Large-Scale Data Collection of Eco-Driving Behavior: Analysis of a Campaign with the iCO_2 Simulation Platform

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Abstract

We describe iCO_2,[1] a simulation platform for collecting driving behavior data. For the user, iCO_2 is designed as a massively multiplayer online game for mobile devices to practice eco-friendly driving. For the researcher, iCO_2 constitutes a Human Computation system that facilitates the collection of large-scale data on driving behavior to better understand compliance and incentive mechanisms for eco-driving and users' preferences. The main contribution of the paper is two-fold. First, we describe the newest version of our iCO_2 simulation platform, which has been extended to a game with a quest system and functions to upgrade the player's vehicle. Second, we present the results of a campaign with iCO_2 that uses a game promoter to attract more than 3000 users in a short time. Our game run on servers in Asia, Europe and America. 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 of players' interaction with game elements and their driving behavior; (3) by looking a longer sessions, we demonstrate that players who show eco-unfriendly behavior at the beginning of the session improve over their playtime.

Keywords: Data collection; data analysis; driving behavior; Human Computation system; Games with a Purpose; massively multiplayer online game

1. Introduction and Motivation

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 (Quinn and Bederson, 2011). As a solution, Games With a

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Purpose (GWAP) have been proposed (von Ahn, 2006). GWAP is a field of Human Computation (Yuen et al., 2009; Krause and Smeddinck, 2011) 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 smart phones, 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 large numbers of users, although it is more difficult to standardize test conditions, and control the environment. Henze et al. (2013) suggested 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 as smooth acceleration and deceleration, keeping the speed limit, and so on.

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“.[2] 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[3], a company that handles mobile games promotion, to attract a large number of users (in the 1000s) to iCO_2 within a short time. This approach constitutes an alternative to the tools and applications that have been used in research projects involving games (Kittur et al., 2008; Biewald, 2012; Chan and Hsu, 2012). To keep players motivated, we provide a quest system and the possibility to upgrade the user’s car as in-game mechanics.

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

- shows to what extent 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 visiting the “Garage”, where users could upgrade and modify their car with the in-game money rewarded from the quests; and
- describes how the driving behavior of users in the simulated environment evolves over time.

[2]https://play.google.com/store/apps/details?id=net.globallabproject.ico2&hl=en
[3]http://home.tapjoy.com/

The paper is structured as follows. Section 2 provides background research on eco-driving games, training applications, crowdsourcing and games with a purpose. Section 3 describes the iCO_2 simulation platform that extends our previous version of iCO_2 (Prendinger et al., 2014b) with a quest system and upgrade functions. In Section 4 we explain the campaign and present usage statistics of iCO_2 during the campaign. Section 5 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. Section 6 summarizes and discusses the most relevant results and describes future work.

2. 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.

2.1. Eco-driving Games and Training Applications

The training of eco-driving is important as it greatly affects world-wide fuel expenditure and pollution emissions (Barkenbus, 2010; Shaheen et al., 2012). Therefore, car manufacturers have started to develop applications that provide drivers with some feedback on the effects of their driving behavior (Eco Driving Tools, 2014; Fiat Eco Drive, 2014).

Most applications for practicing eco-friendly driving are either 2D single-player games (Eco Sports Drive, 2014; Driver Ed To Go, 2014; Truck Fuel Eco, 2014; Moebius, 2014; Fiat Eco Drive, 2014) or full-fledged simulators that can only be played with specific physical apparatus (Eco Simulator, 2014; Green Dino, 2014; Eco Friendly Driving Simulator, 2014; Sabrina et al., 2013). By contrast, iCO_2 is a massively multiuser 3D game that can be controlled by common mobile devices.

2.2. Crowdsourcing and Games with a Purpose

We have defined our project as a Human Computation system (Yuen et al., 2009; Krause and Smeddinck, 2011), rather than a crowdsourcing system. Quinn and Bederson (2011) explain the difference comprehensively. The most important distinction is that crowdsourcing involves the entire problem being tackled by a crowd of humans (Howe, 2008), whereas Human Computation involves only part of a problem being tackled by a crowd of humans.

Our goal is to collect and discern driving behavior in a simulated environment. Our users fill in for a part of the "algorithm" of data collection, which involves them "providing behavior".

More specifically, our game fits the definition of Games With a Purpose given by Quinn and Bederson (2011) and von Ahn (2006), which is explained as an area in the field of Human Computation that aims to use enjoyment as a primary means of motivating users. To draw users of our game, we initially provide a a monetary incentive. Our method to provide the system with users is based on Tapjoy,[4] a games promoter. 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.

[4]https://home.tapjoy.com/

2.2.1. Crowdsourcing

Biewald (2012) presents a number of applications involving crowdsourcing and Human Computation that use the increasingly popular Mechanical Turk from Amazon (Amazon Mechanical Turk, 2014) and involve ethics, business and fun. The tasks involve answering questions that don't require any technical knowledge or performing Google searches. "Sifu" by (Chan and Hsu, 2012) 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.

2.2.2. Games with a Purpose

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

von Ahn and Dabbish (2004) introduced the concept of GWAP with the now well-known ESP game, which had the aim to label images. Here, players are matched and have to guess which label their counterpart is applying to the image that both of them are seeing. Subsequently, the project was improved and re-branded as Peekaboom (von Ahn et al., 2006b) and Phetch (von Ahn et al., 2007).

A similar approach to the previously outlined image tagging endeavors is taken with TagATune (Law and von Ahn, 2009), a game with a purpose that also matches players online one-to-one. They play a game of tagging a piece of music that may or may not be shared by the two and when they are offered each other's music and tags, they try and guess if it is indeed the same sound sample or not. The game resurfaced with the modified intent of gauging the success of machine-run algorithms that tag music (Law et al., 2009).

Foldit (Cooper et al., 2010) puts players in a puzzle-solving game involving the prediction of protein structures. By providing online functionalities such as chatting or ranking, they keep their players engaged with both difficulty and socialization. Chatting and ranking are functionalities iCO_2 does not provide at this point, because we believe those features would distract from the core functionality and purpose of the game.

2.2.3. Comparison of previous Games with a Purpose to iCO_2

Caretaker (Violi et al., 2011) is a project that notably focuses on behavioral data, and the analysis thereof, that pertains to trust. Caretaker places four players in a board-like game that simulates a transport square-shaped network across which they have to travel from corners to center. Three players must ally against the fourth and arrive at the center before this common enemy, despite none of the three knows who the adversary is when the game starts. Their position in the network is the only publicly available information but the game offers a chat system to communicate as they wish. Violi et al. also logged player actions as a method through which they can match and confirm the behavioral information they receive from having the players submit a survey.

