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Driver Acceptance of Advanced Driver Assistance Systems and Semi-Autonomous Driving Systems

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Driver acceptance of advanced driver assistance systems and semi-autonomous driving systems

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Advanced Driver Assistance Systems (ADAS) and semi-autonomous driving systems are intended to enhance driver performance and improve transportation safety. The potential benefits of these technologies, such as reduction in number of crashes, enhancing driver comfort or convenience, decreasing environmental impact, etc., are well accepted and endorsed by transportation safety researchers and federal transportation agencies. Even though these systems afford safety advantages, they challenge the traditional role of drivers in operating vehicles. Driver acceptance, therefore, is essential for the implementation of ADAS and semi-autonomous driving systems into the transportation system. These technologies will not achieve their potential if drivers do not accept them and use them in a sustainable and appropriate manner. The potential benefits of these in-vehicle assistive systems presents a strong need for research.

A comprehensive review of current literature on the definitions of acceptance, acceptance modelling approaches, and assessment techniques was carried out to explore and summarize the different approaches adopted by previous researchers. The review identified three major research needs: a comprehensive evaluation of general technology

acceptance models in the context of ADAS, development of an acceptance model specifically for ADAS and similar technologies, and development of an acceptance assessment questionnaire.

Two studies were conducted to address these needs. In the first study, data collection was done using two approaches: a driving simulator approach and an online survey approach. In both approaches, participants were exposed to an ADAS and, based on their experience, responded to several survey questions to indicate their attitude toward using the ADAS and their perception of its usefulness, usability, reliability, etc. The results of the first study showed the utility of the general technology acceptance theories to model driver acceptance. A Unified Model of Driver Acceptance (UMDA) and two versions (a long version with 21 items and a short version with 13 items) of an acceptance assessment questionnaire were also developed, based on the results of the first study. The second was conducted to validate the findings of first study. The results of the second study found statistical evidence validating UMDA and the two versions of the acceptance assessment questionnaire.

DEDICATION

To my parents.

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INTRODUCTION, LITERATURE REVIEW, AND OVERVIEW OF THE DISSERTATION

1.1 Introduction

Advanced Driver Assistance Systems (ADAS) and semi-autonomous driving systems are technologies that are intended to enhance driver performance and improve transportation safety. These in-vehicle driver assistance systems vary from simple systems that provide drivers with basic information (e.g., vehicle status) to complex systems that take over parts of the driving task, such as the case for semi- or partially-autonomous vehicles. Specific examples of such systems include Adaptive Cruise Control, Collision Avoidance Systems, Intelligent Speed Adaptation, and Lane Departure Warning. The invention and implementation of new advanced driving systems has seen significant progress in the last decade, with the aims of improving safety (e.g., reduction in number of crashes), enhancing driver comfort or convenience, decreasing environmental impact, etc. (Brookhuis et al., 2001; Kusano & Gable, 2012). For some systems, the introduction of these new vehicle technologies is causing the driver's task to slowly evolve from controlling the vehicle to supervising the driver assistance systems. However, this role change may not be readily accepted by all drivers. Some drivers may not trust such automated systems and/or may not be willing to release vehicle control, even in situations where the system may afford safety advantages.

There seems to be general agreement among researchers about the potential positive impact of ADAS and semi-autonomous driving systems in improving transportation safety, and many researchers have estimated significant reductions in the number of accidents and in overall transportation cost (Fagnant & Kockelman, 2015; Manyika, 2013; Maccubbin et al., 2008). However, in-vehicle technologies cannot achieve their potential if they are not accepted or used in a sustainable and appropriate manner by drivers and if road infrastructures are not built to support their implementation (Ghazizadeh, Lee, & Boyle, 2012). This paper will only focus on the first condition: driver acceptance. Driver acceptance is the precondition for successful introduction of a driver assistance system, and its assessment provides a means to estimate drivers' willingness to purchase and use such systems (Najm et al., 2006). Despite the recognized importance, the concept of driver acceptance is not well understood and there is little consistency across researchers in defining and measuring acceptance (Adell, Varhelyi, & Nilsson, 2014).

As noted, advanced driving systems can vary in the level of sophistication and control functionality. In an effort to distinguish different levels of automation, the National Highway Traffic Safety Administration has categorized vehicle automation into five levels (NHTSA, 2013). The categorization covers vehicles with no automated control systems (level 0) to fully automated vehicles (level 4). The scope of this paper includes vehicle technologies that fall into level 0 (no automation; for example, lane departure warning, blind spot monitoring etc.), level 1 (function specific automation; for example, adaptive cruise control etc.), and level 2 (combined function automation; for example, adaptive cruise control in combination with lane centering). It follows that this paper is limited in its scope to consider intelligent driving systems that can assist drivers with relevant information and can take over select driving tasks, but do not assume full control of the vehicle.

1.2 Definition of Acceptance

One unresolved issue in the research on driver acceptance of an in-vehicle driver assistance system has been agreeing upon a definition of acceptance. While many researchers have contributed to the body of literature, a widely accepted definition has yet to be proposed. There is a general understanding of acceptance found in the literature; however, there is very little consistency across studies regarding how to define and measure acceptance (Regan, Mitsopoulos, Haworth, & Young, 2002; Adell et al., 2014). Defining acceptance is critical to assessing acceptance and developing an acceptance model (Adell et al., 2014).

A good review of definitions of acceptance in the literature can be found in Adell et al. (2014) and Adell (2009). In Adell (2009), the author classified the definitions of acceptance found in the literature into five categories. Category 1 used the word 'accept' and Category 2 emphasized the 'usefulness of the system' to define acceptance. Categories 3 and 4 focused on the attitudes towards or the behavioral intention to use a system, whereas Category 5 defined acceptance through actual use of the system. Existence of that many categories of definitions suggests that acceptance is a multifaceted concept and researchers tend to focus on selected aspects of the definition, limiting the scope of each definition. An accepted technology should be used by the majority of the targeted population. Therefore, if acceptance is defined as behavioral intention alone, positive behavioral intention toward using a driver assistance system or acceptance should result in a high adoption rate or use. However, positive behavioral intention may not always result in a high use of technology as the use of technology can be impacted by other factors like cost, compatibility, and other facilitating conditions (Venkatesh et al., 2003). Thus, acceptance should not be defined as behavioral intention alone. On the other hand, defining acceptance as the actual use of the system neglects the attitude of the user toward the technology. Furthermore, defining acceptance as actual use is not always feasible in the design stage of the technology when all that is available is a concept or a prototype.

Other researchers have distinguished between acceptance formed with or without experiencing the technology, as referred to by Schade and Schlag (2003) as "acceptance" and "acceptability", respectively. Pianelli, Saad, and Abric (2007) have drawn a similar distinction naming the two types a priori acceptability and a posteriori acceptability. Basically, acceptability or a priori acceptability involves attitude response of the user based on the description of a future technology or an existing technology that they might not have any direct experience with. It is the expressed intention or willingness to use the technology when it becomes available. The second type (of acceptance or acceptability) also involves attitude response of the user; however, this is a response that is based on experience with the technology. Both types of acceptance (with or without experience) could lead to the use (or not use) of the technology. The problem is that the term "acceptance" is sometimes used in a general way to refer to a driver's response to new technologies, but also in a more specific way to refer to a driver's response with experience or lack of experience of the technology. To avoid confusion, the term acceptance should be reserved for the general definition and should not be used in terms of the factor “experience” which could potentially be one of the factors in an acceptance model.

Driver acceptance can be defined as the reaction and action when exposed to a driver assistance system (Vlassenroot et al., 2010). Ausserer and Risser (2005) defined acceptance “as a phenomenon that reflects to what extent potential users are willing to use a certain system. Whether a system will be accepted or not will depend on the way user needs are integrated in the development of a system” (p. 3). Schade & Schlag (2003) defined acceptance as “respondents’ attitudes including their behavioral reactions after the introduction of a measure” (p. 47). Vlassenroot et al. (2010) distinguished adaptation from acceptance. The authors said, “adaptation will better describe the behavioral outcome (and changes) when drivers have experienced the device and acceptance will be more related to the attitudes, norms and beliefs that may influence the adaptation” (p. 167).

The invention and introduction of driver assistance systems is advancing at a great speed. Surprisingly, the research on driver acceptance is at a very early stage. It is critical for the sake of consistent and fruitful research to have a widely agreed-upon definition of acceptance. The definition of acceptance should cover the attitude (intention to use) and behavior (actual use) dimensions of acceptance and be applicable throughout the life-span of development and implementation. This definition should also facilitate the assessment and modelling of driver acceptance. Considering all these essential characteristics, the definition proposed by Adell (2009) has the potential to be widely accepted. Adell (2009) defined acceptance as “the degree to which an individual incorporates the system in his/her driving, or, if the system is not available, intends to use it" (p. 31). This definition stresses the importance of using the system as well as the intention to use the system. Although this definition proposes the use of the system as the primary measure of acceptance, it also supports the use of behavioral intention as a secondary measure.

1.3 Modelling Driver Acceptance

An acceptance model is necessary to understand how driver acceptance is formed, including what factors affect driver acceptance and how they affect it. Many researchers have attempted to model acceptance of a driver assistance system and have been able to explain variations in acceptance by their model. Some of these researchers adopted models that were based on previously developed theories of technology acceptance (different from driver assistance systems), while others proposed new factors in order to model driver acceptance.

1.3.1 Theories of Technology Acceptance

Several theories of user acceptance of technology have been developed over the last few decades; Theory of Reasoned Action, Technology Acceptance Model, Theory of Planned Behavior, and Unified Theory of Acceptance and Use of Technology are the most frequently used. In each of these theories, technology acceptance was affected and thus predicted by a number of factors. The factors (constructs) of the above mentioned models are listed and defined in Table 1.1. These factors are often measured using self-reported survey items.

The Theory of Reasoned Action (TRA) was developed by Fishbein & Ajzen (1975) to predict human behavioral intention and to explain any human behavior. TRA proposes that behavioral intention can be explained by two predictors: the attitude toward the behavior and the subjective norm. Later, Davis (1985) adapted TRA and developed the Technology Acceptance Model (TAM). TAM is “considerably less general” and is specifically designed to explain user acceptance of information technology (Davis et al., 1989, p. 985). TAM hypothesizes that attitude toward behavior is affected by perceived usefulness and perceived ease of use of the technology. Therefore, the original predictor, attitude toward behavior, was replaced by two new factors in TAM. Originally, TAM did not consider subjective norm to be an influencing factor in technology acceptance; however, this factor was included in the second version (TAM2) of the Technology Acceptance Model (Venkatesh & Davis, 2000).

The Theory of Planned Behavior (TPB), proposed by Ajzen (1991), was an initiative to improve the predictive capability of TRA. TPB retained the two predictors of TRA and introduced a new predictor, perceived behavioral control. This theory has been adopted by many researchers to explain individual acceptance and usage of technology (cited in Legris, Ingham, & Collerette, 2003; Venkatesh et al., 2003) and could potentially be adapted to create a driver acceptance model.

A more recent theory of technology acceptance is the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT was developed combining 8 theories of individual acceptance and has been validated with two longitudinal studies in the domain of information technology (Venkatesh et al., 2003). UTAUT considered four key constructs (Table 1.1) and four moderating factors (gender, age, experience, and voluntariness of use). Among all the theories mentioned above, UTAUT was reported to be the most efficient one for explaining technology acceptance and use behavior (R^2 value is around 0.70) (Venkatesh et al., 2003).

To identify the use of the above mentioned theories in the research of driver acceptance of in-vehicle driver assistance systems, a literature search was done in Google Scholar (scholar.google.com) using the keywords “driver acceptance” and “driver acceptability”. The literature search was kept limited to the articles that have cited the original theory articles (i.e. Fishbein & Ajzen, 1975; Davis et al., 1989; Ajzen, 1991; Venkatesh et al., 2003) and were published after 2005. A summary of the literature search is also presented in Table 1.1. Studies that are listed in Table 1.1 have adopted one or more theories to assess driver acceptance. There have been relatively few studies done to test these models in the context of driver acceptance despite the fact that these models provide a theoretical framework for a driver acceptance model. Based on the literature review, among the above mentioned technology acceptance theories, TAM was found to be the most widely adopted theory for modelling driver acceptance. No article was found that considered TRA to model driver acceptance; however, this theory was included in this section as this is arguably the most fundamental theory of human behavior and other theories (TAM, TPB, and UTUAT) were either based on TRA or significantly influenced by it.

The constructs of the theoretical models are measured by standard survey questions. In the context of driver acceptance research, the questions are slightly modified to match the task (in this case: driving). For example, Adell et al. (2009) used the following questions to measure Performance Expectancy (a construct of UTAUT):

- I would find the system useful in my driving.

- Using the system enables me to react to the situation more quickly.
- Using the system increases my driving performance.
- If I used the system, I will decrease my risk of being involved in an accident.

Each of the above four items was rated using a seven-point scale (with 1 = strongly disagree to 7 = strongly agree.). Performance expectancy is the average of the 4 items.

Table 1.1 Summary of the theoretical models of technology acceptance.

Theory	**Use in driver acceptance research**	**Constructs**	**Definitions**
Theory of Reasoned Action (TRA)	None	Attitude Toward Behavior	"An individual's positive or negative feelings (evaluative affect) about performing the target behavior" (Fishbein & Ajzen, 1975, p. 216).
		Subjective Norm	"The person's perception that most people who are important to him think he should or should not perform the behavior in question" (Fishbein & Ajzen, 1975, p. 302).
Technology Acceptance Model (TAM)	Larue et al. (2015), Kervick et al. (2015), Park & Kim (2014), Rodel et al. (2014), Ghazizadeh et al. (2012), Roberts et al. (2012), Bankosegger (2010), Meschtscherjakov et al. (2009)	Perceived Usefulness	"The degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 985).
		Perceived Ease of Use	"The degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 985).
		Subjective Norm	Adapted from TRA. Included in TAM2 only.
Theory of Planned Behavior (TPB)	Larue et al. (2015), Rodel et al. (2014), Carsten et al. (2008)	Attitude Toward Behavior	Adapted from TRA.
		Subjective Norm	Adapted from TRA.
		Perceived Behavioral Control	"The perceived ease or difficulty of performing the behavior" (Ajzen, 1991, p. 188).

Table 1.1 (Continued)

Theory	Use in driver acceptance research	Constructs	Definitions
Unified Theory of Acceptance and Use of Technology (UTAUT)	Henzler et al. (2015), Kervick et al. (2015), Osswald et al. (2012), Adell et al. (2009)	Performance Expectancy	"The degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447).
		Effort Expectancy	"The degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450).
		Social Influence	"The degree to which an individual perceives that important others believe he or she should use the new system (Venkateshet al., 2003, p. 451).
		Facilitating Conditions	"The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003, p. 453).

1.3.2 Factors Affecting Acceptance of Driver Assistance Systems

In addition to the constructs proposed by the theoretical models, researchers have investigated other factors that can potentially affect driver acceptance of an in-vehicle driver assistance system. Ghazizadeh and Lee (2014) have categorized these factors into five groups: device characteristics, driver characteristics, driver behavior, context and culture, and coaching characteristics. To identify potential factors that affect user acceptance, a systematic review of current literature (published after 2005) was carried out. A literature search was done in the TRID database (http://trid.trb.org/) using the keywords "driver acceptance" and "driver acceptability". The literature search produced a total of 122 results out of which 27 articles were found relevant to this study: studies that measured acceptance of driver assistance systems in some way or discussed the factors that affect acceptance. A total of 33 different factors were identified based on the review of the articles. A summary of this literature review is presented in Table 1.2. A discussion of the factors that appeared the most in the literature is presented below.

Age and Gender: The literature review found age and gender to be the most frequently cited factors by researchers. Nevertheless, only 6 out of the 27 studies considered the effect of these factors. Ervin et al. (2005), Donmez et al. (2006), and Li, Li, & Cheng (2015) reported effects of age on acceptance, whereas Eichelberger et al. (2014) and Ferguson et al. (2007) found no effect of age. Most of the studies that have investigated the effect of gender on acceptance did not find any significant changes in acceptance along this variable (Ervin et al., 2005; Ferguson et al., 2007; Eichelberger et al., 2014), with the exception of Li, Li, & Cheng (2015) who reported higher acceptance for female drivers.

Compatibility: Compatibility can be defined as "the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters" (Moore & Benbasat, 1991, p. 195). Advanced driving technologies are still a new class of innovation, and surprises and conflicts with a driver's mental model should be avoided to gain acceptance (Ghazizadeh, Lee, & Boyle, 2012). Ghazizadeh, Lee, & Boyle (2012) proposed compatibility to be a factor influencing acceptance in their Automation Acceptance Model; however, no empirical studies investigating the effect of compatibility were found in the review.

Trust: Trust in a driver assistance system can be defined as the belief of drivers that the system would perform its intended task with high effectiveness. A number of studies posited trust as an important predictor of driver acceptance (Najm et al., 2006;

Ghazizadeh, Lee, & Boyle, 2012) and some of the studies provided empirical evidence of its predictive ability (Donmez et al., 2006; Ghazizadeh et al., 2012).

Advocacy/Endorsement: This can be defined as the willingness to approve or recommend the purchase and/or use of a driver assistance system. In general, endorsement of the in-vehicle driver assistance systems has been reported as high. For example, Ervin et al. (2005) reported that 90% of the participants indicated willingness to recommend the adaptive cruise control system to a loved one. Nodine et al. (2011) found that 15 out of 18 participants would recommend that their company buy trucks equipped with an integrated driver assistance system. Two other studies (Najm et al., 2006; Stearns & Vega, 2011) proposed an effect of endorsement on driver acceptance of ADAS, however, there have been no empirical studies done on this effect.

Affordability: Affordability is related to the cost of an ADAS. Regan et al. (2006) defined affordability as the monetary amount that drivers are "willing to pay to purchase, install and maintain the system" (p. 141). In some studies, driver acceptance was measured or defined as the willingness to purchase an ADAS, making affordability a potential predictor of acceptance. Although a few studies have considered cost or affordability as an important factor to explain acceptance, there is a need for more research in the future.

Effectiveness: Effectiveness is the extent to which a driver assistance system performs its intended tasks. Regan et al. (2006) considered effectiveness as one of the five constructs that define acceptance. Llaneras et al. (2006) and Buckley et al. (2013) also took effectiveness as a construct of acceptance; however, they did not investigate the change in acceptance due to varying effectiveness. System reliability is often considered to play a role in effectiveness and act as a barrier to acceptance (Regan et al., 2006; Buckley et al., 2013). The literature review identified a number of studies that recognized system reliability factors, such as the rate of false/nuisance alarms, accuracy, etc., as important in the context of driver acceptance (Kallhammer et al., 2007; LeBlanc et al., 2008; Van Houten, Reagan, & Hilton, 2014). It is important to note that the perception of a system's effectiveness is not mutually exclusive with the concept of user trust.

Other factors: Among the other factors, driver characteristics (aggression, DBQ/DSQ scores, traffic violations, education etc.) and usability-related factors (ease of learning, satisfaction) were the most common. Additional factors were also identified in the review, including usefulness, social acceptability, and driving performance. These factors are very similar to the constructs of the theoretical technology acceptance models discussed in section 3.1 and the additional factors listed above. This again points to the need for a unified terminology in this field of research.

Table 1.2 Summary of the systematic literature review.

Index	Study	Country	Factors Considered	Tech. Tested	Sample Size	Equip./ Study Type	Acceptance Questionnaire
1	Li, Li, & Cheng (2015)	China	Gender, Age, Aggression	FCW, LDW, SBZA	33	Instrumented Vehicle	Author-created single question acceptance scale
2	Larue et al. (2015)	Australia	TAM and TPB Constructs	3 warning devices: visual ITS, audio ITS, and an on-road valet system	58	Driving Simulator	TAM/TPB based questionnaire
3	Eichelberger et al. (2014)	USA	Age, Gender, Duration of Ownership	ACC, FCA, LDWS	183	Interview Study	No questionnaire
4	Itoh, Horikome, & Inagaki (2013)	Japan	none	Collision Avoidance System	20	Driving Sim	Author-created 2-item questionnaire
5	Buckley et al. (2013)	Australia	Perceived Effectiveness, Usefulness, Usability, and Cost.	Visual/Auditory ITS	38	Interview	Author-created questionnaire based on TAM

Table 1.2 (Continued)

Index	Study	Country	Factors Considered	Tech. Tested	Sample Size	Equip./ Study Type	Acceptance Questionnaire
6	Regan et al. (2006)	Australia	Usefulness, Effectiveness, Social Acceptability, Affordability, Usability	ISA, FDW, SBR	23	FOT	Author-created questionnaire
7	Najm et al. (2006)	USA	Ease of Use, Perceived Value, Ease of Learning, Advocacy, Driving Performance	FCW, ACC	96	FOT	TAM based questionnaire, Driver Acceptance Scale*
8	Donmez et al. (2006)	USA	System Trust and Acceptance	-	28	Driving Sim	Driver Acceptance Scale*
9	Katteler (2005)	Netharlands	none	Mandatory ISA	120	Naturalistic Study	Author-created single-item questionnaire
10	Tsugawa (2006)	Japan	Cost (Mentioned)	ISA	-	-	Not measured
11	Ervin et al. (2005)	USA	Age, Gender, Income, Education and Self Characterization as Driver	FCW, ACC	96	FOT	Author-created questionnaire

Table 1.2 (Continued)

Index	Study	Country	Factors Considered	Tech. Tested	Sample Size	Equip./ Study Type	Acceptance Questionnaire
12	Ferguson et al. (2007)	USA	Age, Gender, Education	Seat Belt Reminder	1674	Mail-In Survey, Interview	Like-it-or-not questions
13	Kallhammer et al. (2007)	Sweden	Rate of False Alarm	collision Warning and Avoidance Systems	12	Instrumented Vehicle	Acceptable-or-not questions
14	Sayer et al. (2007)	USA	Usefulness, Satisfaction	LDW, CSW, RDCW	78	FOT	Driver Acceptance Scale*
15	Mongeot et al. (2006)	France	Invasion of Privacy (mentioned)	EDR	-	FOT	Not directly measured. Used interview to assess the acceptance
16	Llaneras et al. (2006)		Ease of Use, Effectiveness, Desirability, Usefulness	ACC, Night Vision, Park Aid, Navigation	480	Interview	9-11 item questionnaire
17	LeBlanc et al. (2006)	USA	no factors considered	LDW, CSW, RDCW	78	Questionnaire	Driver Acceptance Scale*
18	LeBlanc et al. (2008)	USA	False Alarms, Nuisance Alarms (discussed)	IVBSS			Not measured

Table 1.2 (Continued)

Index	Study	Country	Factors Considered	Tech. Tested	Sample Size	Equip./ Study Type	Acceptance Questionnaire
19	Wilson et al. (2007)	USA	Ease of Use, Learning, driver Performance, Perceived Value, and Advocacy	RDCW,	78	FOT	Driver Acceptance Scale*
20	Sayer et al. (2008)	USA	DBQ, DSQ	IVBSS	108	FOT	Focus Group and Driver Acceptance Scale*
21	Kourtellis et al. (2009)	USA	Image Quality	Rear-Vision Camera	73	FOT	Not measured
22	LeBlanc et al. (2009)	USA	none	IVBSS	12	FOT	Driver Acceptance Scale*
23	Bogard et al. (2009)	USA	none	FCW, LDW, SCW	8	FOT	Driver Acceptance Scale*
24	Sayer et al. (2010)	USA	none	Crash warning system	18	FOT	Driver Acceptance Scale*

Table 1.2 (Continued)

Index	Study	Country	Factors Considered	Tech. Tested	Sample Size	Equip./ Study Type	Acceptance Questionnaire
25	Nodine et al. (2011)	USA	Ease of Use, Perceived Usefulness, Ease of Learning, Advocacy, Driving Performance, Route Type, Age, Years with CDL, Traffic Violations in last 3 yrs, Prior Experience with Advanced Safety Systems + Driver Experience	IVBSS	18	FOT	Author-created questionnaire, Driver Acceptance Scale*
26	Stearns & Vega (2011)	USA	Satisfaction, Safety, Usability, Perceived Alert Timing, Perceived Alert Frequency, Endorsement (Cost aside)	CICAS	87+18	FOT	Author-created questionnaire
27	Van Houten (2014)	-	Trust, Acceptance, Reliability, and Accuracy	Seat belt gearshift interlock system	-	Instrumented Vehicle	Author-created questionnaire

* - Driver Acceptance Scale was created by van der Laan, Heino, and de Waard (1997)
Abbreviations: FCW- Forward Collision Warning, LDW- Lane Departure Warning, SBZA- Side Blind Zone Alert, ITS- Intelligent Transport System, ACC- Adaptive Cruise Control, FCA- Forward Collision Avoidance, LDWS- Lane Departure Warning System, ISA- Intelligent Speed Adaptation, FDW- Following Distance Warning, SBR- Seat Belt Reminder, CSW- Curve Speed Warning, RDCW- Road Departure Crash Warning, IVBSS- Integrated Vehicle Based Safety Systems, SCW- Side Collision Warning, CICAS- Cooperative Intersection Collision Avoidance System, FOT- Field Operational Test

1.4 Gaps in the Research and Directions for Future Study

Advanced driving systems are becoming more and more prevalent and are positioned to become a dominant force in traffic safety over the next several years. The technology may fundamentally change the role of drivers. Yet, much of the focus in the media and scientific endeavors has been on the technology itself and far less attention has been devoted to user-centered aspects, such as acceptance and utilization. These are very important issues that will impact the efficiency and effectiveness of any implementation of advanced safety systems. To extend the current knowledge and science in the area of driver acceptance, this study recommends the following research directions:

- Comprehensive evaluation of the theoretical technology acceptance models
- Development of a driver acceptance model
- Development of an acceptance assessment scale

In-depth discussion of the above research needs are presented below.

1.4.1 Comprehensive evaluation of the theoretical technology acceptance models

Many models of technology acceptance have been developed and extensively tested by researchers. Some of these models were created by adapting theories of human behavior from social psychology, for example TRA and TPB, whereas others are based on theories that were specifically created for technology acceptance, for example TAM and UTAUT. The predictive ability of these models of technology acceptance have been supported by numerous empirical studies (cited in Legris, Ingham, & Collerette, 2003; Venkatesh et al., 2003). While these models provide a theoretical framework, adoption of these models in the research of driver acceptance has lagged far behind research regarding the performance implications of ADAS and semi-autonomous driving systems, not to mention the pace of technological development itself. Section 1.3.1 presented a brief discussion of the most common models of technology acceptance and their use in driver acceptance research. Larue et al. (2015) compared the ability of TAM and TPB to assess driver acceptance of intelligent transport systems in the context of railway level crossings and reported higher predictive ability for TPB. The author reported that 54% of the variations in behavioral intention to use can be explained by TAM compared to 66% for TPB. Other researchers have also reported the predictive ability of TAM, TPB, and UTAUT constructs in the context of driver acceptance (Table 1.1). Evidently, these models of technology acceptance are potentially capable of explaining and predicting driver acceptance; however, researchers must evaluate the efficiency of these models with comprehensive studies—studies which would also encompass a wide array of different types, levels, and functions of driver assistance systems. Future studies should consider evaluating the predictive ability of each of these models and finding potential improvement opportunities to fit the models to the context of driver assistance systems research.

