Augmenting the Technology Acceptance Model with Trust: Commercial Drivers' Attitudes towards Monitoring and Feedback

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This study evaluates truck drivers' attitudes toward an on-board monitoring system (OBMS), using an extended version of the Technology Acceptance Model (TAM) that accounts for drivers' trust in OBMS. Crashes that involve trucks incur a high cost to society and driver-related factors contribute to about one third of all large truck fatal crashes in the US. Therefore, safety initiatives that can increase drivers' awareness of their risky behaviors are highly desirable. In-vehicle feedback systems are designed to serve this purpose; however, their benefits will not be realized unless their information can positively influence safe driving. Acceptance constructs for the proposed model were measured using a survey administered after the monitoring system was introduced to the drivers but before the system was actually installed in their trucks. In line with the TAM, the results demonstrated that perceived usefulness is the most important determinant of intention to use the OBMS. Trust was also a major determinant of intention to use, suggesting that the acceptance model can be usefully augmented by this construct.

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INTRODUCTION

The Technology Acceptance Model (TAM), built on the Theory of Reasoned Action of Fishbein and Ajzen (1975), posits perceived usefulness (PU) and perceived ease of use (PEOU) as the main determinants of the attitude to use, which in turn predicts behavioral intention (BI) to use and actual system use (Davis, Bagozzi, & Warshaw, 1989). PU measures the degree that operators believe a technology will enhance job performance, while PEOU measures the degree to which using a system would be free of effort (Davis, 1989). PU and PEOU have demonstrated high reliability and validity (Davis & Venkatesh, 1996) and as such, have continued to be the core of the TAM. Attitude, however, has been found to only partially mediate the effect of PU on BI and has been excluded in many TAM adaptations (Davis & Venkatesh, 1996; Venkatesh & Davis, 2000). The resulting parsimonious TAM is shown in Figure 1.

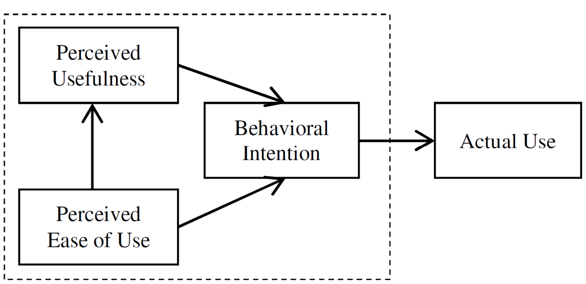


Figure 1. Parsimonious TAM, adapted from Davis and Venkatesh (1996)

Many researchers have used the TAM framework and have added new constructs and relationships to describe user acceptance (for examples, see Bajaj & Nidumolu, 1998; Dishaw & Strong, 1999; Karahanna, Agarwal, & Angst, 2006). However, the TAM has only recently found application in driving assistance systems research. It has been used to assess acceptance of advanced traveler information systems by incorporating travel domain-specific constructs (information attributes, trust in travel information, socio-demographics, and cognition of alternate routes) (Xu et al., 2010). In another study, a version of the TAM that incorporated perceived enjoyment and personal innovativeness constructs was used for evaluating acceptance of GPS devices (Chen & Chen, 2011). Other studies have used the TAM constructs in assessing acceptance of driving assistance systems, suggesting that perceived system disturbance, perceived risk, and social influences strongly affect the intention to use a system (Adell, 2010; Meschtscherjakov, Wilfinger, Scherndl, & Tscheligi, 2009). These studies suggest that the TAM framework is an appropriate tool for assessing drivers' acceptance of driving assistance systems.

Research has shown that the level of trust that individuals place in automation is a major determinant of their reliance on and acceptance of that automation (Lee & Moray, 1992, 1994; Parasuraman, Sheridan, & Wickens, 2008). As such, the present study examines truck drivers' pre-exposure attitude toward an on-board monitoring system (OBMS), using a modified version of the TAM that takes the level of drivers' trust in the OBMS into account. The proposed acceptance model quantifies the effect of trust on acceptance, alongside PU and PEOU—determinants of acceptance in the TAM.

