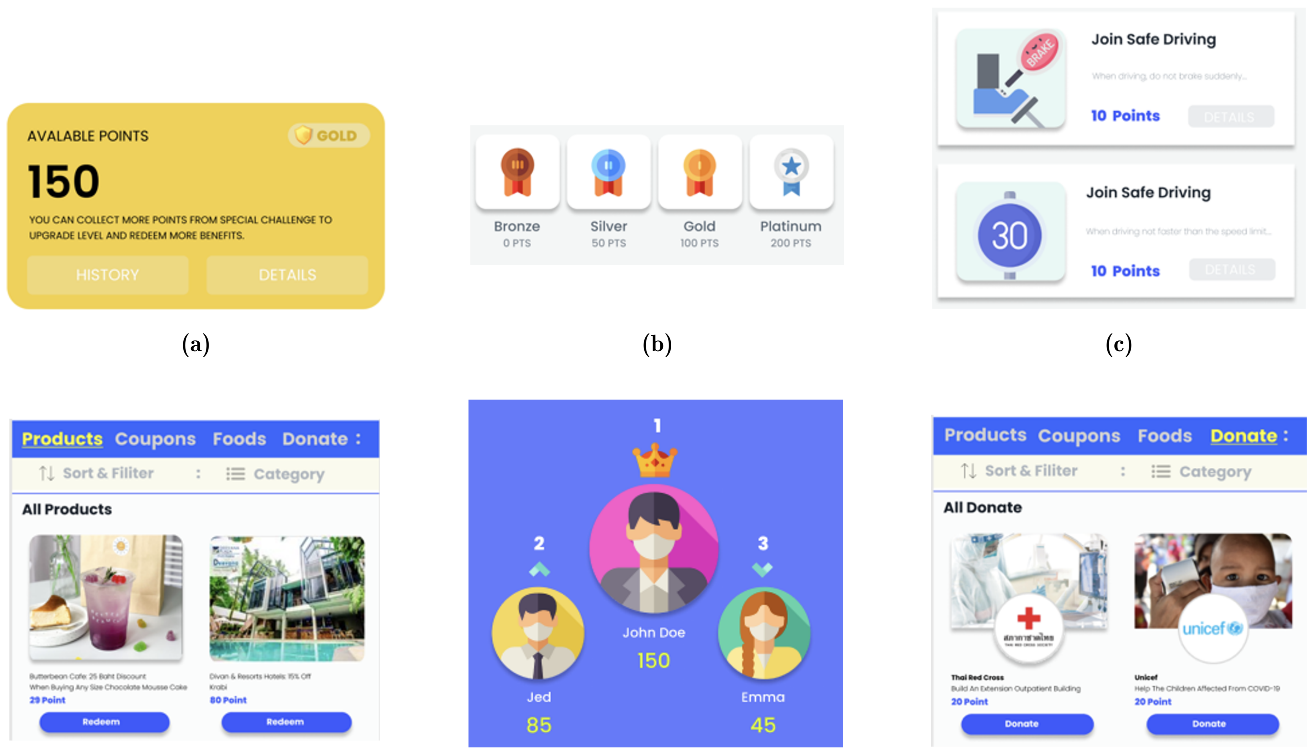
6. The game mechanics involve Gifting and Charity targeting gamification dynamics that focus on Altruism, using a policy where users can share or donate the gifts earned from their good driving habits to their friends or to those in need. The design of this mechanic is shown in Figure 3f.

3.4 Evaluation Metrics

In this study, we evaluate the accuracy of the application's sensors for both speed and location detection using the metrics described in Sections 3.4.1 and 3.4.2. The accuracy of the overspeed detection is discussed in Sections 3.4.3 and 3.4.4.

3.4.1 Accuracy of the Application's Speed Detection

The accuracy of the application's speed detection was evaluated through a test drive using the Roady application. A video of the car's dashboard was recorded while driving for 50 minutes at speeds ranging from 0 to 90 km/h, covering a total distance of 25.5 km. The speeds were captured every second. The average speed error relative to the reference (the car's dashboard), v_e, is defined in Equation 1.



