Gamification of EcoDriving Behaviours through Intelligent Management of Dynamic Car and Driver Information

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Abstract. Driving style is seen not only to become a significant cause of green-house gas (GHG) and other air pollutant emissions but also a critical parameter regarding road safety, with huge social & financial adverse effects. In this work we provide a conceptual architecture of a highly innovative and interactive Serious Games platform that will empower and guide users to adopt an eco-friendly driving style. This will be achieved, without distracting users from safe driving, through a multidisciplinary approach aiming at the development of a user friendly, unobtrusive multi-player gaming environment, where the users will not only play collaboratively/competitively using their mobile device but also using the car itself and their own bodies, thus turning eco-driving into an immersive and highly motivating experience. The sensing infrastructure of the proposed system will not only acquire data related to driving from an OBD sensor that will capture a complex set of parameters related to eco-driving, but will also sense environmental and physiological parameters of the driver, so as to better position the state of the system (car) in context (environment, user). The use of virtual user models and cognitive modeling of the users, will further boost personalization and adaptation of the game itself with respect to the needs of the individual driver. The impact of such a holistic and innovative approach is huge and the foundations laid here are expected to result in a widespread adoption of sensor-based gamification platforms in areas going far beyond eco-driving

Keywords: Gamification · Ecodriving · Augmented reality · Virtual reality

1 Introduction

Road transport is one of the major causes of the environmental pollution. According to a recent study [4] it is responsible for about 30% on the total emissions of CO2 into the atmosphere. Among the actions individuals can take to reduce their green-house gases associated with personal transportation, there is to operate their current vehicles more efficiently [7]. Recent studies [5] have shown that in certain situations the driver's driving style can result in differences in terms of fuel consumption (and therefore CO2 emissions) from 2 up to 35% between a calm driver and an aggressive one [58]. One

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important action to reduce the environmental impact caused by road transport is therefore to educate drivers to adopt a driving style that is as eco-friendly as possible. At this point, it should be also mentioned that numerous studies have underlined the substantial ecological [34], economic but, also, road safety adverse benefits that can be derived from adopting eco-driving behaviors [7, 38]. Road traffic injuries are a major public health problem in the WHO European Region and cause the premature deaths of some 120 000 people every year, they are the leading cause of death in children and young adults aged 5 to 29 years. In addition to these deaths, about 2.4 million people are estimated to be so seriously injured as to require hospital admission each year. Although there are several potential causes of traffic crashes, and the injury severity sustained in the crashes, a leading cause is aggressive driving. Driving style is influenced by a complex mixture of technical, social, psychological [31] and cultural factors, with the latter tending to have a greater influence than the former: How a driver reacts to a given situation is more likely to be influenced by factors such as his age, values, social position, concentration, stress and attitude to risk, than by traffic regulations or the driver's ability to use the vehicle controls [46]. It is more a question of attitude than ability. To change their driving behavior, car drivers have to change their automated behavior into deliberately controlled behaviour – a process that requires considerable effort. More importantly, car drivers need to be motivated to change their behavior [32] (i.e., they need to form an intention [31] to practice eco-driving), and second, they have to put this intention into practice. Many studies have report cultural, technical, and educational barriers inhibiting its adoption. Recent studies [18] also found that eco-driving behaviours are related to time saving and safety goals, therefore, can be easily violated in demanding traffic environments or in time pressure situations. The most important educational element in changing driver behavior is the positive feedback from taking the desired action. Behavioral theory strongly confirms that unless the individual can see or feel the results of his/her actions—preferably on an immediate and continuous basis—that individual is unlikely to maintain the behavior over time. Therefore, as eco-driving results are so small, unless personalized feedback on the collective effort is provided, the driver is unlikely to perceive important changes in his driving style affecting the fuel economy and the society in general. To this end, innovative strategies that will increase driver motivation to make changes in their driving behaviour are required. Serious gaming and Gamification has been positioned as a powerful approach, tool, or set of techniques that guides targeted behaviour change to improve the way that various activities are undertaken so that those involved begin to take the desired actions while they experience more fun, enjoyment, and pleasure in their tasks [47]. The gamification term refers to a designed behaviour shift through playful experiences and became popular in 2010 and dominates especially areas with human interaction and focus on the quality of the experience since then [42]. However, in order to effectively motivate users to adopt desired behaviors, the games should provide information so that the users themselves will be able to evaluate their behaviour and increase their awareness on the negative consequences that it may have. In this context, we aim to develop highly innovative and Interactive Serious Game Platform that will motivate users to adopt an eco-friendly driving style without distracting them from safe driving. The developed playful interventions will be adapted to the user characteristics through an intelligent unobtrusive sensing platform that will utilize late-breaking personalized user models so as to optimize the individuals driving behaviour shift through playful experiences that will take place in the real world and real-time rather than in a virtual/ simulation environment, which is the current state-of-the art in eco-driving education. Our major objective is to provide a highly innovative and interactive Serious Games platform, named GamECAR, empowering drivers to manage their driving behavior by: i) conveying educational messages, ii) encouraging certain activities through game-based elements such as competition or rewards and iii) providing them with user friendly tools that will increase their awareness of their ecodriving state and effectiveness of the intervention strategies. Critically, the proposed system is expected to guide users to adopt an eco-friendly driving style, without distracting them from safe driving, through a multidisciplinary approach aiming at the development of a user friendly, unobtrusive multi-player gaming environment, where the users will not only play collaboratively/competitively using their mobile device but also using the car itself and their own bodies, thus turning eco-driving into an immersive and highly motivating experience. A pipeline of advanced algorithms and data fusion techniques starting from raw measurement processing, feature extraction, EcoDriving indicators and personal profile data will ensure EcoDriving state awareness and a timely optimal intervention strategy will be provided using the digital gaming technology. In addition, a ”personal driving guidance system” will empower drivers to optimize their action plans towards personalized preset goals and guidelines (e.g., maintain speed, switch off engine when stationary, shift up to low revs, etc). Finally the system will provide to the user i) Serious Games (including Augmented Reality (AR) games) responsible for monitoring driving behavior & delivering action personalized plans that will help user to maintain a green driving style without distracting them from safe driving and ii) a multiplayer gaming environment where users can monitor their ecodriving score evolution, set missions and invite other to participate collaboratively or competitively. The rest of the paper is organized as follows, in section 2 we give an overview of the existing eco-driving assisting systems, in section 3 we analyze the details of our approach and finally in section 4 we end with discussion, conclusion and future direction related to this topic.

2 Related Work

The current ecodriving systems can be divided into two major categories: i) the eco-driving real life applications and ii) the simulators. The most representative approaches available in the market are shortly described in the rest part of this section.

2.1 Ecodriving Mobile Applications and Driving Assistance Systems

Smartphone Applications: Studies have shown that eco-driving smartphone applications have impact on fuel efficiency (Tulusan et al., 2012). Greenmeter[43], FuelGood [54], TEXACARe [53] and Geco [40] are good examples of smartphone applications that have been developed in order to track fuel consumption and increase efficiency. Some of them works in real time since others provide a summary at the end of each journey. TEXACARe and Geco provide a score based on actions that have impact in fuel consumption and driver's behavior Remote Control Solution: WeNow [59] is a solution mainly aimed at vehicle fleets and aids them in increasing their overall fuel efficiency. The device of the platform is connected to the OBD II interface of the vehicle in order to be able to collect the relevant vehicle data such as mileage, fuel consumption, etc. Advanced Driver-Assistance Systems: FIAT®eco:DRIVE APP [24], Ford Smart Eco Driving [25], BMW Eco Pro[10], Honda®Insight Eco Assist system [27], Nissan Eco-Drive Support Technology, Subaru Ecology [49] and Mitsubishi ECO Drive Support [36] are fully implemented systems. Some of them are based on apps that communicate directly with the car which purpose is to improve the driving style, lowering fuel consumption and tracking the carbon dioxide emissions. Others are build-in systems providing feedback in real-time for maximizing the fuel efficiency. Finally, one approach acts as a medium between driver's actions and car's engine inputs to avoid non-eco behaviors, although the system turns this functionality off in cases of emergency. traction (e.i. driving at dusk, on slippery surfaces, snowy environments etc.). In this simulator, ecodriving is just an extra feature.