On-Board Monitoring Systems for Commercial Drivers

Large truck crashes are associated with high rates of fatalities and injuries, as well as property damages. In 2010, more than 61,000 large trucks were involved in fatal and injurious crashes in the United States, resulting in 3,675 fatalities and about 80,000 injuries (NHTSA, 2012). The number and severity of truck-involved crashes underscore the importance of enhancing truck driving safety.

The most recent statistics show that 31% of large truck fatal crashes are attributable to driver-related factors—driving too fast, failure to keep in proper lane, and inattentive driving account for 63% of all driver-related fatal crashes (FMCSA, 2011). In-vehicle technologies, such as on-board monitoring systems, that can provide feedback to drivers may help mitigate truck drivers' inattentiveness and enhance their awareness of surrounding conditions.

In the context of driving, feedback is defined as the information provided to the driver regarding the state of the joint driver-vehicle system (Donmez, Boyle, & Lee, 2009). In-vehicle feedback systems can provide benefits in mitigating driver distraction. Research has shown that timely rear-end collision warning can reduce the number of collisions by around 80% for distracted drivers, while even being useful for undistracted drivers (Lee, McGehee, Brown, & Reyes, 2002). Benefits of feedback have also been specifically evaluated in relation to commercial driving. For example, forward collision warning has been shown to increase the average following distance maintained by truck drivers and help avoid 21% of rear-end crashes (Lehmer et al., 2007). In another study, lane departure warning system was shown to reduce the number of lane departures, especially at night and on straight road segments (Orban, Hadden, Stark, & Brown, 2006).

With all the promise that feedback systems have to offer, their benefits will not be realized unless drivers accept them. Research has shown that drivers' attitudes toward driving assistance systems do not necessarily parallel the safety benefits of those systems. For example, drivers are more accepting of assistance systems that only warn them of imminent hazards, compared to automated control systems that initiate action, even when the automated control performs better (Inagaki, Itoh, & Nagai, 2007; Navarro, Mars, Forzy, El-Jaafari, & Hoc, 2010). These studies indicate the importance of assessing drivers' acceptance as part of the development of OBMSs and other driving assistance systems.

OBMS Acceptance Model and Hypotheses

A model based on the parsimonious TAM is proposed to understand the perceptions that affect commercial drivers' acceptance of OBMS (Figure 2). Because this study aims to measure acceptance of the OBMS prior to any driving experience with the system, actual use is not a part of the model. As such, BI will be the indicator of acceptance and the OBMS acceptance model will assess the influence of PU and PEOU on BI. Based on the TAM literature, it is hypothesized that PU and PEOU each have a positive effect on BI and that PEOU has a positive effect on PU (Davis, et al., 1989; Ghazizadeh, Lee, & Boyle, 2012).

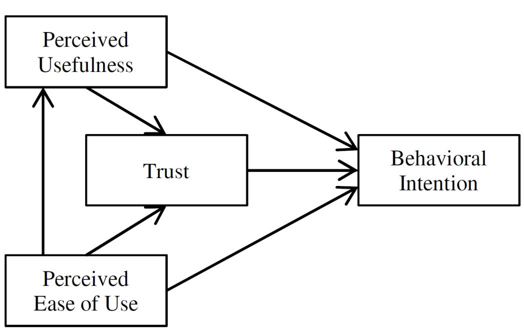


Figure 2. The proposed OBMS acceptance model

Trust is known to be a major determinant of reliance on and acceptance of automation, standing between people's beliefs toward automation and their intention to use it (Carter & Bélanger, 2005; Gefen, Karahanna, & Straub, 2003; Lee & Moray, 1992, 1994; Lee & See, 2004; Parasuraman, et al., 2008; Pavlou, 2003). As such, the TAM model is augmented by trust in the OBMS, which is included in the model as a predictor of BI. It is hypothesized that PU and PEOU, as beliefs, both have positive effects on trust and that trust will in turn have a positive effect on BI. Previous studies suggest that trust does not fully mediate the effect of beliefs on behavioral intentions (Lee & See, 2004), and thus the direct effects of PU and PEOU on BI are retained in the model.