(a) (b) (c)

(d) (e) (f)

Figure 3. The mechanics of the gamification design prototype.

$$v_e = \frac{1}{n}\sum_{i=1}^{n} |v'_i - v''_i| \tag{1}$$

where:

v_e : the average speed error relative to the reference (km/h)

v'_i : the speed from the car's dashboard (km/h)

v''_i : the speed detected by the application (km/h)

n : the number of speed samples captured

In Equation 1, v_e represents the speed difference between the car's dashboard and the speed detected by the Roady application in km/h. The lower the value of v_e, the higher the accuracy.

3.4.2 The accuracy of the application's location

The accuracy of the application's location can be assessed by enabling location identification. In our study, we used 17 reference points selected using the purposive sampling method (Creswell and Poth, 2018). We captured the application's location at all 17 points 50 times each, every 10 seconds. The average distance from the reference point, d_e, is defined in Equation 2.

$$d_e = \frac{1}{n}\sum_{i=1}^{n} \Delta(l'_i, l''_i) \tag{2}$$

where:

d_e : the average distance from the reference point (meters)

l'_i : the location of the reference point (latitude, longitude)

l''_i : the location detected by the application (latitude, longitude)

n : the number of locations captured

In Equation 2, d_e represents the average distance between the location detected by the application and the reference points using Euclidean distance (Δ). The lower the value of d_e, the higher the accuracy.

3.4.3 Accuracy of the Overspeed Detection

The accuracy of the overspeed detection is evaluated using a confusion matrix. It is used to display the classification results between the actual data group and the predicted data group for a sample of size m (Witten et al., 2011). The confusion matrix is shown in Table 2.

Table 2. Confusion matrix.

		Predicted	
		Positive	**Negative**
Actual	**Positive**	TP	FN
	Negative	FP	TN

In Table 2, **TP** refers to the number of events that the application correctly classified as driving over the speed limit. **FP** refers to the number of events that the application incorrectly classified as bad driving habits. **TN** refers to the correctly classified events of good driving habits, while **FN** refers to the number of events that the application incorrectly classified as good driving habits. These values are used to compute **accuracy**, **precision**, **recall**, and **F1-score**, as shown in Equations 3–6, respectively.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

3.4.4 Questionnaires for Usability Test and Gamification Design Evaluation

We evaluated the usability of the Roady application and the gamification design prototype using questionnaires designed based on the model of attributes of system acceptability (MASA) (Nielsen, 1993) and measured using Likert's scale (Likert, 1932). The scale had five levels: strongly agree, agree, neutral, disagree, and strongly disagree. The data width was 0.80. The mean score range for the sample's opinions was 1.00–1.80, with the highest level of agreement rated between 4.21 and 5.00.

Our system usability test comprised 23 questions: 3 for learnability, 10 for efficiency, 3 for effectiveness, 2 for memory retention, 1 for errors, and 4 for satisfaction. The gamification design prototype was evaluated across six gamification dynamics, consisting of 20 questions: 3 related to rewards, 2 to status or respect, 2 to achievement, 5 to self-expression, 5 to competition, 2 to altruism, and 1 to suggestions. The questionnaires were validated by three domain experts specializing in network security, information systems, and human–computer interaction. These experts were selected through purposive sampling to ensure alignment between their qualifications and the evaluation criteria. Their assessments were conducted to strengthen the reliability and validity of the instruments, which were designed to measure usability and user motivation within the context of gamification principles.

4. Experimental Results and Discussion

In this section, we present the evaluation of our work. To do this, we address two research questions:

RQ1: Can we develop a mobile application to accurately assess and track risk factors, specifically focusing on driving over speed limits?

RQ2: Can we use gamification principles to encourage and motivate users toward safer driving practices?

To answer RQ1, we conducted a set of experiments. First, we evaluated the accuracy of the Roady application for (1) location, (2) driving speed, and (3) overspeed detection. Second, we deployed the Roady application to the App Store, tracked driving behavior, and recorded instances of overspeeding. In this experiment, we had 53 participants using the Roady application. These 53 users were recruited through an invitation posted on the university Facebook group, followed by eligibility verification and informed consent. After receiving a user manual, the volunteers tested the application on mobile devices. Finally, a questionnaire was administered to evaluate the usability of the Roady application among 30 participants after using it across six areas: learnability, efficiency, effectiveness, memorability, errors, and satisfaction. We present the accuracy of the Roady application, driving behavior, and usability test results in Sections 4.1, 4.2, and 4.3, respectively.

