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Implementation and Analytics of the Distributed Eco-Driving Simulation iCO_2

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ABSTRACT We describe iCO_2, a simulation platform for collecting driving behavior data. It is designed as the first massively multiplayer online game for mobile devices to practice eco-friendly driving. It facilitates the collection of large-scale data on driving behavior to better understand compliance and incentive mechanisms for eco-driving and users' preferences. We present the results of a campaign with iCO_2 that used a game promoter to attract 2455 users. The results are described from three angles: (1) types of drivers are identified by clustering driving behavior; (2) types of players are identified by relating players' interaction with game elements and their driving behavior; (3) by looking at longer sessions, we demonstrate that players who show eco-unfriendly behavior at the beginning of the session improve their eco-driving behavior throughout their playtime.

INDEX TERMS Virtual reality, human factors, assessment of VR, education and training, entertainment and gaming, serious games, massively multi-player games, multi-player games, user tracking, game analytics.

I. INTRODUCTION

Our world today is tightly interconnected by the Internet, which allows users from almost anywhere to access information anytime in an affordable and immediate manner. For scientists, this situation opens hitherto unknown opportunities for experimental testing of novel online applications. While in principle vast populations can be reached quickly and effortlessly, motivating users to participate in social experiments is a big challenge. It is important to provide an adequate incentive other than money to the users, so that they do not have any motivation to cheat [1]. As a solution, Games With a Purpose (GWAP) have been proposed [2]. GWAP is a field of human computation [3], [4] that seeks to motivate users, such as annotators of pictures or testers of applications, through enjoyment rather than any monetary incentive.

The recent rise of mobile devices—such as smartphones, tablet computers or handheld game consoles—has opened up new opportunities to conduct experiments beyond laboratory studies. Ubiquitous computing access makes it possible to reach a large number of users, although it is more difficult to standardize test conditions, and control the environment. Henze *et al.* [5] suggest a ten-step program to conduct large-scale studies with mobile applications in order to obtain valuable data that cannot be collected in a lab setting: (1) clearly identify the research goals; (2) select a study method; (3) devise an incentive mechanism; (4) choose the target platform(s); (5) design and develop the mobile app; (6) prepare data collection; (7) implement a scheme to obtain informed consent from users; (8) distribute and promote the app; (9) continuously monitor data collection for a designated time period; (10) filter and analyze data to answer the research question.

In this paper, we adhere to these steps and present iCO_2, a massively multiplayer online (MMO) driving game. iCO_2 is designed as a mobile application that allows players to practice eco-friendly driving. Eco-driving is a term used to describe the usage of vehicles in an energy-efficient way, such

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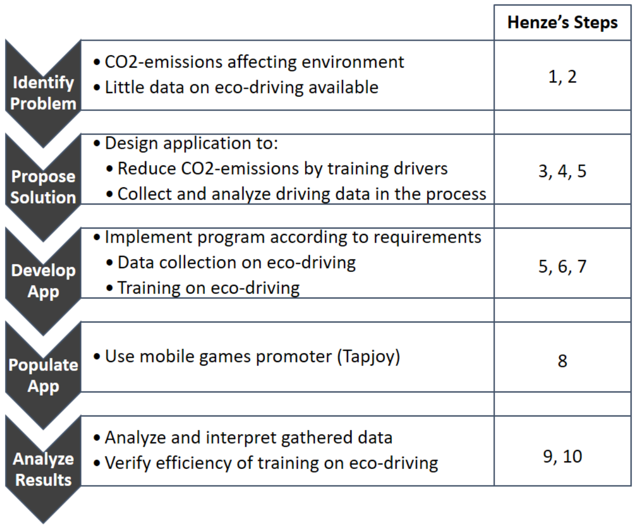

FIGURE 1. Approach of this study. We follow Henze's framework for empirical research through ubiquitous data collection and adapt it to our specific needs. Subsequently, we developed the first massively multiplayer online (MMO) game for mobile devices to practice eco-friendly driving, collect data, analyze it, and evaluate the efficiency of our training.

as smooth acceleration and deceleration, keeping the speed limit, etc.

Notably, iCO_2 is a platform for collecting driving behavior data and in-game decision data from users. It can be accessed as an app on "Google Play".[1] Our data collection platform uses a hybrid strategy to give an incentive to players, which is based on (1) a mobile games promoter to attract players to the game and (2) in-game mechanics to keep them playing. We use Tapjoy,[2] a company that handles mobile games promotion, to attract 3184 mobile users to iCO_2, 2455 of which played the game. This approach constitutes an alternative to the tools and applications that have been used in research projects involving games [6]–[8].

According to Barth and Boriboonsomsin [9], transportation accounts for one third of the carbon dioxide (CO_2) emissions in the United States. As a failure to address an excess of CO_2 emissions might result in irreversible climate change [10]–[12], we deem studying and raising awareness regarding eco-driving behavior to be worthwhile scientific endeavors.

The main research contribution of this paper is a human-computer study with a driving simulator that

- shows the extent to which our eco-driving interface supports eco-driving behavior, i.e., compliance to straightforward eco-driving principles such as smooth acceleration and deceleration;
- investigates the relationship between in-game driving behavior and other in-game behavior, such as refueling, in-game exploring, choice of car upgrades, etc.; and
- describes how the driving behavior of users in this simulated environment evolves over time.

[1] https://play.google.com/store/apps/details?id=net.globallabproject.ico2&hl=en (accessed May 9, 2018)

[2] http://home.tapjoy.com/ (accessed May 9, 2018)

The paper is structured as follows. Section II provides background research on eco-driving games, training applications, crowdsourcing and games with a purpose. Section III describes the iCO_2 simulation platform that extends our previous version of iCO_2 [13] with a quest system and upgrade functionality. In Section IV we explain the campaign and present usage statistics of iCO_2 during the campaign. Section V presents the results regarding driving behavior types and player types. Moreover, we test the hypothesis that iCO_2 players tend to become better at eco-driving in the game. Section VI summarizes and discusses the most relevant results and describes future work.

II. RELATED WORK

In this section, we will first report on eco-driving games and training applications. Then we will explain how our work can be positioned within the crowdsourcing literature.

A. ECO-DRIVING GAMES AND TRAINING APPLICATIONS

The training of eco-driving is important, as it greatly affects world-wide fuel expenditure and pollution emissions [14], [15]. Therefore, car manufacturers have started to develop applications that provide drivers with some feedback on the effects of their driving behavior [16], [17].

Most applications for practicing eco-friendly driving are either single-player games [17]–[21] or full-fledged simulators that can only be played with specific physical apparatus [22]–[25]. By contrast, iCO_2 is the first massively multiuser 3D eco-driving game that can be controlled by common mobile devices.