1.4.2 Development of a driver acceptance model

An acceptance model will ideally list the factors that can explain the variation in driver acceptance and the nature of their effect on acceptance. Thus, the development of an acceptance model is necessary to understand the concept of driver acceptance and to assess its status. A number of studies have explored factors that influence the acceptance of ADAS and semi-autonomous driving systems. The literature review presented in section 1.3.2 identified 33 different factors that can potentially be included in the acceptance model. There have been a few attempts to model acceptance in terms of individual factors by researchers. Vlassenroot et al. (2010) proposed a unified model to assess acceptability of ADAS based on Intelligent Speed Adaptation. The unified model contains 14 factors which is arguably too many for a usable evaluation technique. Ghazizadeh, Lee, & Boyle (2012) proposed the Automation Acceptance Model (AAM) that may be applicable in the context of driver acceptance. AAM is based on the Technology Acceptance Model (TAM) and attempts to augment TAM with the inclusion of Trust and Compatibility as influencing factors. Despite the strong theoretical background, to the best of our knowledge, neither of the above two models has been supported by empirical studies. Hence, there is a need for a validated acceptance model that will act as a standard in the research of driver acceptance. Moreover, research is necessary to develop an acceptance model that applies and expands previous theories and literature to driver acceptance.

1.4.3 Development of an acceptance assessment scale

"Acceptance is a concept with many underlying constructs and an important research priority is the development of a general tool that can be used to validly and reliably measure all of the various constructs that underlie it" (Regan et al., 2002). Measuring acceptance is critical in the research of driver acceptance. However, there is an obvious lack of standardized and reliable assessment tools for measuring acceptance. The Van der Laan scale (Van der Laan, Heino, & de Waard, 1997) is the only tool available to measure driver acceptance that is generally accepted by the scientific community (Table 1.2). Other acceptance assessment techniques include researcher-created surveys, interview etc. The Van der Laan scale measures "direct attitudes" towards the driver assistance system (Van der Laan et a., 1997, p. 2) which may not truly reflect acceptance (Adell, 2014). According to the theory of planned behavior (Ajzen, 1991), behavioral intention (a measure of acceptance) is affected by not only attitude but also subjective norms and perceived behavioral control. An example of the limitations of the Van der Laan scale can be found in Adell, Várhelyi, & Hjälmdahl, (2008). In that study, two intelligent speed adaptation systems, BEEP and AAP, were evaluated. Acceptance of the two systems were assessed using the Van der Laan scale, resulting in a higher score for the AAP system. However, the drivers showed greater willingness to have the BEEP-system in their cars than the AAP. This finding reiterates the fact that acceptance cannot be measured only by attitude, revealing that the use of the Van der Laan scale alone is problematic. Future research efforts should concentrate on developing a standardized and reliable acceptance assessment scale.

1.5 Overview of the Dissertation

The development of new in-vehicle technologies is increasing every year and vehicle manufacturers are aggressively pushing these technologies into the market. It is only a matter of time before every vehicle is equipped with multiple driver assistance systems, whether drivers like them or not. These technologies can potentially make vehicle operation safer and offer new opportunities to enhance the overall transportation system. However, these prospective benefits could be eclipsed if driver acceptance was not ensured before full implementation of these technologies. That is, these technologies cannot make their contribution if drivers do not accept them and use them in a sustainable and appropriate manner in traffic. Research efforts must be made to improve the understanding of driver acceptance which will allow the development of design methodology to ensure acceptance.

Recognizing the importance of research regarding driver acceptance of new vehicle technologies, this dissertation conducted two comprehensive studies to understand how driver acceptance is formed, affected by social and behavioral factors, and can be assessed using tools like questionnaires and surveys. The research aims of the two studies are as follows:

Study 1: Assessment of the technology acceptance models in the context of driver acceptance, modelling driver acceptance of ADAS and semi-autonomous driving systems and development of acceptance assessment questionnaire.

1. Identify factors that affect driver acceptance based on technology acceptance theories and published empirical studies. These factors will be described in the context of a conceptual model of driver acceptance.

2. In the second stage, the effect of the factors, identified in the first stage, will be tested using two experimental approaches—one a survey approach and one a driver-in-the-loop simulator study.

3. Build and refine the acceptance model based on the outcomes in Aim 2—ideally a predictive yet limited model.

4. Develop acceptance questionnaire based on the model built in Aim 3.

Study 2: Validation of the Driver Acceptance Model and the Acceptance Questionnaire.

1. Validate and refine the outcomes of Study 1: the driver acceptance model and the acceptance questionnaire.

The findings of the Study 1 and Study 2 are summarized in Chapters 2, 3, and 4. In Chapter 2, the results of the assessment of theoretical technology acceptance models are presented. Chapter 3 explains the development of the driver acceptance model and the acceptance assessment questionnaire. In Chapter 4, the results of the Study 2 are presented and the validation of the outcomes of the Study 1 is confirmed. Finally, in Chapter 5, conclusions of this dissertation and directions for future studies are presented.

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CHAPTER II

ASSESSING THE UTILITY OF TAM, TPB, AND UTAUT FOR ADVANCED DRIVER ASSISTANCE SYSTEMS

2.1 Introduction

The transportation landscape is changing rapidly. The introduction of in-vehicle technologies, automated vehicles, and advanced road infrastructure will undoubtedly have a significant impact on the safety and efficiency of transportation systems. Although automation in the transportation systems has the potential to significantly reduce the number of vehicle accidents and the overall transportation system cost (Fagnant and Kockelman, 2015; Manyika, 2013; Maccubbin et al., 2008), this is only true if drivers recognize the usefulness of these technologies and integrate them into their driving habits. Hence, driver acceptance is a precondition for successful implementation of vehicle automation (Najm et al., 2006). Although Advanced Driver Assistance Systems include a range of technology and automation, in the current paper, we focus on lower level and currently available in-vehicle assistive technologies; specifically, we examined how driver acceptance of these technologies can be assessed with previously validated theories of human behavior.

In-vehicle assistive technologies have been categorized as Advanced Driver Assistance Systems (ADAS) (Paul, Chauhan, Srivastava, and Baruah, 2016; Hummel, Kühn, Bende, and Lang, 2011), Intelligent Transportation Systems (ITS)

(Dimitrakopoulos, and Demestichas, 2010; Beresford, and Bacon, 2006), semi-autonomous driving systems (Kala and Warwick, 2015), etc. These categories vary with different level of automation. To reduce confusion, in this chapter the in-vehicle assistive technologies will be referred to as Advanced Driver Assistance Systems (ADAS), defined as technologies which can assist drivers with relevant information (for example, a lane departure warning system) and can assume control over a single vehicle function (for example, an adaptive cruise control system) or a combined vehicle function (for example, an adaptive cruise control system combined with a lane centering system) (vehicle automation level 0, 1, and 2 as defined by NHTSA, 2013).

Ensuring safety for drivers and other road users and providing convenience for drivers have been the motivation for many vehicle manufacturers to invent new Advanced Driver Assistance Systems (Trimble, Bishop, Morgan, and Blanco, 2014). ADAS technology has many advantages, such as providing drivers with important information, relieving drivers by occasionally taking over parts of the driving task, and sometimes providing added control to aid drivers in critical situations. These advantages could potentially augment driver performance and reduce crash-related accidents. Based on ADAS potential, initial driver reaction has been very positive. However, the long-term impact of ADAS on the transportation system largely depends on the degree to which drivers adopt them in their driving. These technologies will not achieve their potential if drivers do not move beyond an initial interest to actually accepting them, and using them appropriately in traffic. Thus, the study of driver acceptance of ADAS is crucial in this early stages of development and implementation.

Driver acceptance of ADAS can be defined as the reaction of drivers when they are exposed to an in-vehicle technology and their willingness to adopt the technology while driving. Although there is a general understanding of the term, driver acceptance, among researchers, the research on driver acceptance has suffered from inconsistent attempts at defining, modelling, and measuring acceptance (Regan, Mitsopoulos, Haworth, and Young, 2002; Adell, Varhelyi, and Nilsson, 2014). A review of the different approaches that have been used to research driver acceptance can be found in Chapter 1 and in Adell et al. (2014). Despite the many inconsistencies in how researchers studied driver acceptance, there was common ground in the use of human behavior models for their research. Among these models, the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT) were found to be the most widely adopted models. These models provide a theoretical framework to define, model, and measure driver acceptance. Recognizing the importance of these models in the research on driver acceptance, this study set out to evaluate and compare the predictive ability of these models. Two data collection approaches were used to collect driver acceptance data: an online survey approach and a driver-in-the-loop simulator approach. Data from a sample of 430 participants (43 from the driving simulator approach and 387 from the online survey approach) was collected and analyzed to assess the utility of these models in the context of driver acceptance of ADAS and to identify the best performing model.

2.1.1 Theories of Technology Acceptance

For many years, theories of human behavior have been adopted to model technology acceptance, mostly computer technology, i.e. software (cited in Legris, Ingham, & Collerette, 2003; Venkatesh et al., 2003). Researchers have successfully adopted these theories to study technology acceptance and have gone on to develop new theories specific to technology acceptance (Davis, 1985; Venkatesh et al., 2003). The successful adoption of these theories (both theories of human behavior and theories specific to technology acceptance) has motivated their use in the context of driver acceptance of ADAS. Among these theories, the Technology Acceptance Model (TAM) (Davis, 1989; Davis, Bagozzi, Warshaw, 1989), the Theory of Planned Behavior (TPB) (Ajzen, 1991), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) were found be the most widely adopted by driver acceptance researchers. TPB was developed to explain human behavior in general, whereas TAM and UTAUT were specifically developed to explain technology acceptance. These theories propose several constructs that affect acceptance of a technology, with *behavioral intention to use* and *actual use* of that technology as measures of acceptance.

The Technology Acceptance Model (TAM), built on the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), posits that user Attitude (A) and Perceived Usefulness (PU) influence user Behavioral Intention (BI) to use a technology and eventually its actual use (Figure 2.1a). Attitude, on the other hand, is affected by Perceived Usefulness (PU) and Perceived Ease of Use (PEoU) (see Table 1.1 for the definitions of the constructs). Furthermore, TAM proposed that the effect of PU on BI is partially mediated by A, and the effect of PEoU on A is partially mediated by PU. That means that PU has a significant effect on BI, above and beyond A, and PEoU has a significant effect on A, above and beyond PU. Although this model was built on a sound theoretical concept, Attitude was later removed from the model due to lack of empirical evidence (Larue, Rakotonirainy, Haworth, and Darvell, 2015). The new version of TAM only includes PU and PEoU as constructs (Figure 2.1b). For the purpose of differentiating, from this point on, the initial version of TAM will be referred to as 'Original TAM' (Figure 2.1a) and the later version will be referred to as 'Refined TAM' (Figure 2.1b).

The Theory of Planned Behavior (TPB), also built on the Theory of Reasoned Action (TRA), extended TRA to improve its predictive capability. It proposed that Attitude (A), Subjective Norms (SN), and Perceived Behavioral Control (PBC) are the constructs of BI (Figure 2.1c, see Table 1.1 for the definitions). In TPB, besides BI's direct influence on actual behavior, perceived behavioral control (PBC) indirectly affects actual behavior. The Unified Theory of Acceptance and Use of Technology (UTAUT), on the other hand, proposed four entirely different constructs of behavioral intention and actual behavior: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). UTAUT posits PE, EE, and SI to be predictors of BI; and BI and FC to be predictors of actual use. UTAUT also proposed four moderating factors: age, gender, experience, and voluntariness. The moderating effects in UTAUT are illustrated in Figure 2.1d.

The constructs of these models are measured by survey responses. In the context of driver acceptance of ADAS, the survey items are modified to reflect the perception toward the ADAS.

To identify how these theories have been used in the context of driver acceptance of ADAS, a literature search was done in Google Scholar (scholar.google.com) using the keywords "driver acceptance" and "driver acceptability". The literature search produced a list of 12 studies (published after 2005) that have adopted the concepts of TAM, TPB, and UTAUT in some way to study driver acceptance. A summary of the findings of the studies are presented in Table 2.1. It is apparent from the table that researchers used the survey approach more than the naturalistic or the driving simulator approach to describe the capability of ADAS. It was also found that TAM was adopted in the majority of the studies, and that no study has ever compared the efficiency of the three models in the context of driver acceptance.

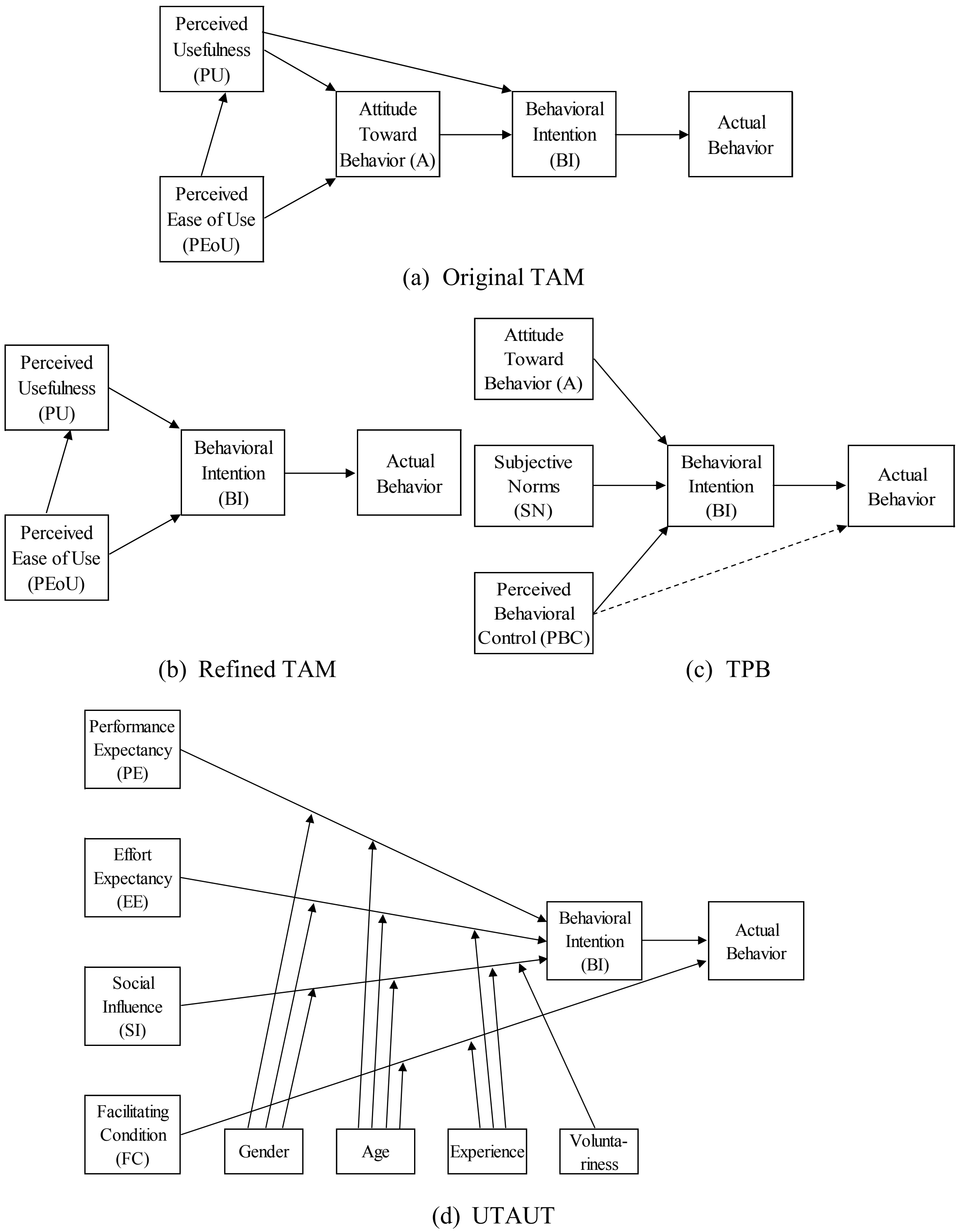

Figure 2.1 Technology acceptance models.

Table 2.1 Summary of the studies that adopted TAM, TPB, and UTAUT in the context of driver acceptance.

Study	Technology Tested	Equipment/ Type of Study	Sample Size	Model(s)/Postulate(s) Tested			Statistical Methods Used*
				Model(s)	**Effects Found**	**R^2/ Adj. R^2**	
Meschtscherjakov, Wilfinger, Scherndl, and Tscheligi (2009)	EcoMatic, EcoPedal, EcoSpeedometer, EcoDisplay, and EcoAdvisor (all of these ADAS provide real-time fuel-efficient driving guidance)	Online survey	57	BI = Age, Gender, Driving Frequency, General Attitude toward Car Technology, Possible Disturbance, Safety Risk, Perceived Suitability of the System	General Attitude toward Car Technology, Possible Disturbance, Perceived Suitability of the System	0.68 (for EcoPedal) 0.67 (for EcoSpeed -ometer)	ANOVA, Linear Regression Analysis
Adell (2010)	SASPENCE (assists in keeping safe speed and safe distance)	Naturalistic Study	38	UTAUT: BI = PE + EE + SI	PE, SI	0.20	Factor Analysis, Linear Regression Analysis
Xu et al. (2010)	Advanced Traveler Information System	Survey	247	BI = U, E, Information Attributes, Trust, Cognition of Alternate Route, Sociodemographics	U, E, Information Attributes, and Trust	-	Structural Equation Modeling
Chen and Chen (2011)	In-vehicle GPS	Face-to-face survey	251	BI = A + U + Perceived Enjoyment (Enj.); A = U + E + Enj. U = E Perceived Innovativeness moderates the effect of A on BI	A, Enj. E, Enj. E Moderating effect was confirmed	0.65 0.52 0.38 -	Hierarchical Linear Regression Analysis
Ghazizadeh, Peng, Lee, and Boyle (2012)	An on-board monitoring system (provides auditory and visual forward collision warning, lane departure warning, and driver behavior warning.	Survey	34	BI = U + E + Trust; Trust = U + E; U = E	PU, Trust U E	0.65 0.27 -	Hierarchical Linear Regression Analysis

Table 2.1 (Continued)

Osswald, Wurhofer, Trösterer, Beck, and Tscheligi (2012)	In-car text input system	Driving simulator	21	BI = A + PE + EE + SI + Anxiety + Perceived Safety + Self Efficacy (Proposed)	No statistical analysis of the effects was done	-	-
Roberts, Ghazizadeh, and Lee (2012)	A real-time (provides visual and auditory warnings) and a post-drive distraction mitigation system.	Driving simulator	36	BI = U + E + Unobtrusiveness	U and E	0.50	Hierarchical Linear Regression Analysis
Park and Kim (2014)	A car navigation system	Online survey	1181	BI = U; BI = A; A = U	U and A are significant predictors of BI	-	Structural Equation Modeling
Rodel, Stadler, Meschtscherjakov, and Tscheligi (2014)	Navigation system, cruise control, automatic transmission, parking assist, automatic parking system, Collision Avoidance System, Adaptive Cruise Control, Blind Spot Detection.	Scenario-based online survey	336	BI, A, E, C (among other factors) are affected by the level of autonomy	An association between BI and A was inferred	-	Friedman Test, Kruskal Wallis Test
Henzler, Boller, Buchholz, and Dietmeyer (2015)	Ecological Driver Assistance System (provides eco-driving recommendations)	Naturalistic study	24	BI = PE + EE	No statistical analysis of the effects were done	-	-
Kervick, Hogan, O'Hora, and Sarma (2015)	A smartphone driver support system (provides information on vehicle speed, headway distance etc. and warns driver if the headway distance is unsafe)	Online survey	333	BI = Perceived Gains + Perceived Risks + SI + Usability	Perceived Gains, SI	0.73	Factor Analysis, Structural Equation Modeling
Larue, Rakotonirainy, Haworth, and Darvell (2015)	A warning systems (warns drivers of an approaching train or a congestion at a railway crossing and provides expected action)	Driving simulator	58	TAM: BI = U + E; TPB: BI = A + SN + C	U A, SN	0.54 0.66	Generalized Linear Mixed Model (GLMM) Analysis

* Most of the studies tested the reliability of the scales based on Cronbach's alpha

2.2 Materials and Methods:

TAM (original and refined), TPB, and UTAUT have been proposed to explain user acceptance in terms of behavioral intention (BI) and actual use. However, it is often difficult to measure actual use of ADAS and semi-autonomous driving systems, and hence, in the context of driver acceptance, Behavioral Intention has been used as the sole measure of acceptance. Therefore, this study used BI as the only measure of acceptance, and tested all the relationships around driver acceptance proposed in these models, comparing their efficiency. The postulates that were tested in this study are given below:

TAM Original

1. Attitude toward Behavior (A) and Perceived Usefulness (PU) are significant predictors of Behavioral Intention (BI) (model: BI = A + PU).
2. Attitude toward Behavior (A) mediates the effect of PU on BI, however the mediation is not a complete mediation. In other words, PU significantly affects BI, above and beyond A.
3. Perceived Usefulness (PU) and Perceived Ease of Use (PEoU) are significant predictors of Attitude toward Behavior (A) (model: A = PU + PEoU).
4. Perceived Usefulness (PU) mediates the effect of PEoU on A, however the mediation is not a complete mediation. In other words, PEoU significantly affects A, above and beyond PU.

TAM Refined

1. Perceived Usefulness (PU) and Perceived Ease of Use (PEoU) are significant predictors of Behavioral Intention (BI) (model: BI = PU + PEoU).
2. Perceived Usefulness (PU) mediates the effect of PEoU on BI, however the mediation is not a complete mediation. In other words, PEoU significantly affects BI, above and beyond PU.

TPB

1. Attitude toward Behavior (A), Subjective Norms (SN), and Perceived Behavioral Control (PBC) are significant predictors of Behavioral Intention (BI) (model: BI = A + SN + PBC).

UTAUT

1. Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) are significant predictors of Behavioral Intention (BI) (model: BI = PE + EE + SI).
2. Gender moderates the effects of PE, EE, and SI on BI.
3. Age moderates the effects of PE, EE, and SI on BI.
4. Experience moderates the effects of EE and SI on BI.

2.2.1 Data Collection and Study Materials

Data collection was done using two experimental approaches: an online survey approach and a driver-in-the-loop simulator approach. Detailed discussions of the two approaches are provided below.

2.2.1.1 Survey study

Borrowing from literature on the Theory of Planned Behavior (e.g., Ajzen, 1991; Elliott et al., 2005; Evans & Norman, 1998, 2003; Holland & Hill, 2007) and from recent studies regarding ADAS acceptance (Lesch, nd; Rodel et al., 2014), a scenario-based survey approach was utilized to introduce ADAS technologies to participants and to gather responses on acceptance. Two ADAS technologies were selected for the purpose of this study. Half of the participants read a description of one ADAS (System 1, see Appendix B for description, this system is the same as the simulated system in the simulator approach) and the other half read a description of another ADAS (System 2, see Appendix B for description), each followed by a text that described a driving scenario. Realizing the possibility of an effect from the driving context (highway vs. city roads, time pressure, fatigue etc.) on the perceived usefulness and hence acceptance of the ADAS, the driving scenario described a very general context. Participants responded to a series of survey questions based on what they read. The survey items were taken or modified from previous studies that involved TAM, TPB, and UTAUT. These survey items were then used to measure the constructs of the three models. Additional demographic questions were also included. The contents of the survey (description of the systems, driving scenario, and survey items) are presented in Appendix A and B.

Participants were recruited and compensated through Amazon Mechanical Turk (https://www.mturk.com). The online survey was created in Survey Monkey (https://www.surveymonkey.com). In order to make sure that the participants were attentive to the survey, two check questions were included that instructed them to provide a specific response. Furthermore, 5 out of the 30 survey items were reverse scaled.

2.2.1.2 Driving Simulator Study

In this approach, participants experienced an ADAS in a driving simulator and, based on their experience, answered several survey questions. The driving simulator that was used for this study was a fixed-based simulator that consists of an open-cab vehicle mock up, including accelerator and brake pedals, steering wheel, dashboard, instrument panel, and center console. The driving environments were presented on five 46-inch widescreen LCD displays which, from the driver's eye point, subtended 200° of forward visual angle. The various driving environments and traffic scenarios were generated using RTI SimCreator and SimVista software.

For the purpose of this study, a level 2 ADAS (NHTSA, 2013) was simulated which fully controlled the vehicle under a variety of traffic and road situations, including longitudinal and lateral control of the vehicle. For longitudinal control, the preferred speed and headway clearances (e.g., Adaptive Cruise Control) could be preset. For lateral control, the system would keep the vehicle at or near the center of the lane, on straight sections as well as in curves. Whenever there was a deviation from the preferred states, the system would make corrective inputs (e.g., speed up or slow down; steer towards the lane center).

Prior to the experimental session, participants were screened via online and phone surveys for the minimum study requirements and for susceptibility to simulator sickness. At the start of the session, drivers completed an informed consent form. Vision was tested with a Titmus Vision Tester (Titmus Optical Inc., Chester, VA), and then the drivers completed a short demographic survey. Following the completion of the questionnaires, participants were introduced to the driving simulator and given a practice trial to acclimatize to the control dynamics. They were monitored for signs of simulator sickness throughout. Following the completion of the training, participants were instructed in the experimental tasks.

The study consisted of a single experimental block aimed at exposing drivers to the ADAS and how it operates under routine situations. The block lasted approximately 8-10 minutes and involved a variety of traffic situations. Drivers began on a feeder road and were instructed to merge onto a two-lane highway. Once they had done so, they were asked to engage the ADAS via a button mounted on the steering wheel and to allow the ADAS system to control the driving for the duration of the driving block. While on the highway, the ADAS reacted intelligently to other proximal vehicles, changed speeds and correctly guided the vehicle through curves. Approximately halfway through the block, the highway merged onto a light industrial road that included several traffic lights. The ADAS continued to maintain appropriate spacing and position in this section and adhered to the traffic light status (i.e., applied brakes for yellow/red lights and drove again when signal turned green). The scenario simulated routine operational conditions and did not include any system failures or conditions that exceed the tolerances of the ADAS. After the driving block, drivers were given the survey. The survey items used to measure the constructs of the models were the same in both data collection approaches (section 2.2.1.1 and 2.2.1.2), except there were no check questions for the simulator study.

