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Cognitive Mechanisms of Behavior Change in the Case of In-Vehicle Fuel Economy Feedback

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ABSTRACT

This paper presents results from a year-long study on driver feedback, driver attitudes, and the adoption of ecodriving behaviors. Narrowly defined, ecodriving represents only the set of behaviors that a driver can use to minimize the energy use of a trip after the trip has begun. The general ecodriving behaviors are moderating acceleration, top speed, and braking. Ecodriving has long been recognized as a potential source of reductions in transportation energy use, with reduction estimates ranging widely from less than 5% to over 20% depending on context. In-vehicle feedback is one way to motivate ecodriving by connecting drivers with salient information suited to their personal goals. Although many studies have tested unique feedback designs, little research has been conducted into the cognitive precursors to driver behavior change that may underlie the adoption or rejection of ecodriving practices, and therefore underlie the effectiveness of any feedback design. This study examines both precursor cognitive factors and driver behavior changes with the introduction of energy feedback, using a framework hypothesizing that attitudes, social norms, perceived control, and goals influence behavior and behavior change. The study finds that the introduction of a feedback interface can both activate these cognitive factors and result in behavior change. Furthermore, the study finds that there was an overall 4.4% reduction in fuel consumption due entirely to one group that showed increases in their knowledge of fuel economy and reported high levels of technical proficiency during the experiment. The second group made no improvement and may have been confused by the feedback. In addition, statistically significant relationships are found in the effective group between the magnitude of cognitive change and the magnitude of behavior change – supporting the theoretical framework. Finally, the baseline (pre-feedback) performance of the drivers was an important model factor, indicating that drivers that already use highly efficient styles do not benefit much from feedback.

INTRODUCTION

This paper presents results from a year-long study on driver feedback, driver attitudes, and the adoption of ecodriving behaviors. Broadly defined, ecodriving is the adoption of driving styles that reduce energy consumption; it is distinguished from buying behavior, e.g., buying a higher fuel economy car, and travel behavior, e.g., trip-chaining or trip reduction. In effect, ecodriving as discussed here represents only the set of in-vehicle behaviors that a driver can use to minimize the energy use of a trip taken by car after the trip has begun. Although it is beyond the scope of this study, the definition of ecodriving is still in flux, and ecodriving can be defined more broadly than it is here depending on the context (Sivak & Schoettle, 2012). The general ecodriving behaviors relevant to this study are moderating acceleration, top speed, and braking. Ecodriving has long been recognized as a potential source of reductions in transportation energy use, with reduction estimates ranging widely from 5% to 25% depending on context (Barkenbus, 2010; Greene, 1986; Sivak & Schoettle, 2012). The wide range in reported effects is likely due to a handful of distinct causes: differences in the duration of the experiment, the vehicle and drive-cycles included, and the effectiveness of the feedback design.

Although many studies have tested unique feedback designs, little research has been has been conducted into the cognitive precursors to driver behavior change that may underlie the adoption or rejection of ecodriving practices, and therefore underlie the effectiveness of any feedback design. This study examines both precursor cognitive factors and driver behavior changes with the introduction of energy feedback. Underlying the design of the experiment is a conceptual framework based on the Theory of Planned Behavior (Ajzen, 1980) as amended by the Extended Model of Goal Directed Behavior (Perugini & Conner, 2000); the framework hypothesizes that attitudes, social norms, perceived control, and goals influence behavior and behavior change. Although these behavior change theories are widely applied in other contexts, this exploratory analysis maintains an open view of the experimental effects. Given that it is currently unclear how contextual factors, e.g., traffic density and drive cycle, might interact with behavior an exploratory analysis is particularly important.

BACKGROUND

The experiment and analysis are grounded in two distinct areas of literature: behavior change and fuel economy feedback. Below we present a brief overview of the relevant prior findings and how they intersect in the current analysis.

Behavior Change Theories

A brief discussion of the social science concepts of agency and structure provides the context for the use of agent-based behavior theories in this study. As in all cases, the model choice limits the bounds of the possible hypotheses and resulting analysis.

While individuals are often assumed to control their own behavior, the agency of drivers—their freedom and ability to choose—is often limited by the structure of both society and socially produced systems. Such structure provides the context in which an individual can act. Driver choices are constrained by social norms and rules, such as traffic flow and speed limits, as well as socially constructed infrastructure such as freeways and traffic calming infrastructure that limit the driver's ability to choose a driving style. More importantly, structural factors such as driving laws or roadway infrastructure are not directly influenced by driving behavior in any single instance of driving—any one driver’s trip to the grocery store is not going to change the rules or the road, but in that trip ecodriving behaviors can be enacted. For these reasons, we use a behavioral model that emphasizes drivers’ agency, but includes structural factors in the analytical model to help explain fuel economy variance. It seems reasonable (although beyond the scope of this discussion) that drivers’ goals, attitudes, or other individual factors should in the long-term influence these structural factors through the democratic or other social processes. Finally, these structural factors may play a role in the formation of driver goals or attitudes, including some pertinent to eco-driving, e.g., traffic signal coordination may create the context in which a driver may form the goal to cruise at a steady speed. ***The Theory of Planned Behavior and Related Models***

The theory of planned behavior (TPB) forms the core framework for this study (Ajzen, 1980). The TPB is one of a number of rational behavior models that include decision-making pre-cursors such as attitudes about the behavior, perceptions of applicable social norms, or perceptions of behavioral control, as shown in Figure 1. The TPB behavioral model has generated a large literature including such applications as recycling behavior (Tonglet, Phillips, & Read, 2004) and drivers' propensity to speed (Paris & Broucke, 2008).

