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The impact of numerical vs. symbolic eco-driving feedback on fuel consumption – A randomized control field trial

Andre Dahlinger[a,*], Verena Tiefenbeck[b], Benjamin Ryder[b], Bernhard Gahr[a], Elgar Fleisch[a,b], Felix Wortmann[a]

[a] ITEM-HSG, University of St. Gallen, Dufourstrasse 40a, 9000 St. Gallen, Switzerland
[b] Information Management, ETH Zurich, Weinbergstrasse 58, 8092 Zurich, Switzerland

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ABSTRACT

Despite the fact that more and more car dashboards are being equipped with powerful, high-resolution displays, allowing for radically new ways to design driving feedback, the question of what impact different design types and features have on real-world eco-driving remains largely unclear. To address this research gap, we conducted a randomized control field trial in Switzerland with 62 road assistance drivers over a period of 10 weeks, covering over 245,000 km. We evaluate the effect of eco-driving feedback on fuel consumption for two types of feedback: numerical feedback (which uses numbers and gauges to present numerical values) and symbolic feedback (which translates numerical values into symbolic representations). Both, numeric and symbolic eco-driving feedback were tested against a control group. Data analyses are performed on the level of 265,939 dynamic road segments with constant road characteristics to account for the significant effect of road attributes on fuel consumption. Results of a fixed-effects regression models reveal that only the symbolic feedback design led to significant reductions of 2–3% in fuel consumption. The effect is robust across different model specifications that control for the influence of road attributes and other covariates. We conclude that the design of eco-driving feedback can have a significant impact on its effectiveness for promoting a less fuel-consuming driving style. We conjecture that there is a large untapped potential for manufacturers to use modern digitalized dashboards that can improve the impact of driver feedback systems.

1. Introduction

Mobility is crucial to our modern society yet relies almost entirely on fossil fuels. Road transportation alone accounts for 18% of the worldwide CO_2 emissions (IEA, 2017). Despite decades of efficiency improvements in technology and infrastructure, carbon emissions from road transport are expected to increase, not only in absolute numbers but also relative to other energy-intensive sectors (ITF, 2010; Sims et al., 2014). Fuel consumption depends heavily on driving style, in particular one should try to avoid heavy accelerations, heavy braking, driving with high revolutions per minute, idling and unsteady speeds (Ericsson, 2001; Gonder et al., 2012). Due to its potential, there have been various major attempts to promote eco-driving, i.e., a less fuel-consuming driving style. For instance, the comprehensive EU research project “ecoDriver”, which investigated the “human element when encouraging ‘eco-driving’” (Carsten et al., 2016, p. 1), was funded with €14.5 million over a period of 4.5 years. The consortium focused on eco-driving

* Corresponding author.
E-mail addresses: andre.dahlinger@unisg.ch (A. Dahlinger), vtiefenbeck@ethz.ch (V. Tiefenbeck), bryder@ethz.ch (B. Ryder), bernhard.gahr@unisg.ch (B. Gahr), elgar.fleisch@unisg.ch (E. Fleisch), felix.wortmann@unisg.ch (F. Wortmann).

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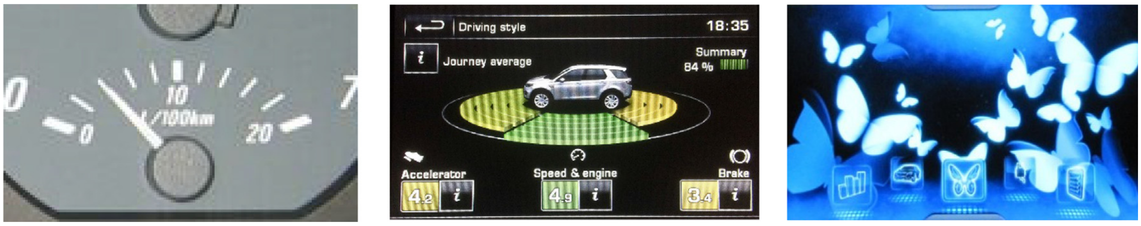


(a) fuel consumption gauge **(b) modern numerical EDFIS** **(c) modern symbolic EDFIS**

Fig. 1. Different EDFIS: (a) a classic fuel consumption display in the BMW 7 from 1982; (b) an example of a numerical EDFIS (in Jaguar/Land Rover cars); (c) an example of a symbolic EDFIS (from Ford's SmartGauge).

feedback information systems (EDFIS) as they seem to be a promising way to reduce fuel consumption significantly in a cost- and time-efficient way. Providing individuals with real-time feedback on the environmental impact of a specific activity has been shown to induce considerable behaviour change and large energy savings in other domains, such as residential energy consumption (Karlin et al., 2015; Tiefenbeck et al., 2018). However, in the mobility context, rigorous field studies specifically designed to examine the effect of EDFIS are scarce and reported results have been mixed (Dahlinger and Wortmann, 2016a). Some studies that were conducted under very controlled conditions find reductions in fuel consumption of up to 32% (Barić et al., 2013). The majority of studies that were conducted under more realistic conditions – albeit with still small samples and over short periods of time – report fuel savings between 4 and 10% (Barkenbus, 2010; Caulfield et al., 2014; Dahlinger and Wortmann, 2016a).

While most of the research on the impact of eco-driving feedback has been conducted within the last 10 years, systems that encourage environmentally friendly driving styles have been embedded in car dashboards for decades. The BWM 7, built 1982, was one of the first vehicles to provide an eco-feedback gauge that displayed the fuel consumption in real-time (Fig. 1a). Until recently, the limited capabilities of analogue displays meant that the visualization of driving-related information was essentially restricted to numbers and gauges, as often used for the mileage display or the speedometer. The increasing digitalization of car dashboards has created more possibilities and room for designer creativity. An almost infinite range of colours and animation features facilitate the delivery of information that is potentially easier for drivers to perceive, process, and to act upon (Carsten et al., 2016; Gilman et al., 2018).