B. GAMES WITH A PURPOSE

iCO_2 is a Game with a Purpose (GWAP): data collection. In particular, we are interested in driving behavior data and data about the players' in-game behavior.

Von Ahn and Dabbish [26] introduced the concept of GWAP with the now well-known ESP game. Its aim was to label images. Players were randomly matched and had to guess which label their counterpart was applying to the image that both of them were seeing. Subsequently, the project was improved and re-branded as Peekaboom [27] and Phetch [28].

iCO_2 follows some design decisions used in previous Games with a Purpose. Von Ahn and Dabbish [29] cite "Challenge" as a key factor for a successful game. Therefore, we included mechanisms such as resource management (fuel, car characteristics) and quests in the game design to create a more challenging experience. Multiplayer experiences, time-sensitive decisions, and randomness are also characteristics mentioned in [29]. We used those features to improve the enjoyment of iCO_2.

iCO_2 constitutes a human computation system, because we aim to collect driving behavior and decision information from a massive quantity of users, while training them in eco-driving and providing them with enjoyment.

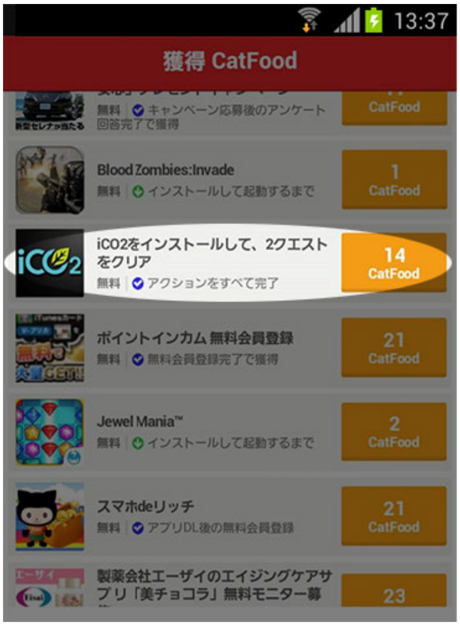

FIGURE 2. iCO_2 on Tapjoy in the real world. Players were rewarded with "cat food", an item in another game, for installing iCO_2 and completing two quests.

C. CROWDSOURCING

Biewald [7] presents a number of applications involving crowdsourcing and human computation that use the increasingly popular Mechanical Turk from Amazon [30] and involve ethics, business and fun. The tasks involve answering questions that do not require any technical knowledge or performing Google searches. "Sifu" by Chan and Hsu [8] is a system that supports language learning by providing tutoring services to readers of news sites and articles. The crowd is recruited from an online social network instead of using the Mechanical Turk.

We note that while these two applications use distinct sources of "crowds for hire", they are acquiring a group of users to participate in their research by performing specific tasks that constitute the experiment as a whole. This further illustrates why we consider iCO_2 a human computation system: iCO_2 is not meant to rely on hiring a crowd to do a (particular) job, but rather to play a game, have fun, and practice eco-driving. As a side effect, the crowd provides data about their behavior.

However, our (research) goal does not necessarily motivate the crowd of users. This is where Games with a Purpose come into play.

To draw users into our game, we initially provide a monetary incentive. Our method to provide the system with users is based on Tapjoy,[3] a games promoter that reaches over 520 million active users per month. Tapjoy works by offering mobile gamers in-game rewards for whatever game they are currently playing, in exchange for engaging with another game, such as our iCO_2 (Figure 2).

[3]https://home.tapjoy.com/ (accessed May 9, 2018)

As mentioned in Section I, providing players with a monetary incentive might give them temptation to cheat. Therefore, we target players' intrinsic motivation [31] with a reward system including new car models and upgrades. Further, we continue to monitor their behavior after the requirements for our payout are fulfilled.

A factor analysis of the motivations of online games players [32] has identified three main dimensions of achievement, social interaction and immersion. In-game rewards would be most relevant to achievement, although some intrinsic motivation related to the social goal of eco-driving could be related to factors listed under social interaction (e.g. 'group achievement') or even immersion.

D. CATEGORIZING DRIVING BEHAVIOR

Hattori *et al.* [33] use a set of rules to model driving behavior. In contrast, we use clustering to identify driver types from our log-data. Our user base is global, while their work focuses exclusively on driving behavior from users in a simulator from one physical location. Further, we collect and analyze additional behavioral data other than driving, such as refueling, car-upgrades, and players' eco-driving evolution over time.

Paruchuri *et al.* [34] model three driving styles in their multi-agent simulation by defining them based on fine-tuning parameters. Instead of simply defining driving styles, we identify four types of drivers with our cluster analysis: eco-accelerator, eco-braker, normal, and reckless (Subsection V-B).

Doniec *et al.* [35] simulated traffic of one intersection, while we populated our system with actual human driving behavior in a $1km^2$ replica of Tokyo with a focus on eco-driving.

Social Psychologists from the London School of Economics identify seven types of drivers with regards to their personality through focus groups and interviews [36], whereas our approach relies on empirical data.

III. THE iCO_2 DATA COLLECTION PLATFORM

The iCO_2 game is a massively multiuser online driving simulator that provides players with a tool to practice eco-driving (see Figure 3). In the game, players drive in a $1km^2$ replica of Tokyo city, where streets are populated both with other players' cars and with computer-controlled cars from our traffic simulator system [37]. As a result, traffic situations occur naturally in the virtual environment, which can be utilized to investigate eco-driving policies [38] or traffic congestion [39].

iCO_2's predecessor version [13] contained two game modes, (1) "Free drive" and (2) "Campaign", where players were paid for completing a quest or task. By contrast, the current version of iCO_2 offers a full-fledged quest system, therefore players can engage in repeated campaign-style interactions.

By completing quests, players were rewarded with virtual currency (within the iCO_2 game), which is the key factor

FIGURE 3. Screenshot of the iCO_2 game, which displays a player driving around the replica of Tokyo. On the top left, the car's velocity and fuel consumption information is displayed. The acceleration/break slider is located on the right.

that motivates players to strive for eco-driving behaviors. Fuel-efficient driving reduces the amount of fuel spent when completing a quest and thereby saves in-game money. If the players manage to save sufficient in-game money, they are able to upgrade their car with components that improve eco-efficiency.

A. FEEDBACK ON ECO-DRIVING MECHANISMS

The game provides players with visual information about the car's fuel/energy consumption. As shown on the top left of Figure 3, the interface displays instant consumption, 10-seconds consumption, 60-seconds consumption, and overall consumption. The timed consumption elements change colors according to the players' eco-efficiency. Green indicates eco-efficiency, whereas red indicates eco-inefficiency.