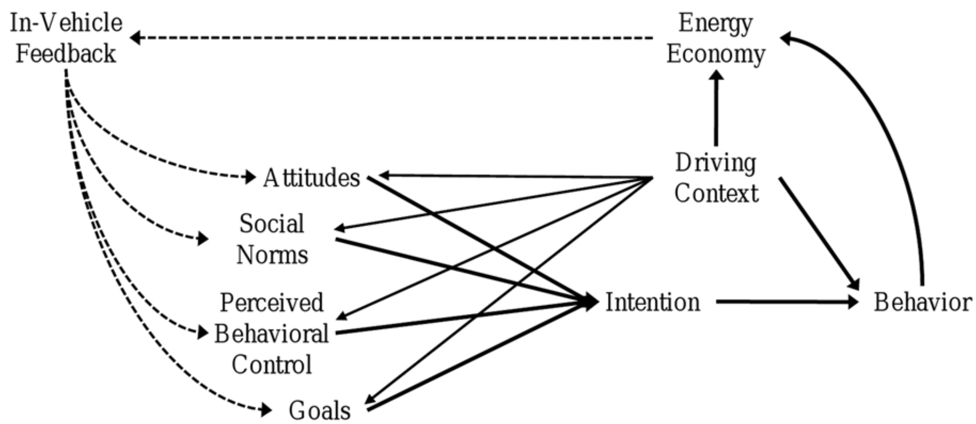

FIGURE 1 Theoretical Cognitive Framework Showing Feedback. Solid lines show the relationships hypothesized by TPB and the EMGDB adapted to the driving context; dashed lines show the additional effects of feedback as hypothesized in this experiment.

Recent studies indicate that a variety of factors not included in the TPB play critical roles in behavior change, notably goals, as described in the extended model of goal directed behavior (EMGDB) (Perugini & Conner, 2000), as well as personality (Jackson, 2005). The TPB was developed as a model to explain behavioral intention and outcome behavior (once the context was taken into account) and was not originally meant as a methodology to modify behavior, although the popularity of the TPB is largely due to researchers interested in behavioral interventions, and the TPB is seen as a model for studying intervention efficacy (Ajzen, 2002).

Review of Driver Feedback Studies

A search for studies that tested the impacts of driver feedback on fuel economy found 14 studies at the time of writing (Ando, Nishihori, & Ochi, 2010; Boriboonsomsin, Vu, & Barth, 2010; *Driving Change: City of Denver Case Study*, 2009; Greene, 1986; Larsson & Ericsson, 2009; Lee, Lee, & Lim, 2010; Satou, Shitamatsu, Sugimoto, & Kamata, 2010; Syed & Filev, 2008; Wahlberg, 2007; M. van der Voort, 2001). The large majority of studies were based on feedback that consisted of a real-time numeric or graphical gauge display of mile-per-gallon (MPG) fuel economy. One summary result is that driver feedback appears to have different effects depending on the duration of exposure. Short term (one or two day) studies reported a higher mean change in fuel economy, often near 10% (Syed & Filev, 2008; M. C. van der Voort, 2001) than long term studies (two weeks to one year) that tend to report effects of less than 5% (Ando et al., 2010; Wahlberg, 2007). The difference between short term and long term studies may be due to the higher likelihood of short term studies to include a positive performance bias as individuals try to drive carefully to perform well in the experiment (in long term studies, it may be less likely that an individual would continue to display such behavior). One experiment found that in the short term, drivers who were simply asked to drive more carefully increased their fuel economy by 10% (Greene, 1986). This suggests that in the very short term, simply participating may be responsible for a large amount of the effect attributed to some feedback designs. Further, the literature on driver feedback is almost universally focused on studies of ad-hoc designs and average fuel economy achieved by test drivers. Thus, the literature is full of specific feedback examples without any clear method by which it would be possible to understand the wide variation in experimental results or improve on existing feedback designs. This study represents a formal application of behavioral theory to the design of a driver feedback experiments.

DESCRIPTION OF THE EXPERIMENT

A driver feedback experiment was conducted in California's Yolo, Solano, and Sacramento Counties from September 2009 to September 2010 with 24 households and 42 individual drivers. The experiment was conducted as a part of the UC Davis Plug-in Hybrid Electric Vehicle (PHEV) Demonstration in which households drove a PHEV for a month in place of their own vehicles as a part of their normal routine (Kurani et al., 2010). Households for the feedback experiment were selected from the pool of participants in the PHEV demonstration. The respondents included a demographically wide range of individuals, from middle to high income, young adult to retired, and single occupant and family households.

The subject's experience and data collection points are shown in Figure 2. Each vehicle was outfitted with a custom feedback device measuring 7 in. by 5 in. mounted directly over the standard center console screen. During phase 1 the feedback showed only the PHEV battery state of charge, simulating information that a commercial PHEV would have. At the beginning of phase 2, the feedback device displayed a variety of energy economy, cost, and emissions information in user-selectable panels. The subjects were given a pamphlet describing the meaning of each information panel, although no ecodriving advice or encouragement was given to the subjects.

The study feedback panels used real-time energy economy rather than fuel economy. One notable reason for using energy economy is that the study vehicles used both gasoline and electricity as primary energy sources, and miles-per-gallon is not a meaningful efficiency measure in this case. To combine the two, gasoline and battery energy were converted to joules (using the lower heating value of gasoline) and then into miles-per-gallon of gasoline equivalent (MPGe) which was represented to drivers as MPG+ ("miles-per-gallon plus").