Caretaker has many similarities to iCO_2 as a Human Computation system: the player's actions and decisions are logged in order to analyze behavioral data. In iCO_2, the situations are potentially much more akin to real life circumstances, with drivers just encountering other motorists they know nothing about, and choosing how to interact with them based on the same variables that would influence them in a real scenario (situation, mood, etc). There is also the massive multiplayer element to iCO_2, which Caretaker does not have.

iCO_2 follows some design decisions used in previous Games with a Purpose. Challenge is cited as a key factor for a successful game von Ahn and Dabbish (2008), in the game design we tried to add mechanisms such as resource management (fuel, car characteristics), to create a more challenging experience. Multiplayer experiences, time-sensitive decisions, randomness are also characteristics mentioned in von Ahn and Dabbish (2008), that can improve the enjoyment and we used in the design of iCO_2.

iCO_2 constitutes a Human Computation system, because we want to collect driving behavior and decision information from a massive quantity of users, while training them on eco-driving and providing them with enjoyment and fun.

3. 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 1). In the game, players drive in a 1km^2 replica of Tokyo city, whereby streets are populated both with other players' cars and with computer controlled cars from our traffic simulator system (Prendinger et al., 2014a). As a result, traffic situations occur naturally in the virtual environment, which can be utilized to investigate eco-driving policies (Prendinger et al., 2013) or traffic congestion (Gajananan et al., 2013).

iCO_2's predecessor version (Prendinger et al., 2014b) contained two game modes, (1) "Free drive" and (2) "Campaign", where players are paid for completing a quest or task. By contrast, the current version of iCO_2 offers a full-fledged quest system, and hence players can engage in repeated campaign-style interactions.

By completing quests, players are rewarded with virtual currency (within the iCO_2 game), which is the key factor that motivates players to maintain 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.

3.1. 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 Fig. 1, 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 read 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

Figure 1: Screenshot of the iCO_2 game, which displays a player driving around the replica of Tokyo city. On the top-left, the car's velocity and fuel consumption information is displayed. The acceleration/break slider is located on the right.

button for acceleration and another button for breaking, we considered an option for a smooth change of pace tantamount; it should feel like using pedals in a real car. In order to achieve these nuances, we decided to provide a slider (shown on the right side in Figure 1), which lets users accelerate, decelerate and maintain constant speeds easily. For the mobile application, this feature was realized by touch controls, while the web player could be operated via mouse.

3.2. Quests

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 arrows, as shown in Fig. 1.

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 number of seats for passengers or space for cargo.

3.3. Garage

With the in-game money rewarded from quests, players can go to the *Garage* and upgrade their car with advanced technology (see Fig. 2). 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 have more passenger or cargo capacity, but high fuel consumption, or a car with a small capacity but less fuel consumption.

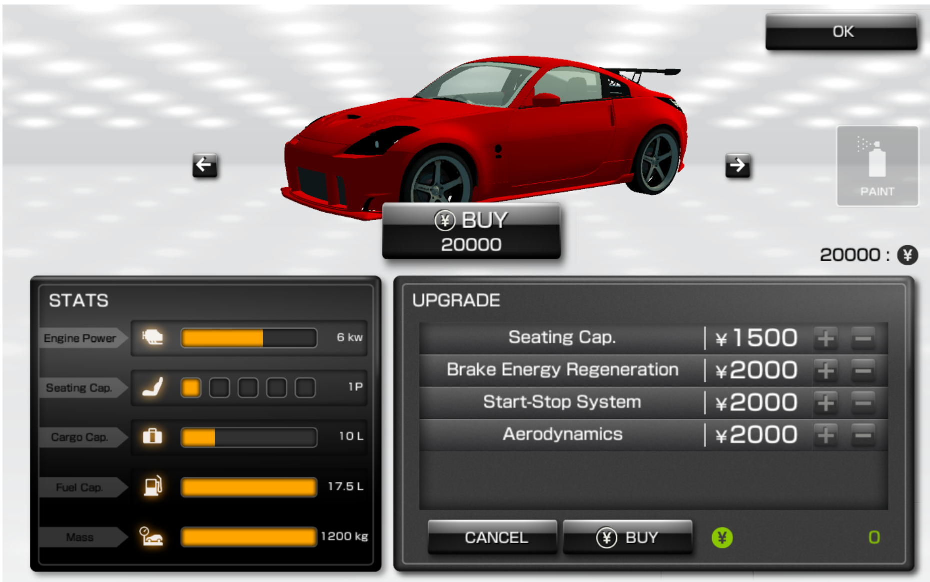

Figure 2: Screenshot of the iCO_2 *Garage*, where the player can buy new vehicles and upgrades as well as repaint the owned cars.

3.4. *Navigator*

In the game, players can use the in-game *Navigator* system (see Fig. 3) 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 augmented reality arrow (see Fig. 1). The arrow points players to the direction they have to follow to reach the start and destination points to the quests' legs.

3.5. *Implementation*

The game was developed with the Unity3D game engine[5], which allows us to seamlessly port the iCO_2 game to different platforms. The game 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.

[5]www.unity3d.com

Figure 3: 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.

The multiplayer feature of iCO_2 is enabled by DiVE (Distributed Virtual Environments) (Prendinger et al., 2014b). DiVE handles the communication among all the iCO_2 components (see Figure 4), which we regard as DiVE clients.

Each client works as follows: The "Profile Client" handles the persistency of the players' profile. Players' profiles are associated to their Facebook accounts. Therefore, players do not need to perform any additional registration to iCO_2 and always retrieve their progress regardless of the platform that he/she is using to play the game. The "Spawn Client" manages where players spawn 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, etc., and stores it persistently in a database. The "Traffic Simulator" system controls the computer-controlled cars and all traffic lights in the virtual scenario.

4. A Campaign with the iCO_2 Simulation Platform

In March 2014, we run a campaign with iCO_2 for one week and collected data of 3184 mobile users. The results of our data analysis will be discussed in the following sections.

4.1. Implementing the Campaign

In our large-scale study, we aimed to follow the ten-step framework proposed in (Henze et al., 2013). 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

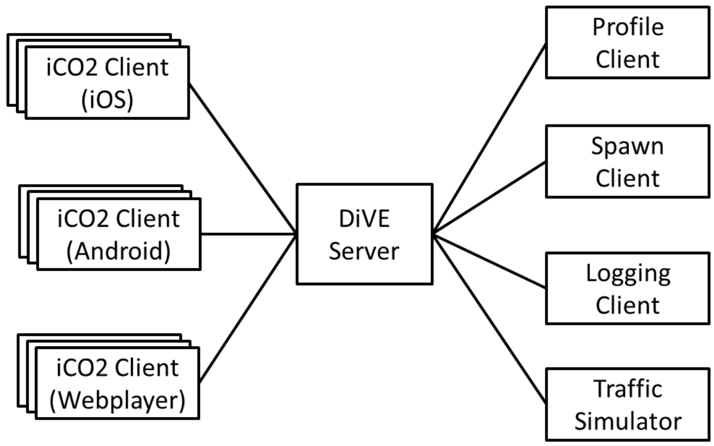

Figure 4: iCO_2 system architecture. The DiVE server supports the communication platform between all the different components that compose the iCO_2 system. The left side shows the clients, in different platforms, controlled by the player. The right side shows the clients that support the iCO_2 system.

