Understanding the Cost of Driving Trips

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ABSTRACT
Driving is the second highest expense for the average American household. Yet few people know the total cost of owning and operating their vehicles, and most cannot estimate accurately how much a common driving trip (like a daily commute) costs. There are an increasing number of viable alternatives for personal transportation, such as car services (e.g. Uber, Lyft), in addition to ridesharing, transit, biking, and walking. Cost is one factor in transportation mode choice, and awareness of the cost of driving is useful in making better informed decisions. To bridge this awareness gap, we built and deployed a system that makes the total cost of each driving trip (including depreciation, maintenance, insurance, and fuel) visible to the user. After this intervention, participants were able to more accurately and confidently estimate costs of their driving commutes, and transfer this knowledge to other trips for which they had not seen a cost.

AUTHOR KEYWORDS
Transportation; driving; mode choice; personal informatics.

ACM Classification Keywords
H.5.2 Information Interfaces and Presentation: User Interfaces

INTRODUCTION
Driving is the dominant mode of personal transportation in the United States. Owning and operating a vehicle is a major household expense. According to the Bureau of Labor Statistics, the average American household in 2015 spent more on driving ($9,503, or 17% of all expenses) than on any other category except housing [1].

Many alternatives to driving alone or owning a private vehicle, including ridesharing (e.g., carpooling), car services (e.g., Uber or taxis), and public transit, are priced on a *per-trip* basis. Cost is one factor people may consider when choosing to change their transportation behavior. In the Transtheoretical Model, the first stage of behavior change is *Precontemplation*, in which people may not be fully aware or informed of the consequences of their actions [11]. Many people do not have a good understanding of the Total Cost of Ownership (TCO) of owning and operating a vehicle, especially on a per-trip basis, because the component expenses (e.g., depreciation, maintenance, insurance, fuel) are incurred on disparate timescales. Furthermore, Thaler and Sunstein argue in *Nudge* that "choice architects" (such as designers of information systems) can make previously invisible information (such as vehicle depreciation per driving trip) *salient*, or visible, in order to inform people's decisions [12]. In this paper, we explore increasing people's knowledge of the TCO of driving trips as a first step toward behavior change in transportation mode choice.

Our contribution is the development and evaluation of a mobile system that estimates the total cost of each driving trip and reports this cost to the driver at the end of that trip. Our model aggregates both fixed and per-trip costs, including ownership (depreciation), fuel, maintenance, insurance, taxes, and fees, and produces a personalized cost estimate for each driving trip, based on the user's specific vehicle and actual fuel use and distance traveled.

Related Work
While a great deal of work in HCI and Personal Informatics focuses on areas such as health, fitness, and diet tracking, relatively little work has looked at transportation [2, 9]. Much of the HCI work on transportation focuses on driving style, rather than mode choice, including areas such as aggressive driving [7] or optimizing fuel economy [13]. HCI researchers have explored how personal transportation mode choice can be influenced by awareness of environmental impact [5] or the convenience and reliability of bus transit [4]. Other decision factors in mode choice include, but are not limited to, travel time and cost.

The transportation literature demonstrates that cost, while not the only factor, can be an effective lever in personal mode choice decisions. Since World War II, transportation planners have explored strategies to encourage people to choose alternatives other than driving alone, as part of Transportation Demand Management (TDM) programs [10]. The goals of TDM include reducing traffic congestion, improving air quality, and reducing the need for parking

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[10, 14, 15]. Best practice TDM strategies often include financial incentives for people who make alternative mode choices for their commute to work. For example, a company or government may provide free or discounted transit passes, free or discounted parking for carpool vehicles, or directly pay cash incentives to people who choose alternatives other than driving alone [3, 10].

SYSTEM

In order to estimate and present to the user the total cost of a driving trip, we developed: (1) a per-trip model of the Total Cost of Ownership for a given vehicle; and (2) an implementation of the model on a mobile device for use in a vehicle.

Cost Model

The Total Cost of Ownership for a vehicle includes both fixed costs, which are incurred regardless of how much or little the vehicle is driven, and per-trip costs. Our model accounts for the fixed costs of time-value depreciation, insurance, taxes, and fees, and the per-trip costs of fuel, per-mile depreciation, and maintenance.

The inputs to our model are fuel used and distance traveled for a given trip. The output is the estimated total cost of ownership applied to that driving trip. To determine the coefficients for our model, we collect: the year, make, model, and odometer reading of the vehicle; its insurance cost; an estimate of how many miles per year it is driven; and published local average current fuel prices.