2.2.2 Participants

A total of 43 participants (20 males and 23 females, aged 21-57 years with M = 40.93, SD = 12.06), each with a valid US driver's license, participated in the simulator study. All simulator participants were native or fluent English speakers, had normal or corrected-to-normal visual acuity (min. 20/40), normal color vision, and no self-reported hearing difficulties. In contrast, 400 participants took the online survey. Of those, 13 participants missed one or both of the check questions and were hence removed from the final dataset, leaving 387 (202 male and 185 female) samples. The participants were 19-73 (M = 35.57 and SD = 11.01) years old. Of the 387 participants, 190 participants read the description of system 1 and the rest (197 participants) read the description of system 2.

2.2.3 Data Processing and Analysis

The two datasets (from the survey study and the simulator study) were merged for analyses in order to increase the power of the tests. As a result, the sample size for the study was 430 (43 from the simulator study and 387 from the online survey study). In the merged dataset, data sources were separated using two new variables, *data-type* (coded as 0 for simulator data and 1 for online survey data) and *system-type* (coded as 0 for system 1 of the online survey and the simulated system, and 1 for system 2 in online survey). The effects of these variables were controlled in each data analysis method.

The data analysis started with assessing the internal consistency of the scales. Once the internal consistency of the scales was verified, regression analyses were done to test the postulates proposed in TAM, TPB, and UTAUT. Statistical analyses were carried out in SAS (version 9.4). The steps of the data analysis are explained below with more detail.

2.2.3.1 Internal Consistency of the Scales

The internal consistency of each scale was tested with Cronbach's alpha. If the α for a certain scale was found to be less than 0.70, correlation matrix analyses were done to identify and remove the item(s) which had contributed to the low reliability. If removing the item(s) did not yield a value greater than 0.70 for α, the authors used the scale as it was intended.

2.2.3.2 Multiple Linear Regression Analyses

Several individual regression analyses on the constructs from TAM, TPB, and UTAUT were done to assess the predictive ability of the models. Before running regression analyses, scatter plots (BI vs the predictor variables) were drawn to check the linearity assumption. To check for the validity of other assumptions, scatter plots for residuals vs predictor variables, residuals vs fitted values, and Q-Q plots were evaluated. To identify the influencing samples, Cook's *D* was calculated and cases that yielded a *D*-value of more than $4/n$ (= 4/430 = 0.0093) were removed from the analysis (Cook and Weisberg, 1980).

To compare the efficiency of each model for explaining the variance in driver acceptance of ADAS, Hotelling's t-test for non-independent correlations was done. To test mediation, the procedure explained by Baron & Kenny (1986) and Kenny, Kashy, & Bolger (1998) was applied. This procedure involved performing three regression analyses for each mediation effect: first, the dependent variable was regressed on the independent variable; second, (if the relationship from step 1 was found to be statistically significant) the independent variable was regressed on the mediator; and third, (if the relationship from step 2 was found to be statistically significant) the dependent variable was regressed on the mediator and on the independent variable. If, in the third step, the effect of the independent variable on the dependent variable was found to be zero (i.e. a non-significant regression coefficient), a complete mediation was found to be present, meaning that the mediator completely accounted for the relationship between the independent and dependent variables. If the effect of the independent variable was not zero in step 3, however, significantly smaller than the effect found in step 1, the mediation was partial.

To test moderation, the procedure explained by Frazier, Tix, & Baron (2004) was applied. In this procedure, the predictor and the moderator variables were standardized and then multiplied together in order to calculate the interaction term. Testing for a moderation effect involved a hierarchical regression technique. In the first step, the outcome variable was regressed on the predictor and the moderator. In the next step, the interaction term entered the regression model; if the interaction term was found to be significant, moderation was present.

2.3 Results

2.3.1 Reliability of Scales and Descriptive Statistics

The internal consistency of the scales was found to be high for most of the scales, with a Cronbach's alpha (α) of 0.7 or more (Table 2.2). Only the SN and SI scales showed poor reliability ($\alpha = 0.48$). Both of these scales used the same survey items (items 22 and 23, Appendix A). The authors decided to use the scales as it was intended. The mean and the standard deviations of the scales are summarized in Table 2.2. The results revealed that most participants had a very low familiarity with ADAS as either described or simulated in this study. Thirty-seven percent of the participants had never heard of a similar system and 99.1% of the participants had never used a similar system while driving.

Table 2.2 Internal consistency of the scales (on the diagonal), bi-variate correlations, and descriptive statistics (N = 430).

Constructs	Mean	SD	BI	A	PU	PEoU	SN	PBC	PE	EE
BI	4.69	1.59	0.91							
A	5.04	1.30	0.89**	0.94						
PU	4.95	1.33	0.85**	0.88**	0.90					
PEoU	5.41	1.02	0.42**	0.49**	0.36**	0.72				
SN/SI	4.56	1.26	0.55**	0.58**	0.58**	0.32**	0.48			
PBC	5.73	1.01	0.36**	0.45**	0.35**	0.77**	0.24**	0.77		
PE	4.85	1.31	0.83**	0.86**	0.96**	0.36**	0.58**	0.34**	0.87	
EE	5.72	1.04	0.38**	0.46**	0.35**	0.86**	0.27**	0.84**	0.33**	0.86

Note: Internal consistency (Cronbach's alpha) statistics are on the diagonal.
** Correlation is significant at the 0.01 level (2-tailed).

2.3.2 Variations in BI due to different data collection approaches

The acceptance score (BI) was found to be different for the different data collection approaches, though not for the different systems. To test these differences, a multiple linear regression analysis was carried out with the *data-type* and *system-type* variables. The *data-type* variable (coded as 0 for simulator data and 1 for online survey data) showed an effect on BI scores (B = -0.69, $SE\ B$= 0.27, β = -0.13, p < 0.05). Hence, acceptance of the systems was significantly higher for participants who experienced the simulated system (BI: mean score = 5.31, SD = 1.35) compared to those who read the description (BI: mean score = 4.62, SD = 1.60). On the other hand, the *system-type* variable (coded as 0 for system 1 of the online survey and the simulated system and 1 for system 2 of the online survey) didn't show any effect on BI (B = -0.01, $SE\ B$= 0.16, β = 0.00, p > 0.05). Therefore, the assessment of TAM, TPB, and UTAUT only included the *data-type* variable in addition to the model constructs to control for the differences in the acceptance score due to the different data collection approaches.

2.3.3 Technology Acceptance Model (TAM)

2.3.3.1 Original TAM

The results showed A and PU to be significant predictors of BI (Test 1 in Table 2.3) and PU and PEoU to be significant predictors of A (Test 3 in Table 2.3). It was found that the original TAM model (BI = A + PU) explained 86% of the variance (Adj. $R^2 = 0.86$) in BI. Among the constructs of the model, A showed a stronger effect on BI. The results also confirmed the mediating effects. PU alone can significantly predict BI, with an estimated effect of 1.03 (*B*, Test 2 in Table 2.3). However, when A enters the regression model, the effect of PU reduces to 0.37. This reduction in effect was found to be statistically significant ($Z = 14.35$, $p < 0.05$), indicating a partial mediation by A. This also confirms that PU has a significant effect on BI, above and beyond A. Similarly, it was found that PU partially mediates the effect of PEoU on A (Test 4 in Table 2.3). The reduction in estimated effect from 0.60 to 0.23 was statistically significant ($Z = 7.53$, $p < 0.05$), confirming the mediation and that PEoU has a significant effect on A, above and beyond PU. For this analysis, 33 highly influencing samples were removed based on Cook's *D* statistic. Although, the *data-type* variable showed an effect on BI (section 3.2), its effect was found to be non-significant in the presence of the model constructs (A and PU) ($B = -0.17$, $SE\ B = 0.09$, $\beta = -0.03$, $p > 0.05$).

Table 2.3 Assessment of Technology Acceptance Model (Original) (N = 397)

Tests	Adj. R^2	*B*	*SE B*	95% *CI*	*β*
1. BI = A + PU					
Outcome: Behavioral Intention	0.86				
Predictor: Attitude		0.76	0.05	0.66, 0.86	0.63**
Predictor: Perceived Usefulness		0.37	0.05	0.28, 0.47	0.32**
2. A mediates the effect of PU on BI					
Step 1 Model: BI = PU					
Outcome: Behavioral Intention	0.78				
Predictor: Perceived Usefulness		1.03	0.03	0.98, 1.09	0.89**
Step 2 Model: A = PU					
Outcome: Attitude	0.81				
Predictor: Perceived Usefulness		0.87	0.02	0.83, 0.92	0.90**
Step 3 Model: BI = A + PU					
Outcome: Behavioral Intention	0.86				
Mediator: Attitude		0.76	0.05	0.66, 0.86	0.63**
Predictor: Perceived Usefulness		0.37	0.05	0.28, 0.47	0.32**
3. A = PU + PEoU					
Outcome: Attitude	0.83				
Predictor: Perceived Usefulness		0.81	0.02	0.77, 0.86	0.84**
Predictor: Perceived Ease of Use		0.23	0.03	0.18, 0.29	0.18**
4. PU mediates the effect of PEoU on A					
Step 1 Model: A = PEoU					
Outcome: Attitude	0.22				
Predictor: Perceived Ease of Use		0.60	0.06	0.49, 0.72	0.47**
Step 2 Model: PU = PEoU					
Outcome: Perceived Usefulness	0.12				
Predictor: Perceived Ease of Use		0.46	0.06	0.33, 0.58	0.34**
Step 3 Model: A = PU + PEoU					
Outcome: Attitude	0.83				
Mediator: Perceived Usefulness		0.81	0.02	0.77, 0.86	0.84**
Predictor: Perceived Ease of Use		0.23	0.03	0.18, 0.29	0.18**

** $p < 0.001$

2.3.3.2 Refined TAM

PU and PEoU were found to be significant predictors of BI, and the refined TAM model (BI = PU + PEoU) was found to explain 79% of the variance (Adj. $R^2 = 0.79$) in BI (Test 1 in Table 2.4). PU showed a stronger effect on BI compared to the effect of PEoU. The results also proved the mediating effect of PU on PEoU's effect on BI. PEoU alone can significantly predict BI with an estimated effect of 0.72. However, when PU enters the regression model, the effect of PEoU reduces to 0.22. This reduction in effect was found to be statistically significant ($Z = 8.21$, $p < 0.05$), indicating a partial mediation by PU. This also confirms that PEoU has a significant effect on BI, above and beyond PU (Test 2 in Table 2.4). For this analysis, 29 highly influencing samples were removed based on Cook's D statistic. Similar to the original TAM analysis, the *data-type* variable showed no effect on BI in the presence of the model constructs (PU and PEoU) ($B = -0.11$, $SE\ B = 0.11$, $\beta = -0.02$, $p > 0.05$).

2.3.4 Theory of Planned Behavior (TPB)

The results showed A, SN, and PBC to be significant predictors of BI, with the model explaining 84% of the variance (Adj. $R^2 = 0.84$) in BI (Table 2.5). Among the constructs, SN and PBC showed very weak effects on BI and PBC showed a negative relationship ($B = -0.08$) with BI. To further investigate the negative effect of PBC on BI with the other model constructs, a hierarchical regression analysis (PBC entered first, then SN, and then A) was done. The results showed a positive effect of PBC on BI ($B = 0.62$, $SE\ B = 0.07$, $\beta = 0.39$, $p < 0.05$). When SN entered the model, the effect of PBC on BI remained positive (for PBC: $B = 0.41$, $SE\ B = 0.07$, $\beta = 0.26$, $p < 0.05$), however when A entered the model, the effect of PBC became negative. The *data-type* variable showed no effect on BI in the presence of the model constructs (A, SN, and PBC) (B = -0.08, SE B = 0.04, β = -0.05, $p > 0.05$). For this analysis, 23 highly influencing samples were removed based on Cook's D statistic.

Table 2.4 Assessment of the Refined Technology Acceptance Model (N = 401)

Tests	Adj. R^2	B	SE B	95% CI	β
1. BI = PU + PEoU					
Outcome: Behavioral Intention	0.79				
Predictor: Perceived Usefulness		0.96	0.03	0.91, 1.02	0.83**
Predictor: Perceived Ease of Use		0.22	0.04	0.15, 0.30	0.13**
2. PU mediates the effect of PEoU on BI					
Step 1 Model: BI = PEoU					
Outcome: Behavioral Intention	0.21				
Predictor: Perceived Ease of Use		0.72	0.07	0.58, 0.85	0.46**
Step 2 Model: PU = PEoU					
Outcome: Perceived Usefulness	0.14				
Predictor: Perceived Ease of Use		0.51	0.06	0.39, 0.63	0.38**
Step 3 Model: BI = PU + PEoU					
Outcome: Behavioral Intention	0.79				
Mediator: Perceived Usefulness		0.96	0.03	0.91, 1.02	0.83**
Predictor: Perceived Ease of Use		0.22	0.04	0.15, 0.30	0.13**

** $p < 0.001$

Table 2.5 Assessment of the Theory of Planned Behavior (N = 407)

Test	Adj. R^2	B	SE B	95% CI	β
1. BI = A + SN + PBC					
Outcome: Behavioral Intention	0.84				
Predictor: Attitude		1.07	0.03	1.00, 1.13	0.90**
Predictor: Subjective Norms		0.07	0.02	0.01, 0.13	0.06*
Predictor: Perceived Behavioral Control		-0.08	0.04	-0.15, -0.01	-0.05*

*$p < 0.05$, ** $p < 0.001$

2.3.5 Unified Theory of Acceptance and Use of Technology (UTAUT)

PE, EE, and SI were found to be significant predictors of BI and were able to explain 78% of the variance (Adj. $R^2 = 0.78$) in BI (Table 2.6). PE was found to be the strongest construct in the model influencing BI. Several moderating effects (see section 2) were proposed in UTAUT. However, the results of this study found no evidence of any moderating effect. Similar to the previous theories, the *data-type* variable showed no effect on BI in the presence of the model constructs (PE, EE, and SI) ($B = -0.13$, $SE\ B = 0.12$, $\beta = -0.03$, $p > 0.05$). Based on Cook's D statistic, 28 highly influencing samples were removed from the analysis.

Table 2.6 Assessment of the Unified Theory of Acceptance and Use of Technology ($N = 402$)

Tests	Adj. R^2	B	$SE\ B$	95% CI	β
1. BI = PE + EE + SI					
Outcome: Behavioral Intention	0.78				
Predictor: Performance Expectancy		0.90	0.04	0.83, 0.97	0.76**
Predictor: Effort Expectancy		0.15	0.04	0.07, 0.22	0.12**
Predictor: Social Influence		0.14	0.04	0.07, 0.21	0.11**

* $p < 0.05$, ** $p < 0.001$

2.3.6 Comparison among TAM, TPB, and UTAUT

The predictive ability of the models assessed was compared using Hotelling's t-test for non-independent correlations. The original TAM was found to exhibit the highest adjusted R^2 (0.86) among the models and accounted for significantly more variance in BI than did the other three models (Figure 2.2). Other differences were also found to be significant, leading to the conclusions that TPB performs better than the current version of TAM (refined TAM) and all models perform better than UTAUT in the context of driver acceptance of ADAS.

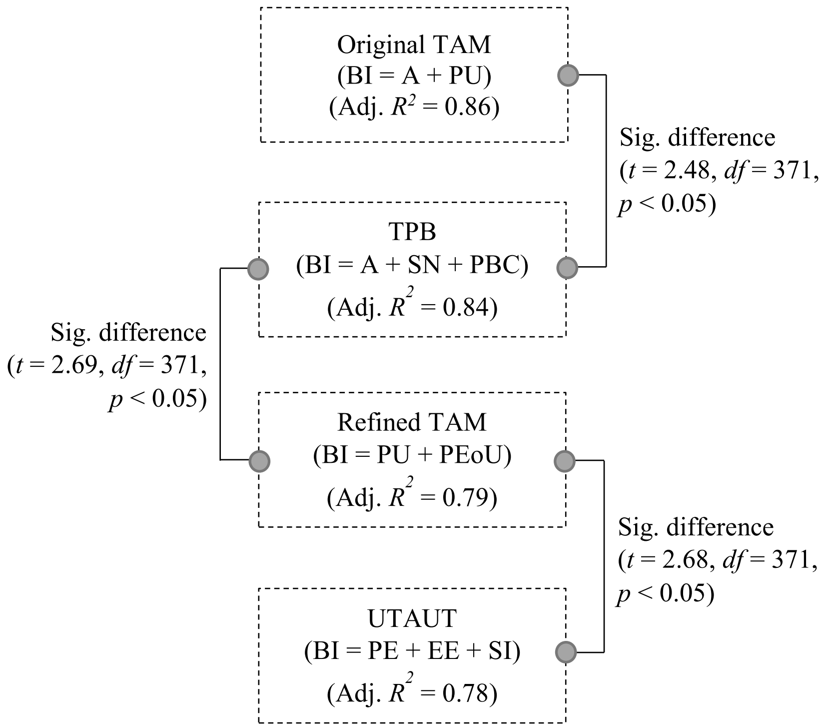

Figure 2.2 Comparison among the models adopted to explain driver acceptance of ADAS

2.4 Discussion

This study utilized and combined two different data collection approaches: an online survey approach and a driving simulator approach, to study driver acceptance of ADAS. The results found that the driving simulator participants showed a significantly higher intention to use such systems compared to the participants of the online survey. This difference in acceptance was to be expected and can be attributed to the trial of the ADAS functionalities in the driving simulator. In the simulator, participants had a chance to interact with the system and to understand the role of the ADAS in their driving. The driving scenario simulated routine operational conditions and the majority of the participants experienced the ADAS without any driving simulator failures. It is very likely that driving simulator participants deemed the simulated system as highly reliable and trustworthy. On the other hand, the online survey participants had to rely on the provided description of the systems to harvest a behavioral reaction. Since these types of in-vehicle technologies are not yet prevalent and since most of the participants were not familiar with ADAS functionalities, the described system was not able to motivate the participants as efficiently as the driving simulator experience. Participants may not have successfully visualized the functionality of the ADAS and their interaction with it. However, previous research on this topic may not agree with the last argument. Meschtscherjakov et al. (2009) asked participants whether they could imagine the technology based on the provided description and pictures: 85.7% of the participants said 'yes'. In a different question, 57.1% of the participants disagreed with the statement that it was difficult for them to respond to the survey items without actually using the technology. These findings, combined with the fact that majority of the studies in Table 2.1 which investigated driver acceptance of an ADAS successfully utilized surveys as a tool, provided enough evidence for the suitability of this approach. Furthermore, the results also showed that the effect of different data collection approaches wasn't significant in the presence of the TAM, TPB, and UTAUT model constructs. In the end, although a survey approach may not present an ADAS as successfully as a driving simulator approach, both approaches obtain similar results in measuring the effects of each construct on behavioral intention and creating models of driver acceptance of ADAS using TAM, TPB, and UTAUT.

The Technology Acceptance Model (both original TAM and refined TAM) was found to successfully model behavioral intention (BI) toward using an ADAS. For the original TAM, attitude toward using an ADAS was found to be the strongest predictor of BI. This relationship implies that drivers intend to use an in-vehicle technology toward which they have a positive affect (Davis, Bagozzi, and Warshaw, 1989). Attitude toward a behavior is formed based on beliefs about the outcomes of performing the behavior and on personal evaluations of those outcomes (Fishbein and Ajzen, 1975). In the context of using an ADAS, the beliefs that may form an attitude should include: the usefulness of the ADAS in enhancing the quality of driving, the effectiveness of the functionality of the ADAS, convenience of the driver, etc. Attitude (A) mediates the effect of these beliefs on BI as it did for the other construct of the original TAM, perceived usefulness. Perceived usefulness (PU), which is defined as a belief, showed a direct effect on BI despite the mediating effect of attitude. The belief of enhanced performance, in this case, is associated with several rewards: increased safety of the drivers and other road users, reduction in violation of traffic rules, personal satisfaction, etc. This perception of improved performance contributes to the behavioral intention to use an ADAS, above and beyond the positive or negative affect associated with that behavior. This study found a larger effect for A on BI compared to PU. Previous studies have reported both a similar (Chen and Chen, 2011) and an opposite result (Park and Kim, 2014). The results also showed that PU and PEoU can significantly predict A. This result supports the fact that attitude toward a behavior can be formed based on relevant beliefs (Fishbein and Ajzen, 1975). Perceived ease of use (PEoU), defined as the belief in the simplicity of a behavior, has two basic mechanisms to affect attitude: self-efficacy and instrumentality (Davis, Bagozzi, Warshaw, 1989). If the behavior is easier to perform, it will create a sense of efficacy and personal control for the performer. Again, an easier system would contribute to enhanced performance with the same amount effort. The enhancement of performance corresponds with the belief of usefulness (PU); however, with its self-efficacy mechanism, PEoU affects attitude above and beyond PU. The same explanation applies to the refined TAM model, where a similar relationship between PU and PEoU was posited and observed in this study. In refined TAM, the mediation of attitude on how personal beliefs (PU and PEoU) effect BI was ignored, and PU and PEoU were considered as predicting variables of BI. The results of this study found evidence to support the postulates of refined TAM; however, this model was outperformed (based on adj. R^2) by the original TAM model.

The results of this study found significant effects of the Theory of Planned Behavior (TPB) constructs (A, SN, and PBC) on acceptance (BI). TAM and TPB used the same scale for A, and similar to TAM, in TPB the strongest effect on BI was observed from A. Subjective norms (SN) showed a positive, though very small effect (compared to the effect of A) on BI. This result provides evidence that the perception of what other important and influencing people think about performing a behavior influences behavioral intention. These influencing people could include family members, colleagues, and even celebrities. In contrast, perceived behavioral control (PBC) exhibited a negative effect on BI in the presence of the attitude construct. Although the effect of PBC was very small, this negative effect means that drivers who possess a positive attitude toward using an ADAS generate a positive behavioral intention to use that ADAS; however, they may expect to have less control over the use of these technologies. This perception of low behavioral control can be attributed to very low familiarity with the technologies used in this study and also to the fact that the survey participants did not get a chance to interact with the described ADAS.

The results of this study also confirmed the predictive ability of the constructs (PE, EE, and SI) of UTAUT. PE, EE, and SI exhibited positive effects on BI with PE showing the strongest effect. Based on the definitions (see Table 1.1) of these constructs and scales used in previous studies, it is apparent that PE is very similar to PU in TAM, EE is very similar to PEoU in TAM, and SI is very similar to SN in TPB. The high correlation between these pairs of constructs and their comparable effect on BI provides statistical evidence to their similarity. UTAUT was able to explain 78% of the variance in BI, the lowest percentage among the four models. Besides the empirical evidence, UTAUT includes a total of 8 factors (4 constructs and 4 moderator variables), which is the highest number of factors among all the models, making the use of this model comparatively demanding. Due to its under-performance and similarities with TAM and TPB and the complex nature of the model, the use of UTAUT to explain driver acceptance of ADAS was shown to be impractical and inadequate.

This study has established that the models proposed by TAM, TPB, and UTAUT are able to explain driver acceptance in terms of behavioral intention in the context of ADAS. The question now is, which model should researchers use? The results of Hotelling's t-test for non-independent correlations showed that the original TAM model is the best performing model with TPB model as the second best. The original TAM model outperformed TPB by only 2% difference in adjusted R^2. Researchers should consider the practical significance of adopting the two models before taking into account this small increase in performance. This study used 20 survey items for the original TAM model and 18 survey items for the TPB model. Both of the models share one construct: attitude. TAM provides a mechanism for explaining the formation of attitude, which was found to be the strongest of the constructs in both models, by proposing that Perceived Usefulness and Perceived Ease of Use can predict Attitude. Of these TAM factors, Perceived Ease of Use has the potential to provide actionable information to the developers of in-vehicle technologies. This factor is not considered in TPB. TPB provides information on normative beliefs, behavioral control beliefs and their effect on behavioral intention. However, the results of this study showed that the effects of these variables are very small compared to the effect of attitude. Considering all these facts, the use of the original TAM model to study driver acceptance could provide more actionable information and explain more variance in behavioral intention compared to other models.

2.5 Limitations

This study involved two data collection approaches and combined the datasets to do the analysis; however, the data collection approaches didn't include the same number of participants. This imbalance in sample sizes may have influenced the effects of the different constructs on behavioral intentions. This is especially a matter of concern where the results showed a significant difference in behavioral intention scores due to different data collection approaches. Secondly, this study required the participants to think about a given driving route to assess the usefulness of the ADAS in their driving. This is not completely realistic since during the purchase of such technologies, people would normally think about their own daily commute to work or school. Settling on a given driving route had the advantages of simplifying their thought process and making sure that every participant had the same experimental set-up. However, participants' actual acceptance of those technologies could be different than the acceptance data that was collected in this study.

2.6 Conclusions

Advanced Driver Assistance Systems are the future of our transportation system. In March, 2016, the U.S. Department of Transportation's National Highway Traffic Safety Administration and the Insurance Institute for Highway Safety announced an agreement with 20 automakers representing more than 99 percent of the U.S. auto market to include automatic emergency braking as a standard feature on cars no later than Sept 1, 2022 (NHTSA, 2016). This historic event gives credence the potential benefits of these technologies; federal authorities and vehicle manufacturers will continue to be motivated to develop such technologies. However, the development and inclusion of such technologies are not enough to gain the potential benefits of these technologies. Driver acceptance has to be ensured for these technologies to achieve their potential. Recognizing the importance of driver acceptance and its research, this study assessed the utility of TAM, TPB, and UTAUT for Advanced Driver Assistance Systems. Two data collection approaches were applied to determine the validity of these theories for modeling driver acceptance and to compare their efficiency. Each model was able to successfully predict driver acceptance in terms of behavioral intention, and among the models, the original TAM model was found to be the best performing model.

Research efforts should be made to validate the findings of this study across a range of in-vehicle technologies. Researchers have also proposed factors outside of TAM, TPB, and UTAUT constructs that can affect behavioral intention to use an ADAS.

Examples of these factors include: trust (Najm et al., 2006; Ghazizadeh, Lee, & Boyle, 2012), compatibility (Ghazizadeh, Lee, & Boyle, 2012), endorsement (Najm et al., 2006; Stearns & Vega, 2011; Nodine et al., 2011), affordability (Regan et al.,2006), reliability (Kallhammer et al., 2007; LeBlanc et al., 2008; Van Houten, Reagan, & Hilton, 2014), etc. Future studies should investigate the predictive abilities of these factors and how these factors can be utilized to augment the theoretical acceptance models.