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. The *second step* is to devise a study method, such as correlational or experimental. 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 the time of the performing the requested task (two quests), the incentive as extrinsic, users earn 'points' that can be used as in-game currency in the game the user played before joining the campaign. However, after the completion of the task, we 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 each we monitored the servers and database to ensure the system was functioning (*ninth step*). The we processed and analyzed the data (*tenth step*).

In Section 5, we present our analysis and insights from our experiment. First, we report on the usage statistics.

4.2. Usage Statistics

Figures 5, 6, 7 and 8 show different usage statistics of the iCO_2 campaign. A 'quest' in iCO_2 encompasses the activity of picking up a passenger or cargo at a starting point and bringing (delivering) the passenger (cargo) to a destination. For both activities, the player has to completely stop the car. In our campaign, the task of the users was to complete two quests. 'Engagement' is a term used by Tapjoy and refers to the requirement of receiving a reward. In our case, players had to complete two quests.

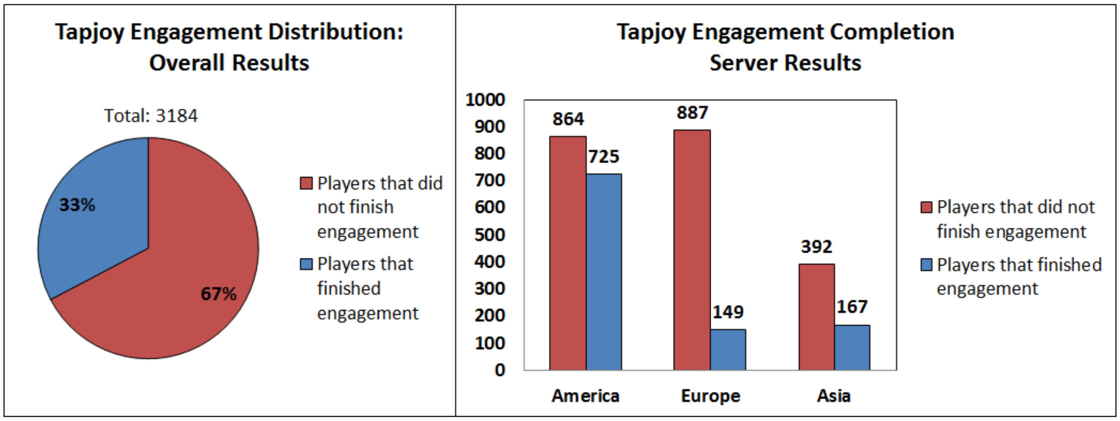

Figure 5: iCO_2 statistics: Engagement.

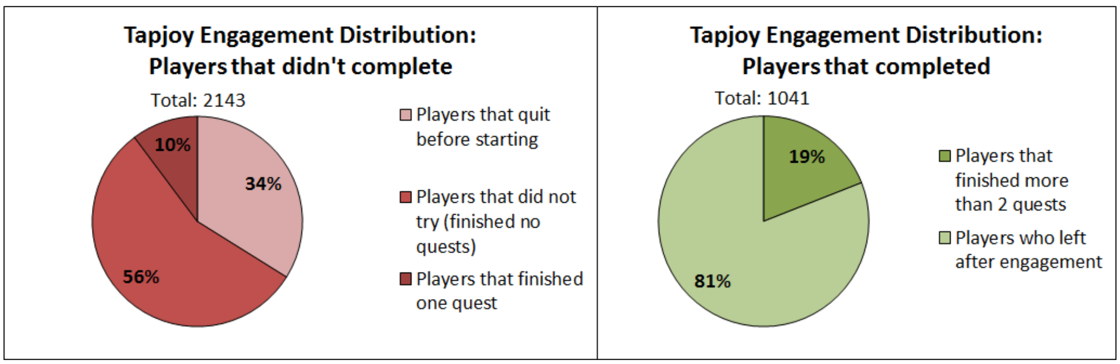

Figure 6: iCO_2 statistics: Completion.

In total, 3184 players have played iCO_2; among them, 33% finished the engagement (see Fig. 5). 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.

Figure 6 shows the number of players that did not complete the engagement. Out of a total of 2143 users that did not finish the engagement, 10% of players finished one quest, 34% quit before even starting, and 56% did not try to finish a quest. In total, 1041 users completed the engagement, 81% left after the engagement and 19% finished more than two quests.

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 an uninterrupted chunk of play time. The majority of players only played the game once, as we can see on Figures A.15, A.16, and A.17 (in Appendix). 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 America.

We can see various iCO_2 statistics in Fig. 7. Graph A shows the play-state switching distribution, Graph B shows the transaction distribution, Graph C shows the car switching distribution, and Graph D shows the car color distribution. The play-state was switched a

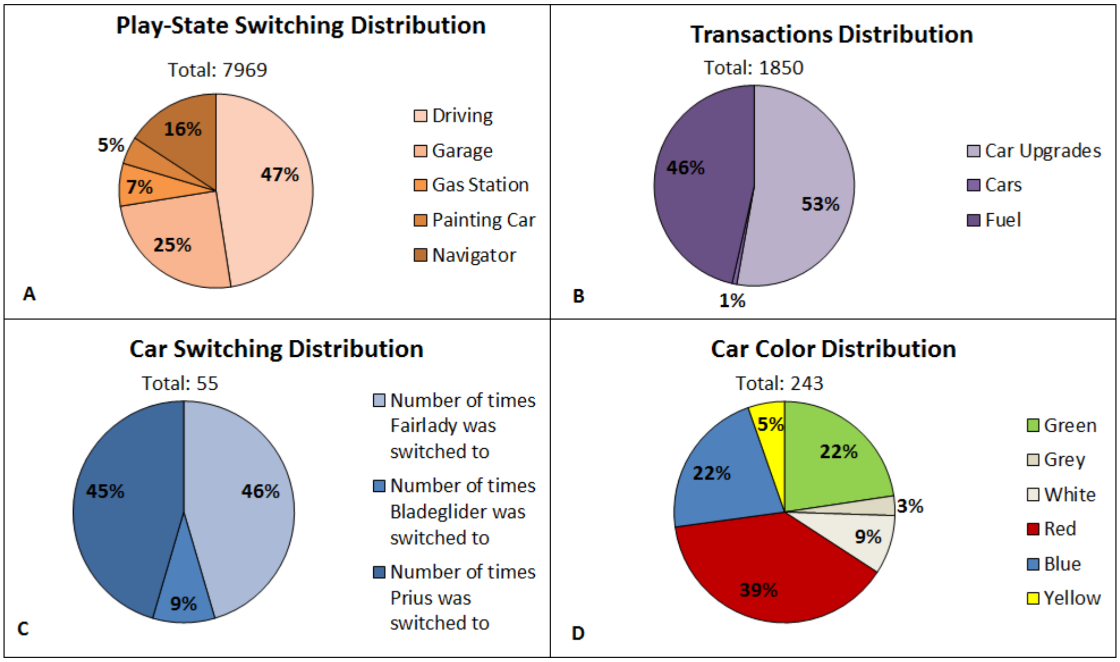

Figure 7: Various iCO_2 statistics.

