The Impact of Abstract vs. Concrete Feedback Design on Behavior – Insights from a Large Eco-Driving Field Experiment

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ABSTRACT
About 17% of the worldwide CO_2-emissions can be ascribed to road transportation. Using information systems (IS)-enabled feedback has shown to be very efficient in promoting a less fuel-consuming driving style. Today, in-car IS that provide feedback on driving behavior are in the midst of a fundamental change. Increasing digitalization of in-car IS enables virtually any kind of feedback. Still, we see a gap in the empirical evidence on how to leverage this potential, raising questions on future HCI-based feedback design. To address this knowledge gap, we designed an eco-driving feedback IS and, building upon construal level theory, hypothesize that abstract feedback is more effective in reducing fuel consumption than concrete feedback. Deployed in a large field experiment with 56 participants covering over 297,000km, we provide first empirical evidence that supports this hypothesis. Despite its limitations, this research may have general implications for the design of real-time feedback.

Author Keywords
Real-time feedback; feedback design; eco-driving; field experiment; construal level theory.

ACM Classification Keywords
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INTRODUCTION
Road transportation of goods and people is a key enabler for modern society's wealth and individual mobility. Unfortunately, this goes along with substantial negative externalities: about 17% of the worldwide CO_2-emissions can be ascribed to road transportation [24]. Many governments impose increasingly stringent fuel emission standards to make vehicle manufacturers improve their fleets' fuel efficiency. However, these developments take decades to become effective and are very expensive to implement [19]. Aside from the drive train technology, driving style has been shown to have a considerable impact on fuel consumption [1]. Therefore, promoting a change towards a more eco-friendly driving style – i.e. a less fuel-consuming and CO_2-emitting –, is a promising lever to reduce fuel consumption of road transportation. Additionally, it has an instant effect and can be achieved with very low costs compared to investments in vehicles technology [3].

Though traditional behavioral interventions, like education or trainings revealed some effects, providing the driver with real-time feedback on his or her driving style seems to be the most promising approach to effectively promote a fuel-efficient driving behavior [1,6,53]. Feedback works by processing, preparing and providing relevant information to the user in a way that fosters changing one's behavior towards a defined direction [30,40]. Information systems (IS) are very well suited as scalable systems to provide timely feedback on behavioral outcomes [7,33,54]. Furthermore, in contexts where information on current performance and consequences regarding a certain behavior is fuzzy or even unknown, IS-enabled feedback interventions have a high potential to create an impact [22]. Changing pro-environmental behavior (PEB) is challenging for exactly these reasons. People often don't know how they should behave and they experience the consequences of their behavior rather indirectly [25]. While the impact of IS-enabled feedback on behavior change has recently received attention by an increasing number of researchers in the realm of PEB in general [25], few studies have evaluated the impact of feedback on eco-driving in methodologically rigorous and realistic settings.

Today, eco-driving feedback information systems (EDFIS) are in the midst of a fundamental change. Increasing digitalization of dashboards and in-car infotainment systems enable virtually any kind of feedback [21,51]. This raises important questions on Human Computer Interaction (HCI) design [16]. Car manufacturers recently started to implement new generations of EDFIS. Most of them use real-time information from the car to provide eco-driving feedback while driving. Yet, the design and content of those systems obviously differ substantially between car models. One of the most striking differences between latest EDFIS is the level of information abstraction. On the one extreme, some cars have EDFIS that provide very rich and detailed numbers on a plethora of different factors to induce eco-driving. This can include information on current fuel consumption, gearing, braking behavior, and others. Such *concrete* feedback makes it constantly apparent what exactly the driver has to do to drive more eco-friendly, i.e. it aims to teach the individual *how* to drive. On the other extreme, there are rather *abstract*, symbolic representations of aggregated information that reflect changes over longer periods. That kind of feedback seemingly aims more towards making salient *why* someone should drive more eco-friendly.

Car manufacturers have been providing EDFIS for years, and despite the large body of research on eco-driving, two knowledge gaps can be identified. Firstly, by far most of the existing studies on eco-driving suffer from severe shortcomings in their research design and therefore do not rigorously answer the question on whether eco-driving feedback has a causal effect on fuel consumption [9]. Second, none of the existing studies has explicitly researched the impact of visual feedback design factors [25]. In particular, providing eco-driving feedback in a rather abstract manner in contrast to rather concrete information can be considered as two fundamentally different design approaches of feedback-driven behavioral interventions. Yet, to the best of our knowledge, the impact of abstract versus concrete feedback design on PEB in general [25] and eco-driving in particular has not been investigated yet. In light of the outlined research gaps, this paper is dedicated to the following research question:

RQ: What is the impact of abstract vs. concrete feedback design on eco-driving?

