SESSION 2B :

MODELLING OF DRIVERS' BEHAVIOUR FOR ITS DESIGN

MODELING DRIVING BEHAVIOUR USING HYBRID AUTOMATA

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ABSTRACT: We present a new approach to the modeling of human driving behaviour, which describes driving behaviour as the result of an optimization process within the formal framework of hybrid automata. In contrast to most approaches, the aim is not to construct a (cognitive) model of a human driver, but to directly model driving behaviour. We assume human driving to be controlled by the anticipated outcomes of possible behaviours. These positive and negative outcomes are mapped onto a single theoretical variable - the so called reinforcement value. Behaviour is assumed to be chosen in such a way that the reinforcement value is optimized in any given situation. To formalize our models we use hybrid automata, which allow for both continuous variables and discrete states. The models are evaluated using simulations of the optimized driving behaviours. A car entering a freeway served as the scenario to demonstrate our approach. First results yield plausible predictions for car trajectories and the chronological sequence of speed, depending on the surrounding traffic, indicating the feasibility of the approach.

1. INTRODUCTION

The dominant paradigm for the modeling of human driving behaviour is information processing in the cognitive domain. The cognitive approach tries to model the relevant cognitive processes of a driver in order to explain and to predict his driving behaviour in certain situations. There is a large number of cognitive processes possibly involved in driving behaviour, for example perceiving, evaluating, goal-setting, deciding, etc. [1], [2]. Therefore, many existing modeling approaches use cognitive architectures (e.g. ACT) [3]. Because the description of dynamic processes is difficult within these modeling frameworks their application poses considerable problems in the domain of driver simulation. An alternative approach is the use of models for vehicle guidance that focus on the interaction between driver and vehicle and are conceptualized according to cognitive action theories [4], [5]. In this framework driver behaviour is described as the result of extensive internal planning and decision processes [6], [7]. These approaches focus on the specification of processes and structures underlying cognition [8]. The cognitive approach – although intuitively convincing – does not only suffer from heavy methodological problems (cognitive processes are intrinsically unobservable [3]), but also leaves open the question whether it is actually necessary to model internal processes in order to predict behaviour.

In contrast to this approach, we propose a new modeling framework for driving behaviour, which uses theoretical concepts from behavioural psychology [9]. The core idea is that in a pragmatic setting what is needed is not a *driver-model* but a model of *human driving* – that is, a formal description of how controllable external variables influence the movement of a car in traffic. The fact that this is mediated by the cognitive processes (and of course by the physical actions) of a living driver sitting inside the car is not essential to questions concerning car movement. Therefore the approach put forward takes driver and car to be one single agent in a traffic scenario, rather than modeling the interaction between them. The theoretical background used in the present approach is a variety of optimization theory which rests on the assumption that human behaviour is gradually adapted to the environment (this may include physical environment, as well as social factors or the behaviour of other organisms) [10], [11]. In our models we are neither interested in the internal processes that lead to the observed behaviour, nor in those that mediate the process of adaptation. Instead, we start with the general assumption that driving behaviour is the result of an optimization process. Thus, the key to modeling driving behaviour is to find out what is “optimal” in a given situation. How the optimization process exactly works is not relevant for our models.

2. BEHAVIOURAL APPROACH

To formalize the concept of optimization we introduce a theoretical variable which will be called “reinforcement value” (due to its theoretical roots in operant behaviour theory). This reinforcement value plays an essential role in our models and simulations, because we assume behaviour to be chosen in order to maximize a theoretical reinforcement value. The reinforcement value of a certain behaviour in a given situation is taken to be a mapping of all anticipated positive and negative consequences of this behaviour onto a single dimension. Thus, in any given situation, all possible behaviours can be assigned a reinforcement value by means of specific evaluative functions. Behaviour is assumed to be the result of this evaluation against positive and negative outcomes, in the way that in each situation the behaviour with the highest expected reinforcement value (with regard to a specific time horizon) is chosen. We would like to stress that this approach – although situated in the domain of behavioural psychology – does not take behaviour to be determined by external factors alone, but to be the result of the specific reinforcement values of a person with respect to the possible behaviours in a given situation.

2.1. Hybrid automata

We use the *theory of hybrid automata* as a formal background to implement these assumptions into a quantitative model. Hybrid automata provide a helpful framework for our models, because they allow both for continuous variables as well as discrete states to describe a system [12]. Within a single state the change of each variable is described by a differential equation. Between states there are certain criteria which specify the transition from one state into another. This way it is possible to specify simple if-then-rules as well as continuous functions and even their interaction.

To apply this formal framework to the aforementioned theory of optimal behaviour we break up the timeline into distinct situations and identify these with the states of a hybrid automaton. The driving behaviour in each situation changes continuously over time – thus we identify the corresponding variables (namely speed and trajectory) with the continuous part of the automaton. Thus, driving behaviour is described by a different set of continuous functions of time in each situation. To incorporate the concept of reinforcement maximization, these continuous functions are not specified a priori but modelled as unknown functions, which are to be maximized against a reinforcement value wich depends upon suitably chosen functions of relevant external variables (e.g. distance to other cars, lateral position, steering angle etc.).

2.2. Exemplary scenario

As an exemplary scenario to apply our modeling approach we take a car entering the freeway. Merging onto the freeway is a rather complex driving task, as several factors have to be considered by the driver. The driver has to stabilize the lateral position of the car, he has to adjust his driving speed to the traffic, find a gap on the freeway, change lane and finally reach travelling speed. Instead of modeling these internal processes our model focuses on observable behaviour, namely trajectory and speed of the ego car. Furthermore, as mentioned before, we model the driver and the car as one unit, omitting intermediate steps like steering or breaking. As long as these driver behaviours are causally dependend on external factors, it is not necessary to include them in the model, since they do not enhance predictive power.

The model is based on the assumption that the driver starts at a given velocity and has a desired travelling speed on the freeway. Moving onto the freeway he tries to minimize forces due to acceleration or trajectory change (trying to avoid unpleasant jerks, as well as possible threat associated with sudden car movements), to stay as far to the right as possible (resulting in a tendency to drive on the rightmost lane, which is also stipulated by the German road traffic regulations) and, of course, avoid collisions with other vehicles. The minimization of forces, accomplished by gradual braking and accelerating, results in smooth movements. It is suppposed that drivers pursue smooth movements due to biological adaptation. Since abrupt movements are associated with aversive stimulus situations like stumbling, running into something or being hit, they are assumed to be aversive per se. Any departure from smooth movements are therefore taken to be the result of restricting factors in the environment (e.g. cars that get into the way of the ideal – that is smooth – trajectory). To formalize these assumptions we assigned corresponding reinforcement values to high forces, collisions etc. The resulting hybrid automaton is depicted in Fig. 1. Note that the timeline is divided into three functionally distinct parts – each being visualized by a circle containing the continuous functions controlling behaviour in this state. The first state stands for the time just before it is possible to enter the freeway. The second state describes the process of filtering into the traffic. The third state is just an exit-state, which corresponds to the fact that filtering onto the freeway is now accomplished. In a more elaborated model, of course, there would have to be a number of new states describing the task of driving on the freeway – possibly completed by additional states corresponding to changes in the environment like new cars entering or overtaking manoeuvres.