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CHAPTER III

THE UNIFIED MODEL OF DRIVER ACCEPTANCE AND ACCEPTANCE ASSESSMENT QUESTIONNAIRE

3.1 Introduction

People travel from place to place to access destinations, activities, goods, and services. In the United States, the most common mode of transportation is by motor-vehicle, a mode that provides an incomparable degree of mobility. Yet for all the benefits and convenience of motor-vehicle, crashes sustained by motor-vehicles were one of the leading causes of death in 2014 in the United States (Centers for Disease Control and Prevention, 2015). Research has confirmed that for over 90% of motor-vehicle accidents, driver error was a contributing factor (Singh, 2015; NHTSA, 2008; Fell and Freedman, 2001). In order to address issues with driver error, automakers and transportation system researchers have been focusing on the development of advanced transportation technologies as a means of providing automated assistance to drivers. Automation in driving has the potential to improve traffic flow, enhance traffic safety, and support the driver by providing useful driving information and warnings (European Commission, 2002; Ministry of Transport, 2004). However, the introduction of these new in-vehicle technologies requires changes in the way people drive. In fact, with some systems, vehicle control is completely transferred from humans to automated systems. This change in role, coupled with distrust in new and unknown technologies, may cause some drivers to refuse to purchase or use such in-vehicle driver assistance systems. The successful adoption of these emerging technologies, therefore, is highly dependent on driver acceptance. Even if the technologies are installed, if drivers do not accept them, they could easily bypass or ignore the technologies. It is often necessary to overcome subjective beliefs against anything new and different to encourage use. Research into driver acceptance of in-vehicle technologies can be helpful for developing appropriate systems which avoid the issues that adversely affect the usage.

More and more vehicles on the market today are equipped with different levels of automated vehicle control systems. These systems vary from those which provide warnings only to those which take full control of the vehicle. In an effort to distinguish different levels of vehicle automation, the National Highway Traffic Safety Administration (NHTSA) has categorized vehicle automation into five levels: level-0 (*No Automation*), level-1(*Function-Specific Automation*), level-2 (*Combined Function Automation*), level-3 (*Limited Self-Driving Automation*), and level-4 (*Full Self-Driving Automation*) (NHTSA, 2013). Level-0 systems provide information to drivers to increase situation awareness (for example, lane departure warning systems, navigation systems, etc.). If multiple control functions of a vehicle operate independently from each other, it is categorized as level-1 automation (for example, lane keeping systems, adaptive cruise control, etc.). On the other hand, when multiple control functions work together and enable the driver to be disengaged from vehicle control for those functions, this is categorized as level-2 automation (for example, lane keeping systems with adaptive cruise control, etc.). Level-3 and level-4 automation provide full vehicle control including all safety-critical functions; for level-3, full vehicle control is limited to specific traffic conditions. This research considered the vehicle automation technologies that assist a driver in the driving task instead of taking full control of the vehicle (level-0 to level-2). Conventionally, these technologies fall under the categories of Advanced Driver Assistance Systems (ADAS) or semi-autonomous driving systems.

Driver acceptance of ADAS and semi-autonomous driving systems can be defined as the willingness to purchase and use these technologies in an appropriate manner in traffic. Many previous studies have attempted to model driver acceptance. Modeling of driver acceptance in those studies has either involved adapting current general technology acceptance models or proposing new constructs that are different from the constructs of general technology acceptance models. Among the general technology acceptance models, the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT) have been adapted in the context of driver acceptance. These models used Behavioral Intention to use and Actual Use of technology as the two measures of acceptance. Due to lack of availability, however, it is often difficult to measure Actual Use of ADAS and semi-autonomous driving systems, and hence, in the context of driver acceptance, Behavioral Intention has been used as the sole measure of acceptance. This study proposes a driver acceptance model, named Unified Model of Driver Acceptance (UMDA), specifically developed for in-vehicle driver assistance systems which considers factors from previous research regarding both general technology acceptance and driver acceptance of ADAS and semi-autonomous driving systems.

3.1.1 Related Works

The Technology Acceptance Model (TAM) (Davis, Bagozzi, and Warshaw, 1989), built on the Theory of Reasoned Action (Fishbein and Ajzen, 1975), was developed to explain user acceptance of computer technologies. TAM proposed two constructs of Behavioral Intention: Attitude and Perceived Usefulness. Attitude is defined as positive or negative feelings about using a technology (Fishbein & Ajzen, 1975), while Perceived Usefulness is defined as the belief in the possibility of improved performance through the use of a technology (Davis, Bagozzi, and Warshaw, 1989). Later, a new version of TAM was proposed that included Perceived Usefulness and Perceived Ease of Use as constructs of Behavioral Intention (Davis, 1989). Davis (1989) defined Perceived Ease of Use as "the degree to which a person believes that using a particular system would be free of effort" (p. 320). Both of these versions have been adopted for driver acceptance models. Chen and Chen (2011) and Park and Kim (2014) adopted the first version of TAM for studying driver acceptance of car navigation systems. Chen and Chen (2011) found that Attitude can significantly predict Behavioral Intention, whereas Park and Kim (2014) found significant predictive effects for both Attitude and Perceived Usefulness. Ghazizadeh, Peng, Lee, and Boyle (2012) adopted the later version of TAM for modelling driver acceptance of an on-board monitoring system that can provide several warnings (for example, lane departure warning). The authors found a significant effect of Perceived Usefulness, but did not find any effect of Perceived Ease of Use. However, other studies reported Perceived Ease of Use as a significant predictor of Behavioral Intention (Xu et al., 2010; Roberts, Ghazizadeh, and Lee, 2012).

The Theory of Planned Behavior (TPB) (Ajzen, 1991) proposed three constructs of Behavioral Intention: Attitude, Subjective Norms, and Perceived Behavioral Control. The concept of Attitude in TPB is the same as in TAM. Subjective Norms is defined as the individual's perception of what important and influencial people think about the use of a technology (Fishbein and Ajzen, 1975), and Perceived Behavioral Control is defined as the perceived freedom of choice in using a technology (Ajzen, 1991). Later, the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) proposed three differently named constructs of Behavioral Intention: Performance Expectancy, Effort Expectancy, and Social Influence. These constructs are comparable to Perceived Usefulness, Perceived Ease of Use, and Subjective Norms, respectively. In addition, UTAUT proposed four moderating variables: Age, Gender, Experience, and Voluntariness. The use of TPB and UTAUT for modelling driver acceptance is limited compared to the use of TAM. Larue, Rakotonirainy, Haworth, and Darvell (2015) applied TPB to assess driver acceptance of an intelligent transport system and found that, of the three constructs, Attitude and Subjective Norms were predictive for Behavioral Intention. Adell (2010) adopted UTAUT to model driver acceptance of an in-vehicle technology which assists in keeping a safe speed and safe distance from other vehicles and found that Performance Expectancy and Social Influence were significant predictors of Behavioral Intention. Other studies (Osswald, Wurhofer, Trösterer, Beck, and Tscheligi, 2012; Henzler, Boller, Buchholz, and Dietmeyer, 2015) have adopted UTAUT to propose new models of driver acceptance; however, these studies have not provided any empirical evidence to support the models.

In addition to the constructs proposed by the TAM, TPB, and UTAUT, researchers have proposed and, in many cases, investigated other constructs that can potentially affect driver acceptance of ADAS and semi-autonomous vehicle technologies. Among these constructs, Compatibility, Trust, Endorsement, Affordability, and Reliability were proposed by most of the researchers (Table 1.2). In addition, demographics such as Age, Gender, Experience, and Personal Innovativeness were also considered by many researchers as important factors for explaining driver acceptance.

Compatibility: Karahanna et al. (2006) defined compatibility as the positive interactions among the driver, the vehicle-automation technology, the driving task, and the traffic conditions. Advanced driving technologies are still a new class of innovation, and surprises and conflicts with a driver's mental model should be avoided to gain acceptance (Ghazizadeh, Lee, and Boyle, 2012). Ghazizadeh, Lee, and Boyle (2012) proposed Compatibility as an influencing factor of driver acceptance in their Automation Acceptance Model; however, no empirical studies investigating the effect of Compatibility were found.

Trust: People are usually more inclined to use an automation they trust (Lee & Moray, 1994; Parasuraman et al. 2008); and distrust or faulty usage can undermine user acceptance of driver-assisting vehicle systems. A study done by Siegrist (2000) reported that higher levels of Trust do not necessarily lead to greater technology acceptance. However, many studies have proposed Trust as an important factor for driver acceptance models (Najm et al., 2006; Donmez et al., 2006; Ghazizadeh, Lee, & Boyle, 2012) and some provided empirical evidence of its predictive ability. For example, Donmez et al. (2006) found positive correlation of Trust with driver acceptance, while Ghazizadeh et al.

(2012) showed significant positive effect of Trust along with Perceived Usefulness on Behavioral Intention.

Endorsement: Endorsement is the willingness to approve or recommend the purchase and/or use of an in-vehicle driver assistance system. Ervin et al. (2005) reported that 90% of the participants indicated willingness to recommend the adaptive cruise control system to a loved one. Nodine et al. (2011) found that 15 out of 18 participants would recommend that their company buy trucks equipped with an integrated advanced driver assistance system. In 2010, Reimer, Mehler, and Coughlin conducted an experimental study to investigate driver reaction to a parallel parking system. The survey responses, along with the heart-rate data, revealed that the automated vehicle technology reduced driver stress which in turn resulted in higher endorsement rates.

Affordability: Affordability, in this context, means driver willingness or perceived ability to spend money to buy an in-vehicle driver assistance system. Many previous studies proposed this factor to be one of the key constructs for the concept of acceptance (Adell and Varhelyi, 2008; Regan et al., 2006; Young et al., 2003; Regan et al. 2002; Biding & Lind, 2002). Affordability would seem to depend on income, but Lichtenstein, Bloch, & Black (1988) hypothesized that the more people are willing to pay, the higher the acceptance will be. However, no empirical evidence was provided with any of the studies.

Reliability: System Reliability plays a role in effectiveness and facilitates acceptance (Regan et al., 2006; Buckley et al., 2013). A number of studies have recognized System Reliability factors, such as the rate of false/nuisance alarms, accuracy, etc., as important in the context of driver acceptance (Kallhammer et al., 2007; LeBlanc et al., 2008; Van Houten, Reagan, & Hilton, 2014). It is important to note that the perception of a system's reliability is not mutually exclusive with the concept of Trust.

Age and Gender: In 2005, Ervin et al. conducted research to understand influence of age and gender on user acceptance of a forward crash warning system and an adaptive cruise control system. The researchers stated that both systems were more acceptable to older drivers than to either middle-aged or younger drivers. With regard to gender, the researchers reported that there was no evidence to support a Gender effect or a Gender and Age interaction effect. Donmez et al. (2006) tested driver acceptance and Trust for two in-vehicle distraction mitigation systems for older and middle-aged drivers. The findings revealed that older drivers were more trusting and accepting of the technology, even when it operated improperly. Li, Li, & Cheng (2015) also reported effects of Age on acceptance, but also found a Gender effect, reporting higher acceptance among female drivers.

Experience and Personal Innovativeness: Previous experience with ADAS was reported to influence driver acceptance. Holtl and Trommer (2013) reported that drivers who are experienced with navigation devices are less likely to accept them. On the other hand, Rodel et al. (2014) reported that, with previous experience, drivers are more likely to accept ADAS. Personal Innovativeness can be defined as the characteristic of adopting technology innovations earlier than others (Agarwal & Prasad, 1998). Chen and Chen (2011) in their research confirmed the moderating effect of Personal Innovativeness on the effect of Attitude on Behavioral Intention.

3.1.2 Objective of the study

The above discussion demonstrates that there have been several attempts to study driver acceptance. These attempts have created a long list of factors that may affect driver acceptance. Only a few studies have proposed a unified model of acceptance specific for in-vehicle driver assistance systems (Vlassenroot et al., 2010; Osswald et al., 2012). Vlassenroot et al. (2010) proposed the most comprehensive model which included 14 factors. Ghazizadeh, Lee, and Boyle (2012), in their Automation Acceptance Model (not specifically for vehicle automation), proposed Trust and Compatibility, in addition to the TAM constructs, as the constructs of acceptance. However, none of these models have been validated with empirical studies. Hence, there is a need for a unified driver acceptance model that includes the most important (most predictive) constructs and is supported by empirical studies. Additionally, there is only one questionnaire available to assess driver acceptance, developed by Van der Laan, Heino, & de Waard (1997). Although, this tool has been highly used in driver acceptance research, it only measures drivers' attitude toward in-vehicle technology (Van der Laan, Heino, & de Waard, 1997) and issues with the use of this questionnaire have been reported by researchers (Adell, Várhelyi, & Hjälmdahl, 2008). Based on the above discussions, the use of a tool that only considers drivers' attitude could be problematic in the context of ADAS and semi-autonomous driving systems. Recognizing these issues, this study develops a driver acceptance model (the Unified Model of Driver Acceptance (UMDA)) and a questionnaire to assess driver acceptance. The UMDA would list the factors that influence driver acceptance and define the nature (positive or negative) of their influence. On the other hand, the questionnaire would provide a quick and convenient tool to measure driver acceptance on a predetermined scale. The acceptance assessment questionnaire would be used to determine and compare driver acceptance of in-vehicle driving systems. Using the findings of previous works, a conceptual model of driver acceptance was created that included 13 constructs. An empirical study ($N = 430$) was conducted using two data collection approaches to investigate the predictive ability of the constructs of the conceptual model. Based on the results, the Unified Model of Driver Acceptance (UMDA) was developed that included the constructs shown to be most important. Finally, two acceptance assessment questionnaires (a long version and a short version) were developed based on the acceptance model.

3.2 Materials and Methods

3.2.1 Conceptual Model

To build the conceptual model, this study considered constructs from the technology acceptance models (TAM, TPB, and UTAUT) and other factors that were proposed by previous studies. TAM, TPB, and UTAUT constructs, Attitude, Perceived Usefulness, Perceived Ease of Use, Subjective Norms, Perceived Behavioral Control, Performance Expectancy, Effort Expectancy, and Social Influence were included in the conceptual model. In addition, Compatibility, Trust, Endorsement, Affordability, and Perceived System Reliability, as proposed by other researchers, were included as constructs as well. The conceptual model included four moderator variables: Age, Gender, Experience (with similar technology), and Personal Innovativeness. "In general terms, a moderator is a qualitative (e.g., sex, race, class) or quantitative (e.g., level of reward) variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable" (Baron & Kenny, 1986, p. 1176). Age, Gender, and Experience were proposed as moderating variables in UTAUT and Personal Innovativeness was considered as moderating variable by Chen and Chen (2011). These driver-characteristic variables are more likely to influence the formation of Attitude than to directly influence Behavioral Intention. Figure 3.1 illustrates the conceptual driver acceptance model.

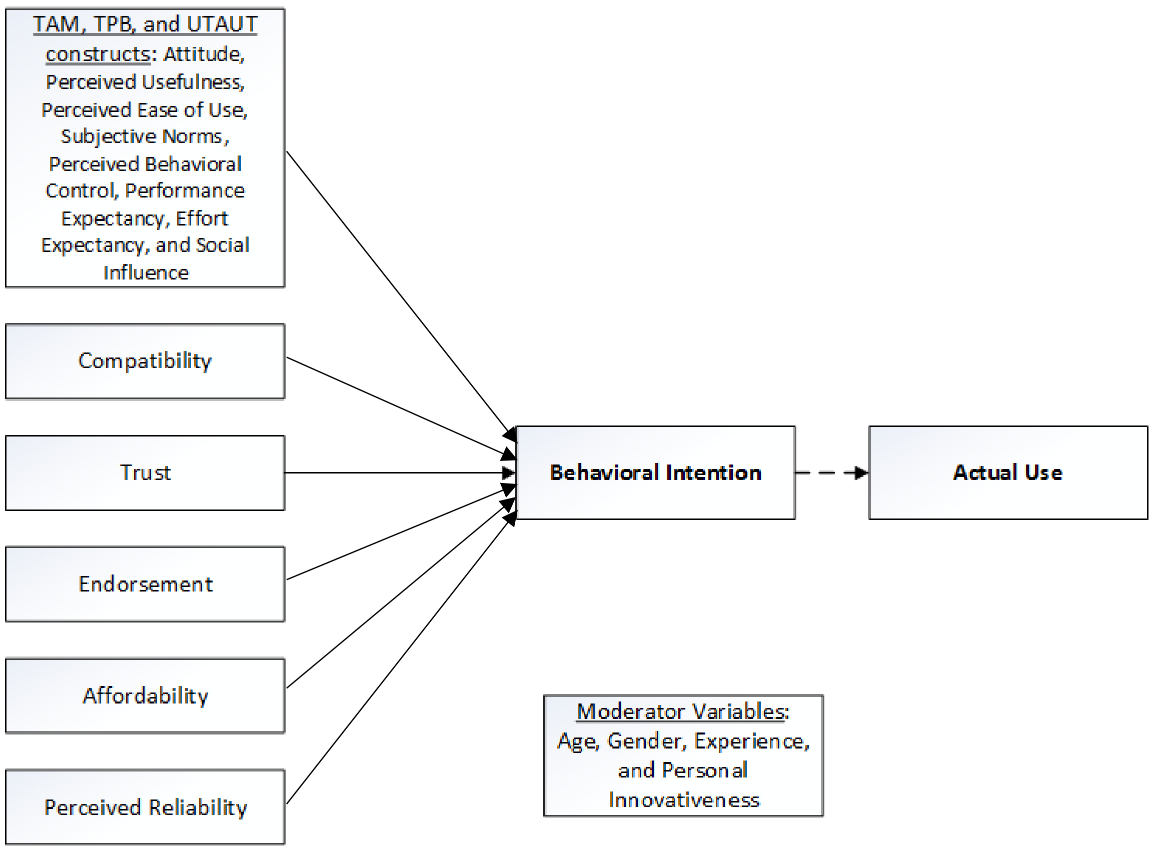

Figure 3.1 The conceptual driver acceptance model.

3.2.2 Data Collection and Study Materials

Due to the large number of variables, this study needed a large sample. Hence two data collection approaches, an online survey and a driving simulation, were used for data collection. These two were the most common data collection approaches adopted in previous studies that investigated driver acceptance (see Table 1.2 and Table 2.1).

3.2.2.1 Survey study

The online survey used a scenario-based design, similar to methods used in related literature on the Theory of Planned Behavior (e.g. Ajzen, 1991; Elliott et al., 2005; Evans & Norman, 1998, 2003; Holland & Hill, 2007) and technology acceptance (e.g. Lesch, nd; Rodel et al., 2014). Each participant read a brief description of an ADAS to begin the survey. Two ADAS were selected for this purpose (see Appendix B for a description of the two systems). Half of the participants were presented with a description of one system (System-1 in Appendix B; this system was also used as the simulated system in the simulator approach), and the other half were presented with a description of the other system (System-2 in Appendix B). Following the ADAS description, a short driving scenario was presented using a general context, without specific details regarding location, time of day, etc. After reading the driving scenario, participants responded to 45 survey items regarding their perceptions of the ADAS system in the driving context. The ratings of the survey items were used to measure different constructs and moderator variables.

The survey was hosted online using www.surveymonkey.com, and participants were recruited and compensated using Amazon Mechanical Turk (www.mturk.com). To ensure quality responses, check questions and reverse-scaled questions were included in the survey. A total of 400 participants completed the online survey, with 387 providing complete and valid responses. The final sample included 202 male and 185 female participants. The average age was 35.57 years (*SD* = 11.01), with a range of 19-73 years.

One hundred and ninety participants read the description of System-1 and 197 participants read the description of System-2.

3.2.2.2 Driving simulator study

A fixed-based driving simulator was used to allow participants to experience an ADAS while driving. The simulator included an open-cab vehicle mock-up, steering wheel, instrument panel, center console, accelerator pedal, and brake pedal. The driving environment was presented on five 46-inch LCD displays. The forward effective visual field of view was 200°. The driving environment was created using RTI SimCreator and SimVista software (Realtime Technologies Inc., Royal Oak, MI).

An ADAS (similar to System-1 in the survey approach) was developed to use in the driving simulator. It included two primary automated functions: speed keeping and lane keeping. The simulator took corrective action when the driver deviated from the preferred states. This was done by accelerating, braking, or steering the vehicle towards the center of the lane.

Participants were screened prior to arrival for qualifications and susceptibility to simulator sickness. At the start of the experimental session, participants provided informed consent, had their vision tested, and completed a familiarization drive using the simulator. Participants then received instructions for completing the experimental tasks. The experimental task consisted of a single experimental block, lasting 8-10 minutes. During the drive, the participant encountered a number of road types (feeder road, 2-lane highway, industrial road), and experienced the ADAS assisting with the drive. No adverse events were presented during simulation. Participants who completed the driving simulator tasks then completed a survey which was same as in the survey study with the exception that it included an extra survey item to measure Perceived Reliability and did not include any check questions.

Forty-eight participants were recruited for the driving simulator approach. Five participants' data were removed from the final dataset due to equipment issues which occurred during the study sessions. All participants (N = 43) had a valid US driver's license, were native or fluent English speakers, and had normal or corrected-to-normal vision, normal color vision, and no self-reported hearing difficulties. The participants had an average age of 40.93 years (SD = 12.06), with a range of 21-57 years. A total of 20 males and 23 females completed the driving simulator experiment.

3.2.2.3 Survey Items

A total of 46 survey items were included in the survey to measure the constructs and moderating variables of the conceptual model. Subjective Norms and Social Influence constructs are very similar by definition and most often are measured by the same scale, which this study also chose to do; consequently, only one of them (Subjective Norms) was included in the data analysis. Table 3.1 lists the survey items and the corresponding constructs. All survey items (except for the questions that included their own scales) were measured on a 7-point Likert scale, where 1 = strongly disagree, 2 = moderately disagree, 3 = somewhat disagree, 4 = neutral (neither disagree nor agree), 5 = somewhat agree, 6 = moderately agree, and 7 = strongly agree. To measure the constructs, participants' ratings on the corresponding survey items were averaged.

3.2.3 Data Processing and Analysis

The two datasets (from the survey study and the simulator study) were merged for analysis in order to increase the power of the tests. As a result, the sample size for the study was 430 (43 from the simulator study and 387 from the online survey study). In the merged dataset, data sources were separated using two new variables, *data-type* (coded as 0 for simulator data and 1 for online survey data) and *system-type* (coded as 0 for System-1 in the online survey and the simulated system, and 1 for System-2 in the online survey).

The data analysis included assessment of the internal consistency of the scales, regression analyses and confirmatory factor analysis. Statistical analyses were carried out in SAS (version 9.4) and in IBM SPSS AMOS (version 23). The steps of the data analysis are explained below with more detail.

3.2.3.1 Internal consistency of the scales

The internal consistency of each scale was tested with Cronbach's alpha. If the α for a certain scale was found to be less than 0.70, correlation matrix analyses were done to identify and remove the item(s) which had contributed to the low reliability.

3.2.3.2 Development of the acceptance model

Before running regression analyses, scatter plots (Behavioral Intention vs the predictor variables) were drawn to check the linearity assumption. To check for the validity of other assumptions, scatter plots for residuals vs predictor variables, residuals vs fitted values, and Q-Q plots were evaluated. To identify the influencing samples, Cook's D was calculated and cases that yielded a D-value of more than 4/N (= 4/430 = 0.0093) were removed from the analysis (Cook and Weisberg, 1980).

Several simple linear regression analyses were done to assess the individual predictive ability of the constructs of the conceptual model. Two approaches were adopted to build the acceptance model: in the first approach, a hierarchical regression analysis was done with forward selection criteria ($\alpha < 0.05$). In every step, variables were added to the regression model based on their correlation with the dependent variable: Behavioral Intention (in descending order). In the second approach, 320 data points (n_1) were randomly extracted from the complete dataset ($N = 430$) to create a model building dataset, and the rest were included in a model validation dataset ($n_2 = 110$). Using the model selection function under PROC REG in SAS on the model building dataset, all possible regression models which included all or a subset of the constructs of the conceptual model were created and the best model was selected based on the adjusted R^2 (higher is better) and AIC (Akaike Information Criterion, lower is better). The selected model was then fit on both the model building and the model validation dataset. To validate the selected model, regression coefficients of the model constructs calculated from both building and validation datasets were compared. Furthermore, the mean squared error (MSE) calculated from the building dataset and the mean squared prediction error (MSPR) calculated from the validation dataset were compared. Hence, an additional benefit of the second approach is that it provided a way to check the validity of the developed model.

The efficiency of the developed acceptance model was compared with the efficiency of the TAM, TPB, and UTAUT models using Hotelling's t-test for non-independent correlations. To test moderation, the procedure proposed by Frazier, Tix, & Baron (2004) was applied. In this procedure, the predictor and the moderator variables are standardized and then multiplied together in order to calculate the interaction term. Testing for a moderation effect involved a hierarchical regression technique. In the first step, the outcome variable was regressed on the predictor and the moderator. In the next step, the interaction term entered the regression model; if the interaction term was found to be significant, moderation was present.

3.2.3.3 Development of the acceptance assessment scale

This study developed two scales (a long version and a short version) to assess driver acceptance. Development of the acceptance assessment scales was based on the developed acceptance model. To create the longer or the full version of the scale (Scale-1), Confirmatory Factor Analysis (CFA) was done to check the loading of the survey items on the respective constructs. After that, a second order latent variable (Acceptance) was introduced in the model and another CFA was done to examine how well the model constructs predict the second order variable. Next, in order to create a short version of the scale (Scale-2), Exploratory Factor Analysis (EFA) was done and the survey items were forced to map on to one factor (named Acceptance). The survey items that yielded a lower factor loading (0.6 or less) were removed from the scale. A CFA was done to examine how well the remaining survey items predict the single factor: Acceptance. Model fitness of the two scales were assessed and compared using the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), and the Tucker Lewis Index (TLI). An RMSEA of 0.08 or less and a CFI and a TLI of greater than 0.90 are considered as indicating a good fit between the model and the data (Kim and Bentler,2006; Kenny, 2015). The chi-square (χ^2), degrees of freedom, and significance level were also reported.

3.3 Results

3.3.1 Reliability of Scales and Descriptive Statistics

The mean and SD of each survey items are presented in Table 3.1. The internal consistency of the scales was found to be high for most of the scales, with a Cronbach's alpha (α) of 0.7 or more (Table 3.2). Only the Subjective Norms scale showed poor reliability ($\alpha = 0.48$). Since this scale has only two survey items, the authors continued to use the scale as it was intended. The bivariate correlations between pairs of scales and mean and the standard derivation of the scales are summarized in Table 3.2. The results revealed that most participants had a very low familiarity with ADAS as either described or simulated in this study. 37% (23.3% for the simulated system and 38.5% for the described systems) of the participants had never heard of a similar system and 99.1% (97.7% for the simulated system and 99.2% for the described systems) of the participants had never used a similar system while driving.