To answer RQ2, we designed a prototype that incorporates gamification principles to encourage and motivate users toward safe driving practices. We then evaluated our gamification design prototype using a survey of 30 participants after using the design prototype. The results are discussed in Section 4.4.

This study was approved by the ethics committee prior to data collection.

4.1 Roady Application Accuracy

4.1.1 Evaluation of the Application's Speed Detection

To ensure that the application can accurately detect speed, we conducted experiments to compare the difference between the speed measured by the application and the speed displayed on the car dashboard. We started the Roady application and recorded a video of the car's speedometer while driving for 50 minutes, covering a total distance of 25.5 kilometers. Speeds ranging from 0 to 90 km/h were recorded and compared every second. We computed v_e and performed the Mann–Whitney–Wilcoxon test (in R) to determine whether the speed error (v_e) was significant at the 0.05 significance level. Additionally, we provided 95% confidence intervals for our findings. The null hypothesis states that there is no difference between the speed displayed on the car's dashboard and the speed detected by the application. The results are shown in Table 3.

In Table 3, the speeds were captured 1,393, 1,242, and 349 times for the speed ranges of 0–30, 31–60, and 61–90 km/h, respectively. The total average speed difference between the application and the vehicle speedometer (v_e) is 1.55 km/h, with an average root mean squared error (RMSE) of 2.23 km/h. For the speed range of 0–30 km/h, we observe a small average error of 0.71 km/h with a p-value greater than 0.05

Table 3. Evaluation results of speed detection on the Roady application.

Speed range oncar dashboard	Speed from the application		Speed on car dashboard		N	v_e(km/h)	RMSE	p-value
	v_i'' (km/h)	S.D. (km/h)	v_i' (km/h)	S.D. (km/h)				
0–30	7.17	10.63	6.51	9.82	1,393	0.71	1.50	0.274
31–60	46.99	8.33	44.73	8.41	1,242	2.26	2.69	< 0.05
61–90	67.71	5.31	65.33	5.34	349	2.38	2.78	< 0.05
Total	**40.62**	**2.67**	**38.85**	**2.29**	**2,984**	**1.55**	**2.23**	**0.015**

(0.274). Therefore, we accept the null hypothesis and conclude that there is no significant difference between the speed from the car's dashboard and the speed detected by the application when driving below 30 km/h. However, as the driving speed increases, the error in the application's speed detection also increases, reaching 2.38 km/h for the 61–90 km/h range. We observe p-values less than 0.05 for the 31–60 and 61–90 km/h ranges. Therefore, we reject the null hypothesis and conclude that the Roady application shows a significant difference in speed detection compared to the vehicle's speedometer when driving faster than 30 km/h. In this study, we used speed limit data from OSM. Without associated speed limit information, the application cannot detect speeding violations. A comparison between the speeds displayed on the vehicle speedometer and those detected by the Roady application is shown in Figure 4.

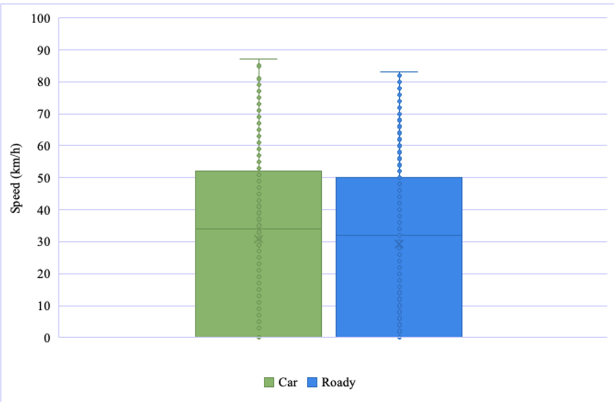


Figure 4. The comparison of speed displayed on the vehicle speedometer and on the Roady application.