The implementation of the input controller for acceleration and breaking was an important design decision. As opposed to many other driving simulators, which feature a single button for acceleration and another button for breaking, we considered an option for a smooth change of speed paramount; it should feel like using pedals in an actual car. In order to achieve these nuances, we decided to provide a slider (shown on the right side in Figure 3), which lets users accelerate, decelerate and maintain constant speeds easily, akin to real-life pedals. For the mobile application, this feature was realized by touch controls, while the web player could be operated via mouse.

B. GAMEPLAY: ENGAGEMENT, QUESTS, LEGS

iCO_2 is an open world driving game with driving-gameplay like the highly commercially successful video game series

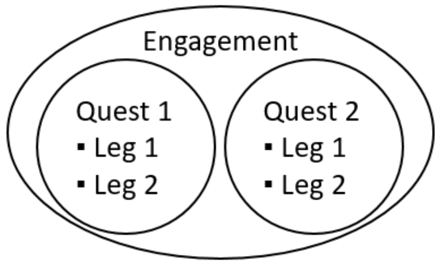

FIGURE 4. Terms used in this study. Our "engagement" consists of two "quests", which are in turn comprised of two "legs".

"Grand Theft Auto" (GTA),[4] on a smaller scale. We provide a natural environment for driving that allows us to further analyze eco-driving behavior.

The quest system in iCO_2 is a mechanism to motivate players to stay in the simulation environment. Each quest consists of a sequential set of legs. In each leg, the player has to transport passengers and/or cargo from a start point to a destination. When a player starts a quest, the first leg is triggered and only after that leg is completed, the next one will be activated. While driving, the player can identify the legs' start and finish points as hovering downward arrows, as shown in Figure 3.

Quests are dynamically generated so that the player always sees multiple simultaneous quests. In that way, the game allows players to carefully plan their route before driving. The player also has to manage the car's accommodations, e.g. to increase the seating or cargo space.

Tapjoy, our promoting platform, uses the term "engagement" to refer to the set of requirements that must be

[4]http://www.rockstargames.com/grandtheftauto/ (accessed May 9, 2018)

FIGURE 5. Screenshot of the iCO_2 *Garage*, where the player can buy new vehicles and upgrades as well as repaint cars.

fulfilled in order to receive a reward. We defined our Tapjoy-engagement as the successful completion of two quests, which consist of two legs each (Figure 4).

C. GARAGE & UPGRADES

With the in-game money rewarded from quests, players can go to the *Garage* and upgrade their car with advanced technology (see Figure 5). By upgrading the car, the players can enhance their car's eco-friendliness. Further, the player can buy a new car that features different configurations, such as engine power, mass, capacity to carry passengers and cargo, etc. Players are also able to customize their car by selecting a different color.

When a player owns more than one car, it is up to him or her to decide which car to use for a quest. Hence, a player is able to choose between a car that has more capacity for passengers or cargo, but high fuel consumption; or a car with a smaller capacity, but less fuel consumption. Car performance data was taken from the specification of the car maker.

D. NAVIGATOR

Players can use the in-game *Navigator* system (see Figure 6) to enhance their route planning. This tool guides the players in the game's scenario by displaying their cars' current position and the current start and finish points of the active quests' legs. Players can zoom in/out the map to better understand the street layout.

Moreover, while driving, players are guided towards the legs' start and finish points by an arrow (see Figure 3). The arrow points players to the direction they have to follow to reach the start and destination points of the quests' legs.

E. IMPLEMENTATION

The game was developed with the Unity3D game engine,[5] which allows us to seamlessly port the iCO_2 game to different platforms; iCO_2 can currently be played on mobile devices (Android and iOS) and in web browsers via the Unity web player. The game is available in English and Japanese.

The multiplayer feature of iCO_2 is enabled by DiVE (Distributed Virtual Environments) [13]. DiVE handles the communication among all the iCO_2 components (see Figure 7), which we regard as DiVE clients.

Each client works as follows: The "Profile Client" handles the persistency of the players' profile, which is associated with their Facebook accounts. Consequently, players do not need to perform any additional registration in iCO_2 and always retrieve their progress regardless of the platform that they are using to play the game. The "Spawn Client" manages where players appear when they enter the game's scenario. With this system, we are able to distribute players evenly throughout the map. The "Logging Client" retrieves players' driving data, such as the car's position, velocity, fuel consumption, and stores it persistently in a database. The "Traffic Simulator" system directs the computer-controlled cars and all traffic lights in the virtual scenario.

During the campaign (as described in Section IV), a logging component was "listening" to the server and storing the positions of all players 10 times per second. Concretely, a line was added to an SQL database every 1/10th of a second. Over the course of the campaign, this resulted in a log file in the order of magnitude of gigabytes. Names of players, a unique ID, position, speed, and car color have been stored in this file. After post-processing, we could collect

[5] www.unity3d.com (accessed May 9, 2018)

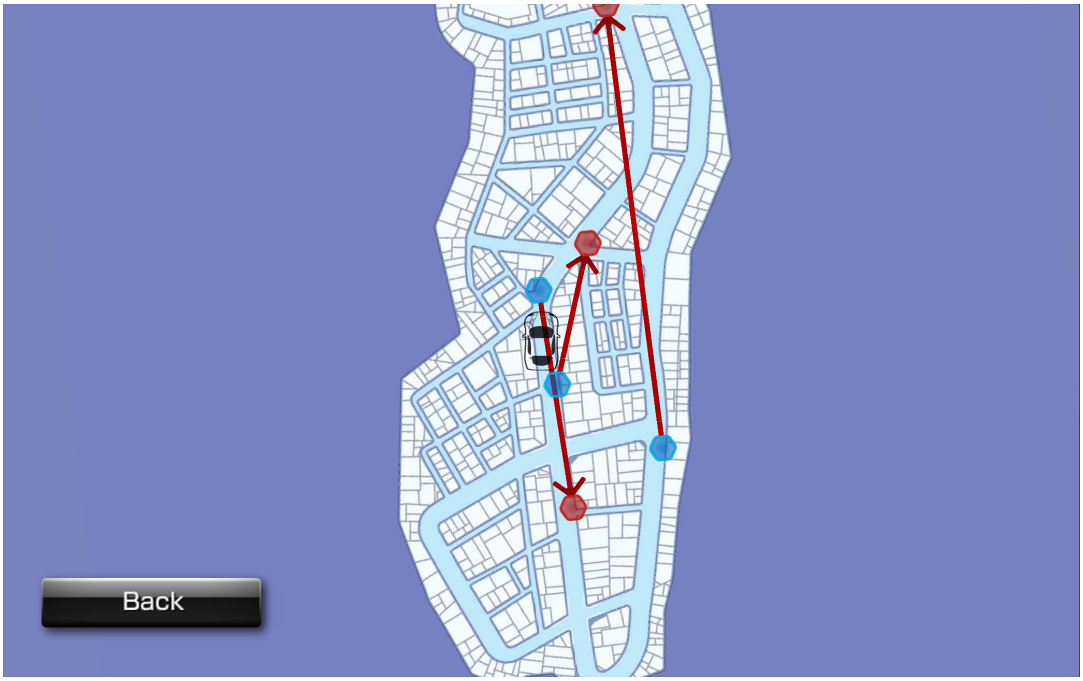

FIGURE 6. **Screenshot of the *Navigator* tool, which guides the player in the virtual scenario. The player's car is represented with the car icon. Blue icons represent the legs' start points, red icons mark the legs' end points. The arrows connect the origin to the destination.**

usage statistics (Subsection IV-B), determine eco-friendliness of drivers (Subsection V-A), and identify types of drivers (Subsection V-B) as well as types of players (Subsection V-C) with a clustering analysis. Finally, we scrutinized user's eco-driving evolution over time (Subsection V-D).