2.2 Ecodriving Simulators & Games

This section presents three simulators (ST Software Simulator Systems with EcoDriving Package, DriveSim and Simescar Silver – Simumak) and four games (EcoDriver, Stagecoach, Truck Fuel Eco Driving and SafetyDrivingSimulator: Car) that focus on teaching principles of EcoDriving to drivers. ST Software Simulator Systems Eco Driving Package [51]: The simulator teaches how to save up to 20% or 30% of fuel by applying another style of driving. It offers a way of experiencing a new driving style arising from being mindful about fuel consumption. The simulator focuses on both the financial and environmental gain obtained from this driving style.

DriveSim simulator [21]: The simulation program DriveSim allows the driver to practice as if he/she were commanding a real vehicle, thanks to its realistic situations and environment. DriveSim scenarios include real traffic and pedestrians. This program offers the possibility of doing different tours with any climatic settings, timing and traction: driving at dusk, on slippery surfaces, snowy environments, with rain or even practice emergency braking with and without ABS. DriveSim provides the opportunity for initial training on track, overtaking practice, driving on urban roads, service roads, roundabouts and efficient driving, among many other options. EcoDriver [22] tests the players driving in an endless, randomly generated environment, in an attempt to demonstrate the advantages of driving safely, economically and in an environmentally friendly way to the player. Players must master a dangerous terrain and treacherous traffic situations, all the while saving fuel and being aware of the situation on the road. Truck Fuel Eco Driving: This game places the player behind the driving wheel of a Renault Premium Optifuel, in order to let them discover the principles of economic driving. Different challenges in urban environments and secondary road networks are posed, in which the player needs to obtain the lowest fuel consumption possible and the highest commercial speed possible.

Table 1 depicts existing worldwide competing technology or products in this market place. Most of the available solutions simply provide educational messages without taking into account specific characteristics of the individual driver. In addition none

Table 1. Related projects and competitive products.

	GamECAR	Greenmeter	Garmin Mechanic with ecoRoute™ HD	FIAT eco:DRIVE APP	CarbonDiem	FuelGood	Honda Insight Eco Assist system	EcoDrive One Speedometer	Simulators (e.g. ST Software Simulator systems Eco driving package , etc. . .)	Games (e.g. EcoDriver,stagecoach ,Truck Fuel eco driving)
Driver behavior sensing	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗
Proper vehicle maintenance	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗
Mixture of social status, financial status parameters	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Environmental sensing	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Physiological data	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Direct feedback while driving	✓	✓	✓	✗	✓	✓	✓	✓	✗	✗
Indirect feedback	✓	✗	✗	✓	✓	✓	✓	✓	✗	✗
Education and feedback support	✓	✗	✗	✓	✗	✓	✓	✗	✗	✗
User models	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Customized personalized Interventions	✓	✗	✗	✗	✗	✓	✗	✗	✗	✗
Interactive Serious Games	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
Information visualization	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗
Customized information visualization	✓	✓	✓	✗	✓	✓	✗	✓	✗	✗
Driver Community Platform	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗
Multiplayer game support	✓	✗	✗	✓	✗	✗	✗	✗	✗	✓
Vendor	**GamECAR**	HUNTER	GARMIN	FIAT	CarbonDiem	Energy Saving Trust	HONDA	JoyNow!	Various vendors	Various vendors

of them guides targeted behaviour change to improve the way that various ecodriving activities are undertaken so that those involved begin to take the desired actions in order to adopt a more efficient driving style.

3 GamECAR Approach and Methodology

An ecodriving coaching solution needs to realize the difficulty of trying to change behavioral patterns that have been internalized over years and should try to take account of a driver's social and cultural preconceptions. For example, it will be hard to encourage a driver to let the car coast in neutral if he or she believes that this is forbidden or wrong. And it will be hard to encourage a driver to shift up early whilst applying moderate gas pedal if he thinks this combination might strain an engine or waste fuel. In addition, unlike private car drivers who respond well to financial incentives for adopting sustainable driving behavior, corporate drivers are not financially motivated, as their fuel costs are reimbursed by their employer. Therefore, a coaching solution needs to be aware of the driver's reservations in order to address them head on, for example, by explaining that regardless of the accelerator pedal position, a modern engine will not inject excess fuel. A powerful approach, that have been proved very effective in guiding targeted behaviour change to improve the way that various activities are undertaken is gamification. GamECAR aims to better understand and change the driving behavior and its relation to a complex mixture of technical, social, psychological and cultural factors by using the Gamification approach. The proposed system aims to provide both direct and indirect feedback in a playful manner to the driver, through user specific Interactive Serious Games that will not distract him/her from safe driving. The distraction monitoring is based on physiological measurements (e.g., heart rate, respiration rate, etc.). It will strengthen the driver's motivation of adopting an ecodriving style through the delivery of personalized feedback, monitoring driving inattention, guidance and education. Through user specific interventions, ecodriving game aims to define an ecodriving score. The score is initially constructed from prior knowledge on the field and then globally updated based on analysis of long-term observations of all drivers' states. This update will be then applied to the individual user models, modifying them accordingly, to fit different needs per driver.

The developed interactive Serious Games platform will empower and guide users to adopt an eco-friendly driving style. This will be achieved, without distracting users from safe driving, through a multidisciplinary approachaiming at the development of a user friendly, unobtrusive multi-player gaming environment, where the users will not only play collaboratively/competitively using their mobile device but also using the car itself and their own bodies, thus turning eco-driving into an immersive and highly motivating experience. The sensing infrastructure of GamECAR, shown in Figure 2 and 1 will not only acquire data related to driving from an OBD sensor that will capture a complex set of parameters related to ecodriving, but will also sense environmental and physiological parameters of the driver, so as to better position the state of the system (car) in context (environment, user). The use of virtual user models and cognitive modeling of the users, will further boost personalization and adaptation of the game itself with respect to the needs of the individual driver.

3.1 GamECAR Architecture

As far as the architectural view is concerned, GamECAR platform consists of various components, depicted in Figure 1, which are described as follows: Car Sensor Network: It consists of the wearable wireless body area sensors and an OBD II sensor, designed to continuously monitor vehicle characteristics, driving style and a cluster of physiological parameters while driving. This car sensor network (CSN), records several parameters such as heart rate and respiration rate, which are used to monitor driver inattention and in order to estimate correlations with the driving style. Mobile Device/Gateway: The CSN system will be connected to the Mobile device (e.g., Mobile phone, Tablet), which will send the data to the Streaming Data Sub-System. This sub-system is initially responsible for fusing the streaming data to the Mobile Device/Gateway wirelessly via Bluetooth, to enable the Real Time Analysis component, where the handling of risk situations is conducted with the use of real-time data mining techniques. The Streaming Data Sub-System also sends data for storage to CSN. Real time analysis conducted in Streaming Data Sub-System, will inter-connect with the AR GAME, so as to produce warnings to drivers in case of danger. It will also interact with the VUM, to update it in case of risk. Offline Analysis Server: It consists of a central server infrastructure that is responsible for Offline Analysis of data and communication with a remote Database, that will be mainly used for scientific analysis and VUM handling. Data from Real Time Analysis conducted in Streaming Data Sub-System will be transmitted once a day through the Internet to the Offline Analysis Server, to aid offline analysis. In the Offline Analysis Server, tests for ecodriving assessment will be carried out, in the direction of a formal ecodriving indicator, reflecting changes in driving styles through the long-term adjustment of the VUM. The adjustment parameters as well as the results will be transmitted to the Remote DB, for storage and feedback to the offline analysis, as well as to the VUM, through data fusion. Data fusion will be carried out under a Big Data analysis scenario, taking into account the VUM adjustments in case of risk in CSN, hence the VUM and data fusion interaction. Additionally, all data obtained from the Streaming Data Sub-System will be stored in the remote DB, to capture driver current status and correlate it to his/her driving behavior history, and combine it with the already fused VUM data to construct a long-term frailty monitoring system. Intervention Sub-System: Implements the Interactive Serious Games supporting AR rendering, interacts with the Offline Analysis Server module, but through the aforementioned offline-online data broadcasting, will also be able to comprise short-term events. This sub-system will receive input from the remote EcoDriving assessment implemented in the Offline Analysis Server, to produce driving style recommendations and vehicle maintenance plans to older vehicles. These changes will then be communicated back to the offline system, in order to reach the VUM, and also be stored for EcoDriving score evaluation.