We estimated depreciation using data from Kelley Blue Book (KBB) [8], a commercial database that provides the locally estimated resale value of vehicles the United States. To estimate the per-mile depreciation, we compared the current value of the vehicle to the value of the same vehicle with an odometer reading of 10,000 miles higher. We divided the price difference by 10,000 as a linear estimate of the per-mile depreciation. To estimate the fixed per-year depreciation, independent of how many miles driven, we compared the current value of the vehicle to the same vehicle and odometer reading, but one year older. We estimated fixed taxes and fees based on publisheds rates for the local jurisdiction. These linear calculations are suitable approximations for short periods such as one week, but an exponential model would be required for use over longer time periods.

In order to allocate the fixed costs to each driving trip, we employed a user-provided estimate how many miles per year the vehicle was driven. We then allocated the annual total fixed costs proportionately to each driving trip, based on the trip distance divided by the annual mileage. For example, if a vehicle had $5000 in total annual fixed costs, was driven 10,000 miles per year, then our model would allocate $5.00 of fixed costs for a trip of 10.0 miles.

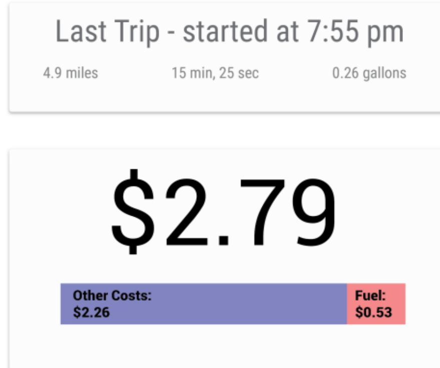

Figure 1: Trip cost meter display.

Implementation

Our system consists of an Android phone and a Bluetooth-enabled On-Board Diagnostics (OBD) interface to the vehicle. The OBD device is used to indirectly determine the fuel usage (from either Mass Air Flow or Manifold Air Pressure data) and to detect the start and stop of each driving trip (from RPM or voltage drop data). We employed a commercial Android application, Torque Pro [6], which offers an API for reading OBD data from the vehicle. We used the GPS sensor on the phone to calculate the driving distance of each trip, based on 1 Hz samples of location data, which offers higher resolution than the 1 km resolution distance data available from the OBD interface.

The phone display is blank before and during driving trips (to avoid distracted driving), and only displays the driving cost immediately after each trip (when the user turns off the ignition). After each trip, the phone audibly alerts the driver, and the driver is then presented with a screen to tap his or her name in order the see the trip cost display. The username screen allows us to track whether the user viewed the cost or ignored the device after each logged trip. The trip cost display (Figure 1) shows the total cost of the driving trip based on our model, breaks out the “Fuel” and “Other Costs” components, and presents the mileage, duration, and fuel usage of the trip.

EVALUATION

We describe an intervention to evaluate the impact of our trip cost meter system on participants’ awareness of the total cost of their driving trips.

Participants

We recruited 14 participants who drove gasoline-powered vehicles (including hybrids) frequently each week in Atlanta, GA, a large urban area of the United States. Nine participants (three female), ranging in age from 19 to 39 (median = 24.5) completed the study. Five participants did not complete the study due to technical problems with the trip segmentation or fuel data reported by the OBD device. Three participants who completed the study were not affiliated with our university.