The ego car is assigned a position (x, y), a current velocity v , and an angle α to the lane. Our model considers the variables v and α to be controlled by the driver via the functions f and g , representing acceleration and steering, respectively. These two functions are optimized for maximal reinforcement value q . We add another car to our model, which is driving on the right lane of the freeway – with position (x_2, y_2) and velocity w . Based on the hypothesis that drivers try to minimize forces on the driver during lane change, we assigned a negative reinforcement value to acceleration forces and angular forces. To accomplish this we let the terms $-f(x)^2$ and $-\tan(g(x)^2)v^2$, respectively, contribute to q . The term $\frac{0{,}1}{\max(9.01, (x - x^2)^2 + ((y - y^2))^2 - 9)}$ serves to assign highly negative reinforcement values to time spent at the same position as the other car. During the terminal state of the automaton we add $-(v - 7)^2$ as a term for deviations from the desired velocity, and $100 \times \min(9, y - 5)$ respectively $100 \times \min(0.15 - y)$ to assign negative credit to time spent outside the road on the right and left side. Finally, the term $-y$ serves as a negative evaluation of driving on the left line.

In the present stage, the parametrization of the model seems rather arbitrary: (7) to represent the desired target velocity, (9) for the size of a car, (5) for the width of a lane, and (50) for the length of the acceleration lane. Especially the weightings of these factors for their relative contribution to q are essentially lucky guesses about the true influence of the incorporated variables on reinforcement value. Hence, the presented numbers are the result of a trial and error procedure based on rough approximations of the relative reinforcement values of the corresponding behaviours. Since the described model serves only as an illustrative example of how hybrid automata could be used to formalize reinforcement maximization theory (and not as an attempt to model true driving behaviour), we try to keep the description as concrete as possible. A generic introduction of the unparameterized model is therefore omitted.

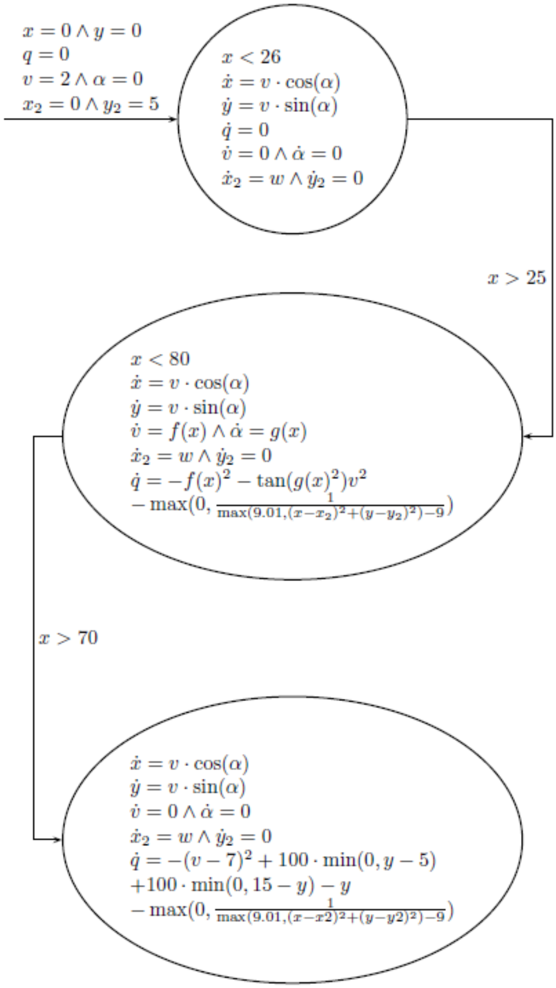

Fig. 1 Model of driver moving onto a freeway with another vehicle already on it. x, y : position, v : velocity, α : angle to freeway direction, x_2, y_2 : position of car 2, w : velocity of car 2, $f\in[0,2]^n$: acceleration (optimized), $g\in[-0.1, 0.1]^n$: steering (optimized), q : reinforcement value (measured at $x - 140$)

3. EVALUATION OF THE MODEL

In order to evaluate the model, we conducted a series of numerical simulations. Instead of calculating the complete state space of the automaton we executed monte-carlo approximations to estimate the expected value of the reinforcement value. To find the behaviour which is optimal relative to the reinforcement value we used a genetic algorithm.

3.1. Results of the evaluation process

First results of the simulation show the feasibility of our approach. Depending on the traffic on the freeway, our model predicts different driving maneuvers, which are rather complex in nature. If there are no cars on the freeway, the ego car “drifts” smoothly to the driving lane. If, however, there is another car on the line, the ego car either enters the freeway in front of the other car or slows down and filters in behind the other car to overtake it after having entered the driving lane (see Fig. 2). The behaviour is chosen depending on the speed of the other car – a car that “gets in the way” of the preferred trajectory changes the optimal behaviour in this situation and thus results in a trajectory that can be described as a best alternative to what would have been done if there had been no other car.