total of 7969 times, mostly towards the driving state (47%), followed by the garage (25%), navigator (16%), gas station (7%) and lastly painting the car (5%). Please note that the percentages do not reflect the time spent in a state, but the act of switching from one state to another state. In graph B, we can see how users spent their in-game currency. Most of it was spent on car upgrades (53%) and new cars (46%), with only 1% spent on fuel. A total of 1850 transactions were made. Users did not switch their cars very often, only a total of 55 switches occurred as denoted in Graph C. Out of these, 46% of players switched to the “Fairlady“, 45% switched to the “Bladeglider“ and only 9% switched to the Prius. As for the color distribution, the users preferred a red car by far (39%), followed by green and blue (22% each) and the less popular white (9%), yellow (5%) and grey (3%). In total, cars were recolored 243 times.

The average time to complete an engagement is shown in Figure 8. The engagement task was designed so it could be easily completed under 5 minutes. However when we look at Figures A.15, A.16, and A.17 we can observe that there are players who needed much longer to complete the engagement, and even across multiple play sessions. Moreover for every server, the median is set around the 4 minute mark. This brought us to consider some outlier groups when studying the time that took for each player to complete the two quests. If we deem all times over 60 minutes outliers, the average engagement completion time drops off to 4 minutes and 23 seconds. It further diminishes to 3 minutes and 53 seconds, if we consider all times over 30 minutes as outliers, to 3 minutes and 26 seconds with outliers over 10 minutes and to 2 minutes and 45 seconds, if we ignore all times over 5 minutes.

In terms of car color, the main difference between the users that finished the engagement and the general population is an increased preference for the color gray in detriment for the color yellow, as we can observe in Figure 9.

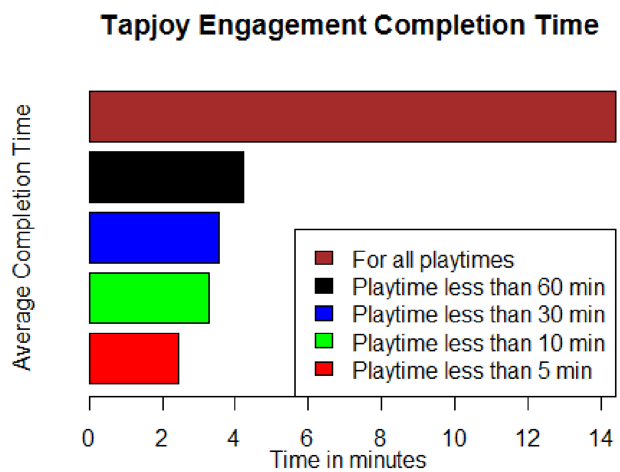

Figure 8: The average engagement completion time for different categories of players. The categorization is done on the basis of whether players finish the engagement (doing atleast 2 quests) in less than a certain threshold time. These categories contains mutually non-exclusive set of players.

The players who finished the engagement seem to have bought more upgrades in relation to refueling. This can make us hypothesize that these players are more interested in exploring the game. Given the fact that very player starts off with a Prius, we can see that Fairlady was the most popular car choice. Player did not switched car very often1. These players seem to partake in every game activity, and as expected from the transactions graph in Figure 10, trips to the garage are more common than trips to the Gas Station. On average the users who completed the engagement played for more 10 minutes, and did an average of 2.1 more quests.

Table 1: This table presents the car switches performed by player who completed the engagement.

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

5. Results

5.1. 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

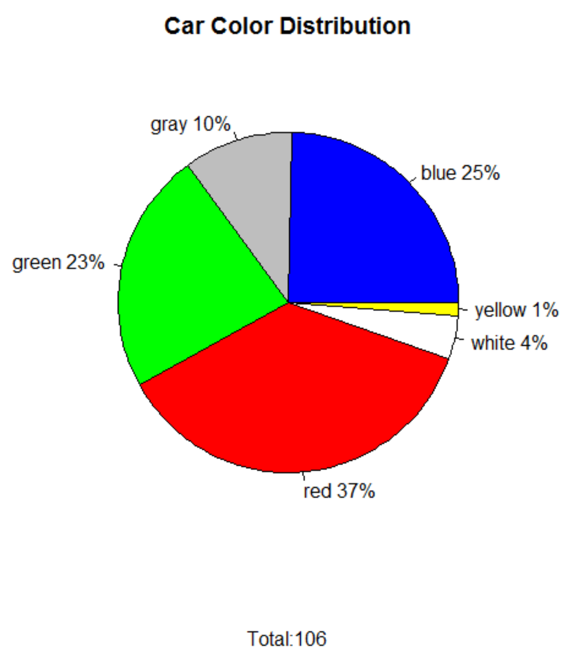

Figure 9: Car color distribution for the users that finished the engagement.

Table 2: This table presents the activity switched during the game for player who completed the engagement.

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

information, speed (the magnitude of the velocity) and average acceleration (the magnitude of the acceleration) is calculated using Equation 1:

$$Speed(i) = \frac{distance(i, j)}{i - j} \tag{1}$$

where $distance(i, j)$ is calculated by the Euclidean distance. i and j represent two neighboring time-stamps. The average acceleration is calculated by Equation 2:

$$Acceleration(i) = \frac{Speed(i) - Speed(j)}{i - j} \tag{2}$$

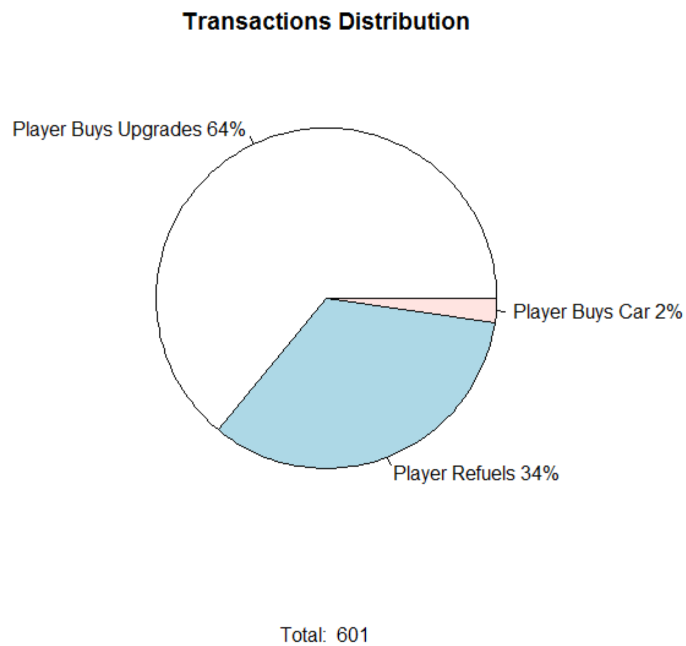

Figure 10: Transactions distribution for the users that finished the engagement.