METHODS

On-Board Monitoring System

The proposed augmentation of the TAM was evaluated as part of a study that examines truck drivers' attitudes toward an on-board monitoring system (OBMS).This OBMS provides real-time feedback in the form of auditory and visual warnings, e.g., forward collision warning, lane departure warning, and driver behavior warning (Boyle & Peng, 2010). Figure 3 shows examples of the OBMS display during normal driving mode (Figure 3a) and when a safety critical warning appears (Figure 3b). The system also provides information on driver state (e.g., inattentive), other non-critical driving information (e.g., speed), and hours of service. In addition to the real-time feedback, safety critical events will be recorded by the OBMS and delivered to the trucking fleet's safety supervisors for coaching purposes.

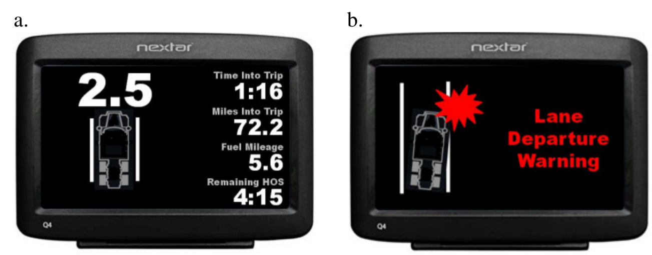


Figure 3.Examples of OBMS's display: a. normal driving display, b. lane departure warning display

Questionnaire Design

Drivers' perceptions of the OBMS were captured through a questionnaire administered after the system was briefly introduced to drivers, but before they had any driving experience with the system. The survey items were designed to capture the four constructs in the OBMS acceptance model: PI, PEOU, trust, and BI. Table 1 shows the grouping of the items under each of the constructs. The PU and PEOU items were derived based on Davis (1989) and Legris, Ingham, and Collerette (2003), which is a review of the various adaptations of the TAM. The items were customized to relate to the driving context and the expected utility of the OBMS. Trust items were adopted from Jian, Bisantz, and Drury (2000) and BI items were derived from Venkatesh and Davis (2000) and Böhm, Fuchs, Pfliegl, and Kölbl (2009). All items were measured using a labeled seven-point Likert scale: 'Strongly Disagree', 'Disagree', 'Slightly Disagree', 'Neutral', 'Slightly

Agree', 'Agree', and 'Strongly Agree'. Responses were coded from 1 (for 'Strongly Disagree') to 7 (for 'Strongly Agree'), so higher ratings indicated more positive attitudes.

The questionnaire included a number of demographic questions, such as age, gender, and driving experience. These questions appeared at the end of the questionnaire, after the OBMS acceptance items.

Table 1. Survey items and their relevance to driver acceptance constructs

Survey item	Construct
I think using the DriveVision Pro will …	
- … make me a safer driver. - … make it easier to drive. - … make me more aware of my surroundings (other vehicles, lane position, etc.). - … reduce distractions. - … reduce sleepiness. - … improve my driving .	Perceived Usefulness (PU)
I think the DriveVision Pro will be…	
- … easy to use - … easy to learn - … easy to understand - … annoying* - … distracting*	Perceived Ease of Use (PEOU)
- I will trust the information I receive from the DriveVision Pro. - I think I can depend on the DriveVision Pro. - I will feel more comfortable doing other things (e.g., adjusting the radio) with the DriveVision Pro.	Trust
- If I had a choice, I would drive a truck equipped with the DriveVision Pro. - If I had the DriveVision Pro in my truck, I would use it. - If I had the DriveVision Pro, I would adjust my driving to its information. - I would recommend the DriveVision Pro to other truck drivers.	Behavioral Intention to Use (BIU)

*These items were mirrored so that higher ratings reflect more positive attitudes.

Procedure

This study was conducted at a trucking terminal that employs approximately 100 drivers. All drivers at this terminal site will eventually drive with an OBMS in their truck cabins (as part of a safety program of their company). However, their participation in this questionnaire study was voluntary.

Information sessions about the study were held at the mandatory quarterly meetings located at the terminal site. Each information session covered general information about the OBMS and a timeline for system installation, as well as specific information about the present study, what participation entailed, what was expected from participants, and how their contribution would be compensated. A description of the study and a copy of consent form were provided to each driver. The drivers were ensured that their participation in the questionnaire study was completely voluntary and participation would have no impact on employment.