ANALYTICAL METHODOLOGY

As shown in Figure 2, the analysis consists of a number of steps. One Hz (one sample-per-second) driving data is summarized with trip-level statistics, and trips are clustered based on contextual factors. Separately, the survey data are synthesized using a principal components analysis (PCA). The PCA and the trip-level dataset are then combined and used in the energy economy (MPGe) model to determine the joint effect of energy feedback and attitudes on fuel economy, while allowing for multiple groups. Finally, the number of trips in each trip category and group is leveled using an overall average distribution shown in Figure 3. The groups are then summarized with descriptive statistics on their cognitive factors (from the PCA) and their change in total fuel consumption.

To determine the outcome of the experiment with the fewest possible assumptions, model-based exploratory analysis was used. Model-based analysis structures data according to latent characteristics available within the data itself (Fraley & Raftery, 1998). This methodology is used to determine 1) cognitive factors (as shown in Table 1); 2) distinct trip types; and, 3) behavioral subgroups, i.e., whether there are identifiable groups who respond differently to the energy feedback.

Cognitive Factors

A questionnaire elicited fuel-economy related attitudes, social norms, perceived behavioral control, goals, and personality factors. Approximately six questions related to each of these five constructs tested different aspects of each, as shown in Table 1. Responses to the attitudinal and personality statements were given on a standard 5-point scale (strongly disagree to strongly agree), responses to the confidence statements were given using a 3-point scale (wild guess to very confident), and the goal section was given as a three-part ranking exercise in which the participant could order up to three goals and assign the importance of each on a 3-point scale (not important to very important) although only the importance rating of the goal was used in the analysis, not the rank. The survey questions were generated specifically for this experiment and refined with pilot subjects before the experiment began. Participants completed the questionnaire three times, as shown in Figure 2. Changes between waves 0 and 1 are attributed to the experimental context of the PHEV Demo, and changes between waves 1 and 2 are attributed to the introduction of the feedback. Wave 1 is therefore used as the baseline cognitive measure, and the difference between waves 1 and 2 as the experimental effect of the feedback device.

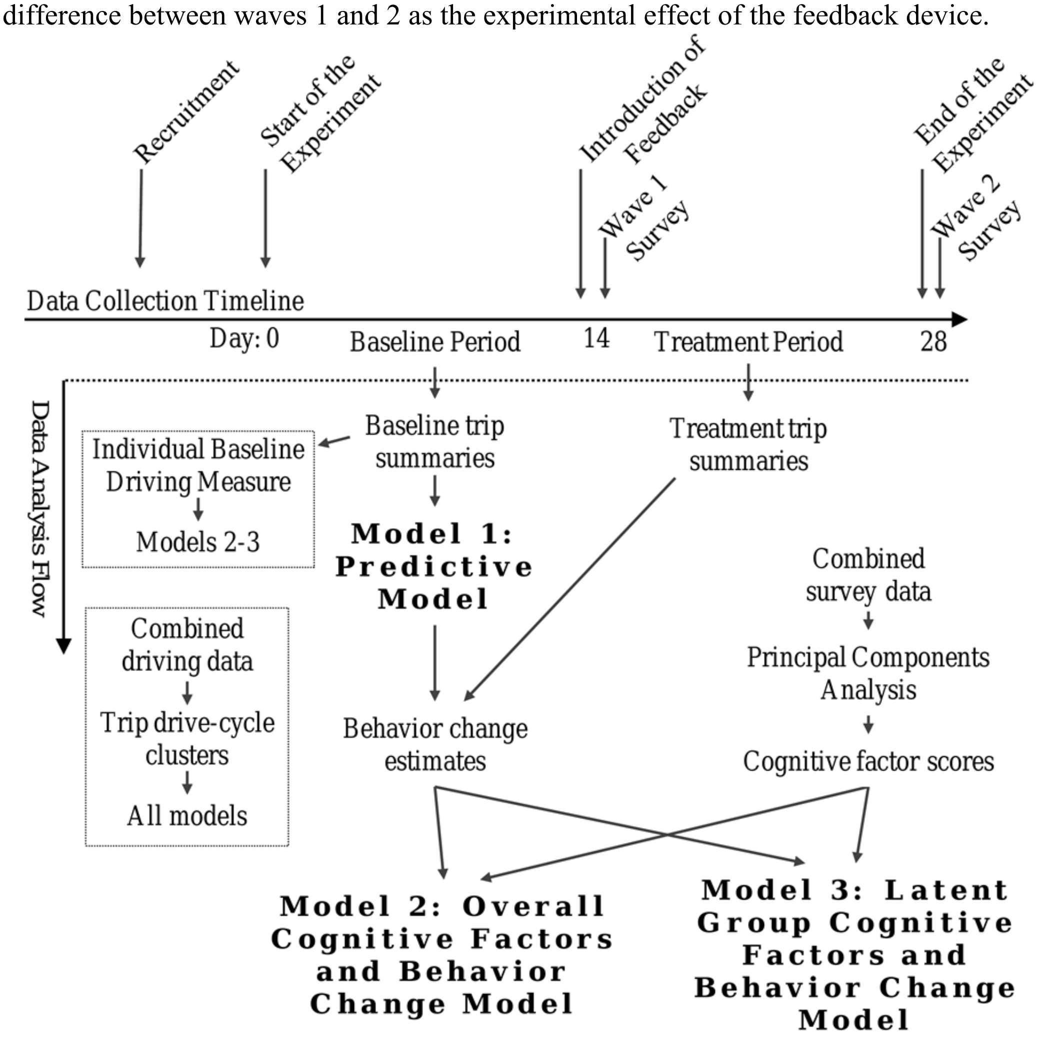

FIGURE 2: Flow of the Experiment and Data Analysis Process. The timeline is approximate and varied according to participant availability. Also, questionnaires not used in the analysis are omitted.