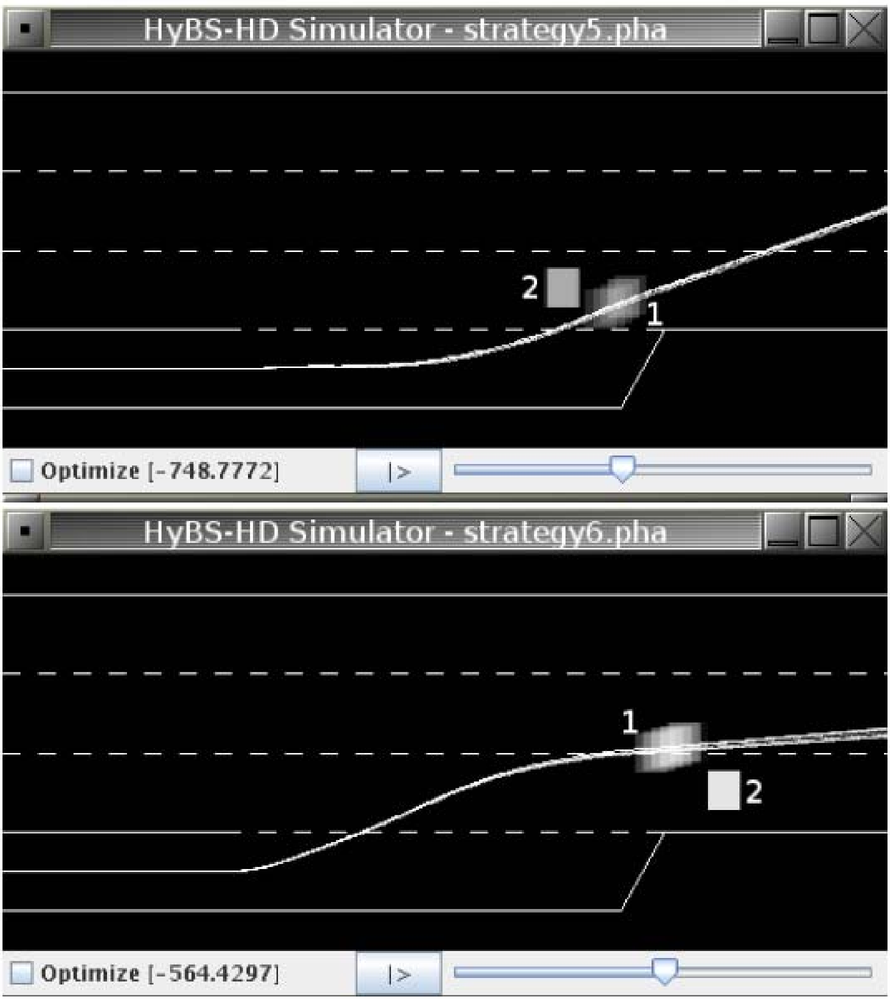

Fig. 2: Two simulation results with differing velocities of the other vehicle. The blurring represents non-determinism of the model.

4. CONCLUSIONS AND OUTLOOK

At least on a qualitative level, the model generates plausible predictions for driving behaviour in this situation. We would like to stress that although our model predicts qualitatively distinct manoeuvres, we did not model a decision process. Neither did we attempt to model a learning process. What our model does is to find an optimal driving trajectory for a given situation, provided a valid evaluation of anticipated consequences. The rationale behind this approach is that behaviour can be best understood if one starts with theoretical assumptions about how an organism would behave, if there were no restrictions from the environment. Formalizing these theoretical assumptions within a behavioural model allows for the deduction of specific instances of behaviour from the underlying principles. Variation in behaviour is understood as the result of external disturbances, which lead to deviations from the optimal behaviour. In the exemplary scenario given above behaviour is "optimal" with respect to the specific preferences (incorporated in the model as reinforcement values) of a driver. The reinforcement value of acceleration forces, for example, may vary considerably between drivers, depending on age, experience or gender. Therefore, the critical point of our modeling approach is to determine the "correct" reinforcement values. Whilst in the present model the corresponding functions are merely plausible assumptions based on a very general behavioural hypothesis ("high forces are aversive"), it would be desireable to derive the exact parameters empirically. This would also allow for the exploration of different driving styles (e.g. "sportive" vs. "play-it-safe"). A differential approach to modeling driving behaviour within the current theoretical framework arises naturally from the fact that variation in reinforcement values leads to systematic variation in driving behaviour. Differences in driver behaviour can therefore be incorporated by letting the reinforcement parameters vary between drivers. Although our approach may seem rather technical, paying little attention to what happens "inside" the driver, the principle of reinforcement maximization does say a lot about the agent in the car. Since the reinforcement values in our model reflect (possibly unconscious) driver preferences, they might as well be interpreted as motivational factors. Shifting the focus away from the information processing accuring in a driver, the proposed model presents a way to formalize a functional approach to driving behaviour. Instead of modeling how a person accomplishes driving, the reinforcement maximization approach gives an account for why people drive the way they do. This perspective can give new insights in the driving process and provide a promising ground for the development of advanced driver assistance systems. Because our approach does not only allow for the deduction of qualitative hypotheses but leads to specific quantitative hypotheses that can be compared to empirical data, it should be possible to derive a more valid simulation using an adequate experimental setting.

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PREFERRED TIME HEADWAY ASSESSMENT WITH THE METHOD OF LIMITS

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ABSTRACT: In the driving task, the distance to the vehicle ahead is an important safety margin that has to be continuously maintained. Time headway (THW) is generally constant within one individual driver. However, many situational factors (e.g. aim of the drive, emotions, motivation, road visibility, traffic) affect this preferred THW. The objective of this paper is to present a method, based on the psychophysical method of limit, capturing drivers' preferred THW while ruling out situational factors. The experimental trial took place in a low fidelity simulator where drivers were experiencing different traffic conditions, expected to affect THW. Preferred THW was assessed after each traffic conditions. The measurements show that a reliable and valid method to assess drivers' preferred THW has been achieved.

1. INTRODUCTION

An important task during driving consists of maintaining a safe distance to the vehicle ahead. The safety indicator time headway (THW) is commonly used to estimate the criticality of a driving situation and is defined as the elapsed time between the back of the lead vehicle passing a point on the roadway and the front of the following vehicle passing the same point [1]. In order to understand parameters used intrinsically by drivers to control a safe distance in a car-following situation, several studies investigated drivers' sensitivity to detect visual changes using mainly psychophysical methods [e.g. 2, 3]. Psychophysics is interested in the relation between physical stimuli, S, and psychological responses, R, where R=f(S) [4]. The results of this research line have been generally incorporated in car-following models. Psychophysical models of car-following, as discussed by Brackstone and McDonald [5], are based on perceptual thresholds. These perceptual thresholds are based on changes in distance, relative speed and the rate of change of the visual angle of the lead vehicle that serve to establish a range within which the drivers of the vehicle would be unable to notice any change to their dynamic conditions and would seek to maintain a constant velocity. Thus far, measures conducted for the benefit of car-following models have neglected investigation of the causes for variability between and within drivers [5]. Another line of research, not related to car-following models and using methods other than psychophysics, has been undertaking investigations to understand these variabilities. Drivers' adopted THW is an outcome of the interaction between individual characteristics and situational factors. It has been shown that there is a high inter-individual variability in the choice of THW but a small intra-individual variability, and that an important determinant for this difference is the perception of one's own acceleration and braking performance [6]. Thus, “close followers” are more efficient in the control of braking, brake harder and adjust the intensity of braking better to the criticality of the situation compared to drivers who prefer to follow at longer THWs. In addition to individual characteristics that are stable over time, several situational factors have been shown to affect the preferred THW including time spent on the driving task [7], intoxication [8], reduced visibility [9] and the composition of traffic [10]. These factors generally cause drivers to adjust THW as a result of a compensatory behaviour in order to reach a certain goal (e.g. keep the driving situation safe). Thus, since adopted THW is the result of preferred THW under the influence of situational factors, it is difficult to capture preferred THW.

This paper presents a psychophysical method to assess perceptual thresholds of preferred THW. The method rules out the influence of situational factors as the choice of a preferred THW is the result of a perceptual decision only and there is no need for the driver to regulate THW according to a certain situation. The preferred THW assessed with the psychophysical method is then compared to the adopted THW when driving in different traffic conditions: a car-following drive next to a platoon of vehicles (i.e. an uninterrupted line of identically closely spaced vehicles) maintaining a THW of either 0.3 sec or 1.0 sec and a control condition with no platoon. Assessment of preferred THW took place after each of the three drives. It was hypothesised that the situational factor of traffic would have an effect on participants’ adopted THW: they would adopt a shorter THW when exposed to vehicle platoons especially with short THWs (0.3 sec). The second hypothesis was that there would be no significant variation of the preferred THW.