3.2 Data Analysis

Towards assessing driver's behavior and driving performance, a large amount of data need to be sampled, transmitted, stored and processed. Sensor devices often failure to provide continuous data streamings, due to transmission errors, threshold errors, or

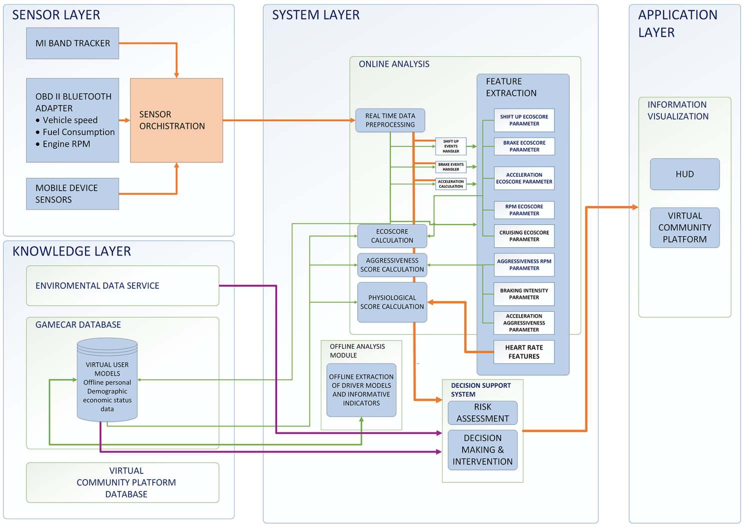

Fig. 1. GamECAR system architecture.

generic system failures. To provide reliable inferences, further data processing is required, which provides more solid results when is based on continuous values without missing entries and other type of abnormalities. Possible data inconsistencies and other anomalies need to be identified while applying data mining techniques is an essential step towards the extraction of ecodriving performance indicators and driving style classification.

The three main input sources of the project are focused on (i) the vehicle, (ii) the environment and (iii) the driver, acquiring and analysing all relevant data available to construct a complete and personalized profile for each instance. The data is then passed to the EcoDriving assistance module, which comprises of three sub-modules, responsible for feedback generation, game elements and information visualization. Functionalities of the online data analysis and offline data analysis are also presented, along with their general design directives and features. These include real time information about 1) Active transmission gear 2) Intake air temperature 3) Engine coolant and oil temperature 4) Fuel type, consumption and tank level 5) Throttle position 6) Engine revolutions per minute (RPM) 7) Calculated engine load 8) Vehicle speed 9) Emission requirements to which the vehicle was designed

all particularly relevant towards constructing and maintaining a multi-fold and accurate model for the driver, which is appropriately parameterized according to his/her vehicle. It is important that these data should be further normalized to account for several varying parameters, such as road type and traffic, weather conditions, etc. Most of this information is readily available from relevant cloud services. The main purpose of this post processing is to prohibit factors beyond driver's control affect the evaluation of his/her Eco friendliness. This is important for conveying a sense of fairness to the participating drivers/players, which in turn preserves engagement and motivation in the long run. Apart from vehicular and environmental data, the monitoring of the driver per se, via indicative biosignals can be proven crucial in forming an accurate profile of not only driving behaviour under certain circumstances, but also of broader personality traits in long-term frames. GamECAR is going to utilize common wearables which provide real time measurements for heart rate, respiration rate and muscle activity. This type of data is highly correlated to the driver's psychological state, and are parsed together with the vehicle data to the EcoDriving assistance module. An overall presentation of the online analysis dataflow is presented in Figure 2

Data Preprocessing. As global telecommunication market shifts towards the 5G era and the fascinating technological advances it proclaims [9, 55], it becomes obvious that new applications and verticals with a tremendous affect in our everyday lives are approaching. The deployment of a highly heterogeneous, always available, brisk and agile network, offering inherent support for billions of interconnected devices with less than 1 millisecond end-to-end latency [6], will transform almost every application from simple daily entertainment to autonomous private transportation. The automotive domain is somehow divided into two separate yet highly consolidating tracks, autonomous driving vehicles (ADV) [56] and vehicle-to-everything (V2X) communication [57], with V2X act as a key technology enabler for ADV by allowing moving vehicles to approach each other more safely, thus enabling traffic flow optimization techniques and increased situational awareness. Vehicle-oriented notifications and alerts are propagated to nearby infrastructure, properly equipped pedestrians or other vehicles, rendering every involving entity capable of reacting fast and efficiently regardless of the situation [26] for instance, to the now hazardous cases of blind intersections, closed curves, lane switching and overtaking which often cause fatal car accidents worldwide. Smart Cities all around the globe are deploying dedicated infrastructure, partially based on resource savvy architectures such as Multi-Access Edge Computing (MEC) or Fog Computing [6, 1] paradigms, for facilitating V2X communication in a seamless manner, since citizen security and effective public/private transportation are considered top priorities. However, one of the keys to efficient and secure V2X communication applications is the ability to deliver informative messages, even based on partially fragmented datasets. Recently, novel signal processing tools such as matrix completion (MC) have been widely adopted for mitigating similar effects in many research fields such as computer vision [60] or signal reconstruction from partial observations. Their strong benefit is that they ensure exact reconstruction of a low rank matrix given a sufficient number of observations [13, 11]. Several modifications of the classical MC problem allowed the application in undirected graphs [28] and subsequently in 3D models[57]. Furthermore, [12] presented the recovery of signals from a sampling of its Fourier spectrum via matrix completion. In this section, motivated by the necessity for fault tolerant systems that will extract information from incomplete datasets, as well as the omnipresent demand of limited data transfer through the congested Smart City networks, we present an efficient and low cost method of managing non-uniformities and uncertainties in vehicle-related data. Capitalizing on the low-rank property of the generated matrices compiled by partitioning and stacking timeseries data, we formulate an approach that offers higher reconstruction quality as compared to the traditional MC approach, at fast execution times. More specifically, the contributions of the proposed work [39] can be summarized on the following points: 1) Formulation of a Laplacian based matrix completion to cope with missing entries in timeseries 2) Establishment of an efficient approach to deal with computational complexity of the issue under investigation This solution will allows us to retrieve adequately detailed information from smaller or compromised datasets through an algebraic interpolation process that intends to effectively fill the missing information gaps without changing the overall essence of the actual dataset. Depending on the use case, the proposed solution could be used for analytics retrieved from artificially reconstructed data or simply as a method of lowering the threshold of the necessary amount of data needed for a specific decision.

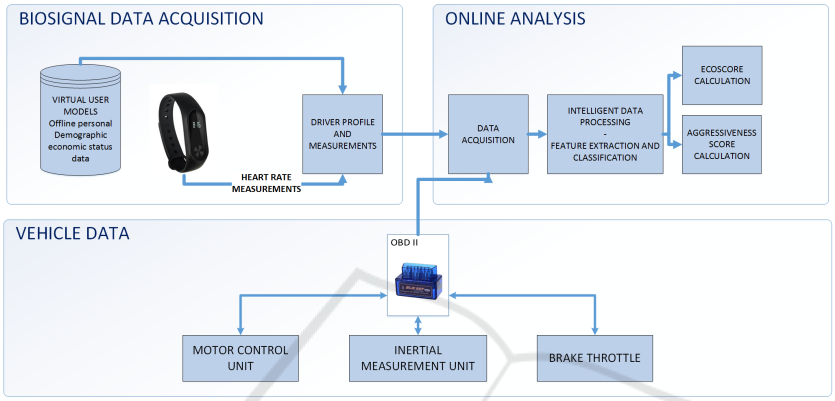

Fig. 2. Online analysis datastream.