As car manufacturers have started to take advantage of these possibilities, more and more car models provide different types of eco-feedback. One key characteristic in the design is the level of symbolic visualization of information. While some eco-driving feedback systems provide detailed numbers on eco-driving parameters, such as braking and acceleration (Fig. 1b), other systems convert these numbers into symbolic representations. One example is Ford Focus' EDFIS, which features a varying number of butterflies depending on how eco-friendly the car is being driven (Fig. 1c). Electric vehicles seem to be more likely to exhibit a larger number of eco-driving feedback elements and a wider range in their design. This may be due to the fact that today's battery-powered electric cars still have a more limited driving range than cars with internal combustion engines. As a result, less energy-consuming driving styles can contribute to mitigating this problem and the associated "range anxiety" experienced by drivers of electric vehicles (Franke et al., 2012). Against the background of different EDFIS design options, the question remains to what extent EDFIS actually affects driver behaviour and, in particular, what impact different design types and features have on eco-driving and fuel consumption.

While there is extensive research on the general effect of EDFIS on fuel consumption, the majority of these studies suffer from small sample sizes, short observation periods and research designs that do not allow for strong causal inference (for a literature review, see Dahlinger and Wortmann, 2016a). Furthermore, we could not find any study that investigates the effect of design elements of visual eco-driving feedback on eco-driving and fuel consumption in the field. Yet, the design of eco-driving feedback is a relevant issue in the transportation research community, as indicated by several studies that either investigate the topic in a different research setting or measure other dependent variables than fuel consumption. Jamson et al. (2015), for example, compared several designs of eco-feedback that aimed at improving the driver's use of the accelerator pedal in a laboratory setting. Their study, however, did not focus purely on visual feedback, but also included the impact of auditory and haptic feedback. The comparison of visual feedback types did not reveal significant effects overall but found effects for certain types of feedback in different driving scenarios; the study did not provide further information to explain these differences. In another simulator study, Kircher et al. (2014) compared an intermittent and a steady visual eco-feedback design, but only with respect to their impacts on driver distraction. While the number of studies assessing the impact of eco-driving feedback designs on metrics of driving performance is still scarce, several researchers have investigated drivers' preferences regarding different types of design. Using an online survey, Meschtscherjakov et al. (2009) found that user acceptance is highest for an "EcoSpeedometer", similar to the BMW 7 fuel gauge (Fig. 1a), but with additional colour-coded indicators for whether the driving is eco-friendly or not. By contrast, the "EcoDisplay", resembling Ford's SmartGauge (similar to Fig. 1c), received lower user acceptance ratings. Similar results about subjective EDFIS design evaluations were found in other surveys (Loumidi et al., 2011; Tulusan, 2013) and in focus group studies (Jenness et al., 2009; Vaezipour et al., 2017). Beyond the transportation research community, scholars from other disciplines, such as environmental psychology or human computer interaction (HCI), have studied the design of similar feedback systems, (Froehlich et al., 2012, 2010; Lockton et al., 2017). In line with feedback intervention theory (Kluger and DeNisi, 1996), HCI research distinguishes between "low-level feedback", which provides detailed information on behavioural outcomes, and "high-level feedback", which aims to strengthen goal-directed performance by highlighting a behaviour's purpose (Froehlich et al., 2010). Yet, empirical evidence on the impact of different feedback design features on behaviour is widely missing (Karlin et al., 2015). Dahlinger et al. (2018) presented preliminary results of a field study in Switzerland, which suggest that symbolic feedback might be superior to numerical feedback, in particular on long trips. However, that analysis did not consider the influence of road conditions, such as speed limits (El-Shawarby et al., 2005; Ericsson, 2001), road type (Ericsson, 2001; Huang et al., 2013), or road slope (Gallus et al., 2017; Wood et al., 2014), despite the fact that these conditions have a very significant influence on fuel consumption. In fact, road conditions might ultimately be more influential than the driving style itself, specifically in mountainous regions (Walnum and Simonsen, 2015). To summarize, there is very limited research on the impact of visual feedback design on driving behaviour. In particular, there is a lack of empirical evidence on the effect of symbolic and numerical eco-driving feedback design on fuel consumption under realistic driving conditions that also reflects crucial covariates.

To address this research gap, we analyse data from a field experiment conducted in Switzerland with 62 roadside assistance drivers over a period of 10 weeks, covering over 245,000 km. In a rigorous randomized control trial research design, we compare the impact of a symbolic and a numerical eco-driving feedback design on fuel consumption. Furthermore, all driving data are map-matched and enriched with information on road characteristics, like type of road, speed limits, and road slope. The analysis is performed at the level of individual road segments, which enables statistical control of the potential influence from road attributes. This approach allows us to provide deeper insights into the determinants of eco-driving and strengthens the robustness of our findings.

In the following section, we describe the eco-driving feedback system deployed, the data collected and how this data was enriched with secondary data on road characteristics. Next, we present the experimental design and describe the driver sample as well as our analytic approach. The results section provides descriptive statistics on the dataset collected and the results of the experiment. The discussion section summarizes the main contributions of this work and draws conclusions with respect to the practical implications of the findings. The article closes with limitations and promising directions for future research.

2. Materials and method

To implement the field experiment, we developed and deployed a proprietary system that collects driving and location data, gives visual eco-driving feedback via a smartphone app, and streams the data to a backend. Hence, we first introduce the system, followed by a description of the study design and procedure.