2. METHOD

2.1. Apparatus

The apparatus (Fig. 1) consisted of a flat table upon which a steering wheel and manual gearbox (Logitech G27) were mounted, offset to the right to replicate the typical UK driving set-up. Corresponding pedals (clutch, brake and accelerator) were located beneath the steering wheel under the table. A 55’’ plasma screen (HITACHI 55PMA550) was placed behind the table. Participants were seated in front of the table on an office chair without wheels. The driving simulation was generated by SCANeR Studio 1.1 software (OKTAL). The driving performance data was recorded at a frequency of 20 Hz throughout each participant’s drive. THW (s) was calculated as follows: distance to the lead vehicle (m) / speed (m/s). The distance to the lead vehicle was measured along the road from the front of the “ego” vehicle to the rear of the lead vehicle.

Fig. 1 Simulator set-up

2.2. Procedure and Design

Each of the drives represented a car-following scenario on a three-lane motorway in the UK. The study was alternating the evaluation of adopted THW and the evaluation of preferred THW (Table 1).

Table 1 Study-plan (the order of simulated drives was depending on the counterbalancing plan)

Order	Drives	Parameters	Time
1	Familiarisation	-	≈ 5 min.
2	THW Assessment (familiarisation)	Preferred THW	≈ 5 min.
3	Simulated Drive (BL /THW03 /THW10)	Adopted THW	6 min.
4	THW Assessment	Preferred THW	≈ 5 min.
5	Simulated Drive (BL /THW03 /THW10)	Adopted THW	6 min.
6	THW Assessment	Preferred THW	≈ 5 min.
7	Simulated Drive (BL /THW03 /THW10)	Adopted THW	6 min.
8	THW Assessment	Preferred THW	≈ 5 min.

2.2.1. Adopted THW

In the simulated drive, participants were asked to follow a lead vehicle with the instruction to remain in the same lane as the lead vehicle throughout in order to get THW data. In two of the drives, a platoon of vehicles was assigned to the left lane maintaining either a short THW of 0.3 sec. (THW03) or a longer THW of 1.0 sec. (THW10). The lead vehicle was constantly driving next to the platoon and at the same speed (110 kph = 70 mph). In a third baseline condition (BL), there was no platoon present. In all three drives, the "ego" car and the lead vehicle drove in the middle lane with random traffic driving on the outer right (fast) lane in order to make participants realise that other cars could move into the gap ahead if this was too large.

2.2.2. Preferred THW

The assessment of participants' preferred THW took place after each simulated drive on the same road, with no other traffic than the lead vehicle.

The simulator took over the lateral and longitudinal control of the vehicle but participants were asked to keep their hands on the steering wheel as if they were driving. The speed of the lead vehicle was the same as in the simulated drive (70 mph). Based on the psychophysics method of limits [11], participants were exposed to a set of increasing THWs, starting from a very short one (0.1 sec.). After a THW was presented for 5.0 sec., the screen was blanked and participants were asked to respond 'yes' if they would normally keep the distance previously displayed or 'too short' or 'too large'. Meanwhile, THWs increased each time in step of 0.1 sec. Once participants have replied, the incremented THW was displayed for another 5.0 sec. The presentation of THWs was stopped once the preferred THW was reached. The same process was repeated with a set of gradually decreasing THWs starting from a very large THW (2.5 sec) (Fig. 2). The presentation of THWs was stopped at the point at which the THW no longer represented drivers' preferred THW. The presentation of the set of increasing and the set of decreasing distances was counterbalanced and the results from both sets were averaged. As the result in each set represented a threshold, which is the lowest THW that participants would normally keep, the output of the THW assessment represents in fact a preferred minimum THW.

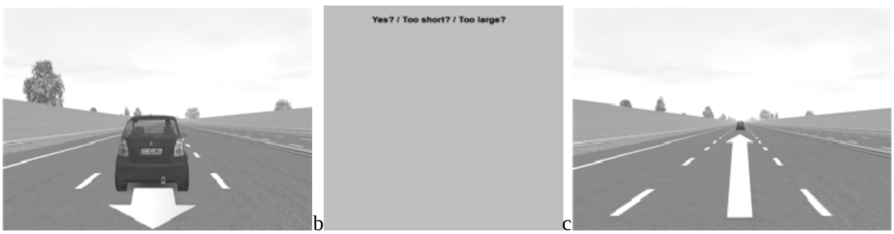

Fig. 2 Starting point at THW= 0.1 sec. of set of increasing distances in a), blanked scene between two THW presentations in b) and starting point at THW= 2.5 sec. of set of decreasing distances in c).

2.2.3. Familiarisation

Prior to the experimental drives, participants performed a familiarisation session to get used to the simulator vehicle dynamics. As discussed above, perception of one's own braking abilities are expected to be a determining factor of preferred THW. In order to facilitate the familiarisation process, the lead vehicle's acceleration was alternatively either negative (-5 s/m²) or positive (3 s/m²) for 20 seconds each. Participants were asked to keep a safe and constant distance to the lead vehicle.

2.3. Participants

A total of 42 participants took part in the experiment (21 males, 21 females) and all were holders of a full driving license for at least one year (*M*= 17.48; *SD*= 10.73). Their age varied between 20 and 64 (*M*= 35.93; *SD*= 11.26) and their mileage between 2000 and 35000 miles a year (*M*= 10369.05; *SD*= 6211.77).

3. RESULTS

Results of averaged adopted minimum THW show an expected effect of the traffic condition (Fig. 3): the mean value is higher in the baseline where there was no traffic present (*M*= 2.61; *SD*= 1.37). There is only a small noticeable difference between THW03 (*M*= 2.04; *SD*= .99) and THW10 (*M*= 2.12; *SD*= .93). The adopted minimum THW changed significantly across the drives [$\chi^2(2)$= 14.96; p= .001], which supports the hypothesis that traffic as a situational factor has an influence on drivers' THW. In contrast, the averaged preferred minimum THW measured following conditions BL (*M*= 1.36; *SD*= .59), THW03 (*M*= 1.30; *SD*= .58) and THW10 (*M*= 1.28; *SD*= .53) did not vary significantly, $\chi^2(2)$= 4.15; p= .125. This supports the idea that each driver has a preferred THW but the adopted THW is influenced by situational factors.