To that end, we describe the design process of how we built our proprietary EDFIS, which was tested with 56 drivers covering approximately 297,000 km. We conducted the study as a randomized controlled trial in the field in order to rigorously assess the impact of a concrete vs. an abstract EDFIS design on driving behavior and fuel consumption as prominent examples of pro-environmental behavior. The design process is based on several iterations and a powerful theoretical lens to understand the potential of abstraction in feedback design, namely construal level theory [47]. We present the main results of the field study and discuss the conclusions of our work and its limitations to motivate future research.

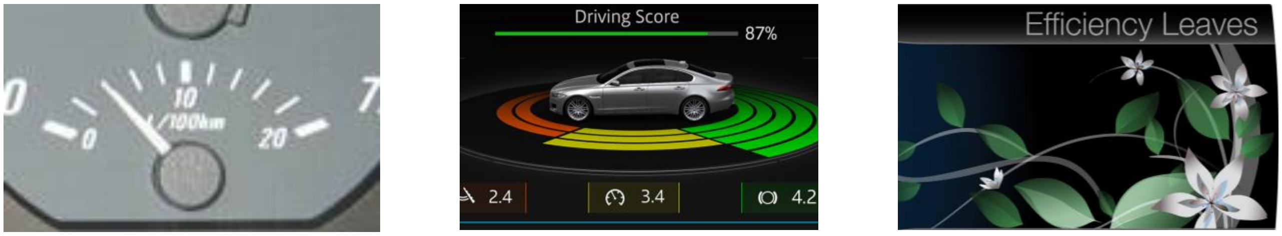
EXISTING SOLUTIONS, RELATED WORK AND THEORY

Existing Eco-Driving Feedback Solutions

EDFIS have existed for decades. In early simple solutions, a classic gauge displayed the current fuel consumption of the car in real-time in the car's dashboard (Figure 1a). Yet, in practice, this might be of limited value, as the current fuel consumption in a regular trip usually fluctuates heavily. Moreover, the depicted information does not give any normative baseline or reference frame that lets the driver evaluate his or her performance. Due to increasing possibilities of car data analysis on the one hand and powerful displays on the other hand, two trends are observable in dashboards of modern cars.

One trend is that modern EDFIS provide a lot of detailed information on several driving parameters that indicate *how* to drive eco-friendly. Taking the EDFIS of Figure 1b as an example, here, three parameters are displayed that reflect acceleration, braking and speeding behavior. Each parameter ranges from 1 (bad) to 5 (good) and is shown as a number as well as a colored bar chart (red=bad score; green=good score) that surrounds a visualization of the car. The top of the screen contains a driving score that reflects an overall score of the trip's eco-driving behavior.

The other trend of EDFIS design uses rather abstract representations of eco-driving related parameters (mostly fuel consumption) and emphasizes *why* one should drive eco-friendly. As depicted in Figure 1c, for example, a well-known symbol is used to represent the environment, in this case a plant. A lower fuel consumption is represented by growth of the plant, i.e. growing branches, leaves and flowers. Like the growth of a plant takes some time, also the EDFIS plant in Figure 1c represents the eco-driving style over a certain driving period. Current fuel consumption is not displayed anywhere in this EDFIS example.



(a) fuel consumption gauge **(b) modern concrete EDFIS** **(c) modern abstract EDFIS**

Figure 1. Different EDFIS: (a) a classic fuel consumption display in the BMW 7 from 1982; (b) a modern concrete EDFIS of Jaguar / Landrover cars; (c) a modern abstract EDFIS from Ford's SmartGauge