	P1	P2	P3	P4	P7	P11	P12	P13	P14
Commute Trip :: Num Trips Viewed	7	10	3	6	7	3	9	2	2
Modeled Cost (from trip logs)	*$7.19*	*$14.34*	*$5.96*	*$2.60*	*$1.35*	*$4.03*	*$3.29*	*$1.58*	*$1.57*
Estimate : Pre	$2.50	$4.00	$5.00	$10.00	$1.50	$5.00	$1.35	$4.00	$0.20
Estimate : Post	$6.58	$13.50	$5.74	$2.00	$1.50	$4.00	$3.30	$2.17	$1.50
Estimate : Follow-Up				$3.00		$.4.00	$4.00		$2.00
Relative Error : Pre	65.2%	72.1%	16.0%	284.9%	10.9%	24.1%	59.0%	152.8%	87.3%
Relative Error : Post	8.5%	5.8%	3.6%	23.0%	10.9%	0.7%	0.2%	37.2%	4.7%
Relative Error : Follow-Up				15.5%		0.7%	21.4%		27.0%
Confidence : Pre→Post→Follow-Up	2→4	3→4	4→4	1→4→1	3→4	2→3→2	3→4→4	3→4	2→4→3
Second Trip :: Num Trips Viewed	3	-	-	-	-	-	-	-	1
Modeled Cost (post hoc)	*$1.11*	*$1.59*	*$7.82*	*$23.23*	*$10.13*	*$1.62*	*$9.33*	*$0.93*	*$1.49*
Estimate : Pre	$0.10	$0.50	$7.00	$15.00	$3.00	$2.00	$2.10	$2.50	$0.15
Estimate : Post	$1.05	$2.00	$7.00	$10.00	$20.00	$2.00	$6.85	$1.50	$1.00
Estimate : Follow-Up				$6.00		$2.00	$7.00		$1.50
Relative Error : Pre	91.0%	68.6%	10.5%	35.4%	70.4%	23.6%	77.5%	168.6%	89.9%
Relative Error : Post	5.3%	25.6%	10.5%	57.0%	97.4%	23.6%	26.5%	61.2%	32.9%
Relative Error : Follow-Up				74.2%		23.6%	24.9%		0.6%
Confidence : Pre→Post→Follow-Up	2→4	3→3	4→4	1→4→1	2→2	2→3→2	3→4→4	3→3	2→3→2

Table 1: Driving data per participant.

Apparatus
We provided each participant with a dedicated Android phone to keep in his or her vehicle, an OBD adapter, and a 20,000 mAh external battery which allowed the system to run for 5-7 days without requiring recharging or an external power source.

Protocol
Each participant completed an entry survey, an intervention with the above trip cost apparatus, and an exit survey and interview. In the entry and exit survey, we asked each participant to identify and provide street addresses for two common driving trips: (1) their commute from home to work (or school); and (2) another common trip, such as home to the grocery store. We then asked each participant two questions for each specified trip: "Estimate the total cost of this driving trip (one-way)"; and "On a scale from 1 ('I have no idea') to 5 ('My answer is correct'), how confident are you in this cost?"

For the intervention, we deployed the system in each participant's vehicle for 5-7 days (until the battery ran out). During the installation, we entered the model coefficients based on the participant's personal vehicle and calibrated our application settings based on how that specific vehicle's OBD protocol reported fuel usage and RPM or voltage data to determine engine on/off events. Calibrating the OBD data for each vehicle was an unfortunately laborious process that greatly impacted our ability to scale the study. Immediately after each driving trip, the system allowed participants to see the estimated total cost of that trip. Participants could not review the trip costs later, so our evaluation reflected their memories of the reported trip cost meter that appeared each time they turned off their vehicles.

During the exit interview, we asked participants to discuss their overall impression of the system and the presented information, anything that surprised them, anything they might do differently as a result of having this information, and additional thoughts and reflections.

After four months, we invited participants to a follow-up session. We asked them the same driving cost estimate and confidence questions regarding their two designated common trips, and asked them in an interview about their transportation behavior and choices.

RESULTS AND DISCUSSION
Nine participants recorded a total of 145 driving trips (6-21 per participant). Of these, 62 trips were commutes between home and work or school, and participants viewed the trip cost for 49 of these. Each participant logged between 3 and 10 commute trips, and viewed between 2 and 10 commute costs. Four participants (P4, P11, P12, P14) took part in the follow-up four months after the intervention. Participants' cost estimates and confidence levels for the pre-intervention, post-intervention, and follow-up session are presented in Table 1. Because the data are not normally distributed and the sample size is small, we used the Wilcoxon signed-rank test to compare the pre- and post-intervention data for participants' cost estimate accuracy and for their reported confidence.

Accuracy
We calculated the relative error of participants' estimates of their driving costs, as compared to the modeled driving cost, for both the pre and post surveys.

$$Relative\ Error = \frac{|Estimate - Actual|}{Actual} \times 100\%$$

For the modeled cost of the commute trip, we used the average cost over all instances of this trip, in either direction, logged during the study.

A Wilcoxon signed-rank test showed a statistically significant change in the relative error of participants' commuting cost estimates after the intervention ($Z=-2.521$, $p=.012$). The median relative errors of participants' commuting cost estimates as compared to the modeled cost values decreased from 65.2% in the pre-intervention survey to 5.8% in the post-intervention survey. Participants' average cost estimates decreased from 85.8% relative error (SD=86.4%) in the pre survey to 10.5% relative error (SD=12.1%) in the post survey. No participant exhibited a worse relative error in their commute cost estimate after the intervention.