Extraction of Informative Indicators. For obtaining all available data from the driver, the vehicle and the surrounding environment of each driving session, a dedicated network of sensors was utilized. More specifically, the driver may wear (i) the Xiaomi MiBand 1S tracker which provides heart rate information, (ii) the Polar H7 band also for recording heart rate signals and (iii) the Spire Stone respirator which measures the expansion and contraction of the individuals' torso and categorizes its breath as calm, tense or focused. An OBD II Bluetooth adapter is attached to the car's parallel port, transmitting vehicle-related data such as speed, fuel consumption, engine RPM and throttle position to a paired mobile device, wirelessly, using Bluetooth communication protocol. On the aforementioned mobile device runs a custom Android application in charge of (i) collecting all wirelessly transmitted data traces from both the wearables and the OBD, (ii) obtain enviromental data related to weather, traffic and road condition from third-party online repositories, (iii) recording additional data from all its embedded sensors, such as 3D acceleration, geolocation data and timestamps, (iv) aggregate all data into one dataset before transmitting them to an online repository for further analysis and long-term storage, the GamECAR Database. The application also includes a real-time data preprocessing module which applies several algorithmic techniques to the accumulated data, as well as a feature extraction module responsible for identifying high level features and detect events while driving. Such events may involve shift up and braking or changes in the vehicle's acceleration and the driver's heart rate. These extracted features are the direct input of the physiological score calculation module and are also cross-correlated with metrics retrieved from the GamECAR Database.

Provided that the GamECAR database contains analyzed data for each user, the physiological score integrates historical, preprocessed and real-time data, thus providing a holistic overview of an individual's behaviour on the road.

Parameters for the Ecoscore Estimation. Based on state of the art gamification approaches [16], the ecoscore aims to penalize high RPM values during gear shift-up and cruising, abrupt braking, high acceleration. In the same direction, the aggressiveness score aims to penalize high lateral acceleration, abrupt braking and high variances in throttle position and RPM. Ecoscore is a driving style indicator, namely a tool that shows drivers' ECO driving performance and, consequently, their efficiency during their trips. By analyzing the driving behavior, individual drivers can dramatically improve their driving style. In this way, we take into account the main parameters which can negatively affect the ecoscore. The used formula for the estimation of the ecoscore aims to penalize high RPM values during gear shift-up and cruising, abrupt braking and high acceleration. Specifically, for the calculation of the ecoscore the following parameters are used:

1) Shift ups RPM ecoscore parameter 2) Brake ecoscore parameter 3) Acceleration ecoscore parameter 4) RPM ecoscore parameter 5) Cruising ecoscore parameter

The shift up RPM ecoscore parameter describes the evaluation of shift-up events as a factor to calculate ecoscore. The general idea is to punish shift up events with RPM values higher than 2500 and reward shift up events with RPM values between 2000-2500. In Figure 3, an example is presented showing how the RPM is affected when a ”gear shift up” event happens. The reward is less if the driver shifted up after several seconds above 2000 rpm. Fig. 4 shows that the duration of a shift up event has an impact

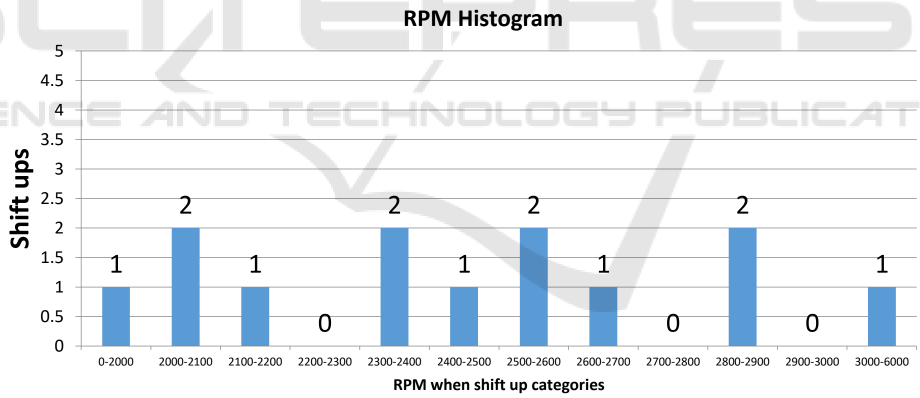

Fig. 3. RPM and gear shift up events.

and specifically different impact for positive and negative factor values. The punishment is more when the duration is several seconds after 2000 rpm. For the estimation of shift up RPM ecoscore we use: (i) the peak RPM during the event, (ii) the time required to complete a shift-up event, (iii) the vehicle speed, (iv) the mean vehicle speed, (v) the mean throttle position, (vi) the speed variance and (vii) the throttle variance.

The brake ecoscore parameter describes the evaluation of break events as a factor to calculate ecoscore. For the calculation of brake ecoscore parameter, we are looking

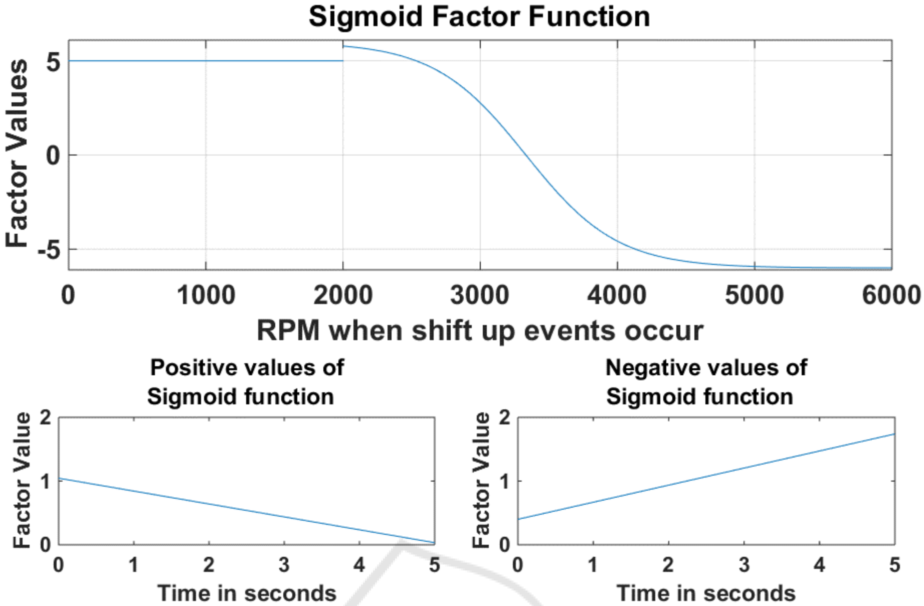

Fig. 4. Shift up events and different impact for positive and negative factor values.

for brake events which are divided into four categories: (i) soft engine brake, (ii) hard engine brake, (iii) pedal brake and (iv) emergency brake.

The acceleration ecoscore parameter describes the evaluation of acceleration events as a factor to calculate ecoscore. The acceleration ecoscore parameter estimation mainly depends on (i) the brake event and (ii) the velocity reached during acceleration event.

The RPM ecoscore parameter describes the evaluation of acceleration events as a factor to calculate ecoscore. For the estimation of RPM ecoscore, we take into account: (i) the RPM event, (ii) an RPM event occurs when RPM $>$ 2500 (these events are also validated from Throttle position values if available), (iii) the maximum RPM value during RPM event, (iv) the duration of an RPM event measured in seconds and (v) the duration of temporal window.

The cruising ecoscore parameter evaluates the ecoscore during cruising. The cruising ecoscore is estimated using: (i) the vehicle speed, (ii) the mean vehicle speed, (iii) the mean throttle position, (iv) the speed variance, (v) the throttle variance and (vi) the temporal window.

Aggressiveness Score Estimation. The aggressiveness ecoscore calculation is based on the following parameters: a) throttle position variance and engine RPM variance, b) braking intensity, c) acceleration magnitude. High variance of engine RPM indicates driver nervousness and improper vehicle handling. For example, significant fluctuations in engine RPM are the result of a driver who is not focused on smooth cruising and overall safe driving. Instead, they tend to accelerate many times for small durations, thus minimizing their fuel efficiency, eco-friendliness and safety for themselves and others. The RPM variance parameter calculation is based on a 30 seconds temporal window for the calculate of RPM position variance. The standard deviation is then normalized and scale it appropriately with experimentally defined parameter μ to contribute to the final aggressiveness score. Furthermore, braking intensity is computed during online analysis, based on the correlation between vehicle deceleration (as measured by vehicle speed decrease) and braking duration. This is intended to contribute to the computation of aggressiveness score in a cumulative manner. Abrupt braking events indicate poor planning from the driver's part and a low level of situation awareness regarding road conditions and surrounding traffic. Finally, lateral and directional acceleration obtained from the mobile device's accelerometer can provide a meaningful measurement of steering and overall driving aggressiveness. While abrupt braking and engine RPM variance are a good metric of aggressiveness in slow sections of the driving route, they fail to provide similarly robust information in situations that require greater velocity. To alleviate this, the lateral and directional acceleration magnitude is integrated across time, so as to provide higher sensitivity for assessing aggressiveness in such cases.