Table 3.1 Survey items and corresponding constructs.

Constructs and Survey Items	Mean	SD
Perceived Usefulness (items – 1, 2, 3, 5) – adapted from Venkatesh and Davis (2000)		
Performance Expectancy (items – 1, 4, 5, 6) – adapted from Venkatesh et al. (2003) and Adell (2009)		
1. I would find the system useful in my driving	5.03	1.55
2. Using the system when driving would increase my safety	5.22	1.43
3. Using the system would enhance effectiveness in my driving	4.97	1.49
4. Using the system would enable me to react to unsafe driving conditions more quickly	4.8	1.63
5. Using the system would improve my driving performance	4.57	1.58
6. If I use the system, I will decrease my risk of being involved in an accident	5.01	1.43
Perceived Ease of Use (items – 7, 9, 10, 12) – adapted from Venkatesh and Davis (2000)		
Effort Expectancy (items – 7, 8, 9, 11) – adapted from Venkatesh et al. (2003) and Adell (2009)		
7. My interaction with the system would be clear and understandable	5.64	1.2
8. It would be easy for me to become skillful at using the system	5.81	1.15
9. I would find the system difficult to use	5.77	1.34
10. Interacting with the system would not require a lot of mental effort.	4.89	1.71
11. Learning to operate the system would be easy for me	5.67	1.27
12. I would find it easy to get the system to do what I want it to do.	5.33	1.26
Attitude – adapted from Van der Laan et al. (1997)		
13. The use of the system when I am driving would be: Bad : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Good	5.19	1.44
14. The use of the system when I am driving would be: Useless : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Useful	5.38	1.42
15. The use of the system when I am driving would be: Desirable : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Undesirable	4.89	1.7
16. The use of the system when I am driving would be: Ineffective : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Effective	5.18	1.44
17. The use of the system when I am driving would be: Sleep-inducing : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Alerting	4.87	1.73
18. The use of the system when I am driving would be: Unpleasant : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Pleasant	4.87	1.56
19. The use of the system when I am driving would be: Extremely Annoying : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Not at all Annoying	4.82	1.68
20. The use of the system when I am driving would be: Irritating : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Likeable	4.87	1.74
21. The use of the system when I am driving would be: Assisting : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Worthless	5.29	1.52
Subjective Norms, Social Influence – adapted from Venkatesh and Davis (2000) and Adell (2009)		
22. People who influence my behavior would think that I should use the system.	4.2	1.52
23. People who are important to me would not think that I should use the system	4.92	1.59
Perceived Behavioral Control – adapted from Venkatesh et al. (2003)		
24. I have control over using the system.	5.68	1.35
25. I have the resources necessary to use the system.	5.66	1.25
26. I do not have the knowledge necessary to use the system.	5.81	1.47
27. Given the resources, opportunities and knowledge it takes to use the system, it would be easy for me to use the system.	5.78	1.16
Compatibility – adapted from Moore and Benbasat (1991)		
28. The system is compatible with all aspects of my driving.	4.77	1.59
29. I think that using the system fits well with the way I like to drive	4.69	1.72
30. Using the system wouldn't complement my driving style.	4.45	1.8

Table 3.1 (Continued)

Constructs and Survey Items	Mean	SD
Trust – adapted from Najm et al. (2006) and Ghazizadeh et al. (2012)		
31. I think I can depend on the system for safe driving.	4.96	1.52
32. I would feel more comfortable doing other things (e.g., checking emails on my smartphone) with the system engaged.	3.31	2.08
33. I would feel comfortable if my child, spouse, parents – or other loved ones – drove a vehicle equipped with the system.	5.33	1.51
Endorsement – adapted from Najm et al. (2006) and Nodine et al. (2011)		
34. I would recommend that my family and friends buy vehicles equipped with the system.	4.63	1.55
35. I would recommend that my child, spouse, parents – or other loved ones –use the system.	4.82	1.55
Affordability – adapted from Regan et al. (2006)		
36. How much would you be willing to pay for the system if it were an optional feature in a new car? __1__ < $250; __2__ $251-$500; __3__ $501-$750; __4__ $751-$1000; __5__ $1001-$1250; __6__ $1251-$1500; __7__ > $1500	2.76	1.74
37. How much would you be willing to pay the system if it could be retrofitted to an existing car? __1__ < $250; __2__ $251-$500; __3__ $501-$750; __4__ $751-$1000; __5__ $1001-$1250; __6__ $1251-$1500; __7__ > $1500	2.59	1.63
Behavioral Intention		
38. If the system is available in the market at an affordable price I intend to purchase the system.	4.26	1.76
39. If my car is equipped with a similar system, I predict that I would use the system when driving.	5.16	1.65
40. Assuming that the system is available, I intend to use the system regularly when I am driving.	4.65	1.76
Perceived Reliability – author-created scale		
41. Based on your experience with the system, how would you rate the system Not at all Reliable : _1_ : _2_ : _3_ : _4_ : _5_ : _6_ : _7_ : Highly Reliable	5.79	1.04
Experience – author created scale		
42. You have just experienced an intelligent driving system. Prior to this experience, please indicate your familiarity with such systems: 1- I've never heard of a similar driving system. 2- I may have heard of a similar driving system. 3- I am moderately familiar with similar systems but never used when driving. 4- I am quite familiar with similar systems but never used when driving. 5- I've had few instances when I used similar systems when driving. 6- I occasionally use a similar system when driving. 7- I regularly use a similar system when driving.	1.96	0.93
Personal Innovativeness – adapted from Agarwal and Prasad (1998) and Chen and Chen (2011)		
43. If I heard about a new technology, I would look for ways to experiment with it.	5.21	1.28
44. Among my peers, I am usually the first to try out new technologies.	4.44	1.65
45. In general, I am hesitant to try out new technologies.	5.27	1.63
46. I like to experiment with new technologies.	5.33	1.28

3.3.2 Variations in BI Due to Different Data Collection Approaches and Different ADAS Systems

A multiple linear regression analysis was completed to investigate the effect of data collection type and ADAS type on Behavioral Intention. There was a significant difference in acceptance score (Behavioral Intention) based on the data collection type ($B = -0.69$, $SE\ B = 0.27$, $\beta = -0.13$, $p < 0.05$), where data type was coded as 0 = simulator and 1 = online survey. Participant acceptance was significantly higher for participants who completed the simulator study ($M = 5.31$, $SD = 1.35$) compared to the online survey study ($M = 4.62$, $SD = 1.60$). However, the type of ADAS system (System 1 or System 2) did not have a statistically significant effect on the BI score ($B = -0.01$, $SE\ B = 0.16$, $\beta = 0.00$, $p > 0.05$). Therefore, for future analyses, a variable will be included to account for the differences in data collection type, but not in system type.

3.3.3 Development of the Unified Model of Driver Acceptance (UMDA)

The individual predictive ability of the conceptual model constructs was evaluated with simple linear regression. The results (summarized in Table 3.3) showed that all the constructs of the conceptual model individually predict BI, hence, all the constructs were considered in building the acceptance model. Among the constructs, Attitude showed the strongest effect on Behavioral Intention, followed by Perceived Usefulness and Performance Expectancy.

Table 3.2 Internal consistency of the scales (on the diagonal), bi-variate correlations, and descriptive statistics ($N = 430$).

Constructs	Mean	SD	BI	A	PU	PEoU	SN	PBC	PE	EE	Com	T	End	Aff	Rel	PI
BI	4.69	1.59	0.91													
A	5.04	1.30	.89**	.94												
PU	4.95	1.33	.85**	.88**	.90											
PEoU	5.41	1.02	.42**	.49**	.36**	.72										
SN	4.56	1.26	.55**	.58**	.58**	.32**	.48									
PBC	5.73	1.01	.36**	.45**	.35**	.77**	.24**	.77								
PE	4.85	1.31	.83**	.86**	.96**	.36**	.58**	.34**	.87							
EE	5.72	1.04	.38**	.46**	.35**	.86**	.27**	.84**	.33**	.86						
Com	4.64	1.45	.81**	.81**	.79**	.40**	.54**	.36**	.78**	.34**	.81					
T	5.14	1.38	.76**	.80**	.77**	.49**	.56**	.48**	.79**	.45**	.73**	.79				
End	4.72	1.49	.81**	.80**	.80**	.43**	.59**	.40**	.80**	.39**	.72**	.81**	.92			
Aff	2.67	1.64	.45**	.40**	.37**	.14**	.22**	.11*	.35**	.13**	.31**	.26**	.34**	.95		
Rel (*n*=43)	5.06	1.04	.66**	.62**	.65**	.32*	.53*	.33*	.65**	.37*	.58**	.60**	.63**	.27	***	
PI	5.79	1.24	.33**	.29**	.24**	.35**	.18**	.36**	.24**	.44**	.24**	.29**	.32**	.23**	.08	.87

Note: Internal consistency (Cronbach's alpha) statistics are on the diagonal.
BI = Behavioral Intention, A = Attitude, PU = Perceived Usefulness, PEoU = Perceived Ease of Use, SN = Subjective Norms, PBC = Perceived Behavioral Control, PE = Performance Expectancy, EE = Effort Expectancy, Com = Compatibility, T = Trust
End = Endorsement, Aff = Affordability, Rel = Perceived Reliability, PI = Personal Innovativeness
* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).
*** Single-item scale.

Table 3.3 Individual predictive ability of the conceptual model constructs (N = 430).

Test	Adj. R^2	B	$SE\ B$	95% CI	β
1. Model: BI = Attitude	0.80	1.10	0.03	1.04, 1.15	0.89**
2. Model: BI = Perceived Usefulness	0.72	1.01	0.03	0.95, 1.07	0.85**
3. Model: BI = Perceived Ease of Use	0.17	0.65	0.07	0.52, 0.79	0.42**
4. Model: BI = Subjective Norms	0.31	0.70	0.05	0.60, 0.80	0.55**
5. Model: BI = Perceived Behavioral Control	0.13	0.56	0.07	0.42, 0.70	0.36**
6. Model: BI = Performance Expectancy	0.69	1.00	0.03	0.94, 1.07	0.83**
7. Model: BI = Effort Expectancy	0.14	0.58	0.07	0.38, 0.44	0.38**
8. Model: BI = Compatibility	0.65	0.89	0.03	0.83, 0.95	0.81**
9. Model: BI = Trust	0.57	0.87	0.04	0.76, 0.80	0.76*
10. Model: BI = Endorsement	0.66	0.87	0.03	0.81, 0.93	0.81**
11. Model: BI = Affordability	0.20	0.43	0.04	0.35, 0.51	0.44**
12. Model: BI = Perceived Reliability (n = 43)	0.42	0.85	0.15	0.54, 1.16	0.66**

*$p < 0.05$, ** $p < 0.0001$

3.3.3.1 Approach 1: Hierarchical Regression

The first approach used to build UMDA was hierarchical regression analysis. Results of each step of this analysis are presented in Table 3.4. In step 7, the Perceived Reliability construct entered the regression model and its effect was found to be non-significant. This construct was only measured for the driving simulator participants; therefore, step 7 regression analysis only used 43 data points. Besides Perceived Reliability, the effects of Perceived Usefulness, Compatibility, and Endorsement were also found to be non-significant. However, since these variables had already entered the model, they stayed in the model according to the forward selection method. After 12 steps, the ultimate model included Attitude, Perceived Usefulness, Perceived Behavioral Control, Compatibility, Endorsement, and Affordability as constructs of Behavioral

Intention. Among the constructs, only Perceived Behavioral Control showed a negative effect on Behavioral Intention, although it showed a positive effect when tested alone. To understand the change in the direction of effect, all the survey items under this scale (items 24, 25, 26, and 27) were regressed on Behavioral Intention. The results found a positive effect of items 24, 25, and 27 and a negative effect for item 26.

Table 3.4 Development of the Unified Model of Driver Acceptance using hierarchical regression ($N = 430$).

Test	Adj. R^2	*B*	*SE B*	95% *CI*	β
Step 1. Model: BI = A	0.80				
Predictor: Attitude		1.10	0.03	1.04, 1.15	0.89**
Step 2. Model: BI = A + PU	0.82				
Predictor: Attitude		0.79	0.05	0.69, 0.89	0.64**
Predictor: Perceived Usefulness		0.34	0.05	0.24, 0.44	0.29**
Step 3. Model: BI = A + PU + PE	0.82				
Predictor: Attitude		0.79	0.05	0.68, 0.89	0.64**
Predictor: Perceived Usefulness		0.30	0.09	0.12, 0.48	0.25*
Predictor: Performance Expectancy		0.04	0.09	-0.13, 0.22	0.04
Step 4. Model: BI = A + PU + End	0.83				
Predictor: Attitude		0.67	0.05	0.57, 0.78	0.55**
Predictor: Perceived Usefulness		0.23	0.05	0.13, 0.33	0.19**
Predictor: Endorsement		0.24	0.04	0.16, 0.31	0.22**
Step 5. Model: BI = A + PU + End + Com	0.84				
Predictor: Attitude		0.58	0.06	0.47, 0.69	0.47**
Predictor: Perceived Usefulness		0.17	0.05	0.07, 0.27	0.14*
Predictor: Endorsement		0.22	0.04	0.14, 0.29	0.20**
Predictor: Compatibility		0.19	0.04	0.11, 0.26	0.17**
Step 6. Model: BI = A + PU + End + Com + T	0.84				
Predictor: Attitude		0.59	0.06	0.48, 0.71	0.49**
Predictor: Perceived Usefulness		0.18	0.05	0.08, 0.28	0.15*
Predictor: Endorsement		0.24	0.04	0.17, 0.32	0.23**
Predictor: Compatibility		0.19	0.04	0.12, 0.27	0.18**
Predictor: Trust		-0.07	0.04	-0.16, 0.01	-0.06
Step 7. Model: BI = A + PU + End + Com + Rel ($n = 43$)	0.80				
Predictor: Attitude		0.61	0.19	0.24, 0.99	0.52*
Predictor: Perceived Usefulness		0.38	0.20	-0.04, 0.79	0.34
Predictor: Endorsement		-0.07	0.12	-0.31, 0.16	-0.06
Predictor: Compatibility		0.01	0.10	-0.21, 0.21	0.01

Table 3.4 (Continued)

Test	Adj. R^2	*B*	*SE B*	95% *CI*	*β*
Predictor: Perceived Reliability		0.19	0.13	-0.07, 0.45	0.15
Step 8. Model: BI = A + PU + End + Com + SN	0.84				
Predictor: Attitude		0.57	0.06	0.47, 0.68	0.47**
Predictor: Perceived Usefulness		0.17	0.05	0.07, 0.27	0.14*
Predictor: Endorsement		0.21	0.04	0.14, 0.29	0.20**
Predictor: Compatibility		0.19	0.04	0.11, 0.26	0.17**
Predictor: Subjective Norms		0.02	0.03	-0.08, 0.04	-0.02
Step 9. Model: BI = A + PU + End + Com + Aff	0.85				
Predictor: Attitude		0.53	0.06	0.43, 0.64	0.44**
Predictor: Perceived Usefulness		0.16	0.05	0.06, 0.26	0.13*
Predictor: Endorsement		0.21	0.04	0.14, 0.28	0.20**
Predictor: Compatibility		0.19	0.04	0.12, 0.27	0.18**
Predictor: Affordability		0.10	0.02	0.06, 0.13	0.10**
Step 10. Model: BI = A +PU + End + Com + Aff + PEoU	0.85				
Predictor: Attitude		0.55	0.06	0.43, 0.66	0.44**
Predictor: Perceived Usefulness		0.15	0.05	0.05, 0.25	0.13*
Predictor: Endorsement		0.22	0.04	0.14, 0.29	0.20**
Predictor: Compatibility		0.19	0.04	0.12, 0.27	0.18**
Predictor: Affordability		0.09	0.02	0.06, 0.13	0.10**
Predictor: Perceived Ease of Use		-0.02	0.03	-0.09, 0.04	-0.01
Step 11. Model: BI = A + PU + End + Com + Aff + EE	0.85				
Predictor: Attitude		0.55	0.06	0.44, 0.66	0.45**
Predictor: Perceived Usefulness		0.15	0.05	0.05, 0.25	0.13*
Predictor: Endorsement		0.22	0.04	0.15, 0.29	0.20**
Predictor: Compatibility		0.19	0.04	0.12, 0.27	0.17**
Predictor: Affordability		0.09	0.02	0.06, 0.13	0.10**
Predictor: Effort Expectancy		-0.03	0.03	-0.10, 0.03	-0.02
Step 12. Model: BI = A + PU + End + Com + Aff + PBC	0.85				
Predictor: Attitude		0.57	0.06	0.45, 0.68	0.46**
Predictor: Perceived Usefulness		0.15	0.05	0.05, 0.25	0.12*
Predictor: Endorsement		0.22	0.04	0.15, 0.29	0.21**
Predictor: Compatibility		0.19	0.04	0.12, 0.27	0.18**
Predictor: Affordability		0.09	0.02	0.05, 0.13	0.10**
Predictor: Perceived Behavioral Control		-0.07	0.03	-0.14, -0.01	-0.04*

*$p < 0.05$, ** $p < 0.0001$

3.3.3.2 Approach 2: Model Building and Model Validation

The results of this approach produced the same model as Approach 1. The model with Attitude, Perceived Usefulness, Perceived Behavioral Control, Compatibility, Endorsement, and Affordability constructs yielded the highest adjusted R^2 (0.86) with the lowest AIC (-327.29). For the validation, this model was then fit on both the model building and the model validation dataset and a few statistics were compared (Table 3.5). The comparison showed no large difference, and hence, the selected model exhibited no validation issues.

Table 3.5 Model building and validation statistics comparison

Regression Coefficients	Model Building Data ($n_1 = 320$)	Model Validation Data ($n_2 = 110$)
Attitude	0.53	0.67
Perceived Usefulness	0.15	0.13
Perceived Behavioral Control	-0.07	-0.07
Compatibility	0.20	0.17
Endorsement	0.22	0.22
Affordability	0.10	0.07
	MSE = 0.35	MSPR = 0.47

3.3.3.3 The Unified Model of Driver Acceptance

Once the constructs of Behavioral Intention were identified, further analyses were done to test the hypothesized moderating effects of Age, Gender, and Personal Innovativeness. Only a moderating effect of Personal Innovativeness on the effect of Endorsement on Behavioral Intention was observed (for Personal Innovativeness*Endorsement: $B = -0.09$, $SE\ B = 0.04$, $\beta = -0.07$, $p < 0.05$). Since almost all the participants had never interacted with a similar system (described or simulated), the distribution of the Experience variable was very skewed and therefore, no analysis was done to test the moderating effects of Experience. After the analyses of moderating effects, the selected acceptance model (6 constructs and 1 moderator variable) was fit on the complete dataset ($N = 430$), controlling for variation due to the *data-type* variable. The *data-type* variable didn't show any effect ($B = -0.11$, $SE\ B = 0.09$, $\beta = -0.02$, $p > 0.05$)

on BI in the presence of the model constructs. For this regression analysis, 35 highly influencing data samples were removed based on Cook's *D* statistic. Deleting these outlying data points improved the model fit (Adj. $R^2 = 0.90$, compared to 0.85, in Table 3.5, step 12). The acceptance model is illustrated in Figure 3.2.

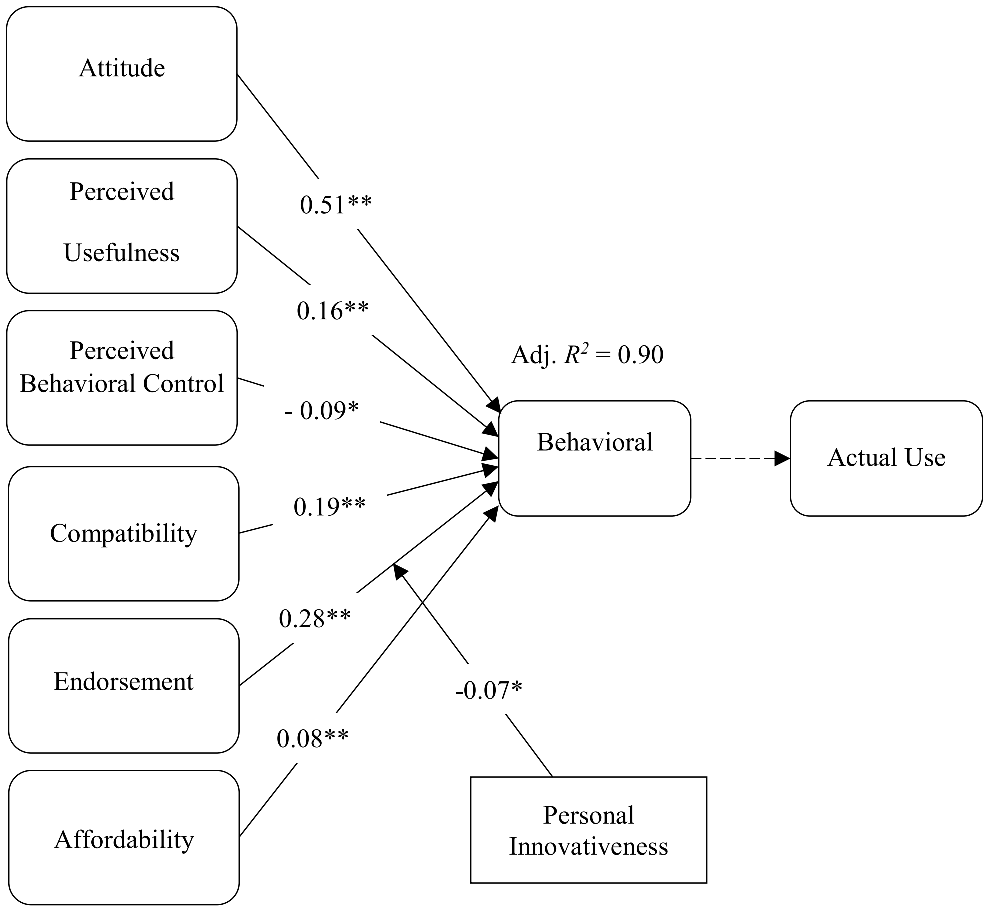

Figure 3.2 Acceptance model (numbers on the arrow represent standardized regression coefficients; * $p < 0.05$; ** $p < 0.0001$).

The predictive abilities of UMDA and the technology acceptance models (TAM, TPB, and UTAUT) were compared using the Hotelling's t-test for non-independent correlations. UMDA was found to exhibit the highest adjusted R^2 (0.90) among the models and accounted for significantly more variance in Behavioral Intention than did the other models (Figure 3.3). All other differences in predictive abilities between each pair of models were found to be statistically significant (Figure 3.3). Supplementary results on the assessment of TAM, TPB, and UTAUT can be found in Chapter 2.

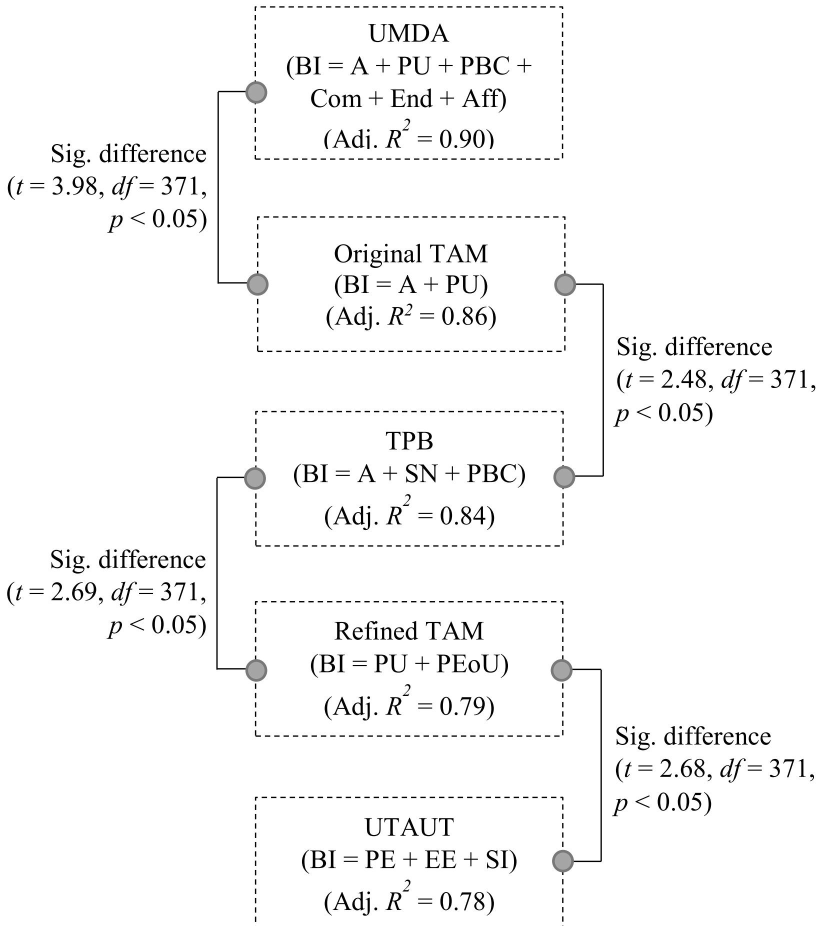

Figure 3.3 Comparison among the models used to explain driver acceptance

3.3.4 Development of the Acceptance Assessment Scale

The results of CFA suggested the removal of item 17 (Table 3.1) from both scales due to low factor loading (i.e., < 0.20). In addition, items 14 and 16 were removed from the scales due to their similarity with items 1 and item 3, respectively.

3.3.4.1 Scale 1

The results of CFA showed good factor loading of the survey items on corresponding constructs. As can be seen in Figure 3.4 (Figure generated in IBM SPSS AMOS, version 23), the six constructs are strongly interrelated. Correlations among the constructs, except between PBC and Affordability, were found to be statistically significant ($p < 0.001$) which supports the existence of a second-order factor (Acceptance). After the addition of the second-order factor, another CFA was done and the results showed good estimated predictability of the constructs (for predicting the second-order factor) (Figure 3.5). The modification indices suggested adding error covariance between items 1 and 2, 2 and 3, 15 and 21, and 19 and 20 (see Figure 3.4 and Figure 3.5). This version of the acceptance assessment scale contains 21 survey items.