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 the data, the acceleration of the car is between -4 m/s^2 and 4 m/s^2 most of the time, and the total range is set from -6 m/s^2 and 6 m/s^2. We define smooth acceleration (and deceleration) as the characteristic of eco-driving and calculate the rate of change of acceleration, i.e., jerk between the two consecutive time-stamps using Eq. 3:

$$jerk(i) = \frac{Acceleration(i) - Acceleration(j)}{i - j} \tag{3}$$

As in Prendinger et al. (2014b), we define 22 categories for the jerk defined in Eq. 3, starting with $[-inf, -100]$ up to $[100, +inf]$. Giving these categories smooth acceleration is defined as the $[-10, 0]$, and $[0, 10]$ intervals.

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 which is used to group 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 (Hartigan and Wong, 1979) 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 Eq. 4

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

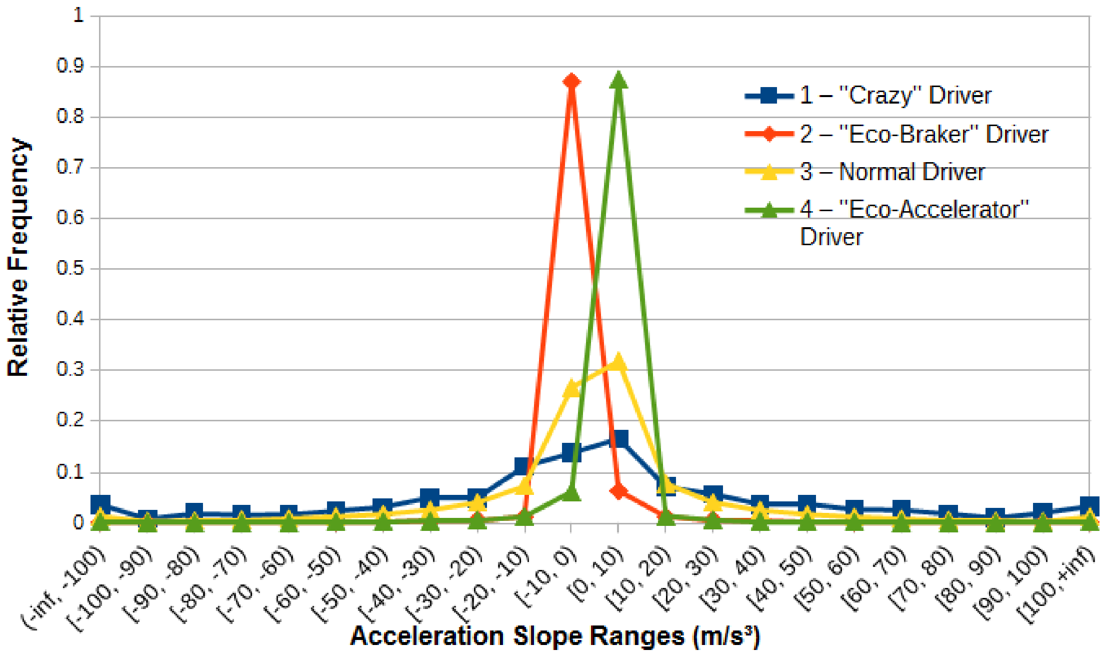

Figure 11: Clustering of users' driving behavior based on the rate of change of acceleration.

We analyzed k from 2 to 15 and selected the k according the elbow criterion Thorndike (1953) that achieves a low SSE, while using the least amount of clusters in order to explain the data. To evaluate the eco-friendliness level of these clusters, we introduce Eq. 5

$$factor_{eco} = F_{r[-10,10]} \tag{5}$$

which corresponds to the relative frequency of the smooth acceleration bin. The closer this factor is to 1, the more eco-friendly the cluster is.

5.2. *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. 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. Using the 'elbow' heuristic to minimize the sum of squares due to error (Equation 4), four clusters are created as shown in Fig. 11. Eco-driving is determined by the relative frequency of smooth acceleration in the interval $[-10, 10)$. Drivers in Cluster 1, "crazy" drivers, have a low presence in the smooth acceleration category, and performed more abrupt brakes and steep acceleration. Clusters 2 and 4 have a high prevalence of smooth acceleration, whereby drivers in Cluster 2 focus primarily on smooth braking, and drivers in Cluster 4 focus on smooth accelerating; hence, we call them group "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.

Detailed results for the clusters are shown in Table 3. Please note that the cluster for "normal" drivers aggregates the vast majority of the drivers and shows an intermediate percentage

Table 3: This table presents a summary of the clusters. Here we present the relative frequency of smooth acceleration for each cluster; the $factor_{eco}$. Moreover the majority of players fits the "Normal" driver profile with a considerable amount of smooth acceleration, mixed with abrupt changes. The percentage of users classified as "Crazy" (8.08%) is less that the sum of the two eco-friendly clusters ("Eco-Brakers" and "Eco-Accelerators"), combined.

Cluster	$factor_{eco}$	% of Users	Cluster Label
1	0.30	8.1	"Crazy" Driver
2	0.93	7.6	"Eco-Braker" Driver
3	0.59	73.1	"Normal" Driver
4	0.94	11.2	"Eco-Accelerator" Driver

of time on the smooth acceleration interval (59%).

The users who finished the engagement did not seem to strive away from the proportions obtained when performing the clustering analysis, which can be seen in Table 3. The main difference

5.3. *Types of Players*

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

First, we are interested in the correlation between painting a car in a particular color and being an "eco-unfriendly" driver.[6] "Eco-unfriendliness" is characterized by the levels of the $factor_{eco}$ parameter in Table 3. This enables us to order our clusters from the most to the least eco-friendly cluster: Cluster 4 $<$ Cluster 2 $<$ Cluster 3 $<$ Cluster 1, or "Eco-Accelerator" $<$ "Eco-Braker" $<$ Normal $<$ "Crazy".