Physiological Score Estimation. Driving is an activity that requires considerable alertness. Insufficient attention, imperfect perception, inadequate information processing, and sub-optimal arousal are possible causes of poor human performance. Understanding of these causes and the implementation of effective remedies is of key importance to increase traffic safety and improve driver's wellbeing. Several non-invasive measurements have been considered in the literature. These include Electroencephalography (EEG) based methods [20, 3, 2], Electrocardiography (ECG) and Heart Rate Variability(HRV) related methods [35, 30, 14], image processing based approaches [33] as well as tissue imaging and blood oxygenation measurement based studies [15]. In several cases the HRV timeseries are used in conjunction with other validated methods such as galvanic skin response[17, 45, 19, 50], thoracic electrical bioimpedance (TEB) [37], EMG [50], respiration [29]. The extracted features from the aforementioned metrics are used in most cases as input to classic classification approaches such as Naive Bayes, SVM , KNN [14], neural networks [20], fuzzy clustering [30]. Recently, a study used ECG data to derive mental stress in open road driving [41]. Electro cardiogram and heart rate variability generate a series of time-domain, frequency domain-features or nonlinear features computed over 24 h, five-minute-long short-term period, or ultra-short-term period for under five-minute duration. Commonly referenced feature is the LF/HF ratio associated with the sympatho-vagal balance [8, 44]. In a healthy organism, there is a dynamic relative balance between the sympathetic nervous system(SNS) and parasympathetic nervous system (PNS). SNS activation increases heart rate, whereas PNS activation decreases it. Spectral analysis of HRV shows several frequency bands, two of which are important here: a low-frequency component (LF; 0.04-0.15Hz) mediated by both PNS and SNS, and a highfrequency component (HF; 0.15-0.4Hz) mediated by PNS activation. As a result, the ratio of LF to HF power is sometimes used as an index of autonomic balance [23]. However later studies prove that this simple rule does not apply in all cases [35] and that it is not a conclusive feature [48]. In most studies a series of features are used all-together with state of the art classification approaches to differentiate stressful situations in a case specific manner.

The physiological score calculation is part of the Online Analysis module, in the same level with the ecoscore and aggressiveness calculation, which together form the computational core for the evaluation of eco-friendliness during each driving session. The main input of the physiological score module comes from the real-time data preprocessing module, which in turn receives its input from the Sensor Layer. The calculation of physiological score is based solely on heart rate measurements due to the seamless connection of available HR sensor to mobile devices without the mediation of propriety services. As features for the physiological score calculation, the value heart rate variability and the window based LF/HF frequency ratio describing the autonomic nervous system balance are considered. Personalized thresholds are extracted based on LF/HF frequency ratio, mean heart rate and standard deviation for a temporal window using simple decision rules. The desired outcome of the physiological score would be a binary decision where TRUE or 1 declares that the driver is in aggravated state and FALSE or 0 if the driver is calm. Thus, two classification approaches are employed:

- Decision Rule 1: The driver is assumed as stressed if his/her heart rate is higher than the mean value plus the standard deviation of his/her heart rate based on the personalized normal driving.
- Decision Rule 2: Given heart rate mean value and heart rate standard deviation and LF/HF ratio for each annotated temporal we employ Random Forest and ADABoost classifiers

For the evaluation a public dataset was employed [52] that includes data for n = 68 volunteers that drove the same highway under four different conditions: (a) No distraction, (b) Cognitive distraction, (c) Emotional distraction and (d) Sensorimotor distraction. Driving with no distraction means driving without secondary activities. This type of driving is called Normal Drive (ND). A cognitive driving means driving under a cognitive stressor. The cognitive stressor was mathematical questions and analytical questions posed orally by the experimenter. An emotional driving means driving under an emotional stressor. The emotional stressor was emotionally stirring questions posed orally by the experimenter in two phases. Sensorimotor driving means driving under a sensorimotor stressor. The sensorimotor stressor was texting back words, sent one by one to the subject's smartphone. The phase layout within each stressful driving contentions; namely cognitive, emotional and sensorimotor stress, was as follows: 1) Phase 1: Driving without distractions for $\sim 80\ s$. 2) Phase 2: Driving while engaging in a secondary activity for $\sim 160\ s$. 3) Phase 3: Driving without distractions for $\sim 240\ s$ (coincided with the detour). 4) Phase 4: Driving while engaging in a secondary activity for $\sim 160\ s$. 5) Phase 5: Driving without distractions for $\sim 120\ s$.

Across all subjects, heart rates were calculated for each selected temporal window. Then, the mean and standard deviation were calculated for each driving phase and for each driver individually. Additionally, we separated each stress-loaded driving condition (e.g., Cognitive, Emotional, Sensorimotor) into two phases; namely the ”quite” phase [Cognitive Drive (CD), Emotional Drive (ED), Sensorimotor Drive (SD)] and the ”original stress” phase [Stress Cognitive Drive (SCD), Stress Emotional Drive (SED), Stress Sensorimotor Drive (SSD)]. In the ”original stress” phases the subjects are directly under a stress event (Phases 2, 4) while as ”quite” phases, it is represented the period of time before, between and after a stress event (Phases 1, 3, 5).

In Figure 5, the heart rate distribution of different drivers for different driving conditions is presented in boxplots. As it can be observed the drivers' heart rate is higher when they drive under stress events in comparison with the normal driving phases

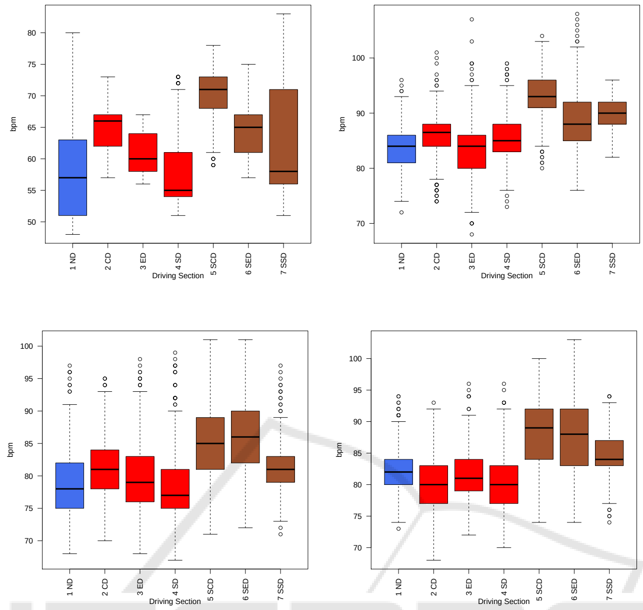

Fig. 5. Boxplot with the heart rate values in different driving sections for the first 4 drivers.

3.3 Gamification

Based on the state of the art approaches[16] and the ideas and concepts of gamification that have been proven to be most effective within an educational context – we can start to map out how the gamification of GamECAR will look. Furthermore, we can marry the different driving activities involved in GamECAR along with a set of desirable behaviours we want the gamified environment to stimulate and generate, from that, the game elements that we can utilise as the basis for the gamification design. In general, our gamified elements should be geared towards encouraging and supporting end users to adopt the following desirable behaviours 1) Improved eco-driving skills 2) Improved safe-driving skills 3) Better knowledge about the impact of different driving practices 4) Increased use of GamECAR while driving 5) Increased sharing of the GamECAR app with others

The selected game elements for GamECAR derive from the identified gamification trends and best practices. As we mapped out there, these trends relate to the identified core drivers typical in gamified environments and to the four game phases that are commonly seen. The diagram in Figure 6 below explains the links between all these ideas and elements:

Based on this knowledge, a set of game elements and design proposals have been developed that reflect the presented gamification strategies. Table 2 shows these game

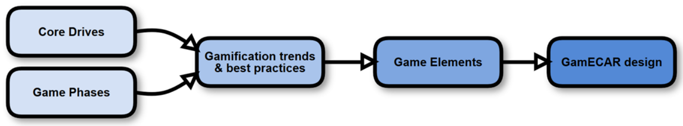

Fig. 6. Gamification approach.

elements, the concrete design proposals, and how they relate to different gamification strategies and trends. The introduced design proposals follow a basic rule. Each of them pursues one of the desirable behaviors in GamECAR, and complies with the presented gamification trends and good practices. The diagram in Figure 7 presents the overall gamification design where all the proposals are connected to work together. The main activity that the user will undertake as part of their interaction with GamECAR is driving.