Related Work on Eco-Feedback

The potential of feedback IS has frequently been shown in several domains of PEB and HCI research [25] such as for residential energy consumption [2,30,38], water consumption [44], transportation choice [15] or fuel consumption [1,6,42,50]. Only a few studies investigated feedback IS that provide actual real-time feedback, i.e. direct information on current performance. IS-enabled feedback has a high potential to reduce the salience bias (tendency to act upon the most salient information) and hence to change behavior when feedback is given in real-time [14,26]. In an exhaustive field study, [44] find reductions in water consumption that are way higher than the effects found in previous studies, where non-real-time feedback IS were used. Although most research on feedback IS does not consider or discuss a possible impact of feedback design factors on its effectivity in changing behavior, there are some exceptions that at least call for more attention on this topic [16,33,34]. In an comparative survey on eco-feedback technologies [16] distinguish between two forms of feedback: "low-level feedback [that] can provide explicit detail about how to change or improve specific behavior" (p. 2002) in contrast to "high-level feedback [that] is summative and can help improve performance towards a goal" (p. 2002). Additionally, they stress that when building a feedback system, one has to "think about why the individual is considering" (p. 2003) to perform a certain behavior. In a follow-up study, [17] compared several display mock-ups for water consumption feedback that were either designed using fine granular information, numbers and statistics or that used a depiction of a lively aquarium that flourished when the residents behaved pro-environmentally. Unfortunately, they did not evaluate the effect of these different eco-feedback IS on water consumption, but only measured subjective preferences.

In the realm of eco-driving behavior, [9] conducted a systematic literature review including all EDFIS studies that used real-time feedback IS. Three conclusions were derived: (1) the grand majority of studies suffer from poor research designs that compromise the validity of the results. Common problems were small sample sizes [e.g. 27,30], short treatment periods [e.g. 8,39], research designs that did not allow for causal inference [e.g. 1,37] or shortcomings in reporting quality [5,39]. (2) Fuel consumption as the dependent variable was measured in very low resolution, which was mentioned before to be a major research gap in the general field of eco-feedback research [25]. For example, [50] – being the only study with a clean experimental research design – measured fuel consumption only as an accumulated value over the whole intervention period. (3) No study included measurement of driving parameters in high temporal resolution, which would allow for deeper insights into how eco-feedback affects fuel-consumption.

In summary, despite a large body of research, we still do not really know empirically, if EDFIS lead to a significant reduction in fuel consumption. Therefore, though not the focus of this work, we provide for the first time a strong empirical basis to investigate the impact of real-time eco-driving feedback on fuel consumption in a clean experimental setup.

Regarding the role of feedback design, we could not find any research that sheds light on the impact of design factors on EDFIS efficacy. Tulusan et al. (2011) asked truck drivers for their preferences on rather concrete and abstract EDFIS, but they did not investigate the effects, different feedback IS might have on actual behavior [49]. In a recently published meta-analysis on eco-feedback, [25] clearly point out this research gap, when they call for future researchers to put "greater attention to the physical design and presentation of feedback displays" (p. 1221) as "the way in which feedback information is presented to users can have an impact on the way in which it is perceived and interpreted, and a subsequent impact on motivation and action" (p. 1222). We think, this gap hits the core of HCI research and see construal level theory as a possible theoretic basis to build upon.

Construal Level Theory

Construal level theory might serve as a vital lens to explain the effect of abstract and concrete feedback on PEB such as eco-driving and hence lead the EDFIS design process. According to construal level theory, high-level construals are relatively abstract, coherent, and superordinate mental representations that constitute "why" aspects of actions [46–48]. Low-level construals in contrast, refer to detail-oriented and concrete interpretations that constitute "how" aspects of actions. For example, when asking a person for her goals regarding a certain action, an example for a high-level construal goal could be “to do well on the exam”, whereas a low-level construal goal could be “to read books”. The psychological construal of an object increases with the psychological distance to it, i.e. the “subjective experience that something is […] far away from the self, here, and now” [47:440]. Psychological distance can be induced in several dimensions, such as spatial or temporal distance [29]. Hence, information on future or past behavior induces higher-level construal by increasing temporal psychological distance [46].