4.1.2 Evaluation of the Application's Location

In this study, we obtain speed limit information from OSM based on the current location. To ensure that the application retrieves accurate data, we evaluate the accuracy of the location coordinates detected by the application. We use 17 reference points selected through the purposive sampling method under various roadside conditions—such as near large trees, small trees, and buildings. The application's location is captured 50 times at 10-second intervals for each reference point. We computed d_e using Euclidean distance and performed the Mann–Whitney–Wilcoxon test (in R) to determine whether the location error (d_e) was significant at the 0.05 significance level. Additionally, we provided 95% confidence intervals for our findings. The null hypothesis states that there is no significant difference between the reference point's location and the location detected by the Roady application. The experimental results are shown in Table 4 and Figure 5.

Table 4. Evaluation results of location accuracy on the Roady application.

Roadside Condition	N (times)	d_e (m)	S.D. (m)	RMSE	p-value
Large Tree	250	2.04	0.77	2.18	< 0.05
Small Tree	400	0.68	0.33	0.76	< 0.05
Buildings	200	1.15	0.60	1.30	< 0.05
Total	**850**	**1.19**	**0.22**	**1.44**	< 0.05

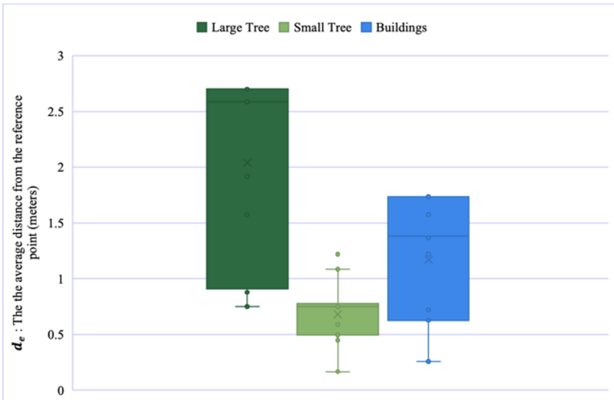


Figure 5. The application's location on various roadside conditions.

Table 4 and Figure 5 show that most errors occur when capturing the location coordinates of road reference points surrounded by large trees, with an average error of $d_e = 2.04$ meters. The location coordinates near buildings have an average error of 1.15 meters, and roads with small roadside trees have an average error of 0.68 meters. The p-value is less than 0.05 for every road condition. Therefore, we reject the null hypothesis and conclude that the Roady application shows a significant difference in location detection compared to the reference points. The deviation in location coordinates can vary due to different environmental factors, such as road width, trees, and buildings. As shown in Figure 5, the d_e values of road references with large trees also exhibit greater variability compared to those with smaller trees.

4.1.3 The evaluation of the Overspeed Limit Detection

In this evaluation, we conducted a test drive covering 7.89 kilometers over a duration of 7.83 minutes, with an average speed of 40 km/h. The speed readings from both the vehicle's speedometer and the Roady application, along with the corresponding road speed limits, were recorded every second (470 seconds in total). The test-driving results are shown in Figure 6. The evaluation results are then presented in the confusion matrix in Table 5. We found that the overspeed events were successfully detected with an accuracy of 87.7%, precision of 92.0%, recall of 78.4%, and F1-score of 84.7%.

Table 5. The evaluation result of the overspeed limit detection.

		Predicted	
		Positive	**Negative**
Actual	**Positive**	TP = 160	FN = 44
	Negative	FP = 14	TN = 252

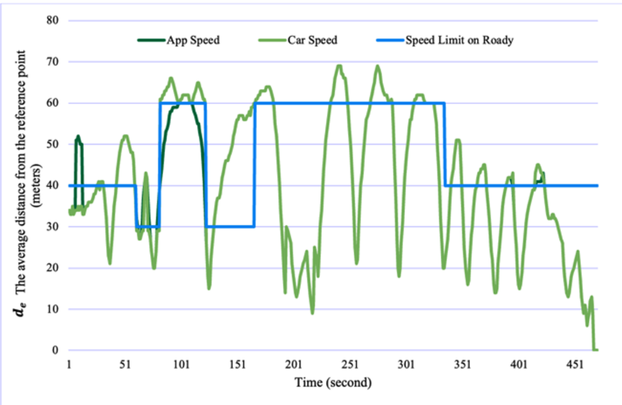


Figure 6. The test driving result for the overspeed limit detection evaluation.