IV. A CAMPAIGN WITH THE iCO_2 SIMULATION PLATFORM

In March 2014, we ran a campaign with iCO_2 for one week and collected data of 3184 mobile users, 2455 of which started to play the game. The results of our data analysis will be discussed in the following sections.

A. IMPLEMENTING THE CAMPAIGN

In our large-scale study, we aimed to follow the ten-step framework proposed in [5]. The *first step* relates to identifying the research goals clearly. The objective of our study is to collect and analyze data on the eco-driving behavior of users in a simulated city environment. Besides understanding player types and in-game behavior, we also wanted to investigate whether our eco-feedback mechanism improves eco-driving over time. To devise a study method, such as correlational or experimental, is the *second step*. This work focuses on correlational research to identify phenomena, including correlation between player type and interaction with game elements, or the evolution of eco-driving behavior over a time period. We used the games promoter Tapjoy to attract users (*third step*). For performing the requested task, users earn points for their time. This extrinsic incentive can be used as in-game currency in the game the user played before joining the campaign. However, after the completion

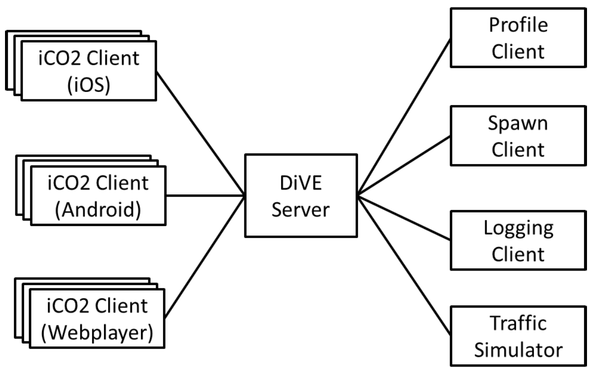

FIGURE 7. **iCO_2 system architecture. The DiVE (Distributed Virtual Environment) server supports the communication platform between all the different components that compose the iCO_2 system. The left side shows the clients, in different platforms, controlled by the player. The right side shows the clients that support the iCO_2 system.**

of the task, it can be assumed that some intrinsic incentive ('fun') prevails. The target platform chosen for this study was Android smartphones and tablets (*fourth step*). Regarding the *fifth step*, iCO_2 is designed as an engaging application that supports data collection at scale. We track the player's position every 100ms and record it in our log server, along with other behavioral information (*sixth step*). Users login with their Facebook accounts and consent to the term of data usage upon a prompt from the application (*seventh step*). Regarding the (*eighth step*), we distribute the application via Google Play, and the games promoter Tapjoy. The Tapjoy campaign ran for a week, during which we monitored the servers and database to ensure the system was functioning (*ninth step*). Then, we processed and analyzed the data (*tenth step*).

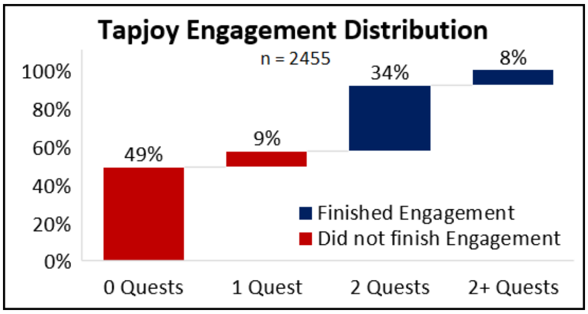

FIGURE 8. iCO_2 statistics: Tapjoy Engagement Distribution. Out of all the users who played iCO_2, 49% left before completing a single quest and 9% finished one quest. 34% completed 2 quests and therefore finished the engagement. A total of 198 players (8%) had the intrinsic motivation to keep playing the game even after the requested task (two quests) was achieved. They completed more than two quests even though the money (i.e. the extrinsic motivation to play the game) was not paid beyond the completion of two quests.

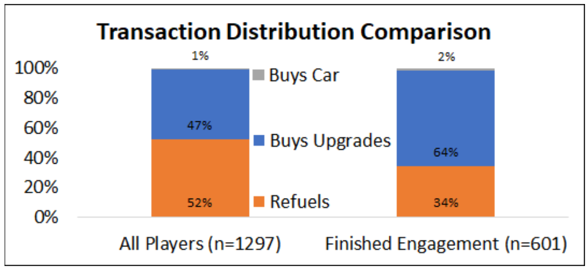

FIGURE 9. Transactions distribution. Players who finished the engagement spent most of their in-game money on car upgrades rather than refueling. This means that they likely understood the incentive mechanisms of the game and complied with them.

In Section V, we present our analysis and insights from our experiment. Before, we report usage statistics in the following Subsection IV-B.

B. USAGE STATISTICS

Figures 8 & 9, and the Tables 1 & 2 show different usage statistics of the iCO_2 campaign. Figure 10 illustrates how these were derived. To finish a quest, the player has to completely stop the car. In our campaign, the task of the users was to complete two quests, as illustrated in Figure 4.

In total, 2455 players have played iCO_2; almost half of them completely finished the engagement (see Figure 8), whereas 49% finished no quests, and 9% finished one quest. 34% of players quit right after the engagement, and 8% finished more than two quests. American players had the highest participation and completion rate, with 725 players finishing the engagement, while 864 did not. European users were most likely to abandon the engagement, with 887 players not finishing and only 149 completing the engagement. 392 Asian users, who were mostly from Japan, did not finish the engagement while 167 did. These numbers include players who quit before starting the game and therefore add up to 3184.

Player retention and churn in online gaming is a complex problem [40], which has been shown to vary across user populations [41], [42]. We can only hypothesize which factors account for differences in observed churn between Asia and Europe, taking into consideration difference in popularity across game genres with greater acceptance of slower-paced and more exploratory games in Asia, as well as differences in escapism (a factor under 'immersion' [32]), or social achievement compared to social interaction.