As individuals base evaluations and decisions on construals of objects rather than the objects themselves [48], higher levels of construal can have a positive influence on a PEB like eco-driving. This is, because construal level has an impact on antecedents of PEB, namely attitude towards PEB and PEB-related norms [4]. A higher construal level can shift a person’s attitude, e.g. about PEB, towards the positive by making pros become more salient [47]. The reasoning is that without advantageous pros, we would not even consider pursuing an action and start evaluating disadvantages [47]. Hence, pros are superordinate features while cons are peripheral, subordinate features. In a high construal level mindset, superordinate feature are activated while subordinate features are neglected so that pros become more vivid and our attitude shifts toward the positive. Construal level theory also predicts that higher construal level increases the impact of peoples’ norms in the decision making process [13]. Moral principles are considered to be higher-level construals, “because of their generalized and decontextualized nature” [13:1205]. Therefore, a low construal level mindset, e.g. induced by proximal events is “less likely to reflect moral principles than judgments of distant events” [13:1205]. Taking into account that abstract representations induce higher levels of construal than concrete representations [47], we hypothesize that abstract feedback is more effective than concrete feedback to reduce fuel consumption.

METHODOLOGY

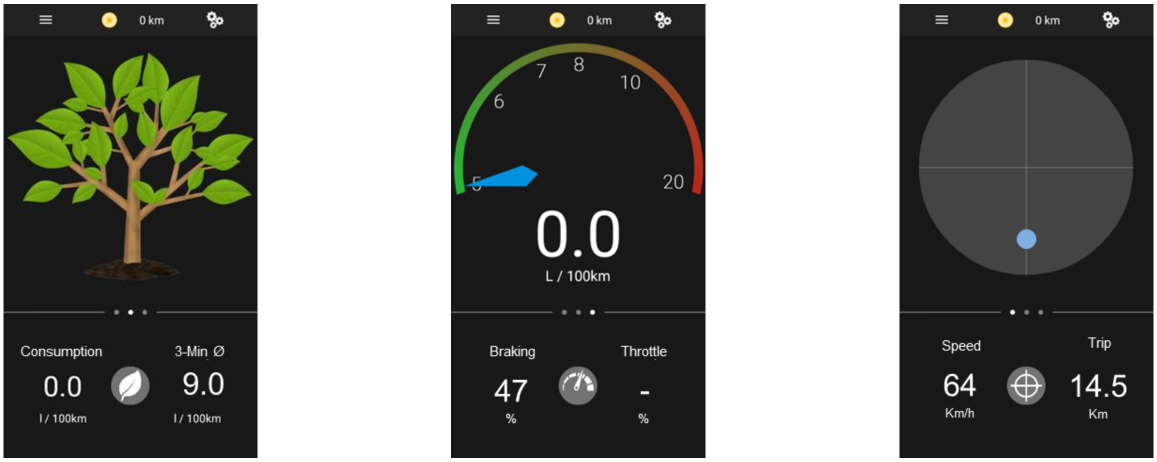
EDFIS Description and Requirements

We developed an EDFIS using methods from design science research [20]. The EDFIS had to fulfill four requirements. First, the EDFIS had to be able to measure a car’s driving parameters, including fuel consumption and GPS-location in real-time. Second, it had to be able to display the current fuel consumption graphically and in sufficient detail to the driver while he is driving. Third, the EDFIS should be easy to use in order to increase adoption and hence avoid loss of data. Fourth, based on construal level theory, the system should be able to provide concrete eco-feedback, abstract eco-feedback and feedback that does not display any eco-driving related information to serve as a control condition.

To meet the first requirement, we used an on-board diagnostic dongle plugged into the car that is able to measure the car’s driving parameters, including fuel consumption. This data is sent via Bluetooth to a smartphone and from there via GSM to our backend. The smartphone additionally provided the geo-positioning data. Furthermore, using the smartphone let us tackle the second requirement as we could use it to display information in high resolution via an app and install the smartphone in the car, so the driver could be provided with the eco-feedback during his or her trip. For the third requirement, we designed the EDFIS such that the drivers would not have to interfere with it while driving in order to increase usage and avoid missing data. Therefore, our smartphone app automatically popped up to provide eco-feedback as soon as the engine was turned on, i.e. the drivers did not need to actively turn on the system. The EDFIS was charged by the car so it could be installed permanently in the car and mounted onto the cars dashboard. Fourth and finally, we developed three feedback screens, two of which provided concrete feedback (Figure 2a) and abstract eco-driving feedback (Figure 2b), respectively. The control screen displayed car data that was unrelated to eco-driving (Figure 2c).