Figure 6 shows the average distance from a reference point over time, with three metrics: App Speed, Car Speed, and Speed Limit on Road. The x-axis represents time in seconds, and the y-axis represents the average distance in meters. We evaluated the Roady application's ability to detect overspeed violations and found a true positive rate of 92%. This high accuracy enables the application to provide real-time feedback to drivers, encouraging them to adjust their speed and comply with limits. By increasing driver awareness of speed-related risks, the application's overspeed detection capability demonstrates its potential to promote safer driving habits and contribute to reducing road accidents.

4.2 Driving Behavior

In this section, we investigate driving risk factors in the study area using the Roady application with 30 participants. The Roady application was deployed to the App Store, allowing participants to download and use it to track their driving behavior in daily life. The application primarily collects data when participants drive over the speed limit. In this study, we recorded data from 53 drivers, including 40 car users and 15 motorcycle users, resulting in a total of 65 driving trips. The summary of the results is presented in Table 6.

Table 6. The user's driving behavior in the Roady application.

	Over the Speed Limit
Car	
Participants	18
Trip	**45 (100%)**
Average Distance (km/trip)	0.22
Average Time (min/trip)	0.24
Detected Event	341 (87.7%)
Average (event/trip)	7.58
Motorcycle	
Participants	6
Trip	**20 (100%)**
Average Distance (km/trip)	0.21
Average Time (min/trip)	0.26
Detected Event	120 (98.4%)
Average (event/trip)	6.00

t-value = 0.4975

Table 6 presents the driving behaviors of both car and motorcycle users. For car users, the results indicate that they exceed the speed limit on every trip (45 trips), with an average of 7.58 occurrences per trip, covering 0.22 km in 0.24 minutes. Similar patterns are observed among motorcycle users, who also exceed the speed limit on every trip (20 trips), averaging 6 occurrences per trip and covering 0.21 km in 0.26 minutes.

The analysis of driving behavior between car and motorcycle users yielded a t-value of approximately 0.4975. The significance of this difference was assessed by obtaining the p-value for the t-value of 0.4975 with 22 degrees of freedom. If the p-value is less than 0.05, we reject the null hypothesis, indicating a significant difference; otherwise, we fail to reject it, suggesting no significant difference in driving behavior.

The results show that exceeding the speed limit is a common issue across all modes of transport. The study suggests that interventions targeting speed management are crucial for both vehicle types, but strategies may need to be tailored differently. The analysis highlights significant behavioral patterns in car and motorcycle usage that can inform targeted safety measures.

4.3 Usability Test

One of the main reasons why many applications are not widely adopted is that they fail usability testing. Usability testing for mobile applications involves evaluating the user experience and effectiveness of an application by observing users as they interact with it. Jakob Nielsen, a prominent usability expert, emphasizes the importance of usability testing to identify and address usability issues early in the development process. Nielsen recommends testing with a small sample size of around five users to uncover most usability problems.

On the other hand, the MASA provides a framework for evaluating the acceptability of a system, including mobile applications, by considering attributes such as usability, usefulness, satisfaction, and other user-centered factors. Integrating MASA into usability testing allows researchers to assess the overall acceptability of a mobile application, providing valuable insights into user acceptance and informing design (Kaikkonen et al., 2005; Nielsen, 1993).

Table 7. The result of the usability test on the Roady application.

Usability Criteria	$\bar{x}$	S.D.	Level
Learnability	4.53	0.70	Excellence
Efficiency	4.52	0.64	Excellence
Effectiveness	4.53	0.63	Excellence
Memorability	4.53	0.64	Excellence
Errors	4.70	0.46	Excellence
Satisfaction	4.53	0.64	Excellence
Average:	**4.53**	**0.64**	**Excellence**

In our study, we conducted a questionnaire-based usability evaluation of the Roady application with 30 participants (15 car drivers and 15 motorcyclists) after using the application across six criteria: learnability, efficiency, effectiveness, memorability, errors, and satisfaction. The results in Table 7 indicate overall excellence in usability, with mean scores ($\bar{x}$) consistently around 4.53 and standard deviations (S.D.) ranging from 0.46 to 0.70. These findings suggest that the system performs exceptionally well across all major usability criteria, providing a user-friendly and efficient experience.