The number of times a player logs into the game helps us to better understand the way players interact with iCO_2, or its re-playability potential. A 'play session' is defined as an uninterrupted chunk of play time. The majority of players only played the game once. On the Europe server, 21.7% of the players opened the game at least twice; that number is 18.8% for Asia, and 10.2% for the Americas. More information on the distribution of play sessions can be found in the Appendix.

We can see the architecture flow and various iCO_2 statistics in Figures 9 & 10 as well as the Tables 1 & 2. Table 1 shows the distribution of activity-switching, Figure 9 shows the transaction distribution, and Table 2 shows the car-switching distribution.

Activity-switches show which transitions are frequent or rare, and indicate how players use different game options. For instance, most players switch between Driving and Garage and Driving and Navigator. The activity was switched a total of 7802 times, mostly towards the driving state. In Figure 9, we can see how users spent their in-game currency. Among all players, most of it was spent on car upgrades (47%) and refueling (52%), with only 1% spent on new cars. A total of 1297 transactions were made. Users did not switch their cars very often, only a total of 39 switches occurred as denoted in Table 2.

The engagement task was designed so it could easily be completed under 5 minutes. We observe some outliers, however, when we focus on users that played 60 minutes or less, the average engagement time indeed drops to 4 minutes and 23 seconds.

To test the compliance of players, we need to determine whether users understood that driving in a fuel-efficient way helps them to save in-game currency, which can be spent on 1) new cars with higher fuel efficiency and 2) upgrades that allow for more passengers and cargo. We found that the players who finished the engagement seem to have bought more upgrades in relation to refueling. This leads us to the hypothesis that these players are more interested in exploring the game than those who quit early.

There are three cars available: the Prius,[6] the Fairlady,[7] and the BladeGlider.[8] Given the fact that every player starts off with a Prius, we note that the Fairlady was the most popular car choice to switch to. Players did not switch cars very often, as we can observe in Table 2. Only 6 switches were performed by players who did not complete the engagement. Players who completed the engagement were those who most likely switched cars. They seemed to partake in every aspect of the game, and, as expected from the transactions graph in

[6]Toyota Prius, a full hybrid electric automobile

[7]A sports car by Nissan known as the Fairlady Z in Japan and a Nissan Z-Car (e.g. Nissan 300ZX) elsewhere

[8]Nissan BladeGlider, a prototype high performance electric vehicle

TABLE 1. This table presents the activity-switches during the game for all players.

Current/Next Activity	CarPainter	Driving	Garage	GasStation	Navigator
CarPainter	-	348	0	1	0
Driving	10	-	1971	566	1257
Garage	356	1472	-	4	9
GasStation	0	524	20	-	6
Navigator	0	1258	0	0	-

TABLE 2. This table presents the car switches by players who finished the engagement. Only 6 players that did not finish the engagement switched cars.

Current Car/Switched Car	Prius	Fairlady	BladeGlider
Prius	-	24	3
Fairlady	3	-	2
BladeGlider	0	1	-

Figure 9, performed more trips to the garage than to the gas station.

V. RESULTS

A. MEASUREMENT OF ECO-FRIENDLINESS OF DRIVING BEHAVIOR

The eco-friendliness of a player's driving is measured in terms of acceleration averaged over time. The car's position is recorded every 100 milliseconds. According to the positional information, speed (the magnitude of the velocity) and average acceleration (the magnitude of the acceleration) is calculated using Equation 1:

$$Speed(t_i) = \frac{distance(t_i, t_{t_i+1})}{t_i - t_{i+1}} \quad (1)$$

where $distance(t_i, t_{i+1})$ is calculated by the Euclidean distance. t_i and t_{i+1} represent two neighboring time-stamps. The average acceleration is calculated by Equation 2:

$$Acceleration(t_i) = \frac{Speed(t_i) - Speed(t_{i+1})}{t_i - t_{i+1}} \quad (2)$$

For each user, the time-stamp associated with the speed and average acceleration is logged into the database for the entire duration of driving. In our data, the acceleration of the car lies between -4 m/s^2 and 4 m/s^2 most of the time; the total range is set from -6 m/s^2 to 6 m/s^2. We define smooth acceleration (and deceleration) as the characteristic of eco-driving, and we calculate the rate of change of acceleration, i.e., jerk between the two consecutive time-stamps using Equation 3:

$$Jerk(t_i) = \frac{Acceleration(t_i) - Acceleration(t_{i+1})}{t_i - t_{i+1}} \quad (3)$$

Similar to [13], we define 22 categories for the jerk defined in Equation 3, starting with $[-inf, -100]$ up to $[100, +inf]$. The smooth acceleration is defined as lying between the range of $[-10, 0]$, and $[0, 10]$.

For each player, we first calculate the probability of jerk distributed over the 22 intervals and then normalize the probability distribution of jerk. After that, an unsupervised machine learning method called clustering is performed. Clustering is used to classify data into different groups, where data from the same group has similar characteristics and data from different groups is dissimilar. In our work, k-means clustering is used [43] to determine different driver types and their characteristics. The sum of squares due to error (SSE) is calculated to determine the optimal number of clusters and their convergence. The smaller the SSE, the better the cluster. The SSE is calculated by Equation 4:

$$SSE = \sum_{i=1}^{k} \sum_{x \in C_i} distance(m_i, x) \quad (4)$$

We analyzed k from 2 to 15 and selected the k according to the "elbow criterion" ([44]) that achieves a low SSE, while using the least number of clusters in order to explain the data. According to this criterion, a k of 4 was selected.

To evaluate the eco-friendliness level of these clusters, we introduce Equation 5:

$$factor_{eco} = F_{r[-10,10]} \quad (5)$$

Equation 5 corresponds to the relative frequency F_r of the smooth acceleration bin, i.e., the frequency of time when the acceleration falls between -10m/s^2 and 10m/s^2. The more time a driver spends in the smooth acceleration ranges as opposed to others, the more eco-friendly his driving behavior is. This factor ranges from 0 (worst) to 1 (best).