Table 2. Corresponce of gamification trends with core drives and game phases.

Gamification Trends	Core Drives	Phases
Storytelling	Unpredictability & Curiosity	Discovery
Goals	Development and Accomplishments , Loss & Avoidance	Scaffolding, Endgame
Challenges and Quests	Social Influence & Relatedness & Development and Accomplishments, Loss & Avoidance	Scaffolding, Endgame
Customization	Ownership & Possession	Scaffolding, Discovery, Onboarding
Progress	Scarcity & Impatience	Discovery, Onboarding, Scaffolding, Endgame
Feedback	Loss & Avoidance, Social Influence	Scaffolding, Endgame
Access / Unlocking of content	Unpredictability & Curiosity	Onboarding, Scaffolding

Building Motivation. After each trip, an overall EcoScore for the trip is be calculated and presented to the user, but as a part of the overall experience, other more concrete behaviours and parameters related to specific driving skills are also calculated and stored as specific data (and accessible as scores or as the trigger for advice/feedback to the user). This includes the following: 1) Fuel consumption 2) Gear change 3) Acceleration 4) Braking 5) Aggressiveness All of these parameters and scores are in fact related to the specific desired behaviours pursued in GamECAR. And there is also an implicit aspect to this: just using the GamECAR application while driving is one of the desired behaviors and therefore just by following this behaviour, the user should improve his or her status within the gamified system. As a part of each specific trip EcoScore, other gamified elements will be earned or achieved during each active driving session. This will include: 1) Driving skills awards 2) Badges 3) Avatar outfits 4) Knowledge cards Game elements will be customized behind the scenes in order to appeal to different types of players during the different phases of the game. GamECAR drivers will gain levels in the game, which require progressively more experience points (XP) as presented in Figure 8. These levels also determine the game phase, with each phase having distinctive characteristics, features and objectives

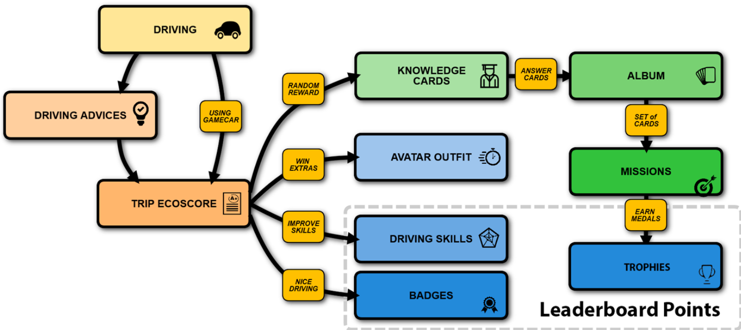

Fig. 7. Overall presentation of gamification design.

Game Phases. The game evolves in four discrete , coherent phases, namely, discovery, onboarding, scaffolding and endgame.

- Discovery phase : Levels 1-4 – estimated completion after 90-120 minutes of driving depending on Ecoscore. This phase's main purpose is to familiarize the participant with the game's elements, scoring features, feedback, levelling system and driving statistics extraction. To this end, the user gets introduced to Levels, Ecoscore, HUD alerts and basic driving statistics.
- Onboarding: Levels 5-14 – estimated completion after 6-8 hours of driving, approximately 9-16 days with 30 minutes of daily driving and a decent number of completed missions. This phase aims to expose the player to more advanced features of the game. Apart from the discovery phase elements, this phase includes leaderboards and leaderboard points (LP), daily missions with lootbox rewards, large-scope missions with XP/LP, knowledge cards, lootboxes (drop likelihood depends on eco-driving performance, up to 5 drops per month) and profile customization (e.g. avatar).
- Scaffolding: Levels 15-39 – estimated time of completion after 45-57 hours of driving, approximately 2.5-4 months with 30 minutes of driving daily and a decent number of completed missions. Scaffolding is the phase of the game that aims at creating desirable habits to the player through his/her core drives. Along with all the aforementioned features, the user now is granted the ability to create his/her own crews in order to recruit other players as he gains a widely respected "veteran" status.
- Endgame: Levels 40-50 (max) – estimated time to reach max level is approximately 1.5-2 months with 30 minutes of driving daily and a decent number of completed missions. In the final stage of the game, the user starts getting personalized messages according to his/her weak driving aspects. He also gains access to advance information visualizations regarding his/her performance compared to global statis-

tics. Finally, most of his visible status is subject to inactivity decay, i.e. it is gradually diminished while the player remains inactive.

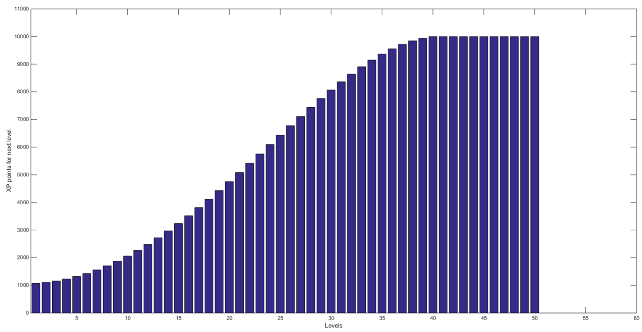

Fig. 8. Experience points distribution required for the player to level up as a function of current level.

The features are then further customized based on the detected type of each player. Players are classified into 3 predefined classes, namely, *Constant Improver*, *Safety enthusiast* and *Smart saver*. The directions according to which the gamification features are customized as shown in Figure 10. The figure shows the core drives that gamification features should take advantage of in order to be most effective depending on each player's type and game phase. The figure is separated in two rows (representing early and late phases of the game) and three columns, corresponding to the three aforementioned player types. During early phases, the focus is on core drives like *Epic Meaning*, while later the focus shifts to *Loss and Avoidance*, *Accomplishment* and *Social Influence* [16]. Similarly, *Accomplishment* and *Ownership* are key drives for the *Constant Improver*, as are Loss and Avoidance and *Ownership* for the *Safety Enthusiast* and *Social Influence* and *Scarcity* for the *Smart Saver*.

Table 3. Game elements correspondence to gamification strategies

Game elements	Story-telling	Goals	Chal-lenges	Customi-zation	Progress	Feed-back	Unlocking
Levels		EcoScore	Missions		Rank	Badges	
Ranking		Rank	Trophies		Rank	Rank, VCP	
Search	Videos	Cards	Cards	Avatar outfit			Cards
Points		EcoScore			Rank	EcoScore	
Virtual Currency				Avatar outfit	Cards		Cards
Special Events	Videos		Badges		Badges		Cards
Social Area		VCP	Coop. Missions	Avatar outfit	Skills	Profile	
Epic Challenge			Missions		Missions		Missions
Customi-zation				Avatar outfit	Avatar outfit		Avatar outfit
Access Item	Videos						Cards
Chat						VCP	
Skills		EcoScore			Skills	Skills	
Rewards		Album	Trophies		Trophies Album, Trophies	Trophies	Cards

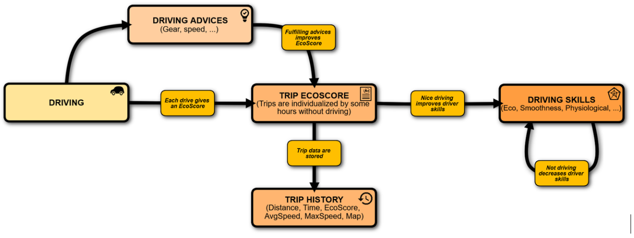

Fig. 9. GamECAR reward system.

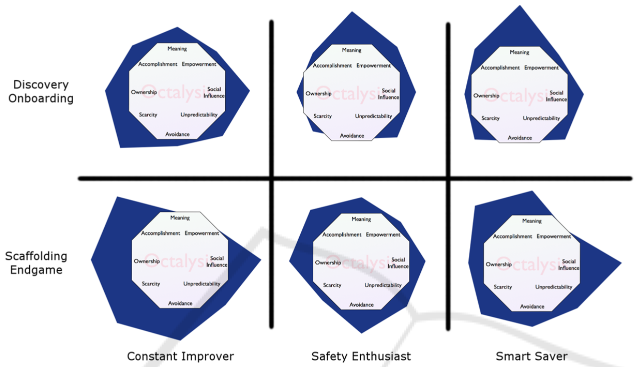

Fig. 10. Distribution of core drives for each phase of the game and each player type.