We use Kendall correlation coefficient to find associations between the data, which enables us to understand the relationship between the ranks of the variables. We performed this analysis for every car color, for each server. In case of the Kendall correlation coefficient, correlations less than 0.10 are considered very weak, correlations between 0.10 and 0.19 are considered weak, correlations between 0.20 and 0.29 are considered moderate, and correlations greater or equal than 0.30 are considered strong.

We noticed that the different servers have distinct biases for the color chosen and how eco-unfriendly a user is according to his profile obtained by clustering the acceleration rate. I CANNOT UNDERSTAND THE PART AFTER "AND HOW...." CAN YOU REFORMULATE IN MORE STRAIGHTFORWARD LANGUAGE?

For example, painting the car green tended to be more associated with driving eco-friendly both in Europe, with Kendall correlation coefficients of -0.22, and in America the association is weak -0.11, while in the Asia dataset, despite the association being weak, it points to a weak relation towards eco-unfriendlyness with a Kendall coefficient of 0.14. Here we can only say that the European server has a slight bias towards being more eco-friendly.

[6] In the real world, such information can be interesting for insurance companies.

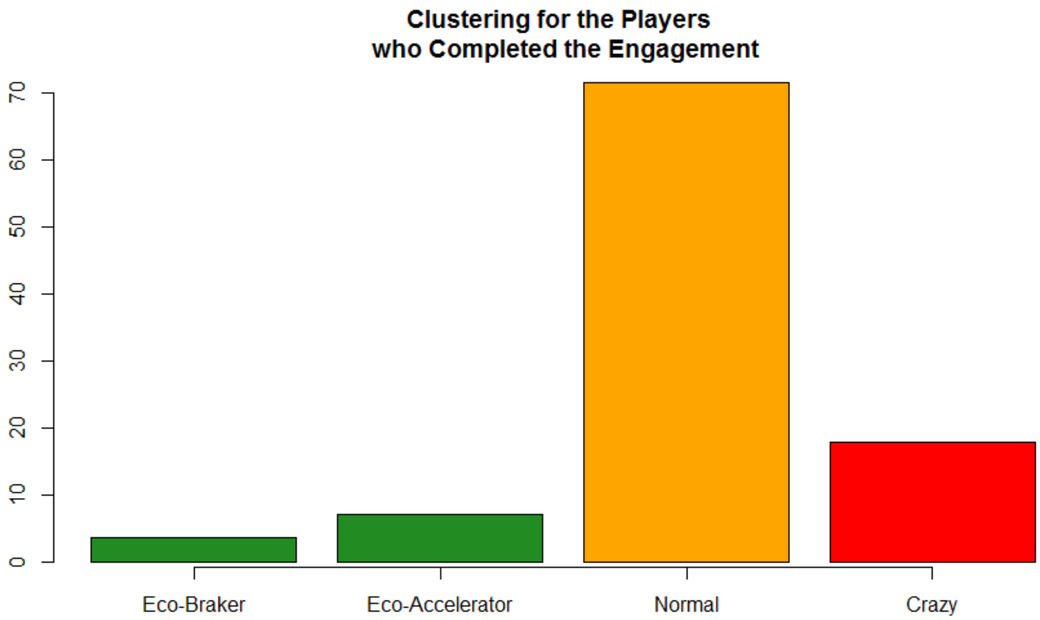

Figure 12: Results of the cluster classification on the users that finished the engagement.

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Painting the car blue is associated with eco-unfriendly driving in Europe (0.60) and and in Asia (0.30), while there is no apparent relation in America (0.001). The red color also seems to have no impact in the America dataset (0.03), whereas the red painted car is associated with eco-friendly behavior in Asia (-0.45), and haS a slight association with eco-unfriendly driving in Europe (0.26).

The color gray seems to be associated with being more eco-unfriendly in a weak way in every server with the correlation coefficients being greater than 0.11 for Asia, up to Europe with 0.17. The color yellow has a moderate association with being more eco-unfriendly in Asia (0.20).

Next, we are interested in types of players as judged from their in-game activities. As explained in Section 3, users have access to five different activities in the game, They can (1) drive, (2) go to the garage, (3) go to 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 spend their time within the game, and what activities they engage in. 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. This is the median time to finish the Tapjoy engagement. I THINK THIS SHOULD BE MADE CONSISTENT WITH THE PLACE WHERE WE ACTUALLY DISCUSS THE DURATION OF PERFORMING THE ENGAGEMENT.....

Table 4: 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

Using the ‘elbow’ heuristic to minimize the Sum of squares due to error (Eq. 4), we found found activity distribution profiles (see Table 4). We obtained four profiles regarding the way users spent their play time. Cluster 1 and Cluster 2 are labeled as “Refuelers”, and “In-Game Explorers”, respectively, as these players spent a great part of their time doing in-game activities others than driving. Then we have a cluster of drivers that basically only drive; the center of mass of this cluster has a driving percentage of 97%, hence we call this group “Pure Drivers”. Finally, there is a cluster of users that engage primarily in driving while performing other in-game activities as well; we label this cluster as “Drivers”.

Figure 13 shows that pure drivers (as players) are prevalent across every type of driver. If we consider being interested in only the driving aspect the profiles “Drivers” and “Pure Drivers”, we see that only the “Normal Drivers” have an equal percentage of players only interested on the driving aspect and those who focused a lot on exploring other game activities, such as browsing and buying upgrades, painting cars, etc. PLEASE RE-WRITE THE PREVIOUS SENTENCE INTO UNDERSTANDABLE FORMAT.

Surprisingly the “Refuellers” have a high prevalence among the eco-friendly drivers (“Eco-Brakers” and “Eco-Accelerators”). One reason to explain this behavior is the fact that the eco-friendly users were more conscious of their fuel tank data.I AM NOT SURE BUT EACH DRIVER CAN SEE THE STATUS OF FUEL ALL THE TIME, DOES NOT HAVE TO GO TO THE GAS STATION, RIGHT? Not surprisingly, the players labeled as “Crazy Drivers” are mostly “Pure Drivers” (35%) and have the lowest prevalence of “Refuelers”. Finally, “Normal Drivers” had the highest percentage of “In-game Explorers”.

5.4. Analysis of Users’ Eco-Driving Evolution

In this section, we aim to test the hypothesis that users become more eco-friendly drivers over time. This is an obvious assumption for an eco-driving interface.