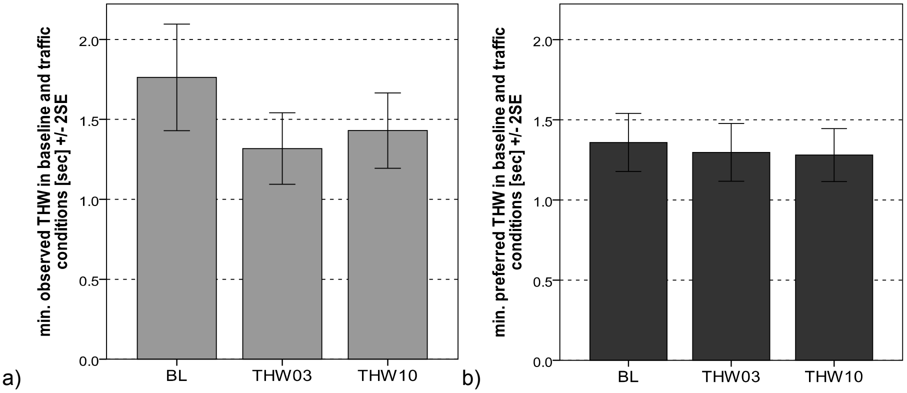

Fig. 3 adopted (a) and preferred (b) minimum THW in the three traffic conditions

An evidence for internal consistency in preferred THW was calculated using the Cronbach's alpha test [6] for the three measurements of preferred minimum THW and showed internal consistency (α = .83). The high correlation between the preferred THWs is another evidence for internal consistency. There is variability in choice of preferred THW between drivers but each driver is consistent in the choice of preferred THW. This reproduces the results obtained from the correlation between the different adopted THWs (Table 2). A similarity between adopted and preferred THW is expected as it is considered that adopted THW is based on preferred THW. Specifically, a significant correlation between preferred and adopted THW in each condition indicates the validity of the method: THW03 (tau=.47), THW10 (tau=.63) and BL (tau=.65).

Table 2 Correlation matrix (Kendall's tau) for adopted minimum THW (a) and preferred minimum THW (b) in the three traffic conditions (* p<.01)

a)	THW03	THW10
BL	.65*	.74*
THW10	.63*	

b)	THW03	THW10
BL	.78*	.78*
THW10	.81*	

4. DISCUSSION AND CONCLUSIONS

The hypothesis that drivers' adopted minimum THW is influenced by traffic but not the preferred minimum THW has been verified. Moreover, preferred minimum THW reproduced the same characteristics as adopted minimum THW, namely that there is a high variability in the choice of THW between drivers but the choice is coherent within drivers. The method developed appears to be a reliable, valid and efficient technique for capturing minimum preferred THW in ruling out situational factors, without requiring the use of an instrumented vehicle. The method can be employed to analyse the relation between drivers' personality or skills and their preferred THW. However, further investigations are needed to understand whether the developed method can be used to assess the influence of situational factors such as traffic, road type and visibility on preferred minimum THW. Situational factors could therefore be included as a variable in further studies. In addition to its use in driver behavioural research, this method could be useful as a prediction tool for driver training to detect unsafe driver behaviour and to coach improvements in driving style.

5. ACKNOWLEDGEMENTS

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ADAPTING TO THE RANGE OF AN ELECTRIC VEHICLE – THE RELATION OF EXPERIENCE TO SUBJECTIVELY AVAILABLE MOBILITY RESOURCES

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ABSTRACT: Range of electric vehicles has been identified as a major barrier for acceptance of electric mobility within studies with inexperienced potential users. However, results suggest that experienced users are able to successfully deal with, and thus, are often satisfied with available range. The relation of experience to the perceived fit of mobility needs and mobility resources and subjectively usable range was examined. Positive experience-related effects were found. A tendency for actively exploring the range of an electric vehicle was linked to more successful adaptation. In conclusion, skepticism about range or even range anxiety may be overcome by assisting potential users explore the fit between mobility needs and mobility resources.

Keywords: electric vehicle, range, field study, mobility needs, user experience.

1. INTRODUCTION

Range of electric vehicles has long been considered a major barrier in acceptance of electric mobility. Market experts as wells as inexperienced potential customers have evaluated the effects of low range resources of electric vehicles as a critical factor for users' purchase intentions and thus for the market success of electric mobility systems [1-3] However, existing data drawn from travel surveys [4, 5] and feedback from expert electric vehicle users [6, 7], show that electric vehicles should indeed easily meet most users' mobility needs.

One possible reason for the gap between subjective and objective mobility needs may be personal safety buffers; these buffers likely exist due to a lack of experience with electric vehicles, that is experience with short-range mobility, as well as to inaccurate conceptions of mobility needs [8]. In addition, it has been recently argued that only a certain share of nominal range is (subjectively) accessible to users and that this usable range depends on existing range skills of a driver [9, 10]. Consequently, novice users may have a lower subjectively accessible range than experienced users given the same objectively available range of an electric vehicle. Hence, experience and practice with an electric vehicle may explain the contradictory findings on range being a barrier for market success of electric vehicles to some extent.

There is a lack of published research on the effect of experience on the perception of range as a barrier in electric vehicle use. The main objective of the present research was to examine the relation of experience to the perceived fit of mobility needs and mobility resources, and to the usable, more specifically the comfortable, range that is available to each individual user. This research also examined whether or not experience was related to general evaluations of range as a barrier for market acceptance and if experience was related to a lower importance rating of range improvements for purchasing intentions.

2. METHOD

The present research was part of a large-scale electric vehicle field trial in the Berlin metropolitan area in Germany. Forty main users drove an electric vehicle for a 6-month period. In this longitudinal study, data was assessed at three time points: prior to receiving the electric vehicle (T0), after 3 months of driving (T1), and upon return of the electric vehicle (T2). These points of measurement represent relevant states in the adoption and experience-acquisition process. Structured interviews (approx. 7 h of audio material per participant), questionnaires (> 1,000 items), travel diaries (all trips occurring within three 1-week periods), and charging diaries (charging processes during two 1-week periods) were used to gain a comprehensive picture of the experience of, and behavior occurring within use of the electric mobility system (for further detail see [7]). The present contribution represents a targeted focus on one topic, within this comprehensive research project.

2.1. Participants

More than 700 people in the Berlin metropolitan area applied via a public online application form, to lease an electric vehicle for a 6-month period. From this sample of potential early adopters of electric vehicles, participants were selected first, according to several must-have criteria (e.g., possibility to install charging infrastructure) and second, ensuring diversification of users in terms of basic sociodemographic and mobility-related variables. If several users scored equally on these criteria selection was random.

The selected sample was, on average, 48.1 (SD = 8.9) years old and consisted of 33 male and 7 female users. Three quarters of users held a university degree. Three quarters of users had not yet experienced driving an electric vehicle. In 43% of households, at least one child under 18 years lived in the family. During the 6 months of electric vehicle usage there were only two dropouts.

2.2. Electric Mobility System

The electric vehicle used in the study had a range of 250 km under ideal conditions (168 km under normal conditions). The electric mobility system was further characterized by a regional focus on the urban area of Berlin, including a network of 50 public charging stations and personal home or office private charging stations available for users (full charge duration duration 4 h).