2.1. Eco-driving feedback system overview

Fig. 2 depicts an overview of the eco-driving feedback system (for details, see Dahlinger et al., 2018). It consists of (1) an on-board diagnostics (OBD2) dongle to read out driving data from the car, (2) a smartphone that serves as the user interface to display eco-driving feedback and to upload the data to (3) the backend server, were all data is stored to enable the ex-post data analysis. The programmable OBD2 dongle was configured so that it could read a list of 18 values from the car's Controller Area Network (CAN) bus with a maximum frequency of 30 Hz. From the OBD2 dongle, the driving data was sent via Bluetooth to an Android smartphone. On the smartphone, our app provided visual driving feedback based on several driving data parameters. The smartphone then streamed all driving data and geo-positioning data via GSM to the backend.

2.2. Design of the symbolic and numerical eco-driving feedback

We developed an Android app that ran on the smartphone, which could provide either one of two different types of eco-driving feedback that served as our two treatments (Fig. 3b, c) or driving-feedback unrelated to fuel consumption, which the control group received (Fig. 3a). For every system and at any time, we were able to remotely control which one of these feedback screens was provided to the driver. We made design choices based on comparable existing eco-driving feedback systems and with a theoretical

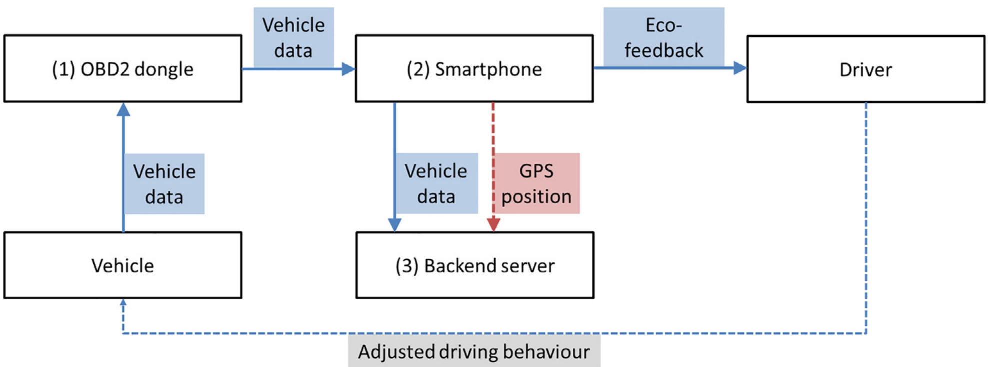
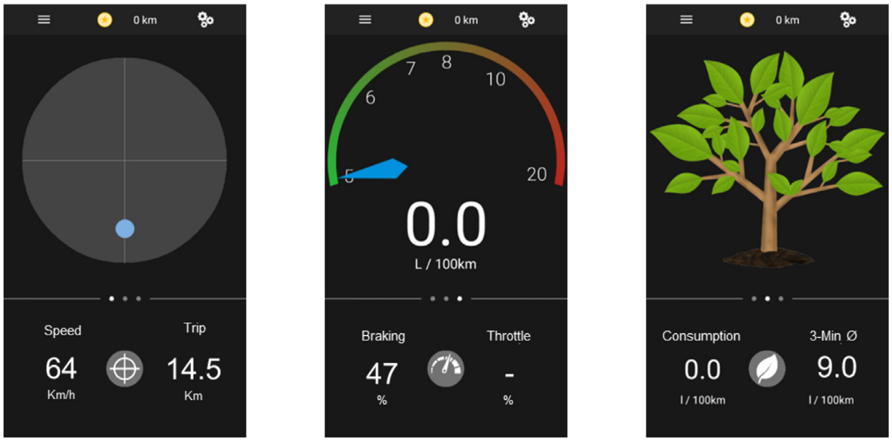


Fig. 2. Conceptual overview of the eco-driving feedback system.



(a) G-radar (b) Fuel gauge (c) Eco tree

Fig. 3. The feedback screens for (a) neutral control feedback, (b) numerical feedback, (c) symbolic feedback.

foundation in construal level theory (Carsten et al., 2016; Dahlinger and Wortmann, 2016b). To develop the different feedback screens, we build upon two common approaches to manipulate construal level, namely abstraction and aggregation (Eyal et al., 2004; Trope and Liberman, 2010). The resulting two types of eco-driving feedback mainly differ in displaying fuel consumption in a numeric vs. a symbolic way (abstraction), where real-time fuel consumption values (no aggregation) were used for numeric feedback and a 3-minute moving average (aggregation) of fuel consumption was used for symbolic feedback. Furthermore, we had to make sure the system was easy and enjoyable to use in order to maximize system usage and data collection (for a detailed description of the theoretical background and design process, see Dahlinger et al., 2018; Dahlinger and Wortmann, 2016b).

The control group was exposed to a “G-radar”, which displays the vector of longitudinal and lateral acceleration of the car, represented as a moving dot within the blue circle (Fig. 3a). In designing the G-radar, we had to strike a balance between minimizing the amount of information that might already have an impact on eco-driving and making the display sufficiently interesting for the control group so that the drivers would use it as much as possible to avoid biases resulting from usage attrition (Hausman and Wise, 1979). On the one hand, exposing also the control group to a non-static screen with driving metrics mitigates differences in potentially confounding Hawthorne effects (also see Section 3.2): The mere presence of a screen with driving metrics may remind the study participants that their behaviour is being monitored, which may alter their behaviour (Macefield, 2007; Tiefenbeck et al., 2018). By exposing all groups alike to a screen with driving metrics, we eliminate that potential source of bias. On the other hand, to minimize the impact on driver behaviour and fuel consumption, the control group’s feedback screens did not include colour coding and displayed no acceleration data. Speed and the current trip-distance were displayed at the bottom of the screen.