At the end of each information session, the research team was available for questions and collected the signed consent forms from the drivers who had chosen to participate. These drivers were then given a copy of the questionnaire and a stamped prepaid envelope so they could send the completed surveys directly to the research team. A compensation check was mailed to each participating driver at the address provided immediately after the project team received a completed questionnaire.

Participants

Thirty-four drivers participated in the study by filling out the questionnaire (response rate ~34%). Each driver received $10 for participating (IRB No. 39876, University of Washington). The drivers were all male, with a mean age of 51 years (*SD* ~7 years) and a mean commercial driving experience of 22 years (*SD* ~9 years).

Data Analysis

Hierarchical regression was used to measure the effects of predictors on BI and trust. Two hierarchical models were developed: Model 1 for measuring the effects of PU, PEOU, and trust on BI and Model 2 for measuring the effects of PU and PEOU on trust. For each model, predictors were added in a stepwise fashion and in descending order based on the strength of their correlation with the dependent variable. An additional regression model, Model 3, was used to measure the effect of PEOU on PU. These models collectively cover all the hypothesized effects shown in Figure 2.

RESULTS

Descriptive Statistics of Constructs

Drivers' responses to questionnaire items were averaged to estimate each acceptance construct (i.e., PU, PEOU, trust, and BI) for each driver. Table 2 reports the mean, standard deviation, and reliability measure (Cronbach's α) of each construct, as well as the correlations between constructs. All statistical analyses were conducted using R 2.14.1 (R Development Core Team, 2011).

Table 2. Means, standard deviations, Cronbach's α, and correlations

Construct	Mean	SD	PU	PEOU	Trust	BI
PU	4.08	1.35	0.90			
PEOU	4.53	1.05	0.37^{*}	0.86		
Trust	4.22	1.07	0.49^{**}	0.44^{*}	0.74	
BI	4.27	1.42	0.76^{***}	0.51^{**}	0.61^{***}	0.86

Notes: Cronbach's alphas are on the diagonal.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

The means of the constructs ranged from 4.08 to 4.53, corresponding to 'Neutral' to 'Slightly Agree' ratings. The standard deviations ranged from 1.05 to 1.42. The internal consistency Cronbach's alphas ranged from 0.74 (for trust) to 0.90 (for PU) indicating acceptable to good reliability for all constructs. All construct pairs were significantly correlated—the highest correlation was observed between PU and BI, $r(32) = 0.76$, $p < .001$, and the weakest correlation was between PU and PEOU, $r(0.37)$, $p = .03$.

Hierarchical Regression Results

The results of the regression models are reported in separate subsections below.

Model 1 (behavioral intention). PU, PEOU, and trust all had significant correlations with BI and with each other (see Table 2). Therefore, they were entered into Model 1, one at a time in the descending order of correlation magnitudes, accounting for the correlations between the constructs. Table 3 contains the results of the hierarchical regression analysis (regression coefficients and model fit indicators).

In step 1, the impact of PU on BI was measured, showing a highly significant PU effect. In step 2, trust was entered in the model and both PU and trust emerged as significant. The F-test for model R^2 difference showed that the amount of additional variation in BI accounted for by the addition of trust was significant, $F(1, 31) = 6.97$, $p = .01$. In step 3, PEOU was entered; however, its effect on BI was insignificant and the variation covered by the model in step 3 showed no significant improvement over step 2, $F(1, 30) = 2.48$, $p = .13$. Based on these results, the model with PU and trust as predictors (step 2) best describes the variation in BI (PU: $b = 0.64$, $t(31) = 5.00$, $p < .001$; trust: $b = 0.42$, $t(31) = 2.64$, $p = .01$).

Table 3.Model 1: Hierarchical regression analysis for predicting behavioral intention (BI)

Construct	**Step 1**	**Step 2**	**Step 3**
PU	0.80^{***}	0.64^{***}	0.59^{***}
Trust		0.42^{*}	0.34^{*}
PEOU			0.25
R^2	0.58	0.65	0.68
Adjusted R^2	0.56	0.63	0.65
F-value	$F(1, 32) = 43.60^{***}$	$F(2, 31) = 29.35^{***}$	$F(3, 30) = 21.33^{***}$
ΔR^2		$F(1, 31) = 6.97^{*}$	$F(1, 30) = 2.48$

Notes: The best model is highlighted.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Model 2 (trust). Based on Table 2, among PU and PEOU (the two constructs that were hypothesized to influence trust), PU has a higher correlation with trust. Therefore, PU was entered in Model 2 in step 1. The effect of PU on trust was found significant. In step 2, PEOU was added to the model, but was found to be insignificant. The model in step 2 failed to account for substantial additional variation compared to step 1, $F(1, 31) = 3.40$, $p = .07$. Based on these results, the model in step 1 best describes the variation in trust (PU: $b = 0.39$, $t(32) = 3.15$, $p = .004$). The results of the hierarchical regression model are shown in Table 4.