Design Rationale for the Concrete, the Abstract and the Control Group Feedback

To develop the concrete and abstract feedback as our experimental stimuli, we tried to adopt existing eco-driving feedback systems from research and car dashboards. Additionally, we applied two common approaches to manipulate construal level (for further details, see [10]). First, we induced high- and low-level construal by priming a “why” and “how” mind-set on the basis of abstract and concrete representations of fuel consumption. A large body of research suggests that a “why” versus a “how” prime is able to manipulate a person’s construal of an object [18,27,47]. Building upon these findings, our low-construal stimulus provided concrete vehicle information and a detailed gauge geared towards “how to drive eco-friendly”. In contrast, the high-construal stimulus depicted goal-related information based on a more abstract representation, i.e. a tree and simple numbers, geared towards “why to drive eco-friendly”. Second, numerous studies have shown that temporally distant events are represented in a more abstract, high-level manner than near events [47,48]. Therefore, we used the three-minute floating average of the fuel consumption in the abstract feedback – thus also reflecting more distant events –, whereas the concrete feedback displayed real-time information of current fuel consumption, i.e. the stimulus just depicts what is happening now. As a pre-test, were able to manipulate construal level with the same approach and very similar stimuli in an online setting [10]. In the following, the stimuli design process is explained in more detail.



(a) abstract feedback **(b) concrete feedback** **(c) control group**

Figure 2. The feedback screens for (a) abstract feedback, (b) concrete feedback, (c) neutral control feedback

In the rationale for the control group feedback, we had to consider three requirements regarding research design. First, to rule out a possible Hawthorne effect as a potential confound of causal inference we provided a visual feedback similar to the intervention feedback instead of a mere data measurement device [31,44]. Second, in order to avoid attrition bias and missing data we also had to make the control group feedback interesting for the drivers to ensure constant usage and maintenance of the system [23]. Third, the control group feedback should not influence eco-driving behavior.

Description of the Feedback Stimuli

In the first EDFIS creation, the abstract feedback showed a tree that updated every second to show the average of the current trip fuel consumption in liters per 100km (l/100km). The smallest tree reflected a value of over 18 l/100km, the biggest tree reflected a value of less than 7l/100km. These thresholds covered most of the fuel consumption range of our sample cars. In testing, it soon became clear that the trip average changed a lot in the beginning (high fuel consumption due to cold motor and acceleration) and changed less, the longer the trip was (decreasing weight of additional values on the fuel average), both of which were not perceived as helpful indications for eco-driving performance. Hence, we changed the tree according to the real-time consumption in the next iteration. Now, the tree fluctuated extremely in size, as current fuel consumption easily changes from over 100l/100km during acceleration to 0l/100km when coasting, which again did not seem very helpful. Therefore, we changed again to a three-minute floating average. The tree's growth now was a smooth experience and its size could be affected by a change in driving style over the whole trip (Figure 2a). At the bottom left a display of the current fuel consumption was included to increase comprehensibility of the EDFIS.

The concrete gauge screen (Figure 2b) displays a classic fuel gauge with real-time information on driving data. The gauge in the middle shows real-time fuel consumption of the car in l/100km, with a maximum of 20 l/100km. The value on the bottom left reflects braking strength in percent (-1g = 100%), the value on the bottom right reflects throttle position in % (throttle fully pushed = 100%) as an indicator for acceleration behavior. Both braking and acceleration behavior are key factors for fuel consumption [1]. This screens is closely orientated on classic eco-feedback screens (Figure 1a), so no iteration was needed in the design process.

Based on the requirements of the design rationale, the control group screen (Figure 2c) provided visual feedback of longitudinal (vertical axis) and lateral (horizontal axis) acceleration, depicted by a floating dot. The g-radar screen also provided current speed in kilometers per hour and the current-trip length. None of the displayed information indicated eco-driving related normative values. As with the concrete feedback screens, the control group screen design did not need further design iterations.

EVALUATION

Study Procedure

For our field study we equipped 72 professional drivers of a road assistance service company with our EDFIS. The sample was recruited via a company-internal mail where patrollers were asked to participate in this voluntary connected-car field study for a period of ten weeks. Out of a possible 92 patrollers, 72 volunteered to participate. No participant was excluded. The participants on average drove approximately 150 km per workday. Except for one, all drivers were male and on average 39.15 (SD = 13.05) years old. The data of eight drivers was excluded, due to technical issues that led to erroneous data. Another eight participants were excluded due to inactivity.