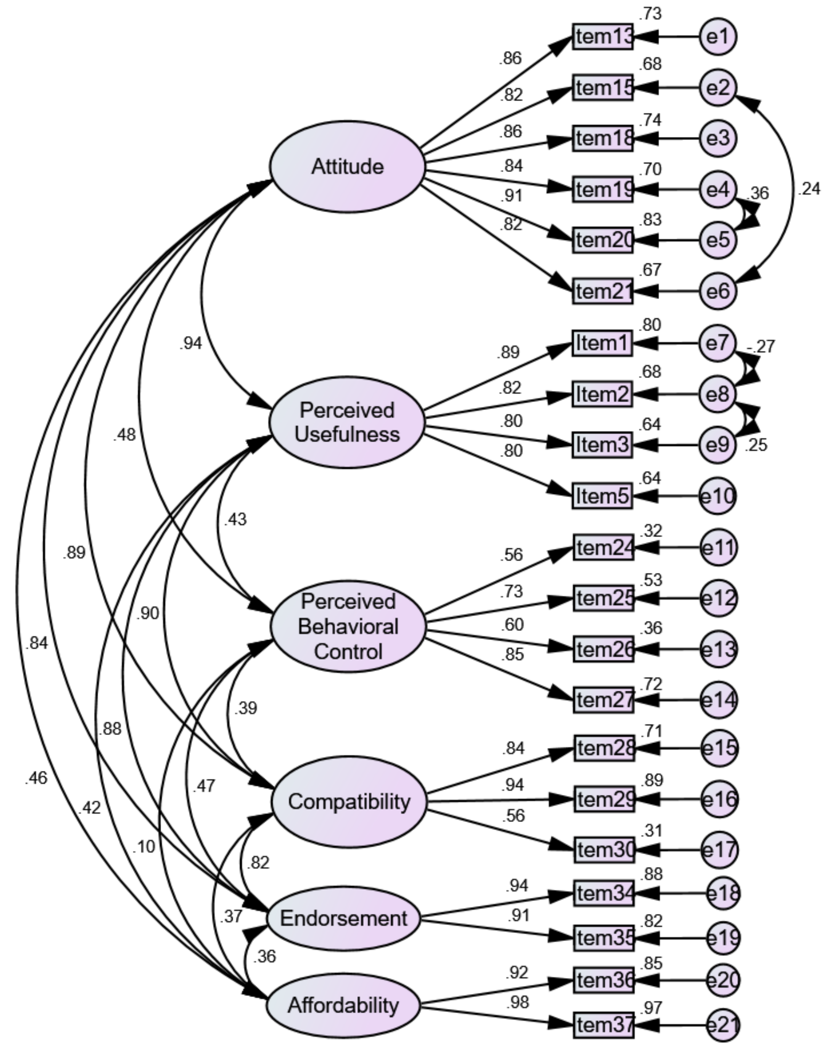

Figure 3.4 Standardized solution for the first-order confirmatory factor model (Standardized regression weights were all statistically significant, $p < 0.001$)

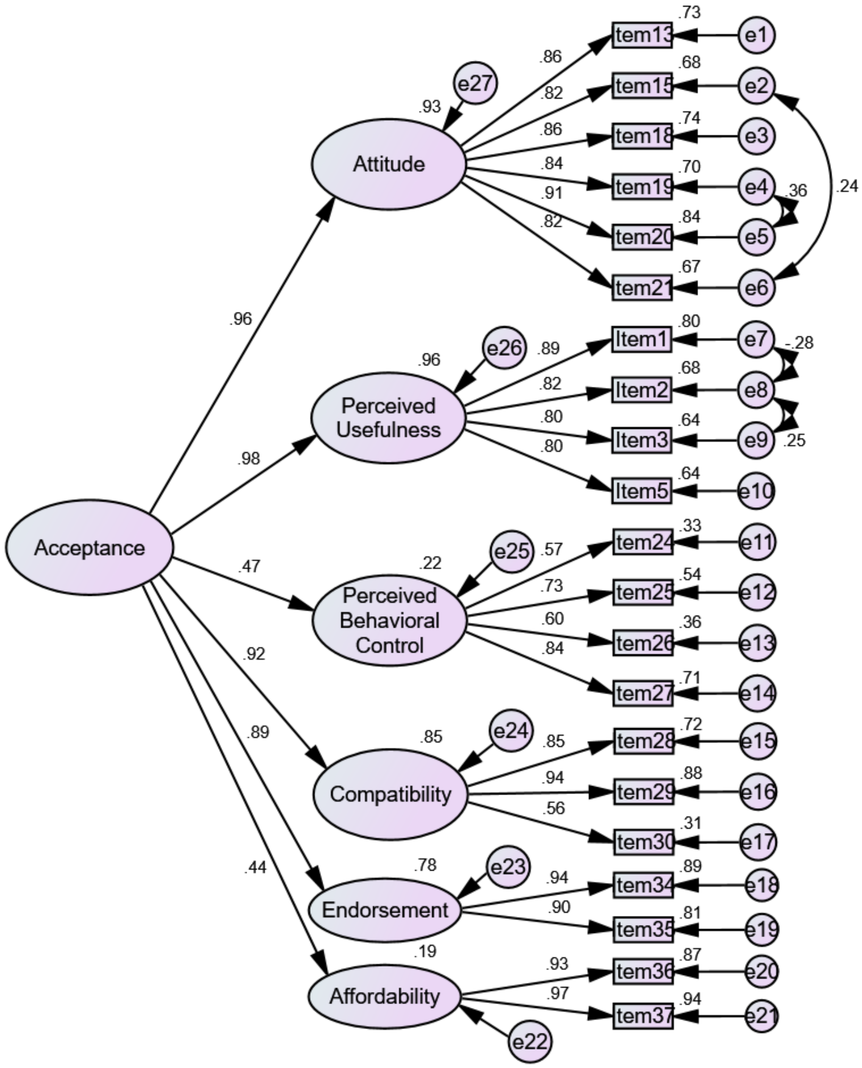

Figure 3.5 Standardized solution for the second-order confirmatory factor model (Standardized regression weights were all statistically significant, $p < 0.001$)

3.3.4.2 Scale 2

The results of the EFA produced a list of 14 survey items which showed a factor loading of greater than 0.6. These 14 items were then used in a CFA to investigate their factor loading on a latent variable: Acceptance. The modification indices suggested adding error covariance between items 3 and 5, 15 and 21, 7 and 9, 8 and 9, 11 and 12, and 13 and 14. In addition, item 2 was deleted due to high standadized error (> 0.4). This version of the scale contains 13 survey items. The final scale is illustrated in Figure 3.6.

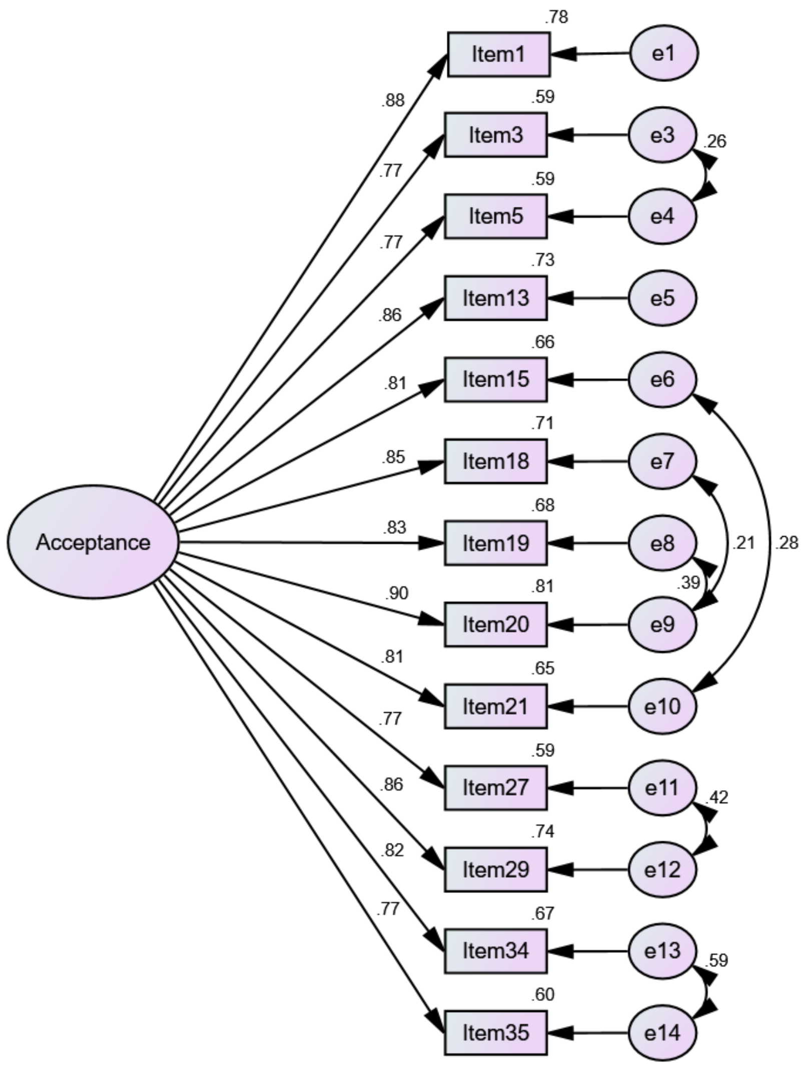

Figure 3.6 Standardized solution for the single-factor confirmatory factor model (Standardized regression weights were all statistically significant, $p < 0.001$)

3.3.4.3 Scale Fit Indices and Predictability of Behavioral Intention

The model fit indices (results of CFA) are summarized in Table 3.6. Both scales showed good model fit, indicating their utility in predicting driver acceptance. To further investigate the two scales effectiveness, composite acceptance scores were calculated for both scales and were regressed on the behavioral intention variable. For Scale -1, the six constructs were measured by averaging the corresponding survey item score. After that, the acceptance score was calculated as the weighted average of the six constructs. The weight of each construct was estimated as the ratio of its factor loading and the sum of the factor loadings of the six constructs. For example, the weight of the Attitude construct was calculated to be 0.2 (0.96 / 0.96 + 0.98 + 0.47 + 0.92 + 0.89 + 0.44 ≈ 0.20). Therefore, for Scale -1, the acceptance score was calculated using the following equation:

$$\begin{aligned} Acceptance = {} & 0.2 * Attitude + 0.2 * Perceived\ Usefulness + 0.1 \\ & * Perceived\ Behavioral\ Control + 0.2 * Compatibility + 0.2 \\ & * Endorsement + 0.1 * Affordability \end{aligned}$$

For Scale -2, the composite acceptance score was calculated by averaging the survey items score. Both of the two scales would generate an acceptance score ranging from 1 to 7 with higher scores being better. The mean acceptance scores generated by Scale – 1 (full version) and Scale – 2 (short version) were found to be 4.72 (min – 1.00, max – 6.95, *SD* – 1.19) and 4.87 (min – 1.00, max – 7.00, *SD* – 1.34) (for comparison, mean Behavioral Intention score was 4.69 (min – 1.00, max – 7.00, *SD* – 1.59)). The results of the regression analyses showed that both scales were able to predict behavioral intention with high adjusted R^2 (Table 3.6).

Table 3.6 Scale fit indices and their predictability of Behavioral Intention

Scales	Model Fit Indices						Calculated Regression Parameters (Reg. Model: BI = Acceptance Score)			
	χ^2	df	χ^2/df	RMSEA	TLI	CFI	Adj. R^2	*B*	*SE B*	β
1. Six first-order factors (A, PU, PBC, Compatibility, Endorsement, Affordability): and one second-order factor (Acceptance)	551.44*	179	3.08	0.07	0.94	0.95	0.87	1.25	0.03	0.93*
2. One-factor (Acceptance)	226.75*	59	3.84	0.08	0.96	0.97	0.88	1.11	0.02	0.94*

Note: * $p < 0.0001$; BI – Behavioral Intention; RMSEA – Root Mean Square Error of Approximation; TLI – Tucker-Lewis Index; CFI – Comparative Fit Index.

3.4 Discussion

This study utilized and combined two different data collection approaches, an online survey approach and a driving simulator approach, to study driver acceptance of ADAS and semi-autonomous driving systems. Since the results found that the driving simulator participants showed a significantly higher intention to use such systems compared to the participants of the online survey, it is important to consider the usefulness of each approach for future research. The difference in acceptance levels was to be expected and can be attributed to the opportunity to experience ADAS functionalities in the driving simulator. Those participants who used the simulator had a chance to interact with the system and to understand the role of the ADAS in their driving. The driving scenario simulated routine operational conditions and the majority of the participants experienced the ADAS without any driving simulator failures. It is very likely that driving simulator participants deemed the simulated system as highly reliable and trustworthy. On the other hand, the online survey participants had to rely on the provided description of the systems to produce a behavioral reaction. Since these types of in-vehicle driver assistance systems are not yet prevalent and since most of the participants were not familiar with the ADAS functionalities, the described system was not able to motivate the participants as efficiently as the driving simulator experience. Participants may not have successfully visualized the functionality of the ADAS and their own interaction with it. However, previous research on this topic seems to disagree with the last argument. Meschtscherjakov et al. (2009) asked participants whether they could imagine the technology based on the provided description and pictures: 85.7% of the participants said ‘yes’. In a different question, 57.1% of the participants disagreed with the statement that it was difficult for them to respond to the survey items without actually using the technology. These findings, combined with the fact that majority of the studies which investigated driver acceptance of an ADAS successfully utilized surveys as a tool (see Table 2.1), provide sufficient evidence to support the suitability of this approach. Furthermore, the results of this study also showed that the results of using different data collection approaches was not significant in the presence of the model constructs. In the end, although a survey approach may not present an ADAS as successfully as a driving simulator approach, both approaches obtain similar results in measuring the effects of each construct on behavioral intention and in creating models of driver acceptance.

The internal consistency of the construct scales was found to be above the acceptable value, except for the Subjective Norms scale. There were two survey items in the Subjective Norms scale: one measured the social pressure by the people who are influencing (idols, celebrities etc.) and the other measured social pressure by the people who are important (family, friend etc.). The lack of internal consistency articulates the fact that participants consider the two type of social pressure differently. Hence, researchers should be careful when using this scale in the context of driver acceptance.

Additionally, due to the lack of internal consistency in this context, the effect of Subjective Norms on behavior intention (Table 3.3) could be problematic to explain. Another finding from the model building analysis that requires caution in explaining is the insignificant effect of Perceived Reliability (Step 7, Table 3.4). This factor was only measured in the driving simulator data collection approach. Therefore, there were may not be enough data points to test its effect in the presence of other factors. Apart from these issues, the constructs of the conceptual model were all found to be able to individually predict behavioral intention. Attitude was found to be the strongest predictor among all constructs, followed by Perceived Usefulness and Performance Expectancy. However, when these constructs were included in the regression model in order to predict behavioral intention (Step 3, Table 3.4), the effect of Perceived Usefulness was much reduced and the effect of Performance Expectancy was found to be non-significant. Perceived Usefulness and Performance Expectancy are beliefs about the outcomes of a behavior and personal evaluations of those outcomes which construct Attitude and eventually Behavioral Intention (Fishbein and Ajzen, 1975; Davis, Bagozzi, and Warshaw, 1989). Therefore, Attitude mediates the effect of these beliefs on Behavioral Intention. The results of this study suggest that Attitude partially mediates the effect of Perceived Usefulness on Behavioral Intention and they together account for the variability in Behavioral Intention that could be explained by Performance Expectancy. The non-significant effect of Performance Expectancy can also be attributed to its high correlation (Pearson's $r = 0.96$, Table 3.2) with Perceived Usefulness.

The Unified Model of Driver Acceptance included six constructs: Attitude, Perceived Usefulness, Perceived Behavioral Control, Compatibility, Endorsement, and

Affordability; and one moderator variable: Personal Innovativeness. The effects of Attitude, Perceived Usefulness, and Perceived Behavioral Control are supported in the findings of previous studies; however, there has been no empirical evidence to support the effect of the other constructs. The effect of Attitude on Behavioral Intention suggests that drivers will be open to using an ADAS or a semi-autonomous driving system if they have a positive affect toward it. Attitude toward a technology is based on belief in improved performance, convenience in performing the task in consideration, social influence, etc. (Davis, Bagozzi, and Warshaw, 1989; Ajzen, 1991). This means that in the context of driver acceptance of ADAS and semi-autonomous driving systems, the usefulness of the assistive systems and driver interaction with them need to be well expressed to create a positive affect toward using these technologies. A social campaign may be launched to educate drivers on the benefits of adopting such technologies and to create social acceptance for them. Perceived Usefulness, which is defined as the belief in improved performance, is connected to several benefits, such as driver convenience and satisfaction, enhanced safety for drivers and other road users, reduced traffic rules violations, etc. The rewards of improved performance should be able to motivate drivers to use in-vehicle technologies.

Although Perceived Behavioral Control showed a positive effect when tested alone, its effect was found to be negative in the presence of other constructs. To understand this change in the direction of effect, Perceived Behavioral Control needs to be considered as a combination of two components: *control over behavior* (includes survey items 24, 25, and 27) and *knowledge* (includes survey item 26). The results suggest that the effect of the *control over behavior* component on BI is positive and greater than that of the *knowledge* component, which has a negative effect on BI. That means that higher control over the use of the in-vehicle driver assistance system and lower knowledge about the technology were found to be associated with higher intention to use that technology. The *control* component corresponds to the interaction with the technology in the simulator or the perceived interaction based on the description in the surveys by means of a mechanism for engaging and disengaging the system and control over the driving task when the system is engaged. On the other hand, the *knowledge* component corresponds to the knowledge required to operate and the usability of the system. The knowledge requirement may not be clear to the participants as they are mostly not familiar with this type of in-vehicle technology. Due the larger effect of the *control over behavior* component, Perceived Behavioral Control showed a positive association with BI when tested alone. However, in the model, other constructs accounted for the variation that could be explained by the *control over behavior* component, leaving only the *knowledge* component as useful. This discussion on the shift in the direction of effect is based on an exploratory analysis which was not planned before the data collection and hence, needs to be confirmed by future studies.

Compatibility was found to be a constructing factor of Behavioral Intention. The significant effect of Compatibility emphasizes that participants want these technologies to fit with the conventional driving task. With fewer surprises and less conflict, these technologies are more likely to be adopted and used. Endorsement was also found to be a constructing factor of Behavioral Intention. It was found that a higher endorsement score leads to a higher intention to use an in-vehicle technology. It is possible that there is a causal relationship between Endorsement and Attitude. A person who has a positive

Attitude toward a behavior would be more likely to advocate for it when appropriate. However, the significant effect of endorsement in the presence of Attitude suggest that Endorsement affects Behavioral Intention above and beyond Attitude. This means, regardless of the Attitude and its correlation with Endorsement, if someone is open to endorse the use of an in-vehicle driver assistance system, s/he will be open to use that technology. Other factors that influence Endorsement may include Perceived Usefulness, Perceived Safety Impact, Trust in the manufacturer, Personal Innovativeness, etc.

Unlike the other constructs, Affordability measures a unique characteristic of a driver's ability to use ADAS and semi-autonomous driving systems. By definition, Affordability can be grouped with Perceived Behavioral Control (Ajzen, 1991); however, historically the scale used for Perceived Behavioral Control never considered the monetary aspect of using a technology. This study is no different. Currently, for most in-vehicle assistive technologies, drivers have the freedom to choose whether to purchase them or not. Regardless of their Attitude, Affordability determines the availability of these technologies to use. Affordability may also determine the quality of the purchased technology and consequently affect user experience and adaptation. In some situations (i.e. driving a company car/truck etc.), individual affordability will not affect the availability of these technologies. However, in those cases, the use of such technologies may include volitional control issues.

UMDA performed better than TAM, TPB, and UTAUT in terms of predicting behavioral intention to use ADAS and semi-autonomous driving systems. It should be noted that UMDA contains six constructs while TAM, TPB, and UTAUT contain three constructs at most each. The improved performance of UMDA (an additional 4% in adjusted R^2 over TAM) could be attributed to the increase in the number of constructs. Although 13 constructs were considered in the conceptual model, only 6 were included in the final model, making it arguably less cumbersome than it potentially could have been. Nevertheless, seen from a different perspective, the doubling of the number of constructs from those proposed by TAM, TPB, and UTAUT resulted in only a small improvement in performance. Additionally, it could be argued that TAM, TPB, and UTAUT have performed reasonably well, with an adjusted R^2 of 0.78 or greater, in predicting Behavioral Intention. Therefore, it is worthwhile to discuss why the newly developed driver acceptance model would be more appropriate to adopt in the context of ADAS and semi-autonomous driving systems acceptance. One of the advantages of UMDA over TAM, TPB, and UTAUT is that it includes three completely new constructs: Compatibility, Endorsement, and Affordability. These constructs capture unique characteristics of driver acceptance. The driving task is unlike other daily activities and, most of the time, involves higher risks. Thus, it may be beneficial to model driver acceptance of in-vehicle driver assistance systems and their (appropriate) use including constructs that are specific to the type of assistance system and the driving task. These constructs will potentially make the model more responsive to changes and provide accurate explanation of driver acceptance. Furthermore, with the higher number of constructs, UMDA can provide additional information to researchers that can facilitate a user-centered design approach of such technologies.

The scales that were developed in this study provide a quick and convenient method to assess drive acceptance. The full version of the scale includes 21 survey items and the shorter version of the scale includes 13 survey items. Both of the scales provides a measure of Acceptance ranging from 1 to 7, with 7 being the best score. It was found that the mean acceptance score generated by the full version (Scale- 1) was closer to the mean Behavioral Intention score with lower variability (*SD*) compared to the mean score generated by the short version (Scale- 2). This indicates that the full version is comparatively more accurate than the short version. Thus, the use of the full version of the questionnaire to assess driver acceptance could provide better results compared to the short version. Another advantage that the full version has over the shorter version is that it provides six sub-scale measures that represent the six constructs in the driver acceptance model. On the other, the shorter version includes easier calculation of the Acceptance score and can assess driver acceptance with the same efficiency. Both of these scales can potentially perform better than the currently available Van der Laan scales (Van der Laan, Heino, & de Waard, 1997). The Van der Laan scales only includes survey items that measures drivers' attitude. Similar to the driver acceptance model, the scales that were developed in this study can provide more information to researchers than the Van der Laan scale and thus provide a relatively accurate measure of driver acceptance. The two versions of the questionnaire are provided in Appendix C and Appendix D with instructions to use the tools.

3.5 Conclusions

Advance driver assistance systems and semi-autonomous driving systems have the potential to make the transportation system safer through reduction in unsafe driver behavior and fatal accidents. Recognizing this potential, new in-vehicle driver assistance systems are being developed every year. In addition, federal authorities are recommending and in some cases requiring some of these technologies as standard features in motor vehicles. On March 31, 2014, the U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA) issued a rule that requires all new vehicles under 10,000 pounds to have rear visibility technology by May 2018 (NHTSA, 2014). On March 17, 2016, NHTSA and the Insurance Institute for Highway Safety announced an agreement with 20 major automakers in the U.S. to include automatic emergency braking as a standard feature by September 1, 2022 (NHTSA, 2016). NHTSA also recommends Forward Collision Warning (FCW) and Lane Departure Warning (LDW) system for safe driving (NHTSA, 2014). These examples reflect a future with more and more in-vehicle driver assistance systems being available and integrated into motor vehicles. As most of these systems require drivers to adapt, ensuring driver acceptance is essential for the successful implementation of these systems.

This study was intended to develop a driver acceptance model of ADAS and semi-autonomous driving systems and a questionnaire to assess driver acceptance. Based on the analyses of the data collected using two approaches, the Unified Model of Driver Acceptance (UMDA) was developed that included six constructs: Attitude, Perceived Usefulness, Perceived Behavioral Control, Compatibility, Endorsement, and Affordability. Two versions of a driver acceptance questionnaire were also created based on the driver acceptance model. Limitations of this study include imbalance in the sample sizes for the two data collection approaches. Results showed a significant difference between the Behavioral Intention scores for the two approaches. Although this difference was not significant in the presence of model constructs, caution should be exercised in future studies that intend to merge data from different sources.

With the acceptance model and the questionnaires, the current driver acceptance can be assessed at any point of time. However, acceptance is a social phenomenon with many underlying constructs and can change continuously. For example, a transport technology may not seem promising to a driver after the initial exposure, yet s/he may discover new advantages after using the system several times. This continuous process of adaptation, however, is difficult to explain with the previously mentioned tools. In the process of adaptation, a driver should discover new characteristics (both positive and negative) of the technology that will change the level of acceptance by affecting the perception of usefulness, usability, reliability of the system, trust, and satisfaction, among other factors. Thus, the change in acceptance due to adaptation can be explained by the change in the constructs and their effects on behavioral intention and actual use.

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CHAPTER IV

VALIDATION OF THE UNIFIED MODEL OF DRIVER ACCEPTANCE AND THE ACCEPTANCE ASSESSMENT QUESTIONNAIRE

4.1 Introduction

In 2014, 32,675 people were killed and an additional 2.3 million people were injured in motor vehicle crashes in the U.S. (National Center for Statistics and Analysis, 2015). An overwhelming 94% of these fatalities were caused by human error (NHTSA, 2015). To reduce the number of accidents on the road, government and private efforts have been made to improve vehicle design and to include intelligent technological features that can improve driver situation awareness by providing information and in some cases additional vehicle control. These advanced technological features are generally named Advanced Driver Assistance Systems (ADAS), and are designed to improve driver performance in order to avoid traffic accidents and/or to mitigate their severity. In spite of the potential benefits, however, there are some barriers to successful implementation of these technologies: achieving driver acceptance is one of them.

Advanced Driver Assistance Systems (ADAS) assist drivers in recognizing and reacting to potentially dangerous traffic conditions. ADAS vary from simple systems that provide drivers with important information to complex systems that take over parts of the driving task. Examples of currently available ADAS include lane departure and collision warning systems, adaptive cruise control, collision avoidance systems, etc. In the last few decades, the invention and implementation of new ADAS has seen great progress. The justifications behind this increasing rate of ADAS development and implementation include improved safety (reduction in number of accidents), comfort to the driving population, environmental impact, etc. (Brookhuis, De Waard, and Janssen, 2001). These types of in-vehicle driver assistance systems, however, require drivers to adjust their role and to release partial or complete control of the vehicle. In addition, the method of providing the driver-support information, if not done appropriately, may distract drivers' attention from the road and the driving task. On the other hand, drivers expect an assistance system to meet high requirements in providing better subjective performance (physical and mental comfort), reliability (low rate of false alarms), and safety (low rate of missed detections) (Gietelink, Ploeg, De Schutter, and Verhaegen, 2006). With evidence available of ADAS technology failure, drivers may be skeptical of the utility of these technologies. These issues may hinder the successful implementation of ADAS, and hence, the study of driver acceptance is of great importance.