2.3. Measures

To assess the perceived fit of mobility needs and available mobility resources in terms of the range of an electric vehicle, two items were combined to generate one indicator score. The items were: "The electric vehicle has fulfilled my daily mobility needs" ("will fulfill" at T0), and "Planning car usage (planning of routes and charging duration) was a big challenge" ("will be" in T0). Users indicated agreement to these statements using a 6-point Likert scale ranging from 1 (*do not agree at all*) to 6 (*fully agree*).

The range comfort zone for each user was assessed using the range game, a method described in detail in [9]. In this game, users engaged in a standardized trip scenario, representing a critical range situation. The resulting score corresponds to remaining range in km (as indicated by a range display in the electric vehicle) that a user is no longer perfectly comfortable with when the distance to the next charging possibility is 60 km (i.e., users' range comfort zone).

Range, as a barrier for market acceptance was evaluated using scores of a question within the structured interview, at two time points: before receiving the car and after 3 months. Specifically, at both times, users were asked "In your opinion, what are the barriers for acceptance of electric vehicles?" All interviews were audiotaped and transcribed. For each user it was analyzed whether he or she mentioned range as a barrier for market acceptance (not necessarily a personal barrier).

The importance of range improvements for an increase in purchase intentions, was assessed using one item from a section in the questionnaire (same questions before receiving the car and after 3 months), where several key aspects of the electric mobility systems (e.g., price, charge duration, etc.) were listed. For each aspect, users rated the importance of improvements for enhancing individual purchase intentions. Users rated the importance on a 6-point Likert-scale ranging from *very unimportant* to *very important*.

Finally, one item was used to assess the extent to which users reported to have actively tested out the range of the electric vehicle (questionnaire after 3 months, T1).

3. RESULTS

The data of 35 users who had no missing data in the main study variables were entered in the analyses. All tests for significance were two-tailed at α = .05. Estimates of effect size were computed using Cohen's d calculated from difference scores according to [11].

There was a strong increase in the perceived fit between mobility needs and mobility resources (*d* = 0.80). As depicted in Figure 1, at the earliest time point, users were relatively positive about the electric vehicle fulfilling their mobility needs and the challenge that trip planning entailed, as evidenced in the interview before receiving the car (*M* = 4.17). This rating was even higher after 3 months (*M* = 4.99). This effect turned out to be significant ($t(34) = 4.75$, $p < .001$). A detailed analysis revealed that this effect was mostly caused by reduced skepticism about the difficulty of planning car usage. Yet, according to verbal protocols, need for planning was still perceived as a special feature of using the electric vehicle. Users that reported to have had actively tested out the range showed stronger experience effects in the mobility fit variable ($r(34) = .42$, $p = .013$).

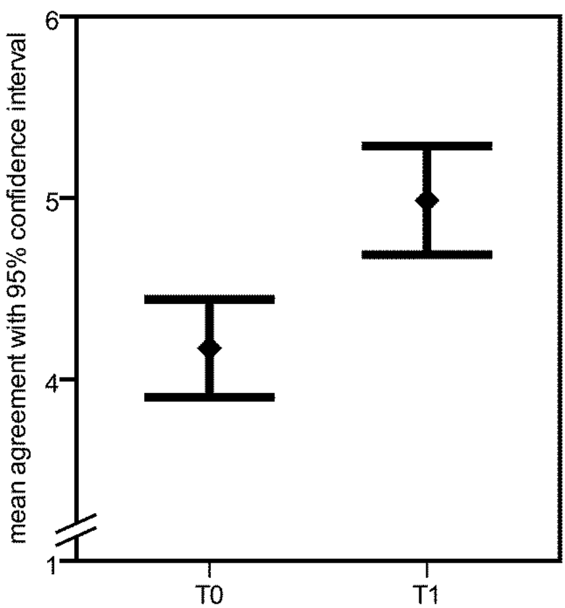

Fig. 1 Perceived fit of mobility needs and mobility resources before receiving the car (T0) and after 3 months (T1)

For the comfortable range variable from the range game a relatively small (*d* = 0.38) but reliable ($t(34) = 2.25$, $p = .031$) positive experience-related effect was found. As depicted in Figure 2, users were in general more comfortable with lower range levels after 3 months than before receiving the car. That is, their comfortable range limit for making a 60-km trip was on average 72.74 km after 3 months, while it was 77.06 km before receiving the car. Another indicator for comfortable range was assessed after 3 months (no data available for the time point before receiving the car): The maximum total trip distance that users were just not comfortable with anymore when using their electric vehicle. As these two scores correlated moderately ($r(34) = -.35$, $p = .049$), the experience effect measured with the range game may also be interpreted as a tendency that users with more experience were more comfortable taking longer trips. Again, users who reported to have had actively tested out the range in questionnaire after 3 months, showed moderately stronger experience effects in the comfortable range score from the range game ($r(34) = -.33$, $p = .059$).

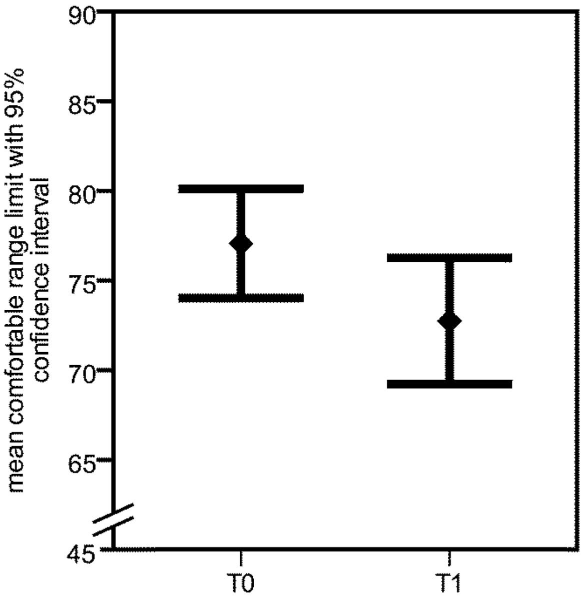

Fig. 2 Users' comfortable range limit (displayed available range) for making a 60-km trip as assessed by the range game before receiving the car (T0) and after 3 months (T1).

When electric vehicles users were asked about market acceptance barriers in electric vehicles, a weak increase ($d = 0.39$) in stating range as a barrier was found that reached the significance level ($t(34) = 2.32$, $p = .027$). These dichotomous data were analyzed using a t-test for easy comparability with the other analyses. Lunney [12] demonstrated that analysis of variance techniques can be validly used for dichotomous data under the given conditions. While 21 of 35 users mentioned range as a barrier for general market acceptance before receiving the car, 30 users mentioned it in the interview after 3 months.