For the numerical feedback, we designed a “fuel gauge”, which displays real-time fuel-consumption as a gauge and in numerical form. Thus, it resembles the more traditional type of eco-feedback in analogue dashboards (Fig. 3b). This design was used in very early eco-feedback systems (Fig. 1a) and has been widely used in similar ways ever since, e.g., in the current model of the BMW 7. In addition to the fuel gauge, information about the brake pedal position and the throttle position is displayed in the lower part of the screen, as these are factors closely related to fuel consumption and appear in a similar form in today’s eco-driving feedback systems (e.g., Fig. 1b).

For the symbolic feedback, we created an “eco tree”, which grows and shrinks as a function of the three-minute floating average of fuel consumption. Our eco tree resembles existing types of eco-driving feedback that provide information in a symbolic way (Fig. 3c). In order to increase comprehensibility of and receptiveness to this eco-feedback, the underlying values of the three-minute floating average of fuel consumption, as well as the real-time consumption, are presented on the bottom right of the feedback screen.

2.3. Study design and procedure

The drivers participating in the field experiment were road assistance patrollers and recruited in cooperation with their employer. Potential participants were invited via email to sign up for our study. As study goals we stated testing new technology to promote sustainable driving. Participation was voluntary and anonymous. A new smartphone was raffled out amongst all participants. Out of the total fleet of 92 patrollers, 72 signed up to participate in our study. Our eco-driving systems were sent out in February 2016 and data collection started as soon as all drivers had successfully installed them. The eco-driving systems included a smartphone to make sure the app is working, and a detailed description on how to install the system and where to put the smartphone, i.e. on the dashboard or attached to the front window to ensure visibility of the feedback (Fig. 4). Qualitative user feedback in pre-tests indicated that the screens are easy to understand, so no further specific instructions were provided.

The study started with two weeks of baseline measurements, in which all drivers were exposed to the G-radar. At the end of the baseline phase drivers were asked to fill out an online survey collecting demographical data. 66 of the 72 participants completed this

Fig. 4. Screenshot from the installation manual which instructed participants how to mount the smartphone.

survey. After exclusion of outliers and inactive drivers (see Section 3.1), useable survey data were available from a total of 56 drivers. For the subsequent treatment phase, the drivers were randomly assigned to one of the following three groups: (1) the "symbolic feedback" group, whose screen displayed the eco tree feedback (N = 23, Fig. 3c); (2) the "numerical feedback" group, who were exposed to the fuel gauge (N = 24, Fig. 3b); or the control group, whose screen continued to display only the G-radar (N = 25, Fig. 3a).

2.4. Description of driver sample

The sample for the field experiment consisted of professional roadside assistance patrollers. Consequently, the participating drivers differ from a sample of regular drivers in several aspects. First, to become a professional roadside assistance patroller, participants had to go through driver trainings that included education on eco-driving and safe driving. Second, drivers have a very high incentive to follow road traffic regulations, as they could risk losing their right to drive – a key requirement for their employment – if they violate the regulations. Third, drivers have no economic incentive to save fuel, as fuel expenses are covered by their employer. Drivers are experienced with in-vehicle interfaces, as all patroller cars are equipped with an extra roadside assistance on-board console. Fifth and last, the fleet of cars is very homogenous, as all participants in our sample drove Chevrolet Captivas of similar make and model. The implications of these sample characteristics on the interpretability of the findings are discussed in the final section of this paper. All but one of the participating patrollers were male. Participants of the final sample ranged in age from 21 to 64 years (M = 38.41; SD = 13.13).

2.5. Road attribute-based segmentation

Fuel consumption depends heavily on road attributes, like road type (Ericsson, 2001; Huang et al., 2013), speed limits (El-Shawarby et al., 2005; Ericsson, 2001), and road slope (Gallus et al., 2017; Wood et al., 2014). For instance, Li et al. (2007) report that fuel consumption increases by a factor of 3.5 when driving up a road with a 4.7% slope. Similarly, Gallus et al. (2017) determined that an increase in the road grade from 0% to 5% accounts for 87% of the explained variance in NO_x emissions. Therefore, after the field experiment had ended, every data point of the final dataset (approximately 14.72 million) was enriched with information on road type, speed limit, and road slope through a professional map-matching service. This degree of granularity enabled an attribute-based segmentation of the trips, such that the attributes – road type (highway, intercity, city, other), speed limit (10–50 km/h, 60–80 km/h, 90–120 km/h), and road slope (downhill $< -3\%$, uphill $> 3\%$; flat) – are constant within each road segment. The logic of this procedure is presented with the following example:

For each trip:

1. with the start of a trip, a new segment "number 1" starts;
2. as soon as there is a change in one of the values of the road attributes (e.g., speed limit changes from 50 km/h to 70 km/h), a new segment "number 2" starts;
3. as soon as there is another change in any of the road attribute values (e.g., slope changes from downhill to flat), a new segment "number 3" starts, and so on.

Having driving data for segments with constant road attribute values allowed us to statistically isolate and analyse the influence of the road attributes. Apart from the work by Ericsson (2001), we are not aware of any other study that applied a road attribute-based trip segmentation in the context of eco-driving research. Ericsson (2001), however, did not include the road attributes as parameters in her principal component analysis, but focused only on driving factors.