The field study was initiated with a two-week baseline phase, where all drivers saw the control group feedback (Figure 2c). At the end of the baseline phase, drivers were asked to participate in a survey covering aspects of their motivation to drive eco-friendly. All questions were answered on 7-point Likert-scales (see Appendix). Measures covered attitude towards eco-driving (four items), subjective eco-driving performance (one item), intrinsic motivation to eco-drive (three items) and general environmental attitude (three items).

In the following eight-week treatment phase, drivers were randomly assigned to being provided either with control group feedback (N = 22), concrete feedback (N = 16) or abstract feedback (N = 18). The intervention was triggered at the same time for all participants. After the treatment phase, all feedback screens were provided to all drivers so they could explore them. After another period of eight weeks, we asked the drivers for their preference on the feedback type.

Analysis of Survey Data on Eco-Driving Motivation and Eco-Driving Feedback Preferences

40 participants took part in the survey on eco-driving motivation. One-way ANOVAs did not reveal significant differences between the groups in any of the measures (Table 1). This indicates that our randomization produced equal groups with respect to drivers' individual take on eco-driving. Therefore, these factors can be ruled out as potentially confounding explanatory variables in the further analysis [12].

Furthermore, we investigated whether the effect of the feedback type on eco-driving was because of one feedback being preferred over the others. 51 of the drivers gave information on their feedback preference. Table 2 indicates rather equally distributed feedback preferences and a Pearson Chi^2-test reveals no significant dependence between assigned group and feedback preference ($chi^2 = 7.22$; $p>0.05$).

	Control	Gauge	Tree	F	p>F
Att eco	4.41 (1.28)	4.98 (1.56)	5.17 (.86)	1.39	.26
Subj eco	4.44 (1.09)	5.0 (1.21)	4.67 (1.07)	.86	.43
Intr eco	3.67 (1.19)	4.58 (1.87)	4.08 (1.16)	1.43	.25
Att env	3.65 (.98)	3.78 (1.38)	4.06 (.75)	.52	.60
N	16	12	12		

Table 1. ANOVAs, means and standard deviations (in parentheses) of eco-driving related constructs; Att eco = attitude towards eco-driving, Subj eco = subjective eco-driving performance, Intr eco = intrinsic motivation to eco-drive, Att env = general attitude towards the environment, N = sample size, Control = control group, Gauge = Eco gauge, Tree = Eco tree

		Feedback preference			
		Control	Gauge	Tree	Sum
Assigned Group	Control	10	3	5	18
	Gauge	4	8	5	17
	Tree	3	7	6	16
	Sum	17	18	16	51

Table 2. Cross table of frequencies; Group = experimental group the drivers were assigned to, Control = control group, Gauge = Eco gauge, Tree = Eco tree

Data Analysis and Results

In order to test our hypothesis, we define fuel consumption as our dependent variable and the feedback group (control, concrete or abstract) as our independent variable. We further include three predictors to control for external influences. (1) We include the day of the experiment as a predictor in the regression in order control for trends in weather or traffic conditions [36]. (2) Average trip speed is included to control for traffic conditions on a trip level as lower average trip speeds are indicators of worse traffic conditions and hence, higher fuel consumption [45]. (3) Ultimately, trip distance was included, as the trip fuel average is influenced by trip distance due to the car consuming more fuel at the start of the trip, when the engine is still cold [52]. To get deeper insights on whether our EDFIS had different effects for different trip lengths, we analyze our data not only for all trips, but cluster them into short (<5 km), medium (5-10 km), large (10-20 km) and very large (>20 km) trips.

We analyzed the data in two steps. First, we checked whether randomization has produced equal groups with respect to the included variables. Therefore, the first regression considers only the baseline phase, where all drivers were provided with the same feedback, i.e. the control screen. Second, we applied a fixed-effects model for the treatment phase in order to test our hypothesis on the effect of the different EDFIS designs on fuel consumption. The regression equation is as follows:

$$\mathbf{fuel_{it} = (\alpha)_i + \beta_1 T_{it} + \beta_2 T_{it} + \beta_3 (speed)_{it} + \beta_4 (distance)_{it} + \beta_5 (day)_{it} + \varepsilon i}$$

where $fuel_{it}$ is the fuel consumption in liters per 100 km by driver i in trip t. We assume dependency of intra-individual observations and hence include an individual fixed effect α_i for each driver. The treatment is in the variables T_{1it} and $T_{2it,}$ which are zero for the trips of the two weeks baseline phase and turn 1 if driver i is provided with the concrete feedback or abstract feedback treatment, respectively. Thus, β_1 and β_2 indicate the treatments effects as the difference in fuel consumption between the control condition and the respective treatment condition. As covariates, we include the average speed per trip, the trip distance and the day.