Analyzing the importance of improvements in range of future electric vehicles for increasing users' purchase intentions resulted in a very weak relation between experience and users' importance-ratings of range improvements ($d = -0.08$) that was not significant ($t(34) = 0.49$, $p = .629$). Users judged improvements in range to be important both before receiving the car ($M = 5.20$) and after 3 months of experience ($M = 5.11$) although they mostly perceived a fit of mobility needs and mobility resources (see above) and also 31 of the 35 users agreed (dichotomization of 6-point scale item) that the range of the present electric vehicle was sufficient for everyday use ($M = 4.97$) after 3 months. This result is comparable to [13]. There the authors also found that users' range requirements did not change with experience with the electric vehicle and users wanted higher range throughout the study.

4. DISCUSSION

The present research examined the effect of experience on the perceived barrier that the range of an electric vehicle constituted. Electric vehicle experience was substantially related to an improvement in the perceived fit between mobility needs and mobility resources, and to an increase in comfortable (and thus, usable) range. In addition, there was some indication that actively exploring range resources led to an enhanced adaptation process. However, this effect did not seem to translate to a more positive general evaluation of range, that is, as less of a barrier for market acceptance. Interestingly, range was mentioned more often as a barrier for general market acceptance after 3 months, than before receiving the car. Finally, user preferences for a higher range remained constantly high over the two points of data collection. Hence, a gap remains between users' positive experience of available range resources (mobility fit) and their wishes for setups with higher available range. It would be fruitful to explore this gap and related variables in more depth in future research.

5. ACKNOWLEDGMENTS

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ECOLOGICAL INTERFACE DESIGN FOR ECO-DRIVING

Mark S. Young and Stewart A. Birrell

ABSTRACT: Eco-driving issues are of high priority at the moment. Research suggests that a change in driving style can reduce fuel consumption and emissions by around 15% in many cases. In response to this need, the UK Foot-LITE project developed an in-car feedback system to encourage safer and greener driving behaviours. In order to balance positive behaviour change against the potential negative effects of distraction, an Ecological Interface Design approach was adopted. The current paper presents a review of eco-driving systems currently on the market, and compares these with the human-centred design process adopted in the Foot-LITE project.

1. ECO-DRIVING

Eco-driving has become a regularly used phase in the motorised transport arena; it is used to describe a driving style which results in an increase in fuel economy. Reducing the unit fuel consumption for a journey not only results in a financial saving for the driver, but also helps to reduce their carbon footprint and the impact of other emissions. Eco-driving is thus an area of great interest at the moment, with concerns about vehicle emissions as well as fuel prices being top priorities for private motorists and fleet managers alike.

Research suggests (e.g., [1]) that a change in driving style (such as obeying the speed limit and anticipating traffic flows) can reduce fuel consumption and emissions by around 15% in many cases. However, maximising these savings through behaviour change is a challenge. Young et al. [1] report that eco-driver training programmes can have a positive effect in the short-term, but once the training has ended, drivers soon revert to their original habits. Instead, they suggest that continual in-car feedback can help to maintain the eco-driving style in the long-term.

2. IN-CAR INTERFACES TO SUPPORT ECO-DRIVING

On the basis of this need, there is now a growing market for in-car feedback on driving style. Some major vehicle manufacturers have already attempted to exploit this opportunity, offering models with some form of eco-driving information integrated into the vehicle's instrument panel. Such fuel efficiency support tools hold the greatest potential to positively influence driver behaviour [2]. Whilst many of these are offered on low-carbon vehicles (hybrid or electric drive), the displays represent an interesting trend in driver-machine interface design.

Examples of these 'smart' or 'green' meters include the Honda Insight (Figure 1) and Ford Fusion (Figure 2) instrument panels. Honda's Eco Assist system is designed to show how efficiently the car is being driven. It does this firstly by providing real time, fuel efficient driving guidance (e.g., if the brake or accelerator is applied aggressively then the speedometer display changes colour from green to blue). It also provides an 'Eco' score (depicted by the number of leaves on the flowers in the centre of the main display) during the drive and at the end of each journey. Similarly, the Ford SmartGauge cluster with Eco Guide can display to the driver instantaneous and historical fuel economy, as well as feedback regarding their efficiency via the quantity of leaves that grow on the dashboard – more leaves means better fuel economy.

Fig. 1 Honda Insight hybrid dashboard and speedometer

Figure 3 shows the in-vehicle display for the Chevrolet Volt. It appears from the available information regarding the Volt's interface that designers have decided to keep away from generic representations of driving economy (such as the green leaves with the Ford and Honda), instead focusing on practical coaching advice to increase efficiency. This is displayed by the green ball on the right of the IP screen, which it is assumed will roll back and forth, changing colour as braking and acceleration levels deviate from the optimal. The centre console display will show historical information about driving performance and will also give efficiency tips to the driver.

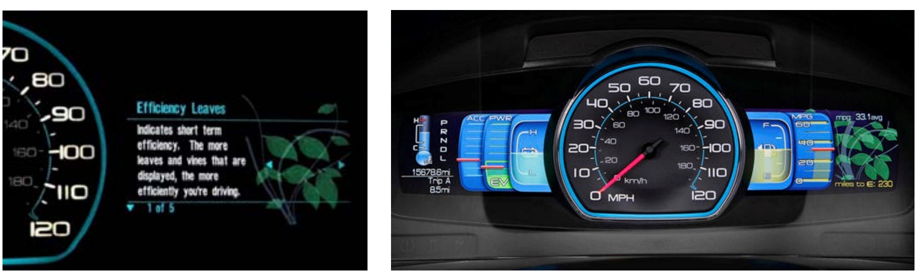

Fig. 2 Ford Fusion hybrid SmartGauge dashboard

Fig. 3 Chevrolet Volt hybrid display

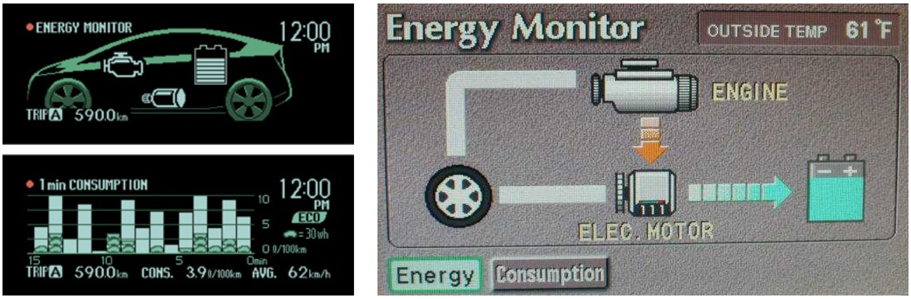

Fig. 4 Screenshots from the 2010 (left) and 2000 (right) Toyota Prius hybrid instrument cluster

The first mass-produced hybrid vehicle to be on general sale in the US and Europe was the Toyota Prius in the year 2000. Figure 4 shows what was to be an entirely new concept for driver-vehicle feedback when the energy monitor was first presented to drivers. The energy monitor (or Power Flow display) shows when the vehicle is running from the engine or electric motor, in an attempt to educate new hybrid drivers of the vehicle state and the way in which the technology works [3]. Whilst these types of displays very effectively reflect current vehicle state, they do not directly educate the driver to improve their driving performance. Performance can only be inferred by trying to maintain the vehicle in electric mode and by using the historical fuel efficiency data. Research has shown that users report that the usefulness of such information degrades with time once the novelty has worn off and drivers become less interested [3].