A principal component analysis (PCA) was performed to find orthogonal (uncorrelated) cognitive factors and to reduce the dimensionality of the data, e.g to find a smaller number of meaningful components, each a linear combination of original item responses. The number of PCA factors was selected using the Very Simple Structure (VSS) methodology which resulted in the selection of five PCA components accounting for 43% of total variance (Revelle & Rocklin, 1979). The final components were then rotated for interpretation and analysis using the varimax method. The components, factor loadings, and interpretations are shown in Table 1.

TABLE 1 Principal Components Analysis of Cognitive Factors. Shading indicates stronger loadings (> 0.5) between the survey item and the rotated component, with red representing negative loadings and green representing positive loadings. Factor interpretations are shown at the top of the table.

Question Wording	Speedy	Motivated to Save Gas	Like to Master Tech	Confidence in MPG Knowledge	Want to be Safer
Driving fast is fun	0.65	-0.29	0.12	0.09	-0.22
Saving gas makes me happy	-0.28	0.53	0.27	0.00	0.18
Driving efficiently is unsafe	0.33	-0.07	-0.27	-0.55	-0.26
Driving is expensive	0.35	-0.01	-0.31	-0.52	-0.23
Using gas lets me do what I need to do	0.37	0.42	0.18	0.12	-0.07
Saving gas is important	-0.27	0.52	0.09	0.18	0.21
Saving time is more important than saving gas	0.60	-0.23	-0.02	0.13	0.34
When driving it is best to "go with the flow"	0.60	0.07	0.01	-0.04	0.35
Most people save gas by driving efficiently	-0.04	0.44	-0.11	0.11	-0.03
I don't care if other drivers think I'm slow	-0.50	0.12	-0.10	0.33	0.08
It is important to drive at or below the posted speed limit	-0.53	0.09	0.22	0.01	0.16
I have had experiences with drivers getting mad at me	-0.11	0.08	-0.08	-0.05	0.41
[My friend] thinks that I waste gas	0.14	-0.24	-0.41	-0.29	-0.14
I like to know all about my car	-0.04	0.06	0.45	0.30	-0.06
I like to master new technologies	0.08	0.07	0.73	0.01	0.08
How I drive can change my fuel economy	0.19	-0.06	0.38	0.14	-0.20
I know how to drive efficiently	0.05	-0.02	0.66	0.14	-0.34
My fuel economy is a result of factors beyond my control	0.03	0.11	-0.40	-0.03	0.43
How I drive is determined by roads and traffic	0.34	0.02	0.30	-0.02	0.39
Confidence in own car mpg knowledge	0.11	0.10	0.19	0.51	-0.05
Confidence in own car driving style estimate	0.15	0.04	0.03	0.78	-0.22
Confidence in test car mpg knowledge	0.13	-0.01	-0.07	0.78	-0.08
Confidence in test car driving style estimate	0.15	0.51	0.06	0.39	0.04
I'm not about to change my driving habits	0.35	-0.29	0.07	0.03	0.16
I'm a perfectionist	-0.03	0.49	0.17	-0.16	-0.33
I like to be the person in a group who has the right answer	0.30	0.28	0.65	-0.15	-0.08
I don't care if I win in competitions	-0.61	-0.23	-0.18	0.13	0.14
I'll try something a second or third time to get it right	-0.09	0.51	0.38	0.02	-0.20
I usually leave things at "good enough"	0.06	-0.75	-0.09	0.03	-0.12
Goal to “Save money related to driving”	-0.11	0.07	0.50	0.03	0.04
Goal to "Save gas"	0.07	0.51	-0.03	-0.02	-0.38
Goal to “Generate less carbon dioxide from driving”	-0.40	-0.15	-0.01	-0.07	0.07
Goal to "Drive less overall"	-0.38	0.22	-0.01	-0.02	-0.36
Goal to "Drive more safely"	-0.11	-0.21	-0.08	-0.05	0.66
Goal to “Get around faster”	0.74	-0.22	-0.12	0.28	-0.12

Contextual and Behavioral Factors

Driving context can have a strong effect on fuel economy, especially given a particular trip and vehicle. Contextual factors, i.e., structure, include the type of roads, frequency of stops, road speeds, and other network, regulatory, traffic, and land-use details. To determine what changes in energy use are due to driver behavior, e.g., ecodriving in response to new energy feedback, it is essential to use a model of fuel economy that clearly separates contextual factors from factors that are influenced by or subject to driver behavior.

As this study focuses specifically on driver behavior in the vehicle, e.g. ecodriving, then weather, traffic, the trip drive-cycle, and trip-making patterns are considered contextual factors exogenous to ecodriving and are therefore included as explanatory model terms to reduce unexplained fuel economy variance and increase the precision of the driving behavior change estimate.

Trip types

The vehicle drive cycle (segment speeds and number of stops) is possibly the most important contextual (non-behavioral) factor affecting fuel economy. A cluster analysis is used in this to synthesize one meaningful trip-level categorical variable from multiple related variables that have non-linear influences on energy consumption. Model-based clustering was used to determine the distinct trip types existing among the 2,024 trips in the observed travel data. The analysis was performed using the R package Mclust which uses the Bayesian Information Criterion (BIC). Trip distance, maximum speed, average speed, stops/mile, and regional traffic speeds were used as the clustering variables. The results were 8 distinct trip types described in Table 2.