B. TYPES OF DRIVERS

In this section, we show how we identified different driver types based on their driving behavior. First, players who played less than four minutes are filtered out, because it took at least that amount of time to complete the training and engagement. For the remaining players, driving behavior data is analyzed for the entire driving time, except for the first two minutes that are considered as training time. During training time, players figure out the controls of the game, which might affect the data analysis. Using the 'elbow' heuristic to minimize the sum of squares due to error (Equation 4), four clusters are created as shown in Figure 11. Eco-driving is determined by the relative frequency of smooth acceleration in the interval $[-10, 10)$ (including -10, excluding 10). Drivers in Cluster 1, "reckless" drivers, have a low presence in the smooth acceleration category and performed more abrupt brakes as well as steep acceleration. Clusters 2 and 4 have a high prevalence of smooth acceleration or deceleration. Drivers in Cluster 2 focus primarily on smooth

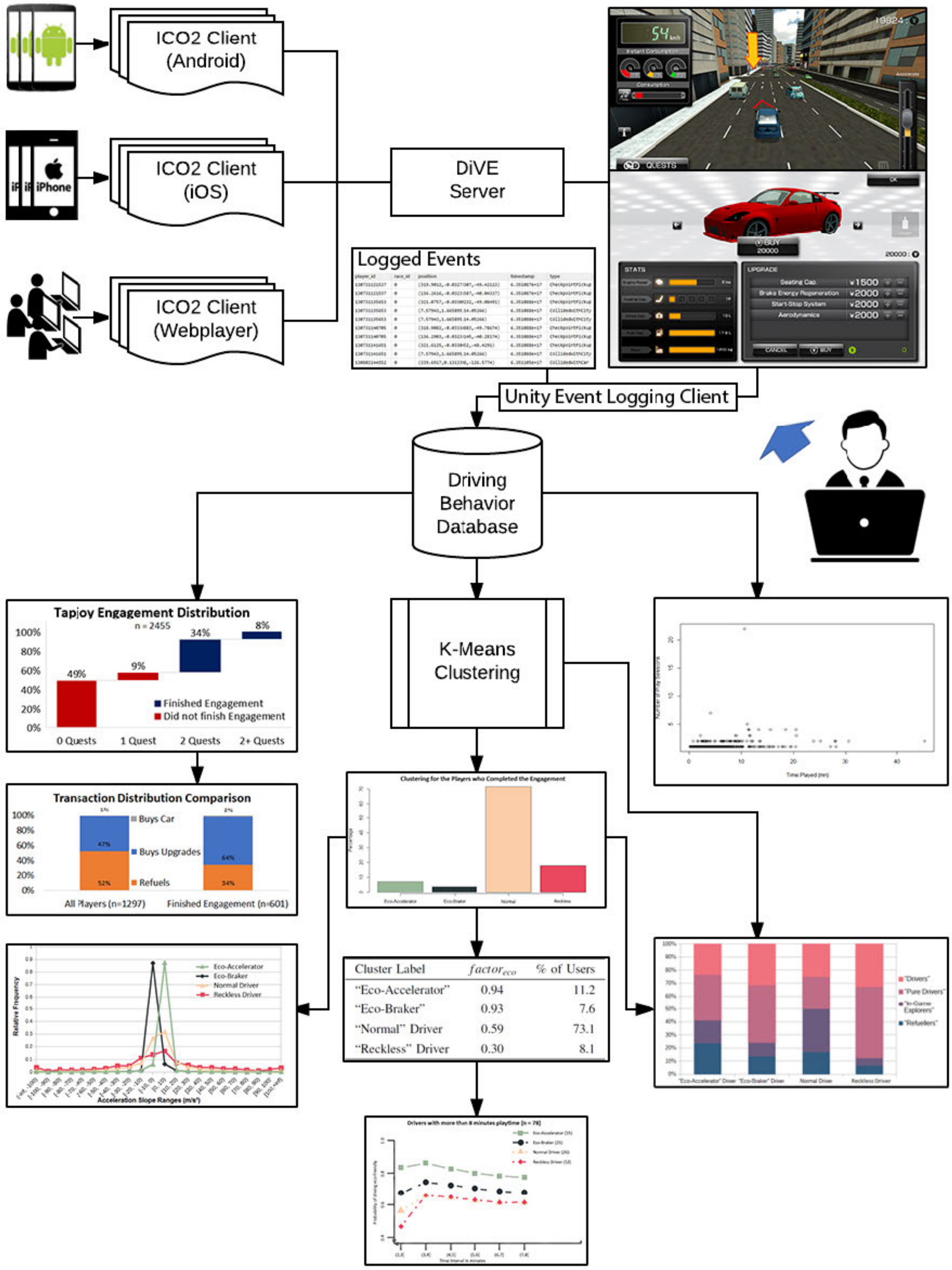

FIGURE 10. **iCO_2 Architecture Flow. Players log in via Android/iOS client or Webplayer. The DiVE (Distributed Virtual Environment) server handles those requests and logs Unity events, such as car position and type of interaction with the environment (e.g. checkpoint pickups, collisions with buildings or other cars). The facilitator accesses these data and creates visualizations of the engagement distribution, transaction distribution comparison, and distribution of play sessions. Via K-Means Clustering, four clusters are identified, and the relative frequency in acceleration slope ranges, probability of eco-friendly driving, in-game activity analysis, and eco-driving evolution over time are calculated and visualized.**

braking, and drivers in Cluster 4 focus on smooth accelerating; hence, we call them "eco-braker" drivers and "eco-accelerator" drivers, respectively. Finally, we have a group of players that perform mostly smooth accelerations but still show abrupt acceleration changes. We label this group as "normal" drivers. Notably, no cluster of highly competent drivers for both smooth acceleration and deceleration emerged.

Detailed results for the clusters are shown in Table 4. Please note that the cluster for "normal" drivers aggregates the vast

TABLE 3. This table presents the activity switched to during the game (for players who completed the engagement).

Current/Next Activity	CarPainter	Driving	Garage	GasStation	Navigator
CarPainter	-	39	0	0	0
Driving	0	-	199	102	372
Garage	41	143	-	1	2
GasStation	0	99	2	-	2
Navigator	0	375	0	0	-