3. Results

3.1. Description of driving data and randomization checks

The raw dataset contained 359,387 segments from 27,573 trips, covering 286,571 km of driving data. The data from eight cars (48,402 segments) had to be discarded, because the OBD2 dongle configuration did not match the cars' CAN-matrices, resulting in an incomplete data collection. Furthermore, we excluded outliers, defined as segments of less than 50 m of length (43,523 segments excluded), extremely long trips of more than 3 h (897 segments excluded), or extremely high average fuel consumption of more than seven standard deviations above the mean (579 segments excluded). The remaining dataset contained 265,939 segments of 22,538 trips, covering 245,819 km of driving data by 62 patrollers.

In line with other road-related transportation research papers (Paefgen et al., 2014), the road attributes were grouped into categories to reduce the number of regression variables, which facilitates the interpretation of the results. Accordingly, speed limits were collapsed into three categories representing the most common speed limits in the Swiss road network for the most common streets (Swiss Federal Council, 1962). Speed limits of 50 km/h or below were put in one category, as they are predominant on city streets in Switzerland. The maximum speed on roads outside cities, yet not highway roads, is 80 km/h. Hence, speed limits between 60 km/h and 80 km/h were defined as the second category. The third category comprises speed limits above 80 km/h, with a maximum speed limit of 120 km/h, the maximum speed limit in Switzerland. Regarding road slope, we defined roads with a slope between −3% and 3% percent as flat. A slope of less than 3% was defined as downhill, and a slope of more than 3% as uphill. The rush hour was defined as the period between 7–9 am and 4–6 pm on weekdays, i.e., Monday to Friday.

The mean fuel consumption over all drivers and the whole period was 9.95 l/100 km (SD = 5.65). The distribution is positively skewed (v = 2.89) and slightly zero-inflated (3368 segments with zero fuel consumption), indicating that drivers were able to coast through some segments without using fuel, i.e., they use the kinetic and gravitational potential energy of the car to move without using the throttle. This finding is to be expected in a mountainous region like Switzerland, where modern cars can actively stop fuel

Table 1
Descriptive statistics of the whole study period over all drivers and by experimental condition. All distances in kilometres. Standard deviations in parentheses.

	Overall	G-radar	Fuel gauge	Eco tree
# participants	62	22	19	21
Ø age (N = 56)	38.41	35.70	34.31	44.40
	(13.13)	(10.29)	(10.52)	(15.70)
Σ km driven	245,819	97,223	61,041	87,554
Σ km driven baseline	50,676	17,955	11,430	21,291
Σ km driven treatment	195,142	79,268	49,611	66,263
# of segments	265,939	106,438	69,036	90,465
# of segments baseline	55,564	20,171	13,039	22,354
# of segments treatment	210,375	86,267	55,997	68,111
Ø fuel consumption per segment	9.95	9.95	10.12	9.83
	(5.66)	(5.63)	(5.75)	(5.60)
Ø segment length	0.924	0.913	0.884	0.968
	(2.000)	(1.965)	(1.818)	(2.128)
Ø segment length – highway	2.695	2.713	2.549	2.766
	(4.239)	(4.302)	(4.088)	(4.327)
Ø segment length – intercity	0.705	0.698	0.722	0.702
	(1.090)	(0.938)	(0.951)	(1.181)
Ø segment length – city street	0.631	0.592	0.687	0.637
	(0.798)	(0.825)	(0.869)	(0.734)
Ø segment length – other	0.533	0.541	0.540	0.517
	(0.640)	(0.717)	(0.645)	(0.635)
Ø segment length – speed limits 90–120	2.529	2.439	2.539	2.615
	(4.347)	(4.297)	(4.285)	(4.383)
Ø segment length – speed limits 60–80	0.795	0.806	0.786	0.788
	(1.139)	(1.169)	(0.939)	(1.278)
Ø segment length – speed limits 10–50	0.528	0.528	0.533	0.524
	(0.628)	(0.673)	(0.662)	(0.599)
Ø segment length – flat segments	1.055	1.045	1.002	1.108
	(2.207)	(2.163)	(2.009)	(2.347)
Ø segment length – downhill segments	0.424	0.415	0.417	0.441
	(0.677)	(0.896)	(0.538)	(0.768)
Ø segment length – uphill segments	0.453	0.437	0.472	0.458
	(0.686)	(0.548)	(0.622)	(0.729)
Ø segment length – rush hour	0.924	0.916	0.880	0.966
	(2.040)	(1.969)	(1.884)	(2.147)
Ø segment length – not rush hour	0.924	0.912	0.886	0.969
	(1.984)	(1.964)	(1.792)	(2.120)

Table 2
Descriptive statistics and ANOVAs for the baseline phase over all drivers and for each group. All distances in km. Standard deviations in parentheses.

	Overall	G-radar	Fuel gauge	Eco tree	F	F < p
Ø age (N = 56)	38.41 (13.13)	35.70 (10.29)	34.31 (10.52)	44.40 (15.70)	3.59	0.03
Ø fuel consumption in l/100 km	9.87 (0.91)	9.91 (0.96)	9.85 (0.82)	9.85 (0.94)	0.02	0.98
Ø segment length	0.929 (0.189)	0.914 (0.170)	0.885 (0.168)	0.984 (0.219)	1.42	0.25
Ø segment length – highway	2.991 (1.539)	2.853 (1.477)	2.975 (1.872)	3.116 (1.447)	0.16	0.86
Ø segment length – intercity	0.722 (0.125)	0.706 (0.139)	0.763 (0.137)	0.714 (0.104)	0.93	0.40
Ø segment length – city street	0.663 (0.177)	0.635 (0.135)	0.687 (0.178)	0.675 (0.210)	0.41	0.67
Ø segment length – other	0.535 (0.070)	0.548 (0.063)	0.537 (0.066)	0.523 (0.078)	0.71	0.50
Ø segment length – speed limits 90–120	2.478 (0.846)	2.329 (0.805)	2.582 (0.971)	2.548 (0.828)	0.48	0.62
Ø segment length – speed limits 60–80	0.798 (0.106)	0.829 (0.111)	0.791 (0.102)	0.776 (0.102)	1.44	0.25
Ø segment length – speed limits 10–50	0.537 (0.077)	0.531 (0.077)	0.534 (0.046)	0.543 (0.091)	0.15	0.86
Ø segment length – flat segments	1.069 (0.209)	1.035 (0.188)	1.017 (0.206)	1.125 (0.223)	1.55	0.22
Ø segment length – downhill segments	0.416 (0.110)	0.402 (0.111)	0.398 (0.096)	0.437 (0.118)	0.78	0.46
Ø segment length – uphill segments	0.453 (0.109)	0.444 (0.090)	0.446 (0.111)	0.465 (0.125)	0.24	0.79
Ø segment length – rush hour	0.943 (0.204)	0.929 (0.200)	0.906 (0.190)	0.974 (0.217)	0.54	0.59
Ø segment length – not rush hour	0.941 (0.179)	0.905 (0.147)	0.898 (0.169)	0.994 (0.201)	1.92	0.16