	Baseline Analysis					Treatment Analysis				
Trip Length	all	< 5 km	< 10 km	< 20 km	> 20 km	all	< 5 km	< 10 km	< 20 km	> 20km
Control Group	-	-	-	-	-	-	-	-	-	-
Concrete Feedback	-.01	.63*	-.17	-.03	.05	.07	-.51	.08	.00	.08
	(.09)	(.31)	(.23)	(.16)	(.15)	(.15)	(.38)	(.19)	(.20)	(.18)
Abstract Feedback	.26**	.30	.26	.21	.21	-.33*	-.64	-.52	-.21	-.35**
	(.08)	(.29)	(.21)	(.15)	(.12)	(.14)	(.38)	(.28)	(.22)	(.11)
Day	.01	-.07*	-.01	.01	.01	.01†	.01**	.01†	.01*	.01†
	(.01)	(.03)	(.02)	(.02)	(.01)	(.00)	(.01)	(.00)	(.00)	(.00)
Avg. Trip Speed	-.04†	-.19†	-.11†	-.04†	-.02†	-.05†	-.18†	-.10†	-.05†	-.03†
	(.00)	(.01)	(.01)	(.00)	(.00)	(.00)	(.01)	(.01)	(.00)	(.00)
Trip Distance	-.01†	-.23*	-.11	-.03	-.01*	-.01†	-.33†	-.05	-.03*	.00†
	(.00)	(.11)	(.07)	(.02)	(.00)	(.00)	(.06)	(.03)	(.01)	(.00)
Constant	10.67†	5.58†	9.57†	10.64†	10.00†	10.82†	7.52†	10.69†	10.62†	10.21†
	(.25)	(1.38)	(.77)	(.48)	(.38)	(.07)	(.59)	(.21)	(.08)	(.07)
R^2	.17†	.25†	.22†	.11†	.10†	.26†	.26†	.29†	.25†	.25†
Observations	4,392	1,236	9,92	1,224	940	21,608	6,139	4,768	5,866	4,835

Table 3. Regression results for fuel consumption in l/100 km including all groups; standard errors in parentheses; significance levels are indicated as *=5%, **=1%, †=0.1%

We consider longer trips to have a higher impact in the regression model and hence perform a weighted regressions based on trip distance. The error term ε captures any unmodeled determinants. The output of the analyses is displayed in Table 3.The results of the baseline phase indicate, as expected, no significant difference in fuel consumption between the drivers that later saw the concrete feedback and the control group. Unfortunately, the drivers that later saw the abstract feedback had a significantly higher fuel consumption ($p = .002$), i.e. the randomization process did not produce equal groups with regard to their fuel consumption during the baseline phase.

However, despite the higher fuel consumption of the abstract feedback group in the baseline phase, in the treatment analysis only the abstract feedback had a significant effect on fuel consumption over all trips. Looking at the group effects for the different trip length clusters, we see this result being confirmed for all trip lengths in tendency, yet only statistically significant for the cluster of very large trips due to the high error terms. In contrast, the effect of the concrete eco-driving feedback remains insignificant over all trips. Taking into account both, the results of the baseline phase and the treatment phase, we see that only the abstract feedback has a significant impact on fuel consumption. This effect goes beyond a regression to the mean as indicated by the significantly lower fuel consumption for the abstract feedback group in the treatment analysis.

CONCLUSION

Summary

In our research, we investigate the impact of abstract versus concrete feedback on eco-driving. Based on existing research we predict that abstract feedback is more effective in reducing fuel consumption than concrete feedback. This hypothesis led the design process of an EDFIS artifact, which we evaluated in a rigorous field experiment with 56 participants that together drove over 297,000km in 21,608 trips. The EDFIS stimuli were developed based on inputs from practice and HCI research, using methods from design science research and theoretical implications from construal level theory. The results indicate that abstract feedback significantly reduces fuel consumption, while concrete feedback did mostly not have an effect, thus pointing towards confirmation of our hypothesis. This effect could not be explained by differences between the groups in respect to their eco-driving motivation, their attitude towards eco-driving nor their preference for a specific type of feedback. Hence, the research at hand is the first to demonstrate the impact of different feedback designs, namely abstract vs. concrete feedback design, on eco-driving behavior in a rigorous field experiment. Practitioners in HCI may consider the power of information abstraction in the design of visual feedback systems.