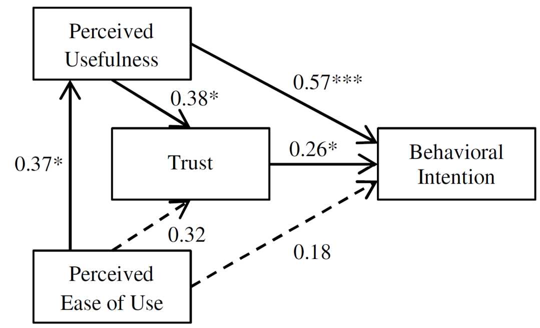
Table 4. Model 2: Hierarchical regression analysis for predicting trust

Construct	**Step 1**	**Step 2**
PU	0.39^{**}	0.30^{*}
PEOU		0.30
R^2	0.24	0.31
Adjusted R^2	0.21	0.27
F-value	$F(1, 32) = 9.94^{**}$	$F(2, 31) = 7.04^{**}$
ΔR^2		$F(1, 31) = 3.40$

Notes: The best model is highlighted.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Model 3 (perceived usefulness). PEOU was the only construct whose effect on PU was examined (see Figure 2). This effect was assessed using a simple regression model and emerged as significant, $b = 0.48$, $t(32) = 2.28$, $p = .03$. PEOU also explained a significant proportion of variation in PU, $R^2 = 0.14$, $F(1, 32) = 5.16$, $p = .03$.

Figure 4 shows the standardized regression coefficients (βs) calculated based on the results of the previous three models. The coefficients are standardized to facilitate comparison among effects.



Notes: Weights on arrows show standardized regression estimates (βs). Dashed arrows show insignificant effects.
$^{*}p < .05$, $^{***}p < .001$

Figure 4. The estimated OBMS acceptance model

DISCUSSION AND CONCLUSION

The results of this study demonstrated that, in keeping with the hypotheses, perceived usefulness (PU) of the OBMS plays the major role in determining drivers' intention to use. Trust in the system was also a determinant of use intentions. However, contrary to the hypothesis, perceived ease of use (PEOU) had little effect on the intention to use, when accounting for both PU and trust. While the larger effect of PU compared to PEOU is in line with the TAM literature, the insignificance of PEOU is not (Davis, et al., 1989). It is interesting to note that previous studies in the driving domain have found a greater effect of PEOU on BI, compared to PU (Chen & Chen, 2011; Xu, et al., 2010). These conflicting results might be due to the differences among modeling frameworks (e.g., inclusion of trust, considering trust as a mediator of the effect of PU and PEOU on BI), as well as differences in the nature of the driving assistance systems and the context of their use.

Few adaptations of the TAM have considered trust as a determinant of acceptance; however, those who have done so have found trust to be a determinant of intention to use. In the context of e-commerce and e-government, it has been shown that trust in the e-vendor can influence intentions to transact on a website (Carter & Bélanger, 2005; Pavlou, 2003). However, these studies have considered trust in the provider more than the technology itself. In the context of driving, trust in the information provided by a traveler information system has been shown to directly affect acceptance (Xu, et al., 2010). The present study confirms this result for the OBMS and shows that trust can play an important role along with the other determinants of acceptance.

Trust is a dynamic belief that can evolve over time and with extended exposure to automation (Lee & See, 2004), just as acceptance is not constant (Kim & Malhotra, 2005). A cross-sectional study, like the one presented here, can provide insight into attitudes at a given time point. However, for a thorough understanding of the dynamics of acceptance, a longitudinal study is needed (Ghazizadeh, et al., 2012). The results obtained in the present work can serve as a first wave for such study.

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