TABLE 2 Trip type cluster descriptions. Trip types are ordered by trip distance on the vertical axis for ease of comprehension. A wide variation in trip characteristics can be seen in both the number of stops and trip speeds, even in adjacent distance categories. Overall MPGe energy economy of the trips (not used in clustering) is shown in the second-to-right column, displaying the non-linear relationships between trip characteristics and energy economy.

Trip	Mean Economy Gal/100Mi	Mean Distance (miles)	Mean Maximum Speed	Mean Average Speed	Mean Stops/Mile	Mean Regional Traffic Speeds
1	3.1	0.9	31	7	8.3	62
2	2.2	1.9	42	13	3.8	62
3	1.9	5.4	48	19	2.4	62
4	2.2	6.0	37	13	6.1	61
5	2.0	10.7	69	21	2.3	63
6	1.8	10.9	53	22	1.8	61
7	1.7	15.8	70	35	0.8	62
8	2.0	64.7	72	44	0.4	61

Demographics

Typical demographic variables such as sex, age, or income are not included in this model since it is assumed that their relationship to driving behavior is mediated by the measured cognitive factors (such as attitudes and goals). With a larger sample size in a future study, however, it will be possible to construct a full path analysis to estimate the strength of the indirect or direct effects of demographics.

DATA AND MODEL DETAILS

Numerous steps were taken to improve the fit of the model by adjusting both the dependent and independent variables. The dependent variable is fuel consumption per 100 miles (gp100m), rather than the standard US MPG fuel economy due to the nonlinear relationship of fuel economy to consumption over fixed distances. Trips with a total distance below 100 m (approximately 0.06 miles) were removed to remove unusual cases such as starting the vehicle to roll up a window, to re-park the vehicle, or other similar short-distance uses of the vehicle. Each independent continuous variable was checked for linearity in its relationship with the dependent variable (gp100m). The final data include 23 individuals and 2,024 trips.

The linear regression models described in the results section were specified using mainly theoretical considerations, with modifications based on model necessities such as parameter reduction and interpretation. The theoretical considerations primarily consisted of including trip-level contextual factors to minimize gp100m variance due to non-ecodriving factors, while not including contextual factors that also "explain" behavioral changes (for instance, including trip speed as a continuous variable could reduce unexplained variance, but would also "explain" trip speed reduction that is actually due to behavior change). The final variables used in the model are shown with descriptions in Table 3.

To estimate the effects of feedback and cognitive factors while accounting for distinct groups and context, two basic types of variables are included in the model. First, trip-level variables that influence efficiency but are not controlled by the driver during the trip are included that explain differences in efficiency due to changes in trip type, drive-cycle, and cold starts. Secondly, person-level initial (pre-feedback) cognitive factors and average fuel consumption rates are included to estimate the influence of initial attitudes on both fuel economy and changes in fuel economy due to feedback.

TABLE 3 Description of model variables.

Variable	Description
gp100m	Gasoline gallons per 100 miles. The 100 mile denominator is used to ensure that gp100m values are easy to use values around 2 (50mpg).
gp100m_i	Individual average gp100m during the baseline period.
Speedy	The driver-specific PCA score from factor 1 as described in Table 1.
Motivated to Save Gas	The driver-specific PCA score from factor 2 as described in Table 1.
Like to Master Technology	The driver-specific PCA score from factor 3 as described in Table 1.
Confidence in MPG Knowledge	The driver-specific PCA score from factor 4 as described in Table 1.
Want to be Safer	The driver-specific PCA score from factor 5 as described in Table 1.
Low temperature	A continuous variable that measures temperatures below a threshold of 24 degrees Celsius.
Cold start	A continuous variable that measures the time between starts and is truncated at an upper boundary of 4 hours.
whpm	Average Watt-hours per mile of battery power during the trip. The purpose of this variable is to absorb PHEV-related EV driving variance.
Trip	Trip type categorical variable, displayed in order of increasing mean trip distance.

RESULTS

The results are split into two sections. In the first section, the basic behavior change analysis is presented with overall results for the experiment. This includes the baseline driving prediction model (Model 1), the overall attitude & behavior change model (Model 2), and associated T-tests and calculations to determine the magnitude of the interface effect. In the second results section is presented the latent-cluster analysis (Model 3) and analysis of the latent groups including differences in the effect of attitudes on behavior change (Figures N-N).

The R package nlme (non-linear mixed effects) was used to fit the pre-feedback prediction model and the feedback effect model. The R package flexmix was used to perform the latent-cluster optimization and model fitting and found two distinct latent groups.

Since Mixed-Effects models do not have a perfect corollary to the linear regression R^2 statistic, the statistic is calculated by 1- RSS/RSS_0 where RSS is the residual sum of squares of the full model and RSS_0 is the residual sum of squares of the null(intercept) model with random intercepts (Xu, 2003).

Prediction Model (Model 1)

The first step in the ecodriving model is to measure changes in driving behavior between the baseline period and the treatment period for each driver. To do so, a mixed effects linear model of gp100m fuel consumption rates was trained on the baseline data and then used to predict gp100m fuel consumption rates for trips in the treatment period. The difference between the predicted rate and the actual rate during the treatment period is termed the residual gp100m and represents the best estimate of behavior change between periods. The prediction model is shown in Table 4. The calculated gp100m residuals are then used as the dependent variable for models 2-4.