There are some limitations in the research design and analysis that should be addressed in future work. Regarding research design, one limitation is the sample size and sample specificity. Though we cover quite a lot of km in driving data, for intergroup comparisons with our three groups, the sample size of 56 drivers is sub-optimal. Additionally, our sample was drawn from professional road assistance drivers.

Therefore, the eco-driving motivation and potential of our participants was restricted by two key factors. First, fuel expenses are covered by the drivers' employer. Second, in case of a customer service request, the drivers' first priority is to get to the spot of the incidence as fast as possible, thereby disregarding eco-friendly driving. If any, however, we argue that this made it harder to find an effect. Therefore, we would in fact expect even stronger results if our research would be replicated with a sample of regular drivers. Another limitation is the design of our experimental stimuli (Figures 2a vs. 2b) that apparently differ in more than one factor from each other. This research tries to shed light on whether there is a potential effect of abstract feedback design on behavior by initially combining several construal level inducing factors. Future research will have to disentangle these factors and distinguish them from competing theories with more clarity [25]. Regarding the control stimulus, we cannot exclude a possible effect of the G-radar on fuel consumption, even though we doubt that it had an effect, as no number or color provides normative feedback to the driver. Additionally, an effect of the G-radar cannot explain the differences in fuel consumption between the groups in the treatment phase as compared to the baseline phase.

Apart from tackling these shortcomings, we see further potential for future research in deepening the analyses in two ways. Firstly, additional data, like weather, traffic, or road conditions should be included as they very likely have an effect on fuel consumption. By including information on the day of travel and average trip speed, we tried to cover some of these potential influences, but they surely struggle with fuzziness and hence, should be replaced by the direct measures. Additionally, information on road conditions like slope or speed limit, are missing in our dataset. Adding such information in the analysis both, improves the validity of the investigated effects and helps to understand the determinants of eco-driving. As a second future research stream, we propose to not only look for main effects of feedback interventions, but try to understand, which specific behaviors are changed in detail. For our example, this would mean to analyze, which specific driving behavior was affected by the different feedback types and how these behaviors are correlated with the outcome variable, i.e. fuel consumption. For example, did we change acceleration behavior, idling behavior or coasting and what is the impact for each of them on fuel consumption? Our modern sensor technology gives us the possibilities to measure many different behaviors in high granularity. This could enable specific and tailored interventions in real-time.

Regarding the theoretical basis, we used construal level theory as it nicely explains why abstract feedback is more effective in changing eco-driving behavior than concrete feedback, but we see that other explanations could contribute to our findings as well. For example, the visualization of the growing tree that we used may contain elements of gamification. The apples that appear on very low fuel consumption could be seen as batches often used in gamification [11,35] and it may be the motivation to "let the apples grow" that drives the user to behave as intended. Future research should challenge these alternative explanations by proper research designs under more controlled conditions, e.g. in a laboratory setting.

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APPENDIX

Construct	Items
Attitude towards eco-driving (α=.87)	"I think eco-driving is…" 1. "Bad – Good" 2. "Senseless – Sensible" 3. "Displeasing –Pleasing" 4. "Not fun – Fun"
Subjective eco-driving performance	"I drive economically and eco-friendly" 1. "Never – Always, on every trip"
Intrinsic motivation to drive eco-friendly (α=.88)	All items to be answered on the scale "disagree – agree" 1. "Eco-driving is fun" 2. "I find eco-driving pleasing" 3. "I enjoy driving economically and eco-friendly"
General Attitude towards the environment (α=.47)	All items to be answered on the scale "disagree – agree" 1. "I behave eco-friendly even if it goes along with significant costs and effort" 2. "I don't think we are heading towards an environmental catastrophe if we continue the way we have lived so far" 3. "For the sake of the environment we should all be willing to limit our current standard of living."

Table 4. List of question items for each measured construct from the survey. Questions were answered on a 7-pont Likert scale. Cronbach's Alpha values in parentheses.

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