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: 7, 8, 9 and 10 minutes. Players who drove less than these times are filtered out. For the remaining players, driving behavior data for their entire driving duration is collected, except for the first two minutes, which is considered as training time. Then, for each group of players that correspond to a different play-time, clustering based on the probability of their jerk distribution (see Eq. 5) is performed to create the driver types clusters after a formal train session of first two min-

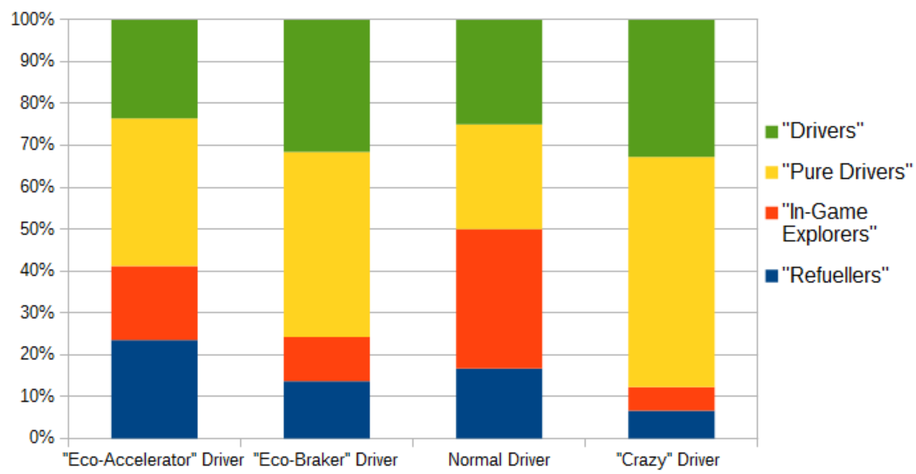

Figure 13: Distribution of the activity clusters among users' driving profile.

utes ends. TO BE SURE: 2 MINS TRAINING TIME, THEN 2 MINUTES CLUSTERING TIME, AND THEN THE REST. RIGHT?

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 as "Eco-friendly", "Gentle", "Normal" and "Crazy".PLEASE BRIEFLY EXPLAIN WHY THE NAMING IS DIFFERENT. 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.

A total of 2045 users were selected.NOT SURE I UNDERSTAND. SELECTED FOR WHAT? IN THE FIGURE YOU HAVE 107+76+66+47. WHAT'S THE MEANING OF 2045?

Figure 14 shows that "Gentle" drivers dominate in all four clusters, whereas "Crazy" drivers have the smallest share. The share of "Gentle" drivers is 32.7%, 32.05%, 31.81% and 29.78% for the players who played more than 7 minutes, 8 minutes, 9 minutes and 10 minutes respectively, while the share of "Crazy" drivers is 17.75%, 15.5%, 13.6% and 17%. WHAT DOES "SHARE" MEAN. I DON'T SEE ANYTHING LIKE THIS IN THE FIGURE...I ONLY SEE NUMBER OF PLAYERS.... The data shows that the order of share of players according to the driver-types across all the groups is: "Crazy" $<$"Normal" $<$"Gentle" $<$"Eco-friendly". This suggests that after due to the result of training (done for first 2 minutes of playtime), only a few drivers continue to drive is least eco-friendly way. PLEASE REWRITE

To further analyze the multi-plot Figure 14, we set a convention to read it by row. For all the plots, it can be seen that the eco-friendliness of the "Crazy" drivers improves significantly over time and becomes comparable with that of the "Normal" drivers. The eco-friendliess of "Gentle" drivers also increases. However, even the the high-performance users, i.e., the "Eco-friendly" drivers continue to maintain their edge over other driver types, although their performance decreases over time.

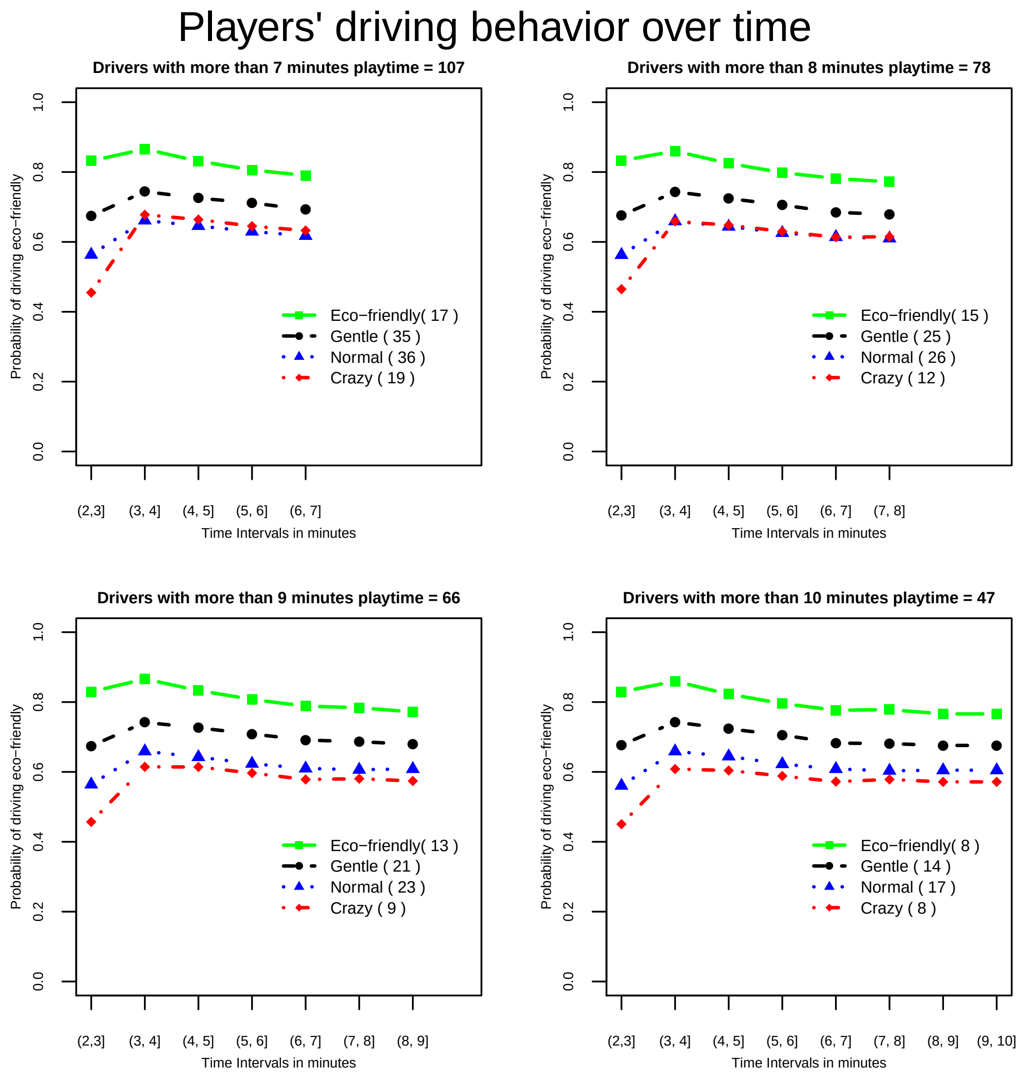

Figure 14: Users' eco-driving behavior over time. PLEASE REMOVE THE BIG CAPTION FROM THE PICTURE; ALSO PLEASE INCREASE FONT SIZE OF X AND Y AXIS LABELS.