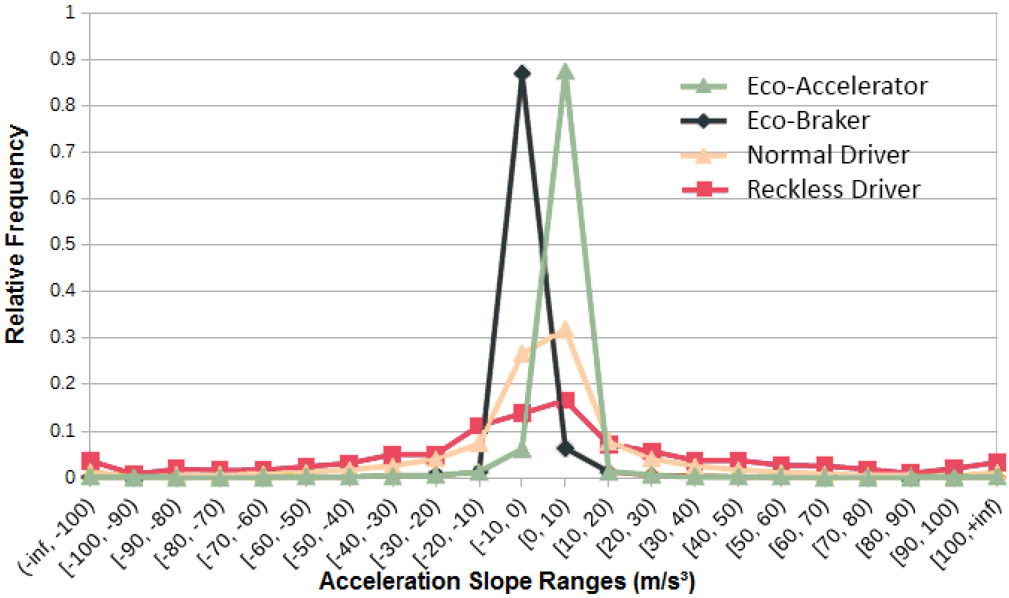

FIGURE 11. Clustering of users' driving behavior based on the rate of change of acceleration. We identify four clusters: Eco-Accelerators, Eco-Brakers, Normal Drivers, and Reckless Drivers. E.g. [−10,0) denotes the acceleration slope interval from including −10 to excluding 0 m/s^3, that is, breaking in an economically friendly way.

TABLE 4. This table presents a summary of the clusters. Here we present the relative frequency of smooth acceleration for each cluster; the $factor_{eco}$.

Cluster Label	$factor_{eco}$	% of Users
"Eco-Accelerator"	0.94	11.2
"Eco-Braker"	0.93	7.6
"Normal" Driver	0.59	73.1
"Reckless" Driver	0.30	8.1

majority of the drivers and shows an intermediate percentage of time on the smooth acceleration interval (59%).

C. TYPES OF PLAYERS

After we classified users according to their driving behavior, we examined how their driving behavior might affect other in-game activities, i.e., what types of *players* there are.

Next, we are interested in types of players as judged from their in-game activities. As explained in Section III, users have access to five different activities in the game, They can (1) drive, (2) go to the garage, (3) go to the gas station, (4) use the navigator tool to plan their routes, (5) paint their car. We performed k-means clustering to understand how the users spent their time within the game, and in what activities they engaged. We aim at extracting profiles of the time distribution of how users spend their time in the game. For clustering, we only considered users who played more than 4 minutes.

Using the elbow heuristic to minimize the sum of squares due to error (Equation 4), we obtained four activity distribution profiles describing how users spent their play time (see Table 5). Cluster 1 and 2 are labeled "Refuelers" and "In-Game Explorers", respectively, as these players spent a great part of their time performing in-game activities other than driving. Further, we observe a cluster of players that basically only drive. The center of mass of this cluster has a driving percentage of 97%, therefore we named this group "Pure Drivers". The final cluster of users engaged primarily in driving while performing other in-game activities as well; we labeled this cluster "Drivers".

Detailed results for the clusters are shown in Table 5. Please note that the cluster for "normal" drivers aggregates the vast majority of the drivers and shows an intermediate percentage of time in the smooth acceleration interval (59%).

The users who finished the engagement (shown in Figure 12), did not seem to deviate from the proportions we obtained when we performed the clustering analysis, which can be seen in Table 4. The main difference was that the presence of "Reckless Drivers" seemed to be accentuated.

Unsurprisingly, the players labeled as "Reckless Drivers" are mostly "Pure Drivers" (35%) and contain the lowest

TABLE 5. Time distribution of means of activity clusters.

Cluster/Label	Gas Station	Garage	Navigator	Driving	Car Painter
1 — "Refuelers"	0.29	0.09	0.04	0.55	0.03
2 — "In-Game Explorers"	0.03	0.24	0.02	0.52	0.18
3 — "Pure Drivers"	0	0.01	0.01	0.97	0
4 — "Drivers"	0.03	0.12	0.04	0.78	0.03

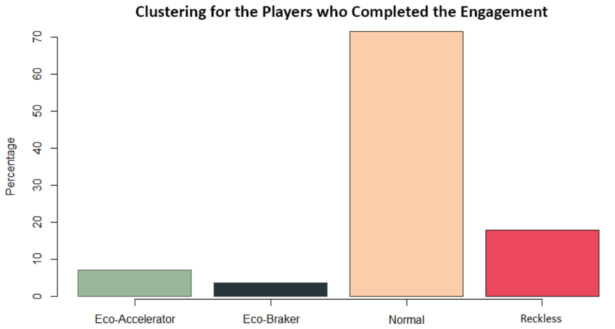

FIGURE 12. Results of the cluster classification on the users that finished the engagement. Most players are normal drivers, followed by reckless drivers. Less than 10% of drivers are Eco-Accelerators and Eco-Brakers, respectively. This indicates that there is big room for improvement.

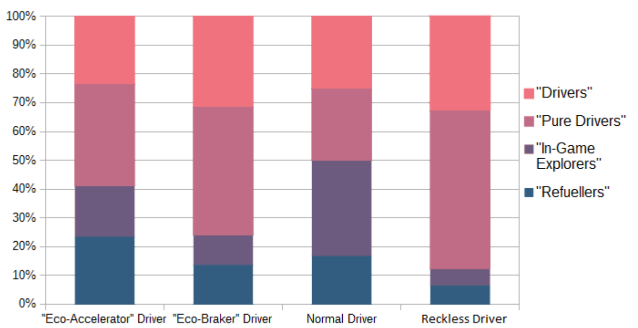

FIGURE 13. Distribution of the activity clusters among users' driving profile.

share of "Refuellers" (Figure 13). One reason to explain this behavior is that eco-friendly users were more conscious of their fuel tank display and therefore filling their tanks more often even though they were not empty. Further, "Normal Drivers" had the highest percentage of "In-Game Explorers".

D. ANALYSIS OF USERS' ECO-DRIVING EVOLUTION

In this Subsection, the aim is to test the hypothesis that players become more eco-friendly due to the compliance and incentive mechanisms of the game and those who show eco-unfriendly behavior at the beginning of the session improve over their play-time.

The approach is to first select the users who drove more than a certain amount of time and then to calculate the variation of the probabilities of them performing smooth acceleration in discrete uniform time-intervals.