Seven of the nine participants did not drive their second designated common trip during the study period, and thus did not see cost estimates for these trips. Using the driving distance from Google Maps and the average fuel economy from actual logged trips, we calculated a post hoc modeled cost for the second common trip using our trip cost model. Overall, participants' cost estimates for the second trip improved on average from 70.6% relative error (SD=46.8%) in the pre survey to 37.8% relative error (SD=29.1%) in the post survey. Five participants improved their estimates, two estimated the same, and two participants' estimates were worse.

In the follow-up four months later, all four participants were more accurate in their commute cost estimates as compared to the pre-intervention survey, indicating that they retained knowledge of their driving costs despite their decreased confidence. For the second common trip, three participants were at least as accurate as in the pre-survey, while P4 was progressively less accurate for both the post-survey and the follow-up.

Confidence

A Wilcoxon signed-rank test showed a statistically significant change in participants' confidence in their commuting cost estimates after the intervention ($Z=-2.588$, $p=.010$). The median values of participants' confidence levels in their commuting cost estimates (on a scale of 1=low to 5=high) increased from 3 in the pre-intervention survey to 4 in the post-intervention survey. Their average confidence increased from 2.6 (SD=0.9) before to 3.9 (SD=0.3) after the intervention. In the post survey, all participants reported a confidence of 4 out of 5, except P11 who reported 3. The confidence increased for all participants except P3, who reported 4 out of 5 in both the pre and post surveys.

Impact on Awareness

In the exit interview, all participants except P3 told us they were surprised by the total cost of their driving trips. P12 initially expected a lower per-trip cost, but "after several days I started to understand you may include the maintenance also . . . . maybe the insurance. . . . And then I realized maybe the cost for each trip is actually higher than expected."

P3 was unique among the participants in describing having previously considered the total cost of ownership of his vehicle, and was also the most accurate and confident in his initial estimates of the two trip costs. "It was in the ballpark of what I was expecting. . . . I realized a lot of my costs are actually payments, insurance, depreciation. . . . It was almost a revalidation that this car costs me more than the fuel [because] you know psychologically we don't see [the other costs]."

Reflecting on Behavior Change

Three of the four participants who took part in follow-up interviews four months after the intervention reported changes in their transportation behavior.

P12 previously drove to school daily. "Every Tuesday I . . . take Lyft instead of driving from my apartment to school" in order to "save some money on gas, and also . . . save some mileage for my car, so I don't have . . . to do the maintenance."

P14, who previously drove to work daily, recently moved. "I live close enough so I can walk and that's one of the benefits I had in mind of moving. So I'm not gonna have to drive that much to save on fuel costs."

After the intervention, P4 stated, "living in such a driving city I think it's still not enough for me to start looking at the public transportation." In the follow-up, P4 reported that he recently moved to a home closer to MARTA, the local subway. "I never thought I would ever take MARTA and I took it now. Now a MARTA believer," because he "didn't want to drive to the airport in rush hour traffic and pay for parking. So instead I paid . . . $5 round trip to do that."

These three participants described cost savings (for fuel, maintenance, and parking) as one of the reasons for their behavior change. Though we cannot directly connect this consideration of cost to our intervention, we are inspired by these results to explore how future studies can better link increased awareness of driving cost (something we clearly established) to transportation choices.

In the exit interviews, P3 and P7 stated that convenience was a more important factor in their transportation decisions than cost, and P13 described convenience as an additional factor. P1, who did not pay for her vehicle, was motivated more by trip time than cost. P1 and P13 were the only participants who expressed environmental impact as a factor in their transportation choices.

Limitations

We acknowledge that the generalizability of our results may be limited by several factors, including but not limited to a potential U.S.-centric bias and the low number and limited diversity of our participants.

CONCLUSION

Prior to using our trip cost meter, most participants exhibited a poor understanding of the total cost of their driving trips. We demonstrated that a simple and short intervention with our trip cost meter increased knowledge of the cost of a common driving trip (e.g., daily commute). Some people were able to transfer this knowledge to other driving trips, for which they had not used the trip cost meter. The three participants who changed their transportation behavior after the intervention each reported cost as one of the factors in their decision.

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