TABLE 4 Baseline gp100m Prediction Model (Model 1)

Dependent: gp100m	**N=912**	**23 Individuals**		**R^2 = 0.43**		
	Value	**Std.Error**	**DF**	**t-value**	**p-value**	
(Intercept)	4.01	0.104	879	38.59	<.0001	***
Low temperature	0.34	0.084	879	4.05	0.00010	***
Cold Start	0.63	0.26	879	2.44	0.015	*
whpm	-0.0048	0.00030	879	-15.76	<.0001	***
Trip 2	-1.11	0.082	879	-13.57	<.0001	***
Trip 3	-1.64	0.085	879	-19.32	<.0001	***
Trip 4	-1.34	0.13	879	-10.07	<.0001	***
Trip 5	-1.71	0.12	879	-14.17	<.0001	***
Trip 6	-1.88	0.12	879	-16.24	<.0001	***
Trip 7	-1.98	0.091	879	-21.77	<.0001	***
Trip 8	-1.97	0.13	879	-15.31	<.0001	***

Behavior Change Models (Models 2-4)

To estimate the influence of the feedback interface and attitude changes on fuel consumption, a fuel consumption rate (gp100m) model from the baseline period using Model 1 was used to predict fuel consumption rates during the treatment period. The difference between these two estimates is the residual fuel consumption rate – the actual measured behavior change plus any error due to additional exogenous factors. Any consistent residual is then attributed to the experimental treatment, and random residuals are attributed to unmeasured factors that could include traffic jams, rainstorms, and the like. Model 2 estimates the relationship between the behavior change (gp100m residuals) and the same model factors that were used in the pre-feedback model, with one addition. Since models 2-4 are measuring behavior change in a constrained environment where there is a real limit to gp100m perrformance, an estimate of each individual's baseline fuel consumption rate is included as an explanatory factor since drivers with low baseline rates (those who are already very efficient) have much less room to improve than drivers with high baseline rates (those who are inefficient to begin with). To measure the overall change in fuel consumption (not controlling for trip pattern or other exogenous factors) a t-test was performed to test the hypothesis that the fuel consumption rate went down during the experimental period. The resultof the t-test indicated that there was a mean drop in the fuel consumption rate of 4.4% (p=0.14, N = 2024).

TABLE 5 Post-feedback Driving Behavior and Attitude Model (Model 2)

Dependent: Residual gp100m	**N=1012**	**23 Individuals**	**R^2 = .036**	
	Value	**DF**	**t-value**	**p-value**
(Intercept)	0.30	930	1.24	0.21

gp100m_i	-0.22	11	-2.02	0.069	.
Save_Gas_i	0.28	11	1.15	0.27	
Speedy_i	-0.43	11	-1.63	0.13	
Confidence_i	0.18	11	0.51	0.62	
Safety_i	-0.12	11	-0.43	0.68	
Techie_i	0.047	11	0.13	0.90	
trip 2	0.061	930	0.91	0.37	
trip 3	0.15	930	2.30	0.022	*
trip 4	0.15	930	1.36	0.18	
trip 5	0.062	930	0.62	0.53	
trip 6	0.22	930	2.53	0.012	*
trip 7	0.15	930	1.95	0.052	.
trip 8	0.12	930	1.09	0.28	
whpm	-0.00053	930	-2.16	0.031	*
temp.cold	0.0018	930	0.030	0.98	
coldstart	-0.11	930	-0.54	0.59	
gp100m_i:Save_Gas_i	-0.15	11	-1.26	0.23	
gp100m_i:Speedy_i	0.23	11	1.83	0.095	.
gp100m_i:Confidence_i	-0.088	11	-0.53	0.61	
gp100m_i:Safety_i	0.072	11	0.53	0.60	
gp100m_i:Techie_i	-0.044	11	-0.26	0.80	

As shown in Table 5, the behavior changes are related to initial performance, certain trip-types, EV status, and the Speedy cognitive factor. The gp100m coefficient indicates that drivers with the best baseline (pre-feedback) performance made the smallest gains (if at all). This could be due either to drivers hitting a performance ceiling or to a regression to the mean due to random factors. The base trip type (milk-run) appears to be associated with the lowest gp100m changes, and other trips are significantly higher. Finally, the Speedy cognitive factor is related to higher gp100m residuals when interacted with baseline performance. This interaction term indicates that the factor is more important for drivers with high consumption rates. Also, the plug-in hybrid additional energy (whpm) is related to lower fuel consumption in the treatment period, indicating that either ecodriving behaviors are more effective in hybrid mode, or drivers were additionally motivated by the hybrid mode feedback.

Group Discovery, Interpretations, and Outcomes

Conducting a cluster analysis together with a regression model allows the identification of groups of people (if such groups exist) who differ in the impacts of certain explanatory variables on their fuel consumption rate - that is, for which model coefficients differ across group. In a *latent* cluster analysis, group membership is not decided a priori (e.g. on the basis of particular, pre-selected characteristics of the participants), but rather probabilistically specified and identified in the context of estimating the regression model for MPGe. Thus, performing the latent cluster analysis simultaneously with the regression model estimation permits the identification of groups *best suited for the application at hand* – i.e. groups that are maximally distinct with respect to their regression model coefficients, and represent truly distinct people rather than simply being split by outcome performance. This obviates the need for ad hoc experimentation to identify suitable clusters (with no guarantee that the "optimum" set had been found), and is particularly appropriate in exploratory research when there is little prior guidance regarding the nature of the different clusters.