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 fatigue.

It is interesting to notice that for all the four driver types across all the four groups, the peak improvement occurs between 3 minutes 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. PLEASE MAKE SURE THE 4 MINUTES MEDIAN IS CONSISTENT WITHIN THE PAPER. Thus, it can be hypothesized that players' motivation to "perform" somewhat decreases once they get paid. I DELETED THE TEXT FOR IN-GAME

CURRENCY. THE RECEIVED CURRENCY FOR A DIFFERENT GAME, NOT ICO2.

Overall, our results support the hypothesis that the players who drive less eco-friendly in the beginning of their play-time, improve their driving over time.

6. Conclusions

I CHECKED THIS SECTION ONLY ROUGHLY.

In this paper, we describe iCO_2, a game-like simulation platform for collecting large-scale driving behavior data and other data on users' in-game activities, such as upgrading the user's car, while offering a virtual environment for the practice of eco-driving. 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 eco-friendly. In this way, our system is related to other activities aimed at attracting users' work, such as Games with a Purpose or crowdsourcing. The proposed version of iCO_2 extends the previous version (Prendinger et al., 2014b) by a quest system and a "garage" to improve the capabilities of the player's vehicle.

The main technical contribution is our iCO_2 campaign. Since our simulation platform is developed as a mobile app, we could 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 results 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 is to use the information of player types ("Eco-Braker", "Crazy", etc) 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 the players who appear to be less eco-friendly in the beginning of their play-time improve as they play further. 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 having smooth acceleration in discrete uniform time-intervals.

Almost 20% of the users continued to play the game after the required two quests were completed. The usage data also revealed some interesting details about users' in-game behavior, such as play-state switching, transaction, car switching and car color switching.

Future work will also try to increase the re-playability of the game to be able collect data of users over time. This opens up entirely new ways of feedback mechanisms to users as we may learn the user's behavior and reactions.

7. Acknowledgments

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Appendix A. Play Sessions

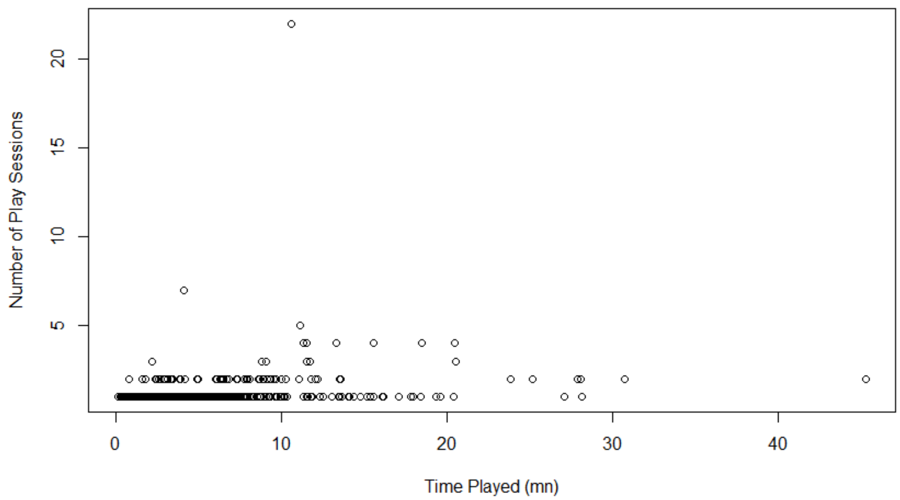

Figure A.15: Distribution of play sessions by total play time for Europe.

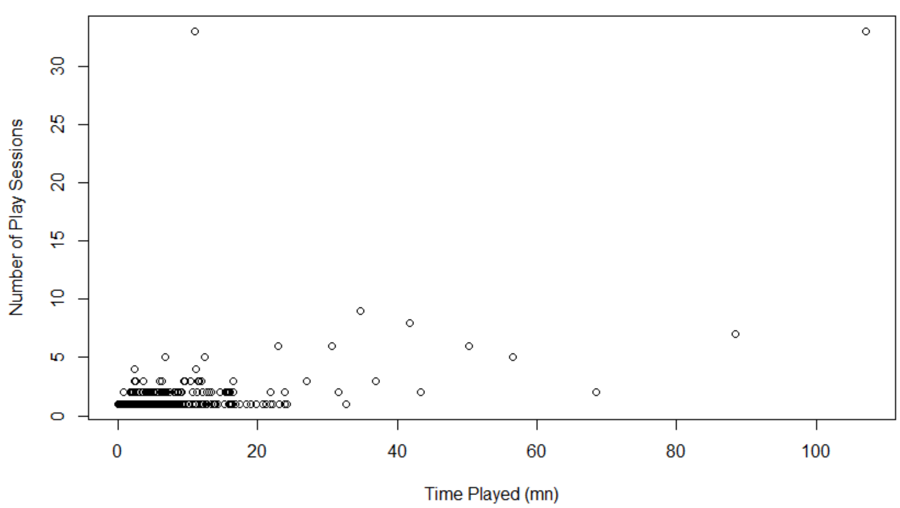

Figure A.16: Distribution of play sessions by total play time for Asia.

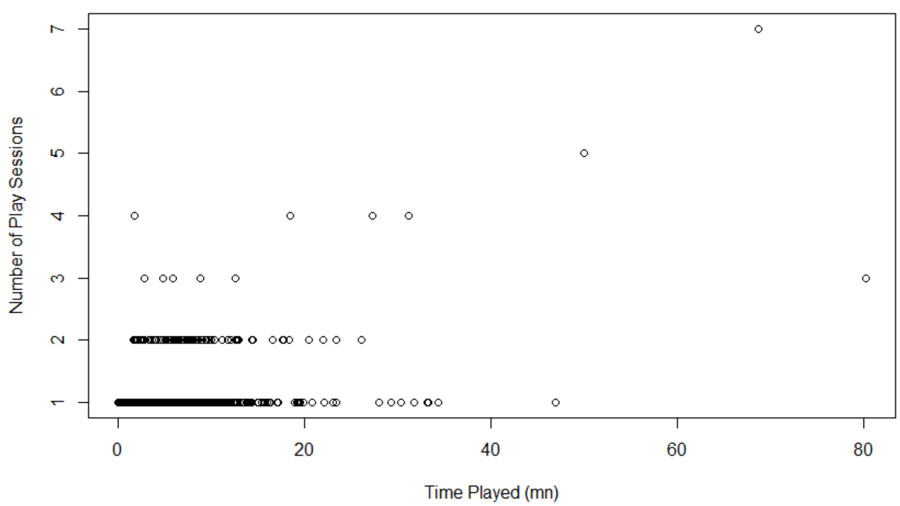

Figure A.17: Distribution of play sessions by total play time for America.