injection (“engine braking”).

Table 1 provides descriptive statistics over all groups and for each individual group. The data reveals differences between the groups in the total number of kilometres driven. This is partly due to differences in group size. Another reason could be differences in working days schedules and holidays.

To check whether the randomization produced equal groups, ANOVAs were conducted on the driving statistics for the baseline phase (Table 2). To account for differences in total kilometres driven, we weighted the ANOVAs with the sum of kilometres driven by each driver. Note that for four drivers no driving data for the baseline phase were available.

Table 2 reveals that the randomization successfully produced balance between the groups as they do not differ significantly on any but one dimension. That exception is age, where subjects of the eco tree group were significantly older on average than the other two groups [$F(2, 54) = 3.59$, $p = .03$]. Research on the influence of age on driving style indicates that younger drivers tend to drive more aggressively and consequently consume more fuel. However, this effect is primarily caused by very young drivers in the early twenties (Rhodes and Pivik, 2011; West and Hall, 1997) and should thus not affect our sample of professional drivers that are in their mid-thirties. This is also corroborated by the fact that there are no significant differences between the three groups with regard to their driving patterns and fuel consumption in the baseline phase.

3.2. Data analysis

For the main analysis, we use a fixed-effects regression model. The unit of observation is a single road segment, where within each segment the three road attributes are constant. We include an individual-level fixed effect to eliminate all variance from fixed differences between drivers or their cars (e.g., differences in weight). The dependent variable is mean fuel consumption per segment; the experimental condition (control group vs. numerical vs. symbolic feedback) is the key independent variable. In order to achieve deeper insights into the determinants of fuel consumption and to control for exogenous influences, we present different specifications of the regression model that include covariates stepwise. While the basic model 1 analyses only the main effects (i.e., considers only the experimental conditions), model 2 also includes the covariate “day” as a counter for the days since the start of the study to control for temporal trends that affect all groups alike. Models 3, 4, and 5 add one of the road attributes (i.e., road type, speed limit, or road slope). In model 6, all road attributes are included jointly, and model 7 ultimately adds rush hour as final covariate. The full specification (model 7) of the regression is as follows:

$$\mathrm{Fuel}_{ij} = \alpha_i + \beta_1 T_{1ij} + \beta_2 T_{2ij} + \beta_3 \mathrm{Day}_{ij} + \beta_4 \mathrm{Road\ type}_{ij} + \beta_5 \mathrm{Speed\ limit}_{ij} + \beta_6 \mathrm{Road\ slope}_{ij} + \beta_7 \mathrm{Rush\ hour}_{ij} + \varepsilon_{ij}$$

where Fuel_{ij} is the fuel consumption in l/100 km by driver i in segment j. The model includes an individual fixed effect, α_i, for each

Table 3
Results for the regression analyses. Regression coefficients with standard errors in parentheses; * = significance level of 10%, ** = significance level of 5%, *** = significance level of 1%.

	Model						
Variable	1	2	3	4	5	6	7
Numerical feedback	0.303***	0.064	−0.023	0.028	0.052	−0.008	−0.006
	(0.102)	(0.121)	(0.121)	(0.114)	(0.117)	(0.116)	(0.116)
Symbolic feedback	−0.024	−0.242*	−0.235**	−0.241**	−0.251*	−0.232**	−0.231***
	(0.135)	(0.139)	(0.110)	(0.114)	(0.134)	(0.106)	(0.106)
Day		0.007***	0.008***	0.008***	0.007***	0.008***	0.008***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Intercity			1.859***			1.817***	1.814***
			(0.122)			(0.112)	(0.112)
City			2.068***			1.760***	1.754***
			(0.187)			(0.147)	(0.147)
Other			3.423***			2.678***	2.673***
			(0.146)			(0.159)	(0.159)
60–80 km/h				0.834***		−1.088***	−1.086***
				(0.091)		(0.122)	(0.123)
10–50 km/h				3.552***		1.248***	1.250***
				(0.157)		(0.206)	(0.206)
Slope – downhill					−4.346***	−5.269***	−5.27***
					(0.150)	(0.135)	(0.135)
Slope – uphill					9.209***	8.367***	8.368***
					(0.211)	(0.182)	(0.181)
Rush hour (1: yes)							0.177***
							(0.045)
Constant	9.896***	10.001***	8.564***	8.764***	9.733***	8.605***	8.555***
	(0.042)	(0.047)	(0.081)	(0.073)	(0.044)	(0.080)	(0.083)
R^2	0.025**	0.025***	0.086***	0.090***	0.191***	.262***	0.262***
N	265,939	265,939	265,939	265,939	265,939	265,939	265,939