The research field focusing on driver acceptance of ADAS is currently in a very early stage, as most of the research effort has been invested in the development and testing of such technologies. Several studies have been done to explore factors that influence acceptance of ADAS. These studies have identified a long list of influential factors. Prior to this study, there had been only one unified model proposed to assess acceptability of ADAS (Vlassenroot et al., 2010). However, this unified model contains 14 factors, which may be too many for a usable evaluation technique. There is no specific direction currently on how to assess acceptability of ADAS. Some researchers have adopted the Technology Acceptance Model (TAM), the Theory of Planned Behavior

(TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT) to model driver acceptance. Recognizing the need of a driver acceptance model specifically, beyond a general technology acceptance model, this dissertation has developed a driver acceptance model (the Unified Model of Driver Acceptance) along with two versions of acceptance assessment questionnaire (Scale-1 and Scale-2). The results of the study that developed the acceptance model and the questionnaire are summarized and discussed in Chapters 2 and 3. In order to validate the findings, data was collected using two approaches: a driving simulator approach and an online survey approach. The utility of TAM, TPB, and UTAUT in the context of ADAS acceptance was also assessed.

4.2 Methods

This study began by investigating the effects of the constructs of TAM, TPB, and UTAUT on Behavioral Intention to use ADAS. It tested the postulates (listed in section 2 of Chapter 2) of TAM, TPB, and UTAUT and found the utility of these theories in the context of ADAS acceptance; these findings are summarized in Chapter 2. In Chapter 3, the Unified Model of Driver Acceptance (UMDA) was developed based on previous technology acceptance models in general and driver acceptance models, specifically. In addition, two versions of a driver acceptance assessment questionnaire were developed in Chapter 3. In this chapter, the findings of Chapters 2 and 3 were tested on different ADAS to determine the validity of the models and the questionnaire.

4.2.1 Data Collection and Study Materials

Two data collection approaches were used: a driving simulator approach and an online survey approach. Detailed description of the two approaches are provided below:

4.2.1.1 Driving Simulator Approach

For this approach, an ADAS that provides warnings of lane departure and eminent collision (see the description of System-1 in the Appendix E for more details) was simulated in a high-fidelity driving simulator. The driving simulator included a Nissan Maxima cab mounted on a six degree-of-freedom hexapod motion base. The actual vehicle controls used were the steering wheel, accelerator and brake pedals, and gear shift. The simulator modeled a mid-sized sedan with an automatic transmission. Three large screens delivered approximately 180 degrees of visual angle to the front of the vehicle, two built-in LCDs functioned as side mirrors, and another screen was placed behind the simulator, providing an immersive virtual environment for driving scenarios.

The experimental sessions started with the informed consent signed by the participants, followed by a demographic survey. Next, a researcher explained the controls of the simulator and then the participants completed a familiarization drive that lasted 5-8 minutes. After the familiarization drive, the participants were briefed on the functionalities of the simulated ADAS. The simulated system was able to detect and provide warnings for lane departure, imminent crashes with other moving vehicles, pedestrians crossing the road, and other stationary objects that were in close proximity to the path of the vehicle. This briefing was followed by the experimental drive in which the drivers experienced the simulated lane departure and collision avoidance warning systems. The simulated driving scenario started in a city with several 4-way-stop intersections. The participants were instructed to continue driving straight and the city road led to a 4-lane highway. Just before entering the highway, the participants heard the first collision avoidance warning as a pedestrian was crossing the road. A few minutes later, the participants heard a second collision avoidance warning due to a stopped vehicle that was parked close to the highway. Other than these two fixed warnings, participants heard a lane departure warning whenever the subject vehicle departed the lane and a collision avoidance warning whenever the subject vehicle was dangerously close to the vehicle in front of it. The experimental drive lasted 8-12 minutes. Participants were closely monitored for any symptoms of simulator sickness, and before and after every drive their susceptibility to simulator sickness was assessed with a simulator sickness survey adapted from Kennedy, Lane, Berbaum, and Lilienthal, (1993). After the experimental drive, participants were given an acceptance survey. The responses of the survey items were used to measure the constructs of the models.

4.2.1.2 Online Survey Approach

In the online survey approach, each participant read a description of an ADAS. Two ADAS were selected for the survey approach (System-1 and System-2, see Appendix E). Half of the participants read the description of System-1 and the other half read the description of System-2. Participants were instructed to think about their daily commute or their most frequent commute to work and/or school and to consider how the described ADAS can assist them in this commute. They then responded to several survey questions based on the description of the ADAS and their perception of its utility. The survey items used in this approach were the same as in the simulator approach. To make sure that the participants were attentive to the survey, two check questions were included that instructed them to provide a specific response and 5 survey items were reverse scaled. Participants were recruited and compensated through Amazon Mechanical Turk (https://www.mturk.com). The online survey was created in Survey Monkey (https://www.surveymonkey.com).

4.2.1.3 Survey Items

A total of 44 items were included in the survey to measure the constructs and moderating variables of the conceptual model. Since Subjective Norms and Social Influence constructs are very similar by definition and most often are measured by the same scale, this study chose to follow this precedent. Table 4.1 lists the survey items and the corresponding constructs. All survey items (except for the questions that included their own scales) were measured on a 7-point Likert scale, where 1 = strongly disagree, 2 = moderately disagree, 3 = somewhat disagree, 4 = neutral (neither disagree nor agree), 5 = somewhat agree, 6 = moderately agree, and 7 = strongly agree. To measure the constructs, participants' ratings on the corresponding survey items were averaged. For example, Perceived Usefulness was measured averaging the responses of items 1, 2, 3, and 5.

4.2.2 Participants

Thirty-seven participants (22 males and 15 females) were recruited from the student population of Mississippi State University for the simulator data collection study. These participants were 18 – 48 years old (M = 23.68 years, SD = 6.71), native or fluent English speakers, with self-reported normal or corrected-to-normal visual acuity, and no self-reported hearing difficulties. For the online survey study, 402 people were recruited through Amazon Mechanical Turk to participate. Of these, 17 participants missed one or both of the check questions and were removed from the final dataset, leaving a final sample of 385 participants (214 males and 171 females; 20-75 years old, *Mean* Age = 35.44 years, *SD* Age = 11.20). Of the online survey participants, 62.6% were college graduates or higher, 95.1% had normal (20/20) or corrected-to-normal visual acuity, 97.7% had no hearing difficulties, and 96.6% were currently able to drive at the time of the survey administration. The description of System-1 (also simulated in the driving simulator approach) was read by 192 participants, and the description of System-2 by 193 participants.

4.2.3 Data Analysis

The datasets from the two approaches were merged. In the complete dataset, data sources were separated by a new variable: *data-type* which was coded as 0 for the simulator data and 1 for the online survey data. Another variable called *system-type* (coded as 0 for System-1 of the online survey and the simulated system, and 1 for System-2 of the online survey) was also included to distinguish the data for the two different driver-assistance systems.

The data analysis included assessing the internal consistency of the construct scales (with Cronbach's alpha), multiple regression analyses, and confirmatory factor analyses. For the assessment of the internal consistency, if the alpha value for any of the scales was found to be less than 0.70, bivariate correlation analyses were done to identify and remove the item(s) that had contributed to the poor internal consistency. Before running regression analyses, the validity of the assumptions was checked using scatter plots of residuals vs predictor variables, residuals vs fitted values, and Q-Q plots. To identify and remove highly influencing samples (outliers), Cook's *D* statistics was used; the cases that had a Cook's *D*-value of more than 4/*N* (= 4/422 = 0.00947) were removed from the analysis (Cook and Weisberg, 1980). Finally, confirmatory factor analyses were done to validate the two versions of the acceptance assessment questionnaire. Model fitness of the questionnaire was assessed using the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), and the Tucker Lewis Index (TLI). The acceptable values for RMSEA, CFI, and TLI were taken to be 0.08 or less, over 0.90, and over 0.90 respectively (Kim and Bentler, 2006; Kenny, 2015). Statistical analyses were carried out in IBM SPSS (version 23) and IBM SPSS AMOS (version 23).

4.3 Results

4.3.1 Reliability of Construct Scales and Descriptive Statistics

The mean and SD of the survey items are presented in Table 4.1. The internal consistency of the scales was found to be acceptable; the Cronbach's alpha for all the scales was equal to or greater than 0.70. The mean and the standard deviation of the scales and the bivariate correlation between them are presented in Table 4.2. It is apparent that the scales (representing different constructs) are generally highly correlated with each other. The results also showed that 15.4% (17.9% for System-1 and 12.4% System-2) of the participants had never heard of, and 96.4% (94.7% for System-1 and 98.4% for System-2) of the participants had never used, an ADAS similar to the one that they were exposed to (through the simulator or the description) during the study.

Table 4.1 Survey items with observed mean and SD (N = 422).

Constructs and Survey Items	Mean	SD
Perceived Usefulness (items – 1, 2, 3, 5) – adapted from Venkatesh and Davis (2000)		
Performance Expectancy (items – 1, 4, 5, 6) – adapted from Venkatesh et al. (2003) and Adell (2009)		
1. I would find the system useful in my driving	5.18	1.47
2. Using the system when driving would increase my safety	5.46	1.36
3. Using the system would enhance effectiveness in my driving	5.21	1.39
4. Using the system would enable me to react to unsafe driving conditions more quickly	5.42	1.36
5. Using the system would improve my driving performance	4.73	1.50
6. If I use the system, I will decrease my risk of being involved in an accident	5.36	1.44
Perceived Ease of Use (items – 7, 9, 10, 12) – adapted from Venkatesh and Davis (2000)		
Effort Expectancy (items – 7, 8, 9, 11) – adapted from Venkatesh et al. (2003) and Adell (2009)		
7. My interaction with the system would be clear and understandable	5.76	1.09
8. It would be easy for me to become skillful at using the system	5.87	1.11
9. I would find the system difficult to use	5.93	1.24
10. Interacting with the system would not require a lot of mental effort.	4.92	1.80
11. Learning to operate the system would be easy for me	5.80	1.19
12. I would find it easy to get the system to do what I want it to do.	5.51	1.18
Attitude – adapted from Van der Laan et al. (1997)		
13. The use of the system when I am driving would be Good	5.32	1.44
14. The use of the system when I am driving would be Useful	5.57	1.34
15. The use of the system when I am driving would be Undesirable	5.34	1.71
16. The use of the system when I am driving would be Effective	5.37	1.32
17. The use of the system when I am driving would be Alerting	5.46	1.35
18. The use of the system when I am driving would be Pleasant	4.92	1.46
19. The use of the system when I am driving would not be Annoying	4.33	1.82
20. The use of the system when I am driving would be Likeable	5.15	1.51
21. The use of the system when I am driving would be Worthless	5.75	1.47
Subjective Norms, Social Influence – adapted from Venkatesh and Davis (2000) and Adell (2009)		
22. People who influence my behavior would think that I should use the system.	4.41	1.52
23. People who are important to me would not think that I should use the system.	4.98	1.59
24. Most of my family and friends would believe I should use this technology.	4.71	1.50
25. Most of my family and friends would use this technology	4.56	1.59
Perceived Behavioral Control – adapted from Venkatesh et al. (2003)		
26. I have control over using the system.	5.84	1.26
27. I have the resources necessary to use the system.	5.72	1.27
28. I do not have the knowledge necessary to use the system.	5.94	1.34
29. Given the resources, opportunities and knowledge it takes to use the system, it would be easy for me to use the system.	5.86	1.12
Compatibility – adapted from Moore and Benbasat (1991)		
30. The system is compatible with all aspects of my driving.	5.09	1.52
31. I think that using the system fits well with the way I like to drive	5.08	1.59
32. Using the system wouldn't complement my driving style.	4.90	1.79

Table 4.1 (Continued)

Constructs and Survey Items	Mean	SD
Endorsement – adapted from Najm et al. (2006) and Nodine et al. (2011)		
33. I would recommend that my family and friends buy vehicles equipped with the system.	5.01	1.52
34. I would recommend that my child, spouse, parents – or other loved ones –use the system.	5.14	1.57
Affordability – adapted from Regan et al. (2006)		
35. How much would you be willing to pay for the system if it were an optional feature in a new car? __1__ < $250; __2__ $251-$500; __3__ $501-$750; __4__ $751-$1000; __5__ $1001-$1250; __6__ $1251-$1500; __7__ > $1500	2.80	1.64
36. How much would you be willing to pay the system if it could be retrofitted to an existing car? __1__ < $250; __2__ $251-$500; __3__ $501-$750; __4__ $751-$1000; __5__ $1001-$1250; __6__ $1251-$1500; __7__ > $1500	2.74	1.63
Behavioral Intention - adapted from Adell (2009)		
37. If the system is available in the market at an affordable price I intend to purchase the system.	4.49	1.76
38. If my car is equipped with a similar system, I predict that I would use the system when driving.	5.37	1.62
39. Assuming that the system is available, I intend to use the system regularly when I am driving.	5.00	1.70
Experience – author created scale		
40. You have just experienced an intelligent driving system. Prior to this experience, please indicate your familiarity with such systems: 8- I've never heard of a similar driving system. 9- I may have heard of a similar driving system. 10- I am moderately familiar with similar systems but never used when driving. 11- I am quite familiar with similar systems but never used when driving. 12- I've had few instances when I used similar systems when driving. 13- I occasionally use a similar system when driving. 14- I regularly use a similar system when driving.	2.48	1.06
Personal Innovativeness – adapted from Agarwal and Prasad (1998) and Chen and Chen (2011)		
41. If I heard about a new technology, I would look for ways to experiment with it.	5.31	1.16
42. Among my peers, I am usually the first to try out new technologies.	4.57	1.62
43. In general, I am hesitant to try out new technologies.	5.33	1.48
44. I like to experiment with new technologies.	5.47	1.22

4.3.2 Variations in Behavioral Intention due to different data collection approaches and ADAS Type

There was no significant difference in Behavioral Intention observed due to the difference in the data collection approaches or in ADAS types. To test these differences, a multiple linear regression analysis was carried out with the *data-type* and *system-type* variables. The *data-type* variable (coded as 0 for simulator data and 1 for online survey data) showed no effect on Behavioral Intention (B = -0.48, $SE\ B$= 0.28, β = -0.09, $p >$ 0.05). Similarly, the *system-type* variable (coded as 0 for System-1 of the online survey and the simulated system and 1 for System-2 of the online survey) did not show any effect on Behavioral Intention (B = -0.12, $SE\ B$= 0.16, β = 0.04, $p >$ 0.05). Therefore, these two variables were not considered further in the assessment of the models.

Table 4.2 Internal consistency of the scales (on the diagonal), bi-variate correlations, and descriptive statistics ($N = 422$).

Constructs	Mean	SD	BI	Att	PU	PEoU	SN	PBC	PE	EE	Com	End	Afford
BI	4.95	1.57	0.92										
Att	5.25	1.19	.89**	0.93									
PU	5.15	1.28	.88**	.89**	0.92								
PEoU	5.53	0.99	.45**	.58**	.49**	0.70							
SN	4.67	1.28	.70**	.69**	.69**	.41**	0.83						
PBC	5.84	0.96	.40**	.53**	.43**	.71**	.36**	0.76					
PE	5.17	1.26	.86**	.89**	.98**	.50**	.68**	.45**	0.90				
EE	5.84	1.00	.48**	.59**	.51**	.84**	.44**	.81**	.51**	0.88			
Com	5.02	1.44	.83**	.85**	.80**	.50**	.64**	.46**	.80**	.50**	0.85		
End	5.08	1.47	.83**	.81**	.79**	.50**	.71**	.44**	.78**	.52**	.74**	0.90	
Afford	2.77	1.6	.49**	.41**	.43**	.12*	.38**	.15**	.43**	.18**	.40**	.43**	0.95

Note: * Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

4.3.3 Assessment of TAM, TPB, and UTAUT

4.3.3.1 Original TAM

Table 4.3 presents several individual regression analyses on the constructs from the original TAM. According to the findings of Test 1 (Table 4.3), the original TAM model (BI = A + PU) was able to explain 87% of the variance in Behavioral Intention. The test also revealed that Behavioral Intention was significantly influenced by Attitude and Perceived Usefulness with stronger effect for Attitude. Attitude was found to be significantly influenced by Perceived Usefulness and Perceived Ease of Use (Test 3). In addition, the mediating effects of Attitude and Perceived Usefulness were also confirmed from Test 2 and Test 4, respectively. Test 2 depicts that, individually, Perceived Usefulness can significantly predict Behavioral Intention (Adj. $R^2 = 0.81$, $B = 1.04$). The addition of Attitude to this model reduced the effect of Perceived Usefulness from 1.04 to 0.47. This significant reduction in effect ($Z = 12.92$, $p < 0.05$) indicates a partial mediation by Attitude for the effect of Perceived Usefulness on Behavioral Intention. This also confirms that Perceived Usefulness has a significant effect on Behavioral Intention, above and beyond Attitude. On the other hand, it was found that Perceived Usefulness partially mediated the effect of Perceived Ease of Use on Attitude (Test 4). According to Test 4, Perceived Ease of Use individually was able to explain 37% of the variability in Attitude. Adding Perceived Usefulness to the model significantly reduced the effect of Perceived Ease of Use from 0.73 to 0.20 ($Z = 11$, $p < 0.05$), confirming the mediation effect of Perceived Usefulness. These results validate the findings presented in Chapter 2 related to original TAM and provides more evidence of the utility of this model in the context of driver acceptance. Based on Cook's *D* statistic, 28 highly influencing samples (outliers) were removed from the data set.

Table 4.3 Assessment of Technology Acceptance Model (Original) (N = 394)

Tests	Adj. R^2	B	$SE\ B$	95% CI	β
1. BI = A + PU					
Outcome: Behavioral Intention	0.87				
Predictor: Attitude		0.68	0.05	0.58, 0.79	0.55**
Predictor: Perceived Usefulness		0.47	0.05	0.37, 0.56	0.40**
2. A mediates the effect of PU on BI					
Step 1 Model: BI = PU					
Outcome: Behavioral Intention	0.81				
Predictor: Perceived Usefulness		1.04	0.03	0.99, 1.09	0.90**
Step 2 Model: A = PU					
Outcome: Attitude	0.81				
Predictor: Perceived Usefulness		0.83	0.02	0.79, 0.87	0.90**
Step 3 Model: BI = A + PU					
Outcome: Behavioral Intention	0.87				
Mediator: Attitude		0.68	0.05	0.58, 0.79	0.55**
Predictor: Perceived Usefulness		0.47	0.05	0.37, 0.56	0.40**
3. A = PU + PEoU					
Outcome: Attitude	0.83				
Predictor: Perceived Usefulness		0.75	0.02	0.70, 0.79	0.81**
Predictor: Perceived Ease of Use		0.20	0.03	0.14, 0.26	0.17**
4. PU mediates the effect of PEoU on A					
Step 1 Model: A = PEoU					
Outcome: Attitude	0.37				
Predictor: Perceived Ease of Use		0.73	0.05	0.64, 0.82	0.61**
Step 2 Model: PU = PEoU					
Outcome: Perceived Usefulness	0.30				
Predictor: Perceived Ease of Use		0.71	0.06	0.60, 0.81	0.55**
Step 3 Model: A = PU + PEoU					
Outcome: Attitude	0.83				
Mediator: Perceived Usefulness		0.75	0.02	0.70, 0.79	0.81**
Predictor: Perceived Ease of Use		0.20	0.03	0.14, 0.26	0.17**

** $p < 0.001$

4.3.3.2 Refined TAM

The refined TAM does not consider Attitude as a construct, only Perceived Usefulness and Perceived Ease of Use. This study validated that Perceived Usefulness and Perceived Ease of Use significantly influence Behavioral Intention in the context of driver acceptance. The refined TAM model (BI = PU + PEoU) was able to explain 81% (Adj. $R^2 = 0.81$) of the variability in Behavioral Intention (Test 1 in Table 4.4). However, as compared to the effect of Perceived Ease of Use, Perceived Usefulness showed much stronger effect on Behavioral Intention. The results of Test 2 (Table 4.4) confirmed the mediating effect of Perceived Usefulness for the effect of Perceived Ease of Use on Behavioral Intention. Perceived Ease of Use alone can significantly predict Behavioral Intention. Addition of Perceived Usefulness in the model significantly reduced the effect ($Z = 11.27$, $p < 0.05$) of Perceived Ease of Use on Behavioral Intention from 0.80 to 0.08, indicating a partial mediation by Perceived Usefulness. This also confirms that Perceived Ease of Use has a significant effect on Behavioral Intention, above and beyond Perceived Usefulness. These results validate the findings presented in Chapter 2 related to refined TAM and provides more evidence of the utility of this model in the context of driver acceptance. Based on Cook's D statistic, 29 highly influencing samples (outliers) were removed from the data set.

Table 4.4 Assessment of the Refined Technology Acceptance Model (N = 393)

Tests	Adj. R^2	B	$SE\ B$	95% CI	β
1. BI = PU + PEoU					
Outcome: Behavioral Intention	0.81				
Predictor: Perceived Usefulness		0.99	0.03	0.93, 1.05	0.87**
Predictor: Perceived Ease of Use		0.08	0.04	0.01, 0.16	0.05*
2. PU mediates the effect of PEoU on BI					
Step 1 Model: BI = PEoU					
Outcome: Behavioral Intention	0.27				
Predictor: Perceived Ease of Use		0.80	0.07	0.67, 0.92	0.52**
Step 2 Model: PU = PEoU					
Outcome: Perceived Usefulness	0.29				
Predictor: Perceived Ease of Use		0.72	0.06	0.61, 0.83	0.54**
Step 3 Model: BI = PU + PEoU					
Outcome: Behavioral Intention	0.81				
Mediator: Perceived Usefulness		0.99	0.03	0.93, 1.05	0.87**
Predictor: Perceived Ease of Use		0.08	0.04	0.01, 0.16	0.05*

** $p < 0.001$

4.3.3.3 Theory of Planned Behavior (TPB)

The TPB model was able to explain 87% (Adjusted R^2 = 0.87) of the variance in Behavioral Intention with Attitude, Subjective Norms, and Perceived Behavioral Control being significant predictors (Table 4.5). Among the constructs, Attitude showed a stronger effect than Subjective Norms on Behavioral Intention, while Perceived Behavioral Control displayed a negative relationship (B = -0.05). These results validate the findings presented in Chapter 2 related to the assessment of TPB and provides more evidence of the utility of this model in the context of driver acceptance. Based on Cook's D statistic, 35 highly influencing samples (outliers) were removed from the data set.

Table 4.5 Assessment of the Theory of Planned Behavior (N = 387)

Test	Adj. R^2	*B*	*SE B*	95% *CI*	β
1. BI = A + SN + PBC					
Outcome: Behavioral Intention	0.87				
Predictor: Attitude		1.02	0.04	0.94, 1.09	0.82*
Predictor: Subjective Norms		0.22	0.03	0.15, 0.28	0.18*
Predictor: Perceived Behavioral Control		-0.08	0.04	-0.15, -0.01	-0.05*

*$p < 0.05$, ** $p < 0.001$

4.3.3.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT model (BI = PE + EE + SI) explained 82% of the variance in Behavioral Intention with Performance Expectancy and Social Influence being significant predictors (Table 4.6). Among the constructs, Performance Expectancy showed stronger effect in the model. Several moderating effects (see section 2 in Chapter 2) were proposed in UTAUT. However, the results of this study found no evidence of any moderating effect except for the moderating effect of Experience influencing the effect of Social Influence on Behavioral Intention (for Experience * Social Influence: B = -0.12, $SE\ B$= 0.06, β = -0.08, $p < 0.05$). These results do not completely validate the findings presented in Chapter 2 related to UTAUT but still, provide additional evidence of the utility of this model in the context of driver acceptance. Based on Cook's D statistic, 25 highly influencing samples (outliers) were removed from the data set.

Table 4.6 Assessment of the Unified Theory of Acceptance and Use of Technology ($N = 397$)

Tests	**Adj. R^2**	***B***	***SE B***	**95% *CI***	***β***
1. BI = PE + EE + SI					
Outcome: Behavioral Intention	0.82				
Predictor: Performance Expectancy		0.79	0.04	0.72, 0.87	0.69**
Predictor: Effort Expectancy		0.07	0.04	-0.01, 0.15	0.05
Predictor: Social Influence		0.29	0.04	0.22, 0.35	0.24**

* $p < 0.05$, ** $p < 0.001$

4.3.4 Validation of the Unified Model of Driver Acceptance (UMDA)

The results found that all constructs (Attitude, Perceived Usefulness, Perceived Ease of Use, Compatibility, Endorsement, and Affordability) of UMDA, can significantly predict Behavioral Intention (Table 4.7). Attitude showed the strongest effect on Behavioral Intention among the constructs and Perceived Behavioral Control showed a negative effect. The moderating effect of Personal Innovativeness influencing the effect of Endorsement on Behavioral Intention (for Personal Innovativeness*Endorsement: B = -0.10, $SE\ B$= 0.04, β = -0.07, $p < 0.05$) was also observed. Based on Cook's D statistic, 37 highly influencing samples (outliers) were removed from the data set.

Table 4.7 Assessment of the Unified Theory of Acceptance and Use of Technology ($N = 385$)

Tests	Adj. R^2	*B*	*SE B*	95% *CI*	*β*
1. BI = Att + PU + PBC + Com + End + Aff					
Outcome: Behavioral Intention	0.91				
Predictor: Attitude		0.45	0.06	0.34, 0.56	0.36**
Predictor: Performance Expectancy		0.28	0.04	0.19, 0.37	0.24**
Predictor: Perceived Behavioral Control		-0.08	0.03	-0.14, -0.02	-0.05*
Predictor: Compatibility		0.15	0.04	0.08, 0.22	0.14**
Predictor: Endorsement		0.26	0.03	0.20, 0.32	0.26**
Predictor: Affordability		0.07	0.02	0.03, 0.10	0.07**

* $p < 0.05$, ** $p < 0.001$

4.3.5 Comparison among TAM, TPB, UTAUT, and UMDA

UMDA performed the best with an adjusted R^2 of 0.91, while the original TAM and TPB models performed similarly with an adjusted R^2 of 0.87. The UTAUT and refined TAM models performed the worst among the models with adjusted R^2 of 0.82 and 0.81, respectively. Results of the Hotellings t-test for non-independent correlations showed that the UMDA accounted for significantly more variance in Behavioral Intention than other models (for the difference with original TAM: $t = 4.96$, $df = 375$, $p < 0.05$).

4.3.6 Validation of the Acceptance Assessment Scale

The results of the Confirmatory Factor Analysis (CFA) showed good factor loading of the items on the corresponding constructs of the first version of the acceptance assessment questionnaire (Scale-1) (Figure 4.1, generated in IBM SPSS AMOS). The factor loading of the constructs on the second-order factor (Acceptance) was also found to be greater than the acceptable value. The modification indices suggested adding error covariance between items 6 and 10. Similarly, for Scale-2 (the second version of the acceptance assessment questionnaire), the results of CFA showed good factor loading of the items on Acceptance (single factor) (Figure 4.2). The modification indices suggested adding error covariance between items 5 and 9, and 6 and 8. After adding the error covariances, both models representing the two versions of the acceptance assessment questionnaire (Scale-1 and Scale-2) exhibited acceptable values of RMSEA, CFI, and TLI to indicate a good fit (Table 4.8). Furthermore, the Acceptance score for every participant was calculated based on Scale-1 and Scale-2, and these scores were then regressed on Behavioral Intention to validate the ability of the scales to generate an acceptance score that is predictive of the Behavioral Intention to use an ADAS. The results of the regression analyses showed that both scales generate an acceptance score that can significantly predict Behavioral Intention with an adjusted R^2 of 0.87.