As well as the original manufacturer offerings, there are also various aftermarket options available for eco-driving information. For instance, a selection of satellite navigation products offer eco-routing options, some of which also connect with the vehicle's on-board diagnostics (OBD) to provide real-time feedback on driving. More recently, one or two smartphone applications have also emerged using the handset's own GPS and accelerometers to detect driving behaviour and provide feedback on the display.

However, regardless of the medium, the design of these interfaces must take into account (and support) the primary information needs of the driver. One criticism of some of the existing displays is that they only state the current performance of the car, and provide little feedback as to how the driver might improve their behaviour. Moreover, road safety remains a top priority alongside eco-driving concerns, and managing any potential conflicts between safe and eco-driving should be a key objective of any such system. Finally, with the visual modality being by far the primary information source for driving (e.g., [4]), in-car interface designs must not present an excessive visual demand for the driver. If the driver's limited attentional capacity has been absorbed by such an in-car secondary task, it could impair their reactions to critical events in the roadway.

3. HUMAN-CENTRED DESIGN FOR ECO-DRIVING

In an effort to balance these objectives, the UK Foot-LITE project developed an innovative in-car feedback system to encourage safer and greener driving behaviours. An Ecological Interface Design ('EID'; [5]) display was developed, representing a novel and revolutionary way of dynamically presenting complex information to the driver in an integrated and intuitive way [6].

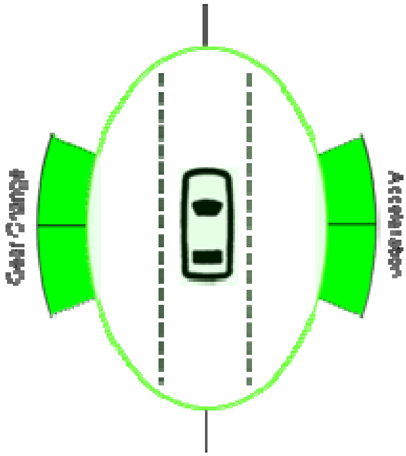

Fig. 5 Foot-LITE EID display (UK RD 4017134-41)

Figure 5 shows one aspect of the EID developed for the Foot-LITE project. The car is mobile in the central oval of the display, and currently sits within a 'green zone' in terms of lane positioning, cornering speeds, and headway to vehicles in front. Meanwhile, eco-driving parameters are presented in the outer oval, with acceleration/braking and appropriate gear use being displayed dynamically (again in a 'green zone' in this example). Any behaviours which exceed set tolerances in the system result in amber or red indicators on the relevant aspect of the display, providing the driver with direct feedback about how their driving affects each parameter. Returning to the 'green zone' offers positive reinforcement to the driver about their behaviour. This design, plus several derivatives of it, has been protected by a UK Registered Design (4017134-41). A key feature of the EID was the integration of complex information from two priorities (eco-driving and safe driving) onto a single direct perception display, in order to facilitate behaviour change while not distracting the driver or causing an unacceptable increase in workload.

3.1. Design process

The visual interface was developed through a human-centred design process (Figure 6). Firstly, the benchmarks for driving performance were established through a literature review [1], which covered both the scientific literature on in-car displays as well as industry codes of practice, design guidelines, and ISO standards. Alongside the literature review, a Cognitive Work Analysis

(CWA; [7]) established the functional and user requirements that would be reflected on the interface. Naikar and Lintern [8] suggested that CWA offers a formative (as opposed to normative) design methodology, supporting revolutionary rather than evolutionary design. Vicente [9] further makes the argument that CWA is particularly useful for systems that have no precedent. Foot-LITE, as a first-of-a-kind vehicle system, warranted a formative approach, and so the project offered an excellent opportunity to apply CWA from idea conception to interface design.

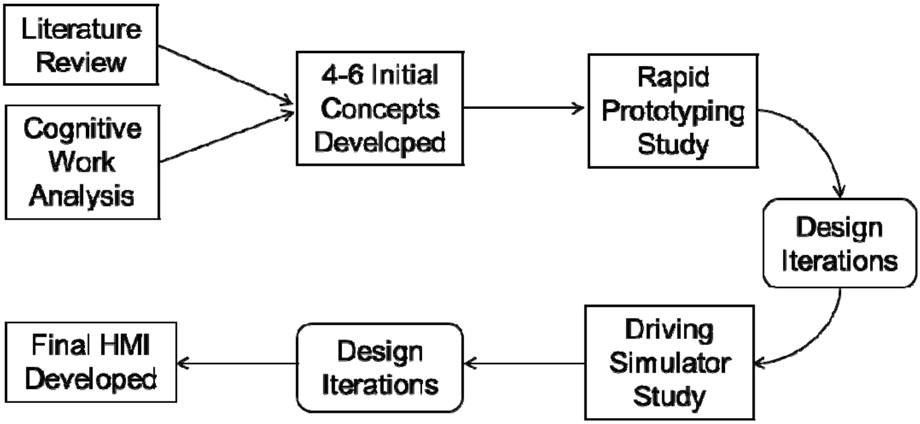

Figure 6: Design cycle process

An initial set of four to six design concepts was generated from these requirements, which were evaluated by subject matter experts as well as potential users in a rapid prototyping study. Through questionnaires and desktop evaluations, the number of concepts was reduced to two – a conventional 'dashboard'-type concept, and the more novel EID display (see [6] for more details on the rapid prototyping study and the generation of the EID). Iterations were made to the designs based on the subjective and objective feedback from the study, and both were subject to large scale empirical testing in the Brunel University Driving Simulator. Results from the simulator trials [10] demonstrated that both designs had the desired effects on safe and eco-driving behaviour (in terms of reduced speed and acceleration) while avoiding negative impacts of increased workload or driver distraction (using a peripheral detection task). However, the EID performed better in terms of its perceived demand on driver attention (a 17% reduction over the dashboard-type interface), and was also preferred by participants in the study. Thus the EID was recommended for use in the Foot-LITE system.

4. CONCLUSIONS

The rapid development of in-vehicle interface technologies, coupled with the prominence of eco-driving, has resulted in numerous products to give drivers feedback about their performance. Whilst these may or may not have positive effects on eco-driving awareness and behaviour, it is clear from the work in the Foot-LITE project that more could be achieved with a usercentred approach to interface design.

The use of CWA to inform the design ensured that a novel and innovative concept was developed, which proved effective in promoting smart driving behaviours as well as minimising additional driver workload and distraction. When compared to a conventional concept (akin to existing systems on the market), the EID was found to be easier and was preferred by drivers, while delivering its stated objectives in terms of performance. In our view, the unique benefit of the EID over existing systems is that it combines complex information onto one direct perception display, with both safety and eco-driving advice integrated on the same interface.

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