driver. The treatment indicators T_{1ij} and $T_{2ij,}$ are zero for the baseline phase and take the value of 1 if the driver i is provided with the numerical feedback (T_1) or symbolic feedback (T_2) treatment, respectively. Thus, β_1 and β_2 indicate the treatments effects – in other words, the difference in fuel consumption between the control condition and the respective treatment condition. The coefficient β_3 captures general time trends in fuel consumption and the coefficient vectors β_4, β_5, and β_6 describe the influence of different road types, speed limits, and road slopes, respectively. The last covariate, rush hour, is a dummy variable that is set to zero if the data was not generated during rush hour and takes the value of 1 during rush hour. The regressions are weighted by segment length to account for the difference in segment length. The covariates "day" and "road slope" are normalized for better interpretability of the constant term and of the influence of the feedback, i.e., day is centred to its mean (representing the mid of the experimental period) and road slope is normalized by making "flat" the zero-category. Table 3 contains the results of the stepwise regression analyses. Note that as in any regression, for each variable, one category serves as the base case, which is represented in the constant term (here: control group, highway, speed limit 90–120 km/h, flat slope).

As the results in Table 3 show, the coefficients for the symbolic feedback indicate a very robust positive effect of the symbolic feedback, i.e., fuel consumption is significantly reduced by approximately 0.2–0.3 l/100 km, which divided by the normalized constant translates to 2–3% savings in all model specifications after controlling for the day as a covariate. The treatment effect of numerical feedback, by contrast, is consistently not significant, i.e., we do not find empirical evidence for a fuel reduction effect of this treatment. The results for each model are presented in the following paragraphs.

Model 1 suggests that when only the treatment parameters are taken into account, the numerical feedback significantly increased fuel consumption compared to the control group, while the symbolic feedback showed no significant impact on fuel consumption.

In model 2, the day is included as a covariate to account for general time trends that affect all experimental conditions alike. In this specification, the coefficient for the numerical feedback becomes insignificant, while the coefficient for the symbolic feedback indicates a marginally significant fuel-reduction of about 2.5%. Two explanations are conceivable for the positive, significant effect of the day variable. First, a seasonal (e.g., holiday-related) increase in traffic and traffic jams could be a second reason, as limited traffic flow tends to cause higher fuel consumption (Bao et al., 2017; Garcia-Castro et al., 2014; Jiang et al., 2015). Furthermore, subjects may exhibit altered behaviour (in this case, more eco-friendly driving) when they know that their behaviour is being measured or observed, a phenomenon referred to as the Hawthorne effect. These effects have been shown to weaken over time as study subjects get used to the measurement equipment (Tiefenbeck, 2016).

Model 3 includes the road segment type in the regression model. The coefficients of the treatment parameters remain nearly the same, but the effect of the symbolic feedback is now significant at the 5% level. Regarding the type of road, the results indicate that the fleet had the lowest fuel consumption on highways as compared to intercity, city, or other road types. A reason for this may be that highway roads are predominantly flat compared to other type of roads, which is an important factor considering that Switzerland is a very mountainous country. The crosstabulation of road type and road slope (Table 4) confirms this explanation. It shows that

Table 4
Crosstab of road type and road slope for all segments.

			Slope			
			Flat	Down	Up	Total
Road type	Highway	# segments	35,127	2,794	2,997	40,918
		# segments (%)	85.83	6.82	7.34	100.00
	Intercity	# segments	64,081	5,648	5,003	74,732
		# segments (%)	85.77	7.54	6.69	100.00
	City	# segments	22,507	3,151	3,110	28,768
		# segments (%)	78.26	10.92	10.82	100.00
	Other	# segments	87,755	16,432	17,334	121,521
		# segments (%)	72.21	13.52	14.27	100.00
		Total	209,470	28,025	28,444	265,939
		Total (%)	78.77	10.54	10.70	100.00

there are more flat road segments on highway roads as compared to city roads and “other” roads. However, this is not the case for the comparison between highway roads and intercity roads. Hence, another explanation could be that on highway roads it is easier to maintain a steady speed due to fewer changes in road attributes. In line with this reasoning, the data indicates there are less road attribute changes, as the mean length of highway segments (M = 2.695 km; SD = 4.263) is more than three times that of intercity segments (M = 0.705 km; SD = 1.029).

Model 4 presents the impact of speed limits as covariates. The coefficients reveal that the participants consumed the least fuel on roads with speed limits between 90 km/h and 120 km/h and by far the most at slow speed limits of 10–50 km/h. However, similar to model 3, the speed limit variable might be confounded by other road attributes, specifically road type.

In model 5 we analyse the impact of the third road attribute: the slope of the road. The slope coefficients’ direction is as expected, i.e., the drivers consumed less fuel when driving downhill and more when driving uphill. The fuel savings from driving downhill are smaller in absolute terms than the fuel consumption increase when driving uphill and hence support our explanations of the observations in model 3 and 4.

Having analysed the influence of different road attributes individually, model 6 includes them all in a single regression. Likewise, the coefficients of road type and road slope change only slightly. By contrast, the speed limit coefficients change considerably and are now in line with existing research (El-Shawarby et al., 2005): while still significant, the point estimate for the slow speed limit cluster (10–50 km/h) shrinks to a third of its effect in specification 4, and the coefficient for speed limits of 60–80 km/h even changes sign. These results indicate that the road type and the speed limit clusters are correlated, which is confirmed when looking at the correlation matrix of the road attributes (Table 5). The pattern of the relationship between speed limits and fuel consumption now confirms the expected pattern, i.e., lowest fuel consumption for medium speeds and highest fuel consumption for low speeds.