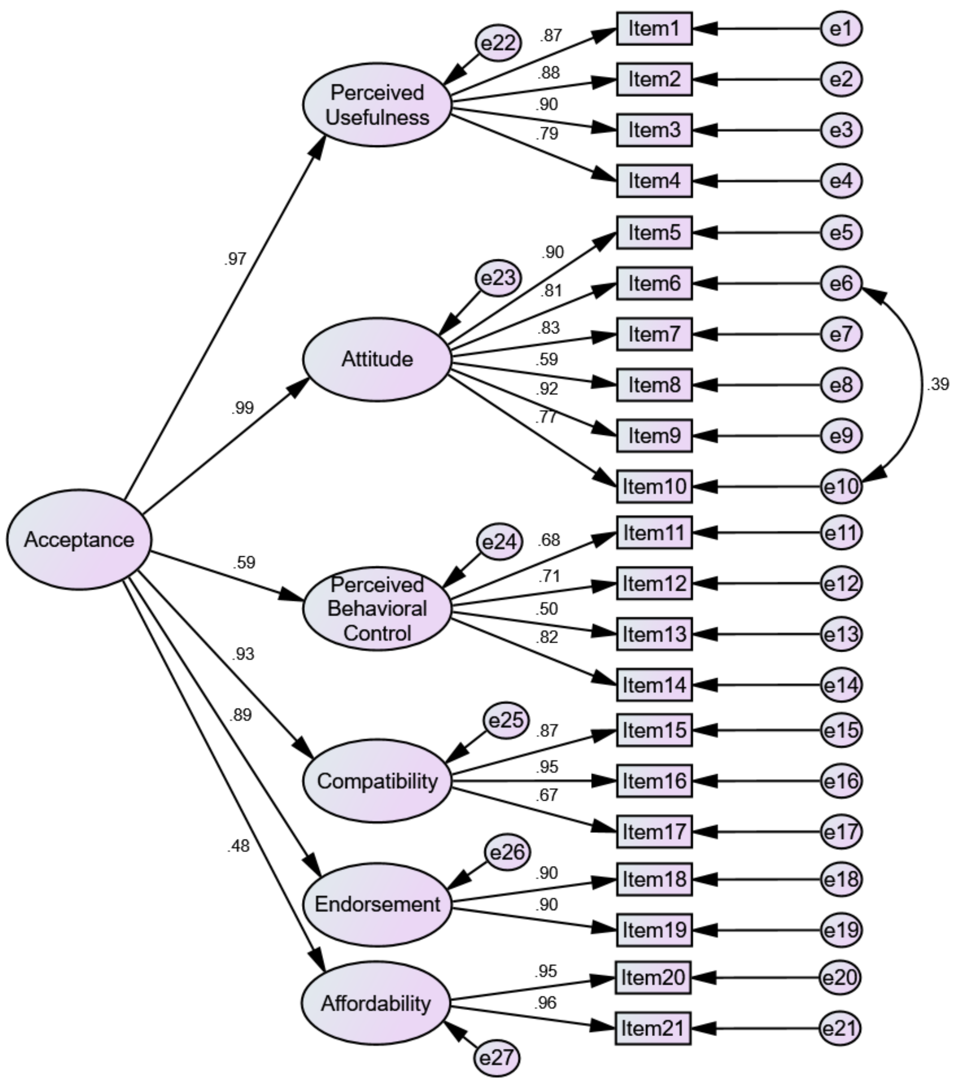

Figure 4.1 Results of Confirmatory Factor Analysis for the Scale-1.

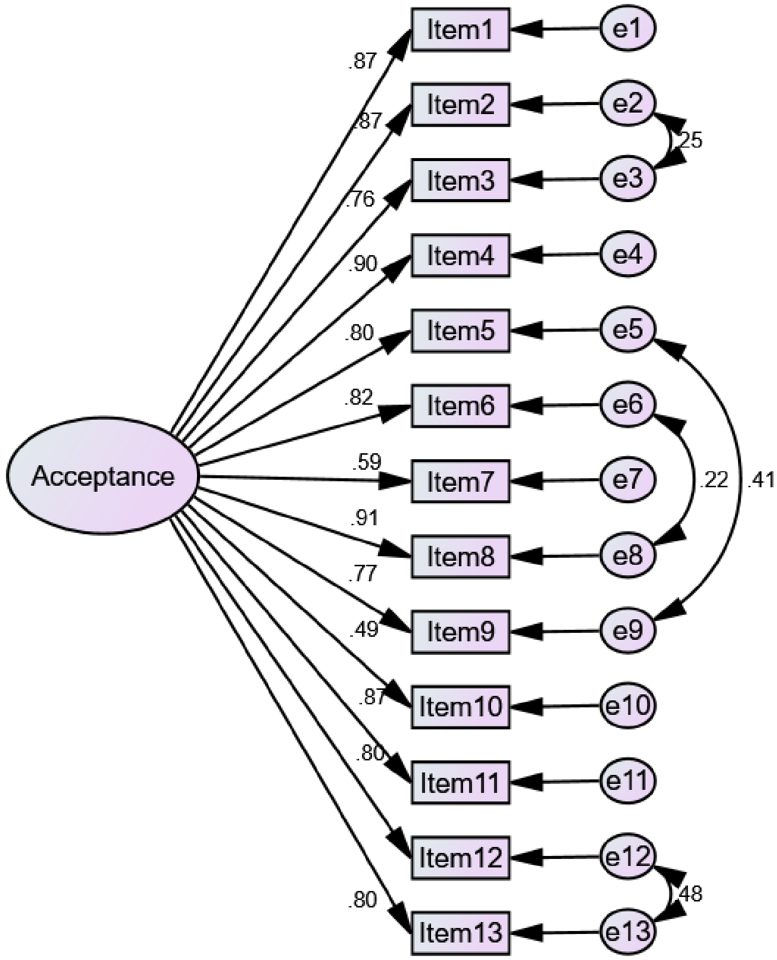

Figure 4.2 Results of Confirmatory Factor Analysis for the Scale-2.

Table 4.8 Scale fit indices and their predictability of Behavioral Intention.

Scales	Model Fit Indices						Calculated Regression Parameters (Reg. Model: BI = Acceptance Score)			
	χ^2	df	χ^2/df	RMSEA	TLI	CFI	Adj. R^2	*B*	*SE B*	β
1. Six first-order factors (A, PU, PBC, Compatibility, Endorsement, Affordability): and one second-order factor (Acceptance)	414.76*	182	2.28	0.06	0.96	0.97	0.87	1.21	0.02	0.93*
2. One-factor (Acceptance)	139.08*	61	2.28	0.06	0.98	0.98	0.87	1.13	0.02	0.93*

Note: * $p < 0.001$; BI – Behavioral Intention; RMSEA – Root Mean Square Error of Approximation; TLI – Tucker-Lewis Index; CFI – Comparative Fit Index

4.4 Discussion

This study was intended to validate the findings of the previous study summarized in Chapters 2 and 3 with two data collection approaches: a driving simulator approach and an online survey approach. Similar to the previous study, participants who experienced the ADAS in driving simulator showed higher Behavioral Intention to use an ADAS compared to the participants who read about the ADAS in the online survey approach. However, this difference was not found to be statistically significant. On the other hand, unlike the previous study, participants were more familiar with the ADAS presented in this study. In the previous study 37% of the participants said that they have never heard of an ADAS similar to the one that they were exposed to; for this study only 15.4% of the participants responded the same. Nevertheless, in both the studies more than 96% of the participants said that they have never used a similar ADAS. This unfamiliarity and low hand-on experience may hinder driver acceptance of the ADAS and hence initiatives should be taken to inform drivers on the benefits and functionality of such technologies and to create social acceptance for them.

The assessment of TAM, TPB, and UTAUT produced almost the same results as did the assessment in the previous study. In this study, for the original TAM, Attitude and Perceived Usefulness were found to be significant predictors of Behavioral Intention. Attitude showed a stronger effect on Behavioral Intention compared to the effect of Perceived Usefulness, however, the difference in the effect of the two constructs was not as big as was found in the previous study. Other postulates of the original TAM were supported by the results of this study and none of the related results were different from the previous study. The assessment of the refined TAM also supported the results of the previous study and validated the postulates proposed by the model in this context. The assessment of TPB showed that Attitude, Social Norms, and Perceived Behavioral Control to be significant predictors of Behavioral Intention. The results found positive effects for Attitude and Social Norms with stronger effect from Attitude and a negative effect for Perceived Behavioral Control. Although TPB proposed a positive effect, this study and the previous one found a negative effect for Perceived Behavioral Control on Behavioral Intention in the context of driver acceptance of ADAS. For UTAUT, the results of this study found Performance Expectancy and Social Influence to be significant predictors of Behavioral Intention. However, unlike the results of the previous study, this study didn't find any effect of Effort Expectancy. Finally, even though the previous study did not find any evidence of moderating effects, this study found moderating effect of Experience influencing the effect of Social Influence on Behavioral Intention.

The Unified Model of Driver Acceptance (UMDA) developed in the previous study was able to explain 90% (Adj. R^2 = 0.90) of the variability in Behavioral Intention. The results of this study provided statistical evidence of the direct effects of Attitude, Performance Expectancy, (a negative effect of) Perceived Behavioral Control, Compatibility, Endorsement, and Affordability, and the moderating effect of Personal Innovativeness influencing the effect of Endorsement on Behavioral Intention. The evidence provided by this study was able to validate UMDA. Similarly, this study was also able to provide statistical evidence in support of the two versions of assessment questionnaire (Scale-1 and Scale-2). Both scales showed good structural consistency and were able to generate an acceptance score that can significantly predict Behavioral Intention with similar efficiency as found in the previous study.

4.5 Conclusions

Advanced Driver Assistance Systems and semi-autonomous driving systems are the future of our transportation system that could eventually lead to a fully automated transportation system. Achieving driver acceptance is a barrier to the successful implementation of these system. Recognizing the research need, this dissertation developed a driver acceptance model (the Unified Model of Driver Acceptance) and two versions of an acceptance assessment questionnaire. In this study, the driver acceptance model and the acceptance assessment questionnaire were validated using two systems (ADAS). Future study should focus on finding the utility of these tools (the model and the questionnaire) in the context of other ADAS.

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CHAPTER V

CONCLUSIONS AND FUTURE STUDY

ADAS and semi-autonomous driving systems are the future of transportation systems. These technologies offer significant reductions in vehicle crashes and fatal accidents on the road. The potential benefits of adopting these in-vehicle technologies have been recognized by several federal and private research organizations. Furthermore, automakers are developing and introducing new and improved technologies every year. It is an important time to study driver acceptance of ADAS and semi-autonomous driving systems, as many researchers have identified achieving driver acceptance as a barrier to the successful implementation of these technologies. The aims of this dissertation were to summarize and synthesize the different approaches adopted by researchers to study driver acceptance, assess the utility of (general) technology acceptance models in the context of driver acceptance, and develop a driver acceptance model and an acceptance assessment questionnaire. The findings of this dissertation are listed below:

Literature Review. The results of the literature review identified inconsistency in the current approaches adopted by researchers. It was found that researchers have defined acceptance differently and have adopted several models and numerous factors to model driver acceptance. The various approaches adopted to study driver acceptance indicate that driver acceptance is a complex concept with multiple dimensions and that researchers are not all addressing the same dimensions in their research.

Evaluation of Existing Models. The results of the first study showed that the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT) can successfully model driver acceptance of ADAS and semi-autonomous driving systems. These models perform reasonably well, explaining more than 75% of the variance in acceptance (Behavioral Intention).

Development of a driver acceptance model. The Unified Model of Driver Acceptance (UMDA) was developed in the first study as a technology acceptance model designed specifically for driver-assistance technology and was validated in the second study of this dissertation. This model includes six constructs of driver acceptance: Attitude, Perceived Usefulness, Perceived Ease of Use, Endorsement, Compatibility, and Affordability. The UMDA was able to perform better than TAM, TPB, and UTAUT in the context of driver acceptance and explained 90% of the variance in Behavioral Intention.

Development of acceptance assessment questionnaire. This dissertation also developed and validated two questionnaires (a long version and a short version) to provide means for the assessment of driver acceptance. The questionnaires showed good internal consistency and were able to generate acceptance scores that were highly correlated to Behavioral Intention.

The findings of this dissertation improve the understanding of the multifaceted concept of driver acceptance and provide researchers and developers with tools to define and assess driver acceptance of ADAS and semi-autonomous driving systems. Future research should focus on validating the findings of this dissertation with different driver-assistance systems and experimental methods (for example, in a field operation test study). Future research should also focus on the process of driver adaptation as these in-vehicle technologies are being implemented and how the adoption of these technologies would affect driving skill and behavior (for example, situation awareness).

APPENDIX A

SCALES USED TO MEASURE CONSTRUCTS

Perceived Usefulness (items – 1, 2, 3, 5) – adapted from Venkatesh and Davis (2000)

Performance Expectancy (items – 1, 4, 5, 6) – adapted from Venkatesh et al. (2003) and Adell (2009)

1. I would find the system useful in my driving
2. Using the system when driving would increase my safety
3. Using the system would enhance effectiveness in my driving
4. Using the system would enable me to react to unsafe driving conditions more quickly
5. Using the system would improve my driving performance
6. If I use the system, I will decrease my risk of being involved in an accident

Perceived Ease of Use (items – 7, 9, 10, 12) – adapted from Venkatesh and Davis (2000)

Effort Expectancy (items – 7, 8, 9, 11) – adapted from Venkatesh et al. (2003) and Adell (2009)

7. My interaction with the system would be clear and understandable
8. It would be easy for me to become skillful at using the system
9. I would find the system difficult to use
10. Interacting with the system would not require a lot of mental effort.
11. Learning to operate the system would be easy for me
12. I would find it easy to get the system to do what I want it to do.

Attitude – adapted from Van der Laan et al. (1997)

13. The use of the system when I am driving would be:

    Bad : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Good

14. The use of the system when I am driving would be:

    Useless : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Useful

15. The use of the system when I am driving would be:

    Desirable : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Undesirable

16. The use of the system when I am driving would be:

    Ineffective : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Effective

17. The use of the system when I am driving would be:

    Sleep-inducing : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Alerting

18. The use of the system when I am driving would be:

    Unpleasant : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Pleasant

19. The use of the system when I am driving would be:

    Extremely Annoying : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Not at all Annoying

20. The use of the system when I am driving would be:

    Irritating : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Likeable

21. The use of the system when I am driving would be:

    Assisting : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Worthless

<u>Subjective Norms</u>, <u>Social Influence</u> – adapted from Venkatesh and Davis (2000) and Adell (2009)

22. People who influence my behavior would think that I should use the system.

23. People who are important to me would not think that I should use the system.

Perceived Behavioral Control – adapted from Venkatesh et al. (2003)

24. I have control over using the system.

25. I have the resources necessary to use the system.

26. I do not have the knowledge necessary to use the system.

27. Given the resources, opportunities and knowledge it takes to use the system, it would be easy for me to use the system.

Compatibility – adapted from Moore and Benbasat (1991)

28. The system is compatible with all aspects of my driving.

29. I think that using the system fits well with the way I like to drive

30. Using the system wouldn't complement my driving style.

Trust – adapted from Najm et al. (2006) and Ghazizadeh et al. (2012)

31. I think I can depend on the system for safe driving.

32. I would feel more comfortable doing other things (e.g., checking emails on my smartphone) with the system engaged.

33. I would feel comfortable if my child, spouse, parents – or other loved ones – drove a vehicle equipped with the system.

Endorsement – adapted from Najm et al. (2006) and Nodine et al. (2011)

34. I would recommend that my family and friends buy vehicles equipped with the system.

35. I would recommend that my child, spouse, parents – or other loved ones – use the system.

Affordability – adapted from Regan et al. (2006)

36. How much would you be willing to pay for the system if it were an optional feature in a new car?

1	2	3	4	5	6	7
< $250	$251-$500	$501-$750	$751-$1000	$1001-$1250	$1251-$1500	> $1500

37. How much would you be willing to pay the system if it could be retrofitted to an existing car?

1	2	3	4	5	6	7
< $250	$251-$500	$501-$750	$751-$1000	$1001-$1250	$1251-$1500	> $1500

Behavioral Intention

38. If the system is available in the market at an affordable price I intend to purchase the system.

39. If my car is equipped with a similar system, I predict that I would use the system when driving.

40. Assuming that the system is available, I intend to use the system regularly when I am driving.

Perceived Reliability – author-created scale

41. Based on your experience with the system, how would you rate the system

Not at all Reliable : 1 : 2 : 3 : 4 : 5 : 6 : 7 : Highly Reliable

Experience – author created scale

42. You have just experienced an intelligent driving system. Prior to this experience, please indicate your familiarity with such systems:

1- I've never heard of a similar driving system.

2- I may have heard of a similar driving system.

3- I am moderately familiar with similar systems but never used when driving.

4- I am quite familiar with similar systems but never used when driving.

5- I’ve had few instances when I used similar systems when driving.

6- I occasionally use a similar system when driving.

7- I regularly use a similar system when driving.

<u>Personal Innovativeness</u> – adapted from Agarwal and Prasad (1998) and Chen and Chen (2011)

43. If I heard about a new technology, I would look for ways to experiment with it.
44. Among my peers, I am usually the first to try out new technologies.
45. In general, I am hesitant to try out new technologies.
46. I like to experiment with new technologies.

Note. All items (except for the questions that has scales given) was measured on a 7-point Likert scale, where 1 = strongly disagree, 2 = moderately disagree, 3 = somewhat disagree, 4 = neutral (neither disagree nor agree), 5 = somewhat agree, 6 = moderately agree, and 7 = strongly agree. To measure the constructs, participants’ ratings on the survey items under each scale was averaged.

APPENDIX B

DESCRIPTION OF THE DRIVER ASSISTANCE SYSTEMS AND DRIVING SCENARIOS – STUDY 1

System 1

You have recently bought a new car and among its features is a driver assistance system that is designed for safe driving. The system can be turned on using a button on the steering wheel. The system can be turned off at any time by pressing the same button on the wheel or by pressing on the brake pedal. Once the system is turned on, it will:

- Keep your car in the lane it is currently travelling in
- Keep the car at a constant speed, slowing down around curves as necessary
- Keep a safe distance from other vehicles and obstacles around you
- Stop at a safe distance from stopped vehicles and obstacles and at intersections with red lights.

The driver assistance system cannot automatically change lanes. If you need to change lane, you will need to disengage the system. If the system stops the vehicle at an intersection, it can automatically start moving the vehicle once the traffic light is turned green and eventually it will drive the vehicle at the set speed, if the traffic conditions allow.

Now, suppose that you need to commute to work that takes about 30 minutes on each way. Commuting to work could sometimes be frustrating, however, you are used to it. You live in a suburban area outside a large city, where you work. Your commute includes driving through the residential area in your town, then driving about 20 miles on an interstate followed by driving through the city center. The traffic is generally sparse until you enter the city. Driving in the city involves several signalized intersections, therefore frequent stop-and-go traffic. You are thinking about whether you should use the driver assistance system described above while commuting to work.

System 2

You have recently bought a new car and your car is designed with a feature that can monitor driver alertness based on driving behavior. The system uses a front camera to detect the lane position of the vehicle and based on the information gathered, it evaluates driver alertness. If the system detects a drop in driver alertness, it gives a soft audible and visual warning. If driver alertness further drops, it will give a hard warning with a chime that must be acknowledge by pressing a button on the steering wheel. If the vehicle is stopped and the driver's door is opened, the system will reset itself. The system can be turned off at any time using settings in the instrument cluster.

Now, suppose that you need to commute to work that takes about 30 minutes on each way. Commuting to work could sometimes be frustrating, however, you are used to it. You live in a suburban area outside a large city, where you work. Your commute includes driving through the residential area in your town, then driving about 20 miles on an interstate followed by driving through the city center. The traffic is generally sparse until you enter the city. Driving in the city involves several signalized intersections, therefore frequent stop-and-go traffic. You are thinking about whether you should use the driver assistance system described above while commuting to work.

APPENDIX C

ACCEPTANCE ASSESSMENT QUESTIONNAIRE – FULL VERSION

Instructions:

Step 1: Introduce the ADAS in consideration to the participants with either hand-on experience or written description.

Step 2: Administer the Acceptance Assessment Questionnaire. All items (except for the items 20 and 21, that has scales given) are measured on a 7-point Likert scale, where 1 = strongly disagree, 2 = moderately disagree, 3 = somewhat disagree, 4 = neutral (neither disagree nor agree), 5 = somewhat agree, 6 = moderately agree, and 7 = strongly agree.

Step 3: Calculate the sub-scale factors using the following equations-

Perceived Usefulness = average of the responses on items – 1 through 4

Attitude = average of the responses on items – 5 through 10

Perceived Behavioral Control = average of the responses on items – 11 through 14

Compatibility = average of the responses on items – 15 through 17

Endorsement = average of the responses on items – 18 and 19

Affordability = average of the responses on items – 20 and 21

Step 4: Calculate Acceptance Score using the following equation-

Acceptance = 0.20* Perceived Usefulness + 0.20*Attitude + 0.10*Perceived Behavioral Control + 0.20*Compatibility + 0.20*Endorsement + 0.10*Affordability

Questionnaire

1. I would find the system useful in my driving
2. Using the system when driving would increase my safety
3. Using the system would enhance effectiveness in my driving
4. Using the system would improve my driving performance

5. The use of the system when I am driving would be good

6. The use of the system when I am driving would be desirable

7. The use of the system when I am driving would be pleasant

8. The use of the system when I am driving would not at all be annoying.

9. The use of the system when I am driving would be likeable

10. The use of the system when I am driving would be assisting

11. I have control over using the system.

12. I have the resources necessary to use the system.

13. I have the knowledge necessary to use the system.

14. Given the resources, opportunities and knowledge it takes to use the system, it would be easy for me to use the system.

15. The system is compatible with all aspects of my driving.

16. I think that using the system fits well with the way I like to drive

17. Using the system would complement my driving style.

18. I would recommend that my family and friends buy vehicles equipped with the system.

19. I would recommend that my child, spouse, parents – or other loved ones – use the system.

20. How much would you be willing to pay for the system if it were an optional feature in a new car?

__1__	__2__	__3__	__4__	__5__	__6__	__7__
< $250	$251- $500	$501-$750	$751-$1000	$1001-$1250	$1251-$1500	> $1500

21. How much would you be willing to pay the system if it could be retrofitted to an existing car?

__1__	__2__	__3__	__4__	__5__	__6__	__7__
< $250	$251- $500	$501-$750	$751-$1000	$1001-$1250	$1251-$1500	> $1500

APPENDIX D

ACCEPTANCE ASSESSMENT QUESTIONNAIRE – SHORT VERSION

Instructions:

Step 1: Introduce the ADAS in consideration to the participants with either hand-on experience or written description.

Step 2: Administer the Acceptance Assessment Questionnaire. All items are measured on a 7-point Likert scale, where 1 = strongly disagree, 2 = moderately disagree, 3 = somewhat disagree, 4 = neutral (neither disagree nor agree), 5 = somewhat agree, 6 = moderately agree, and 7 = strongly agree.

Step 3: Calculate the Acceptance Score by averaging the responses on the survey items.

Questionnaire:

1. I would find the system useful in my driving
2. Using the system would enhance effectiveness in my driving
3. Using the system would improve my driving performance
4. The use of the system when I am driving would be good
5. The use of the system when I am driving would be desirable
6. The use of the system when I am driving would be pleasant
7. The use of the system when I am driving would not be at all annoying.
8. The use of the system when I am driving would be likeable
9. The use of the system when I am driving would be assisting
10. Given the resources, opportunities and knowledge it takes to use the system, it would be easy for me to use the system.
11. I think that using the system fits well with the way I like to drive
12. I would recommend that my family and friends buy vehicles equipped with the system.

13. I would recommend that my child, spouse, parents – or other loved ones – use the system.

APPENDIX E

DESCRIPTION OF THE ADAS USED IN THE ONLINE SURVEY – STUDY 2

System 1 (Level 0 Automation)

This system combines the functionalities of a Lane Departure Warning (LDW) system and a Forward Collision Warning (FCW) system. It can be turned on by pressing a button on the steering wheel. The system can be turned off at any time by pressing the same button on the wheel. Once activated, the system will sound an alarm if the vehicle leaves its current lane and will continue alerting the driver until s/he corrects the vehicle position. If the turn signal (indicator) is ON, the system will assume that the driver intends to change lanes and no alarm will be sounded for drifting off the lane. The system can also detect and warn drivers of imminent crashes with moving vehicles. It can detect pedestrians crossing the road and also stopped vehicles on or beside the road and sound an alarm as needed. The lane departure warning sound is a shorter, softer chime than the forward collision warning, which makes the two warning sounds easily distinguishable. If the driver wants to turn on/off a specific functionality (LDW or FCW), s/he can do this before taking off by using the settings in the menu display.

System 2 (Level 2 Automation)

This system combines the functionalities of a lane keeping system and a collision avoidance system. It can be turned on by pressing a button on the steering wheel. The system can be turned off at any time by pressing the same button on the wheel. Once activated, this system takes over the function of keeping the vehicle in the lane it is currently travelling in. It can detect existing lane markers with the help of a front-facing camera. If the system detects that the vehicle is drifting from the lane, it sounds a soft chime with a flashing icon on the dashboard and generates corrective steering torque to keep the vehicle in the lane. If the turn signal (indicator) is ON, the system will assume that the driver intends to change lanes and no warning will be given and no corrective action will be taken to prevent drifting from the lane. The system can also detect imminent crashes with other moving and stopped vehicles on the road and with pedestrians crossing the road. If it detects an imminent crash, it sounds an alarm with a flashing icon on the dashboard and takes complete control of the vehicle, autonomously deciding on an action (braking if the vehicle speed is low or steering if the speed is high) to avoid the crash. If the driver wants to turn on/off a specific functionality (lane keeping or collision avoidance), s/he can do this before taking off by using the settings in the menu display.

Now think about your typical commute to work/school and how the above mentioned system can contribute to your driving. Based on your assessment of the system's functionalities and contributions to your driving, please rate how much you agree or agree with the following statements.