For this application, the gp100m model was run in flexmix, allowing the coefficients for the initial attitudes to vary by group. The program finds the best-fitting attitudinal coefficients for the selected number of groups, and returns a BIC for each number of groups. The BIC shows whether the addition of each group makes the predictive ability of the model better or worse – indicating if additional groups are really present in the sample. In this case the BIC indicated that there are two distinct groups within the sample, based on the relationship between initial attitudes and fuel economy. The groups found by flexmix (the highest probability grouping structure) are then written to the data table and used in the rest of the analysis as the group definitions.

The two latent groups of drivers determined using the finite mixtures algorithm are interpreted below using group-level means of the pre and post-feedback cognitive factors shown in Figure 4. The two groups are clearly distinguished by their cognitive scores and outcome fuel economy, and are interpreted as “Fast & Unsure” and “Techie Trainees”.

The Fast & Unsure group had high initial freeway speeds (Figure 5) but became increasingly interested in safety and lost confidence in their knowledge of fuel economy over the course of the experiment, indicating that they had trouble understanding the screen and found it distracting. They showed no average decrease in fuel consumption in the experimental period, and no relationships between their attitudes and changes in fuel consumption. A t-test between periods showed that there was no statistically significant change in the fuel consumption rate for this group.

The Techie Trainees showed an increase in confidence of their knowledge of MPG, and significant relationships between their attitudes and levels of behavior change. Again, the driver’s baseline performance is an important factor in the level of behavior change. When it is taken into account, the relationships are very sensible: desire to save gas led to higher savings, and concerns about safety led to reduced savings. The effect of baseline performance can be seen clearly in Figure 3, where baseline gp100m is plotted against behavior change for each group. A t-test for this group showed an average 5.5% decrease in fuel consumption per mile (N=1617, p=.0038).

TABLE 6 Latent Group Model (Models 3-4)

Dependent: Residual gp100m **R^2 = .038**

Model 3: Group 1, “Fast & Unsure” (N=4, Individuals)				**Model 4: Group 2, “Techie Trainees” (N=19, Individuals)**			
	Value	**p-value**			**Value**	**p-value**	
whpm	-0.00075	0.0082	**				
trip 2	0.055	0.36					
trip 3	0.13	0.031	*				
trip 4	0.030	0.79					
trip 5	0.056	0.57					
trip 6	0.20	0.014	*				
trip 7	0.13	0.072	.				
trip 8	0.10	0.31					
temp.cold	-0.036	0.48					
coldstart	-0.014	0.94					
(Intercept)	1.46	0.98		(Intercept)	0.56	0.013	*
gp100m_i	-0.46	0.98		gp100m_i	-0.35	0.00087	***
Save_Gas_i	3.46	0.97		Save_Gas_i	0.36	0.060	.
Speedy_i	-8.10	0.96		Speedy_i	-0.16	0.48	
Confidence_i	-0.23	1.00		Confidence_i	0.21	0.41	
Safety_i	-5.50	0.97		Safety_i	-0.49	0.055	.
Techie_i	-10.8	0.94		Techie_i	0.17	0.54	
gp100m_i:Save_Gas_i	-1.61	0.97		gp100m_i:Save_Gas_i	-0.18	0.050	*
gp100m_i:Speedy_i	3.60	0.96		gp100m_i:Speedy_i	0.065	0.58	
gp100m_i:Confidence_i	-0.14	1.00		gp100m_i:Confidence_i	-0.11	0.36	
gp100m_i:Safety_i	2.34	0.97		gp100m_i:Safety_i	0.26	0.036	*
gp100m_i:Techie_i	4.81	0.94		gp100m_i:Techie_i	-0.09	0.49	

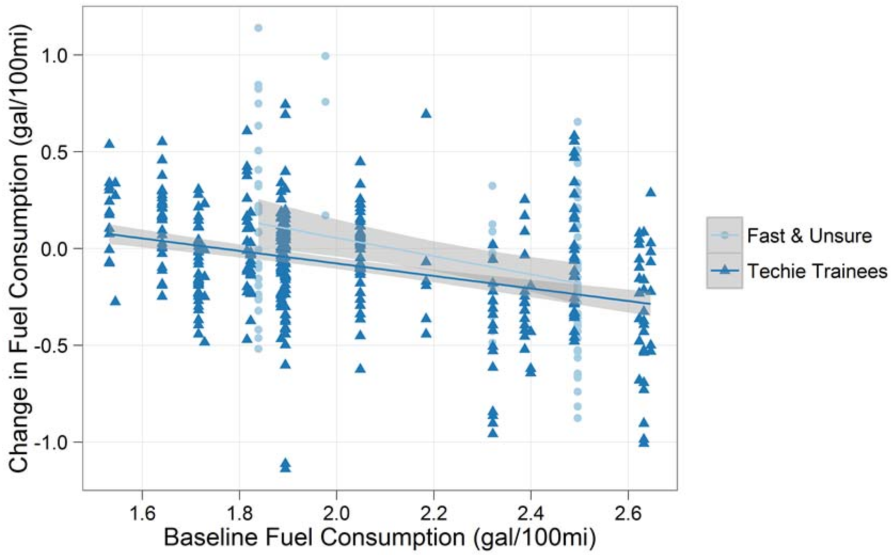

FIGURE 3 Fuel Savings (gp100m) due to the Interface and Initial Fuel Consumption Rate. A clear trend shows that higher initial fuel consumption rates (inefficient driving) are related to greater savings. This is likely due to the lack of "wiggle room" that high-performing drivers have, in comparison to low performing drivers, who have more room for improvement. On the left of the chart are high baseline performers who made little or no gain in the treatment period. On the right are low baseline performers who made large gains, up to approximately 11% decrease in gp100m on the far right.