4.4 Gamification Design Prototype Evaluation

To answer RQ2, we evaluated our gamification design prototype using a survey of 30 participants (15 car drivers and 15 motorcyclists) after they used the Roady application. The results are shown in Table 8. Most of the gamification dynamics were found to be highly effective in engaging users, with mean scores ($\bar{x}$) of 4.57 and standard deviations (S.D.) of 0.65, which correspond to an excellence level. The findings indicate that our well-designed gamification strategies significantly enhance user interaction and motivation. Two dynamics, self-expression and competition, were rated at a good level, indicating that the design is effective but provides slightly lower engagement compared to other dynamics. This suggests that future designs should emphasize elements that promote self-expression, such as avatars and leaderboards ranking individuals closer to them rather than the entire community Park and Kim (2021).

Table 8. The evaluation result of the gamification design prototype towards human desires.

Gamification Dynamics	$\bar{x}$	S.D.	Level
Rewards	4.67	0.55	Excellence
Status or Respect	4.62	0.68	Excellence
Achievement	4.65	0.53	Excellence
Self-Expression	4.43	0.75	Good
Competition	4.40	0.75	Good
Altruism	4.63	0.64	Excellence
Average:	**4.57**	**0.65**	**Excellence**

To address RQ2, we evaluated a gamification prototype for the Roady application with 30 participants. The results showed high perceived effectiveness of the gamification design, with mean scores across dynamics ranging from 4.40 to 4.67 out of 5. In the future, we plan to integrate gamification features into the application. We believe that these gamification strategies have the potential to significantly influence driving behavior and enhance road safety.

5. Conclusion

This research focuses on designing and developing a framework and a mobile application (Roady) to assess risk factors associated with driving over the speed limit. The hypothesis is that a mobile application can effectively detect and alert users to incidents of exceeding the speed limit. We designed a prototype that incorporates the gamification principle to encourage and motivate users toward safe driving practices. We then conducted a set of experiments to evaluate our work using *RQ1* and *RQ2*.

For RQ1, the experiments show that the Roady application can accurately assess and track risk factors for driving over the speed limit. Roady accurately captures speed with a small error (v_e) of 1.55 km/h compared to the vehicle speedometer; the faster the driving speed, the higher the error. The location coordinates can be accurately captured with a low error (d_e) of 0.68 meters for clear areas with small side trees. The experiments demonstrate that we can successfully detect overspeed events with an accuracy of 87.7%, precision of 92.0%, recall of 78.4%, and F1-Score of 84.7%. The Roady application was deployed to the App Store, where 53 users participated in a test drive on the university campus. The findings revealed that all users exceeded the legal maximum speed on every trip (65 trips), underscoring the persistent risk of road accidents. To evaluate usability, an experiment was conducted with a sample of 30 participants, equally divided between car drivers (15) and motorcyclists (15). The results indicated a high level of usability, with a mean score of $\bar{x} = 4.53$ (S.D. = 0.64) across six aspects, ranging from 4.52 to 4.70. These findings suggest that the Roady application effectively assesses and tracks risk factors while maintaining a high level of usability.

For RQ2, we designed a prototype that incorporates the gamification principle and evaluated it against human desires in six gamification dynamics. The experiment produced excellent results, with mean scores of $\bar{x} = 4.57$ and S.D. = 0.65. This indicates that our well-designed gamification strategies can significantly enhance user interaction and motivate users toward safer driving practices.

In conclusion, the Roady framework and application demonstrate promising results in accurately identifying risk factors associated with exceeding speed limits, achieving high levels of accuracy, usability, and user motivation. The insights gained from the application can foster a culture of safety that resonates throughout communities, ultimately reducing traffic accidents and their associated societal costs. As more drivers adopt safe habits, the positive ripple effects can enhance public health, lower insurance costs, and reduce the burden on emergency services. In this way, the Roady application serves as a vital tool not only for individual drivers but also for creating safer roads and a more responsible driving culture at the national level.

Future research should rigorously evaluate the long-term impact of the Roady application on driving behavior. Moreover, data generated by Roady should be systematically analyzed to produce evidence-based recommendations for policymakers aimed at enhancing traffic regulations and road safety strategies.

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Declaration of Interests

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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