The main tool for customizing the game experience and stimulating the appropriate core drives are mission objectives, which are customized according to these diagrams. For example, a mission for the Constant Improver should challenge him to beat his/her previous performance or invite him to exceed the scores of his/her peers. Similarly, a player in the *Safety Enthusiast* should face missions that are somewhat easier than the corresponding missions for the other two categories, but place a heavy focus on consistent performance and calm/eco-friendly road behaviour. Finally, missions posed to the Smart Saver should feature as either objective or highlight the benefits of ecodriving regarding reduced fuel consumption and positive environmental impact.

Use Cases. In this section two use cases are presented, the case of a new player and the case of an experienced player.

1. A new user. John is a sales representative for a large pharmaceutical company. He lives on the outskirts of Athens but travels a great deal across mainland Greece to meet with clients and maintain his relationships. He has become increasingly interested in environmental issues, every since the birth of his two children and he is worried about the impact that pollution is having on air quality and on the environment in general. His job requires him to drive a lot but he wants to do something. John read about GamECAR and immediately cherished the idea: he wanted to improve his driving, be more fuel efficient and reduce his carbon footprint. Since John was paying for his fuel consumption, reducing his fuel bills would be great. But he

needed help with his driving style. How would he know if he was actually having any impact? Also, he leads a busy life and often would be rushing around without really thinking about the way he was driving. Having something he could switch on at the start of each journey, something that would give him feedback and something where he had targets he could aim for would be great. He downloaded the GamECAR application and got started. First, he set himself up as a user. It was a quick process and allowed him to create his own profile and avatar.

2. The experienced user. Jaime was introduced to GamECAR by his work friend John. They had been friends for years and really enjoyed competition. They would battle over football and over tennis. And now they had GamECAR. Jaime spent some time becoming familiar with the game and, like John, started to get his scores up and his driver ranking up. He liked the way the app gave you individual targets around different driving skills and allowed you to track your progress. But he wanted more engagement. After a few weeks of using the application, he opened it up one day and was given a Loot Box. At first, he didn't know what it was. But once he opened it, he started to understand the world of Knowledge Cards and Missions. Having been driving with GamECAR for a few weeks, he already had some good knowledge of what helps you to be a better, more eco-friendly driver so the Knowledge Cards should be simple! Once he answered the cards he had been given, a Mission opened up. It was tough.

4 Discussion and Conclusion

Current self-management systems related to ecodriving, despite their complexity and sophisticated nature, are practically proven inefficient, since they do not take into account a mixture of complex characteristics including age, sex, social status, financial status, physiological measurements, driving behavior measurements and vehicle characteristics. The proposed system is designed to fill this commitment gap by introducing an innovative and interactive Serious game that guide targeted Driving behavior changes to improve the way that various EcoDriving activities are undertaken so that the drivers involved will be educated to take the desired actions and more importantly will be familiar with AR displays and applications while driving. Though GamECAR is expected to be beneficial solution in the field of ecodriving education, the use of such systems is not without challenges and limitations, most notably that of realism gap due to the vast number of parameters that needs to be implemented. But they are still obstacles to overcome, even if the system was flawless there are still lots of steps to be taken before the use of AR driver-assistance systems in real life, such as ethical issues like the ban of using technological means while driving. Additionally, Augmented reality head up displays (AR HUD) are not yet fully capable of coping tasks like that, the limited field of view and the low refresh rate are two examples of device limitations that need to be improved. Ultimately, the AR technology has a limited target group, people that are in early adulthood since it is challenging for someone older to get used to cutting-edge technologies. On the other hand, the use of gamification in our system is a favorable way to teach teenagers how to drive using the AR drive-assistance system from the very beginning.

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References

1. Akrivopoulos, O., Chatzigiannakis, I., Tselios, C., Antoniou, A.: On the deployment of healthcare applications over fog computing infrastructure. In: 2017 IEEE 41st Annual Computer Software and Applications Conference (COMPSAC). vol. 2, pp. 288–293 (July 2017). https://doi.org/10.1109/COMPSAC.2017.178
2. Al-shargie, F., Tang, T.B., Badruddin, N., Dass, S.C., Kiguchi, M.: Mental stress assessment based on feature level fusion of fnirs and eeg signals. In: Intelligent and Advanced Systems (ICIAS), 2016 6th International Conference on. pp. 1–5. IEEE (2016)
3. Al-shargie, F., Tang, T.B., Badruddin, N., Kiguchi, M.: Simultaneous measurement of eeg-fnirs in classifying and localizing brain activation to mental stress. In: Signal and Image Processing Applications (ICSIPA), 2015 IEEE International Conference on. pp. 282–286. IEEE (2015)
4. Alessandrini, A., Cattivera, A., Filippi, F., Ortenzi, F.: Driving style influence on car co2 emissions. In: 2012 international emission inventory conference (2012)
5. Alessandrini, A., Orecchini, F., Ortenzi, F., Campbell, F.V.: Drive-style emissions testing on the latest two honda hybrid technologies. European Transport Research Review **1**(2), 57–66 (2009)
6. Amaxilatis, D., Akrivopoulos, O., Chatzigiannakis, I., Tselios, C.: Enabling stream processing for people-centric IoT based on the fog computing paradigm. In: 2017 22nd IEEE International Conference on Emerging Technologies and Factory Automation (ETFA). pp. 1–8 (Sept 2017). https://doi.org/10.1109/ETFA.2017.8247674
7. Barkenbus, J.N.: Eco-driving: An overlooked climate change initiative. Energy Policy **38**(2), 762–769 (2010)
8. Bianchi, A., Mainardi, L., Meloni, C., Chierchiu, S., Cerutti, S.: Continuous monitoring of the sympatho-vagal balance through spectral analysis. IEEE Engineering in Medicine and Biology Magazine **16**(5), 64–73 (1997). https://doi.org/10.1109/51.620497
9. Bianchi, G., Biton, E., Blefari-Melazzi, N., Borges, I., Chiaraviglio, L., Cruz Ramos, P., Eardley, P., Fontes, F., McGrath, M.J., Natarianni, L., et al.: Superfluidity: a flexible functional architecture for 5G networks. Transactions on Emerging Telecommunications Technologies **27**(9), 1178–1186 (2016)
10. BMW: Eco pro (2012), http://www.bmw.com.af/com/en/insights/technology /efficientdynamics/phase_1/measures_ecopro.html
11. Cai, J.F., Candès, E.J., Shen, Z.: A singular value thresholding algorithm for matrix completion. SIAM Journal on Optimization **20**(4), 1956–1982 (2010)
12. Candes, E.J., Plan, Y.: Matrix completion with noise. Proceedings of the IEEE **98**(6), 925–936 (2010)
13. Candès, E.J., Recht, B.: Exact matrix completion via convex optimization. Foundations of Computational mathematics **9**(6), 717 (2009)
14. Castaldo, R., Xu, W., Melillo, P., Pecchia, L., Santamaria, L., James, C.: Detection of mental stress due to oral academic examination via ultra-short-term hrv analysis. In: Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the. pp. 3805–3808. IEEE (2016)
15. Chen, T., Yuen, P., Richardson, M., Liu, G., She, Z.: Detection of psychological stress using a hyperspectral imaging technique. IEEE Transactions on Affective Computing **5**(4), 391–405 (oct 2014). https://doi.org/10.1109/TAFFC.2014.2362513