In model 7, we add rush hour as additional explanatory variable. The effect goes in the expected direction, i.e., drivers consumed more fuel during rush hour, probably due to more traffic on the road. There are no strong changes in the other coefficients, which may be due to the fact that the delineation between rush hour and non-rush hour time is fuzzy. Once again, regardless of the model specification, the point estimates for the main effect of the two eco-driving feedback conditions are robust and very similar across specifications 3 through 7, all indicating a positive effect on fuel consumption only through the symbolic feedback.

4. Conclusions

The results of our study suggest that the design of eco-driving feedback can have a significant impact on its effectiveness for fostering eco-driving. The presented data from a field experiment indicates that only the symbolic feedback design, operationalized in our study with the eco tree, significantly reduced fuel consumption by approximately 2–3%. The treatment effect is remarkably robust across different model specifications that control for different factors that affect fuel consumption. In contrast to previous studies (Martin et al., 2013; Stillwater and Kurani, 2014; Tulusan et al., 2012), we find that the drivers that were exposed to numerical feedback in the form of the eco gauge did not reduce fuel consumption. Compared to most existing studies on eco-driving feedback, the results presented are based on a large dataset, covering a long time period and a rigorous research design. External validity is increased by applying the research in the field and internal validity is high due to the randomized control trial research design. In the following we present implications for practitioners and for the research community.

In light of our results, it becomes clear that practitioners should pay careful attention to the design elements for feedback systems

Table 5
Correlation matrix of the road attributes. ** = significance level of 1%.

	Road type	speed limit	Road slope
Road type	–		
Speed limit	0.496^{**}	–	
Road slope	0.008^{**}	-0.012^{**}	–

in cars. More specifically, our results indicate that symbolic visualization may enhance the potential impact of eco-driving feedback on fuel consumption. Yet the vast majority of existing eco-feedback systems seem to apply classical feedback design principles of displaying numerical information represented by numbers and gauges. Most vehicle manufacturers continue to use design schemes that date back to when car dashboards were not yet digitalized, when numbers and gauges were the only possible ways to display information (see Fig. 1a). Hence, we see a huge untapped potential for manufacturers to use modern digitalized dashboards to improve the impact of driver feedback systems.

Regarding the implications for eco-driving research, we take into account both the strengths and the limitations of our research. To the best of our knowledge, a large portion of the existing eco-driving studies have either been conducted in a lab, have a very small sample size, or have applied research designs that do not allow for strong causal inference (Dahlinger and Wortmann, 2016a; Shadish et al., 2002). This may explain to some extent the heterogeneity in the fuel savings reported, which range from zero (e.g., Larsson and Ericsson, 2009) up to 32% (Barić et al., 2013). Consequently, the reliability and validity of many study outcomes may be challenged. Along with a handful of other examples (e.g., af Wahlberg, 2007; Stillwater and Kurani, 2011; Tulusan et al., 2012), we consider our experiment to be one of the few studies that investigates feedback on eco-driving under realistic driving conditions, with a larger sample size, a research design that is strong in causal inference, and an explicit reflection of important covariates (road attributes). Therefore, we call for future research to adopt our approach and even further increase the sample size to ensure validity of the research outcomes.

A major limitation to the generalizability of our results is the sample specificity, namely that all drivers were professional roadside assistants and predominantly male. However, we conjecture that the proficiency of the drivers produced, in fact, more conservative results as if we had exposed regular drivers to the treatments for three main reasons. First, to become a roadside assistance patroller, all drivers had to go through eco-driving trainings, which has shown to effectively promote eco-driving (Beusen et al., 2009). This implies that our sample already started out from a higher level of awareness or knowledge on eco-driving than the general population, which probably reduced the potential room for improvement and marginal effect of the eco-driving feedback intervention among our drivers: In fact, prior research has revealed high ex-ante levels of consumption as the largest savings predictor in feedback studies (Allcott, 2011; Tiefenbeck et al. 2018). A counter argument for this could be, however, that without training, drivers may not know how to react to the symbolic feedback. Second, the driver's first priority is to get to their customer in case of a breakdown as quickly as possible, and even though eco-driving has been shown to have only minor effects on trip duration (Barth and Boriboonsomsin, 2009), saving fuel may not have been a priority for our professional drivers on those trips. Third and last, the professional drivers, as compared to regular drivers, have no economic incentive to save fuel, because their employer covers the fuel expenses. A further limitation is that the used eco-driving screens differ in more than one aspect, thus making it difficult to isolate which of these aspects was the key driver for the observed differences. For example, besides the visual symbolization of the fuel consumption values, the eco-tree also used a moving average, while the fuel gauge displayed instantaneous information. We used construal level theory to explain the higher efficacy of the eco-tree, and thus would expect this effect to still hold when using the moving average for both types of feedback (Dahlinger and Wortmann, 2016b). future research should disentangle these design aspects to get a better understanding on the impact of systematic feedback design elements on pro-environmental behaviour (Karlin et al., 2015). Additionally, the research could be extended to include summative ex-post feedback (e.g. Satou et al., 2010) as well as measures of subjective perception of the systems by the user, such as technology acceptance (Davis, 1989) or driver distraction (Rouzikhah et al., 2013; Schmitt et al., 2018).

Private mobility is by far the most predominant type of road transportation. Therefore, we would expect that promoting deployment of symbolic eco-driving feedback on the dashboards of private cars would have the biggest impact worldwide in reducing CO_2 emissions. However, corporate car fleets do also contribute considerably to road transportation and our research has shown that even for professional drivers, we saw a reduction in fuel consumption. Hence, our results may be of particular interest to fleet managers trying to reduce their fuel consumption costs.

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