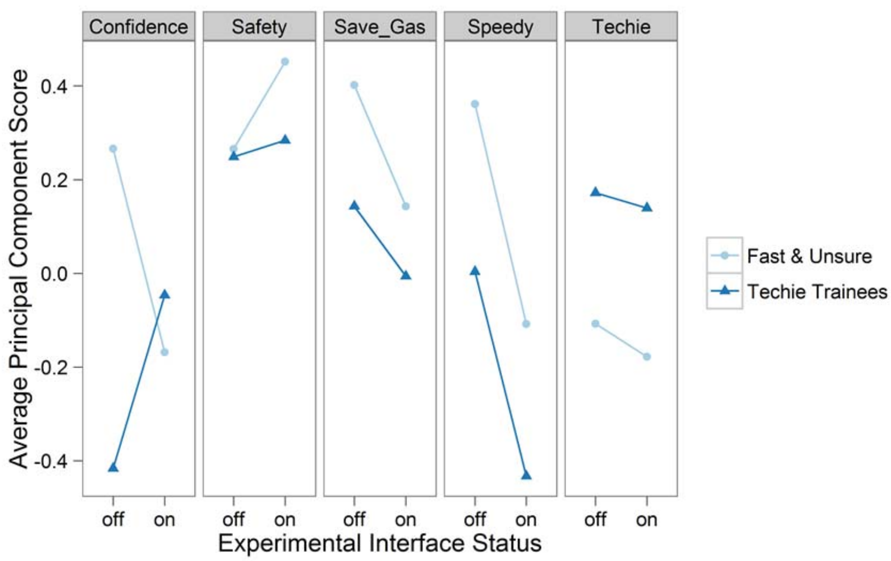

FIGURE 4 Attitude Measurements by Group and Interface Status. Similar trends (although different mean values) in the attitude change between experimental periods can be seen in these group averages.

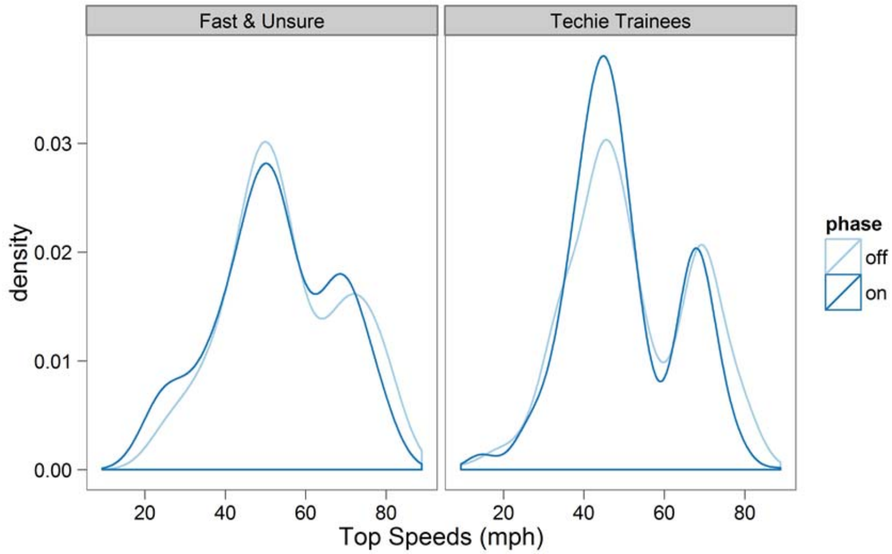

FIGURE 5: Trip Maximum Speed Density Plot showing the density (frequency divided by total count) of the top speeds of each trip included in the study, as recorded from an on-board data-logger. The plots show high freeway speeds for the Fast & Unsure in both phases, although both groups show reductions between the phases. The slight reduction in the Fast and Unsure high speeds was not enough to result in an average reduction in fuel consumption.

CONCLUSIONS

The original purpose of this study was to add to the ecodriving feedback literature by incorporating lessons from behavioral theories that have been used in behavioral fields for many years, a theoretical foundation which encouraged us to study not only the aggregate energy outcome of feedback, but also the intermediate cognitive effects. This focus on the cognitive basis of behavior change yielded a number of insights, the most significant of which are outlined below.

Ecodriving feedback effects vary by drive-cycle, cognitive grouping, and baseline performance, with shorter trips, more technical drivers, and low-efficiency drivers all showing the greatest gains.

Two groups were found based on their initial (pre-feedback) responses to a behavioral questionnaire. The drivers most influenced by feedback had low knowledge of fuel economy, low interest in fast driving, and high technical competency.

When separated by cognitive group, the Fast & Unsure group (N=4) was found to be ineffective in reducing fuel consumption, although the group did reduce freeway speeds. The simultaneous reduction in MPG knowledge and confidence indicates that this group was confused by the feedback and tried unsuccessfully to reduce fuel consumption. This group may benefit from additional training or education to help achieve the possible reductions.

The Techie Trainee group (N=18) was found to respond to the feedback largely as expected: the group made a statistically significant 5.5% reduction in fuel consumption in the second period, and the reductions were related to their initial cognitive factors when baseline performance was taken into account.

The strong influence of baseline performance indicates that the feedback was unable to influence high-performing drivers. This performance ceiling indicates that to be more effective for this subgroup, additional forms of feedback that incorporate off-road behaviors such as carpooling, mode-shifts, or other behaviors could help engage this group that is already at the top of the driving behavior ladder.

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