16. Chou, Y.k.: Actionable gamification. Beyond Points, Badges, and Leaderboards (2015)
17. Ciabattoni, L., Ferracuti, F., Longhi, S., Pepa, L., Romeo, L., Verdini, F.: Real-time mental stress detection based on smartwatch. In: Consumer Electronics (ICCE), 2017 IEEE International Conference on. pp. 110–111. IEEE (2017)
18. Cristea, M., Paran, F., Delhomme, P.: The role of motivations for eco-driving and social norms on behavioural intentions regarding speed limits and time headway. World Academy of Science, Engineering and Technology **6**, 1307–6884 (2012)
19. De Santos Sierra, A., Sanchez Avila, C., Guerra Casanova, J., Bailador Del Pozo, G.: A stress-detection system based on physiological signals and fuzzy logic. IEEE Transactions on Industrial Electronics **58**(10), 4857–4865 (2011). https://doi.org/10.1109/TIE.2010.2103538
20. del R Millan, J., Mourino, J., Franze, M., Cincotti, F., Varsta, M., Heikkonen, J., Babiloni, F.: A local neural classifier for the recognition of EEG patterns associated to mental tasks. IEEE Transactions on Neural Networks (3), 678–686 (may 2002). https://doi.org/10.1109/TNN.2002.1000132
21. DriveSim: Drivesim simulator (2014), http://drivesimsimulator.com/en/
22. Eco-Drive, Q.A.: Ecodriver (2015), http://www.play-ecodriver.ch/en/
23. Electrophysiology, T.F.o.t.E.S.o.C.t.N.A.S.o.P.: Heart Rate Variability : Standards of Measurement, Physiological Interpretation, and Clinical Use. Circulation **93**(5), 1043–1065 (mar 1996). https://doi.org/10.1161/01.CIR.93.5.1043
24. Fiat: eco:drive app (2014), http://ecodrive.driveuconnect.eu/
25. Ford: Smart eco driving (2013), https://ford.devpost.com/submissions/16640-smart-eco-driving
26. Hobert, L., Festag, A., Llatser, I., Altomare, L., Visintainer, F., Kovacs, A.: Enhancements of v2x communication in support of cooperative autonomous driving. IEEE communications magazine **53**(12), 64–70 (2015)
27. Honda: Insight eco assist system (2017), http://world.honda.com/INSIGHT/eco/
28. Kalofolias, V., Bresson, X., Bronstein, M., Vandergheynst, P.: Matrix completion on graphs. arXiv preprint arXiv:1408.1717 (2014)
29. Kontaxis, S., Lázaro, J., Hernando, A., Arza, A., Garzón, J.M., Gil, E., Laguna, P., Aguiló, J., Bailón, R.: Mental stress detection using cardiorespiratory wavelet cross-bispectrum. In: Computing in Cardiology Conference (CinC), 2016. pp. 725–728. IEEE (2016)
30. Kumar, M., Weippert, M., Vilbrandt, R., Kreuzfeld, S., Stoll, R.: Fuzzy Evaluation of Heart Rate Signals for Mental Stress Assessment. IEEE Transactions on Fuzzy Systems **15**(5), 791–808 (oct 2007). https://doi.org/10.1109/TFUZZ.2006.889825
31. Lauper, E., Moser, S., Fischer, M., Matthies, E., Kaufmann-Hayoz, R.: Psychological predictors of eco-driving: A longitudinal study. Transportation research part F: traffic psychology and behaviour **33**, 27–37 (2015)
32. Magana, V.C., Munoz-Organero, M.: Gafu: using a gamification tool to save fuel. IEEE Intelligent Transportation Systems Magazine **7**(2), 58–70 (2015)
33. McDuff, D., Gontarek, S., Picard, R.: Remote measurement of cognitive stress via heart rate variability. In: 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. pp. 2957–2960. IEEE (aug 2014). https://doi.org/10.1109/EMBC.2014.6944243
34. Mensing, F., Bideaux, E., Trigui, R., Ribet, J., Jeanneret, B.: Eco-driving: An economic or ecologic driving style? Transportation Research Part C: Emerging Technologies **38**, 110–121 (2014)
35. Mili, G.: Low to High Frequency Ratio of Heart Rate Variability Spectra Fails to Describe Sympatho-Vagal Balance in Cardiac Patients. Coll. Antropol **29172**(1), 295–300 (2005)
36. Mitsubishi: Eco drive support (2013), http://www.mitsubishi-motors.com/en/innovation/technology/library/eco_drive.html

37. Mohino-Herranz, I., Gil-Pita, R., Ferreira, J., Rosa-Zurera, M., Seoane, F.: Assessment of mental, emotional and physical stress through analysis of physiological signals using smartphones. Sensors **15**(10), 25607–25627 (2015)
38. Mundke, R., Malewar, S., Arya, K.: Use of data recorder for driver rating. Tech. rep., SAE Technical Paper (2006)
39. Nousias, S., Tselios, C., Bintzas, D., Orfila, O., Jamson, S., Mejuto, P., Amaxilatis, D., Akrivopoulos, O., Chatzigiannakis, I., Lalos, A.S., Moustakas, K.: Managing nonuniformities and uncertainties in vehicle-oriented sensor data over next generation networks. In: IEEE Internaltional Conference on Pervasive computing and communications (2018)
40. Nouvelles, E.: Geco (2014), https://www.geco-drive.fr/
41. Parvaneh, S., Toosizadeh, N., Moharreri, S.: Impact of mental stress on heart rate asymmetry. In: Computing in Cardiology Conference (CinC), 2015. pp. 793–796. IEEE (2015)
42. Reiners, T., Wood, L.C.: Gami cation in Education and Business. Springer (2015)
43. research, H., technology: Greenmeter (2018), http://hunter.pairsite.com/greenmeter/
44. Rigas, G., Goletsis, Y., Bougia, P., Fotiadis, D.I.: Towards driver's state recognition on real driving conditions. International Journal of Vehicular Technology **2011** (2011)
45. Salai, M., Vassányi, I., Kósa, I.: Stress detection using low cost heart rate sensors. Journal of healthcare engineering **2016** (2016)
46. Saynor, B.: Ecowill deliverable 6.1: Guidelines for delivering short-duration ecodriving training courses (2011)
47. Schuller, B.W., Dunwell, I., Weninger, F., Paletta, L.: Serious gaming for behavior change: The state of play. IEEE pervasive computing **12**(3), 48–55 (2013)
48. Shaffer, F., McCraty, R., Zerr, C.L.: A healthy heart is not a metronome: an integrative review of the heart's anatomy and heart rate variability. Frontiers in Psychology **5**(September), 1–19 (2014). https://doi.org/10.3389/fpsyg.2014.01040
49. Subaru: Ecology (2016), http://www.subaru.com.mt/eco_driving.html
50. Sun, F., Kuo, C., Cheng, H., Buthpitiya, S., Collins, P., Griss, M.: Activity aware mental stress detection using physiological sensors. Mobile Computing, Applications, and Services **76**, 1–20 (2012)
51. Systems, S.S.S.: Eco driving package (2007), https://www.stsoftware.nl/
52. Taamneh, S., Tsiamyrtzis, P., Dcosta, M., Buddharaju, P., Khatri, A., Manser, M., Ferris, T., Wunderlich, R., Pavlidis, I.: A multimodal dataset for various forms of distracted driving. Scientific data **4**, 170110 (2017)
53. Texa: Texacare (2016), http://www.energysavingtrust.org.uk/scotland/ businesses–organisations/ transport/fuelgood-driver-training
54. Trust, E.S.: Fuelgood (2016), http://www.energysavingtrust.org.uk/scotland/ businesses-organisations/transport/fuelgood-driver-training
55. Tselios, C., Tsolis, G.: On QoE-awareness through virtualized probes in 5G networks. In: 2016 IEEE 21st International Workshop on Computer Aided Modelling and Design of Communication Links and Networks (CAMAD). pp. 159–164 (Oct 2016). https://doi.org/10.1109/CAMAD.2016.7790351
56. Vlachos, E., Lalos, A.S., Berberidis, K., Tselios, C.: Autonomous driving in 5g: Mitigating interference in ofdm-based vehicular communications. In: 2017 IEEE 22nd International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD). pp. 1–6 (June 2017). https://doi.org/10.1109/CAMAD.2017.8031619
57. Vlachos, E., Lalos, A.S., Moustakas, K., Berberidis, K.: Efficient graph-based matrix completion on incomplete animated models. In: Multimedia and Expo (ICME), 2017 IEEE International Conference on. pp. 1548–1553. IEEE (2017)
58. Wengraf, I.: Easy on the gas: The effectiveness of eco-driving. Royal Automobile Club Foundation, Tech. Rep. (2012)

59. WeNow: Wenow (2016), https://www.wenow.com/en/eco-driving-your-way-towards-energy-efficiency/
60. Zhou, X., Yang, C., Zhao, H., Yu, W.: Low-rank modeling and its applications in image analysis. ACM Computing Surveys (CSUR) **47**(2), 36 (2015)