To implement this approach, four different play-times are chosen arbitrarily: 7, 8, 9 and 10 minutes. Thus, four groups of players are created in which only those who played more

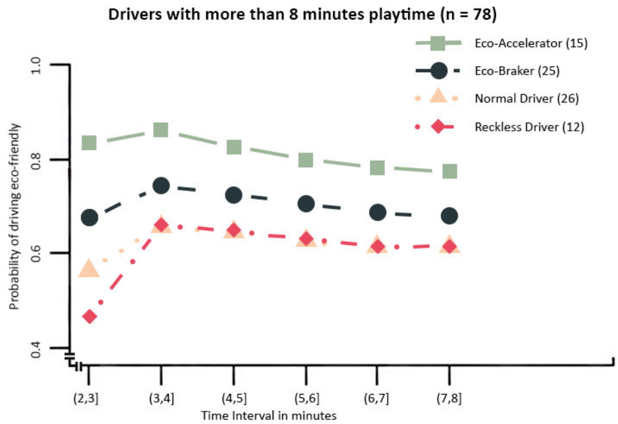

FIGURE 14. Eco-Driving Evolution of all players who played for at least 8 minutes and finished the engagement. (2,3] denotes the time intervals from one timestamp after minute 2 to minute 3. The figure starts at a probability of 0.4 to zoom in on the improvement to above 0.6 of normal and reckless drivers. The peak of behavior change occurs between 0 and 5 minutes. After 8 minutes, the values stabilize.

than the specified play-time are chosen and the rest are filtered out. For players in each group, the first two minutes of play-time is considered training time. After the player is trained, clustering based on the probability of their jerk distribution (see Equation 5) is performed for each group of players to determine the player-types.

Using the elbow heuristic to minimize the sum of squares due to error (Equation 4), the appropriate number of clusters k are found to be four. These driver types are named "Eco-Accelerator", "Eco-Breaker", "Normal" and "Reckless", which reflects their driving behavior. After the clustering of players across the four groups, the four clusters in order of increasing number of players are: "Reckless" $<$ "Normal" $<$ "Eco-Breaker" $<$ "Eco-Accelerator". This suggests that after the formal training session, the eco-friendly drivers constitute the largest share of all the players.

Figure 14 shows: (1) four different types of drivers filtered according to their driving time; (2) the number of drivers in each group; (3) the distribution of users within the four clusters of driver types, and (4) the time-varying distribution of the eco-friendliness of different driver types.

The filtering of players based on different play-times was performed on a total of 2045 users. The players who drove above the four specified play-times for 7, 8, 9, and 10 minutes are 107, 78, 66 and 47 respectively. The performance of eco-friendly driving over time for 8 minutes is shown in Figure 14. We do not observe any further change in the probability of eco-friendly driving for 9 and 10 minutes.

It can be seen that the eco-friendliness of the "Reckless" drivers improves significantly over time and becomes comparable with that of the "Normal" drivers. The eco-friendliess of "Eco-Breakesr" also increases. However, the high-performance users, i.e., the "Eco-Accelerators", continue to maintain their edge over other driver types, although their performance decreases over time. One explanation is that users prioritize the quests. The nature of quests requires a player to accelerate and decelerate the car (to stop), which will increase the player's distribution in non-smooth acceleration zones. Another explanation could be the cognitive fatigue of players as they drive for longer periods of time.

Also, it is interesting to notice that for all the four driver types across all the four groups, the peak improvement occurs between 3 to 4 minutes of playtime. Here we would like to argue that this finding is correlated with the fact that the median time for performing two quests (i.e. completing the engagement) is 4 minutes and players get paid only when they finish an engagement and the money is paid only once. Thus, the player has no extrinsic motivation to continue playing once the engagement in the game is achieved. Thus, it is likely that players' motivation to "perform" somewhat decreases once they get paid and they simply leave the game; start to use it as a racing game or engage in other in-game activities like transactions, car-switching, coloring the car, etc.

Overall, our results support the hypothesis that players become more eco-friendly while playing iCO_2 and those who show eco-unfriendly behavior at the beginning of the session improve over their play-time.

VI. CONCLUSION & DISCUSSION

In this paper, we describe iCO_2, the first game-like simulation platform for mobile devices of its kind for collecting data on large-scale driving behavior and related in-game activities. We offer a virtual environment for the practice of eco-driving and collect statistics on user behavior, such as driving behavior, upgrading the user's car, and car choice. As a research tool, iCO_2 can be seen as a human computation system where humans provide driving behavior. This allows us to better understand how users interact with a game that motivates them to drive in an eco-friendly way. In this regard, our system is related to other activities aimed at attracting users' work, such as Games with a Purpose (the purpose of iCO_2 being the collection of large-scale data on driving behavior and training on eco-friendly driving) or crowdsourcing. The proposed version of iCO_2 extends the previous version [13] by a quest system and a "Garage" to improve the capabilities of the player's vehicle.

Our contributions are (1) the iCO_2 campaign to provide our platform with human driving behavior as data, (2) the analysis of these data, and (3) the confirmation of our hypothesis that we can improve users' driving behavior if they engage with our simulator for a certain amount of time.

The investigation of learning processes in educational online games is an active research topic [45], [46] but previous work in comparable application domains such as household energy consumption [47] and household logistics [48] support the hypothesis of a positive effect of online games. Investigating the actual dynamics of learning in eco-driving was however outside the scope of the research reported here.

Since our simulation platform is developed as a mobile app, we were able to use a mobile games promoter to attract users to our game. Fortunately, data of more than 3000 users could be collected in about one week. We were interested both in results about eco-driving behavior and statistics about the usage of our system.

The campaign and its analysis is an important step towards understanding players of mobile games that have a 'serious' aspect, such as sustainable behavior. The next step is to use the information of driver types ("Eco-Accelerator", "Eco-Braker", "Normal", "Reckless") and classify the user's behavior in real-time. This classification can be used to alert the user during the game.

Using the data, we tested the hypothesis that players become more eco-friendly while playing iCO_2, and that those drivers, who show eco-unfriendly behavior at the beginning of the session improve over their play-time. The approach is to select the players who played more than a certain amount of time and calculate the variation of the probabilities of them accelerating smoothly in discrete uniform time-intervals. The usage data also revealed some details about users' in-game behavior, such as activity-switching, transactions, and car model switching.

In future work, we intend to increase the re-playability of the game, to be able to collect data of users over time. For example, the quests shall be parameterized, i.e. the more quests the user performs, the more money they earn, so that then they can upgrade the car to accommodate more cargo and passengers. In addition, the generation of quests will be determined dynamically depending on the car-type of the user. We further consider studying the impact of offering a fixed reward versus an increasing reward scheme [49].

We also intend to predict the eco-friendliness over time beforehand based on past behavior and display it to the driver, so that the appropriate corrective steps can be taken. These planned developments shall open entirely new ways of testing compliance, incentive, and feedback mechanisms with users as we may learn their behaviors and reactions. Furthermore, a comparison with real-world data would strengthen our hypothesis that we can train people to improve their eco-driving.

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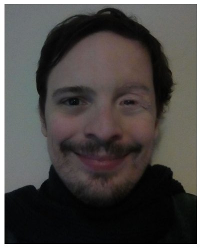

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