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Digitalization in the transport sector: a quantitative investigation of the adoption of ADAS Technology in trucks from the perspective of the Technology Acceptance Model

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Al coraggio della mia famiglia,

alla vitalità di mia madre,

alla tranquillità di mio padre,

ai sorrisi di mio fratello

e alla fedeltà del nostro Pepe.

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Abstract

Nowadays, digitalization is changing the way of doing business at a global level and being digital is critical for the companies' success.

Road transport remains the European primary mode for freight, with projections indicating a tripling in demand from 2015 to 2050, while these vehicles constitute only 1.5% of road traffic, they are involved in 15% of all road fatalities within the EU. This can contrast with EU's long-term 'Vision Zero' aim with the goal of eliminating all fatalities and serious injuries on European roads by 2050. Thus, the focus of this study is specifically on the digital transformation within the transportation sector through the implementation of sensor technologies, such as Advanced Driver Assistance Systems (ADAS) in trucks. However, despite the mandate for manufacturers to integrate these systems, some can still be disabled by truck drivers. Therefore, this thesis conducts a case study on the driver technology acceptance of these new technologies on trucks with a quantitative study based on 95 surveys.

The findings of this research show which key factors influence technology adoption in this specific sector, namely Attitude Toward Using Technology, Perceived Safety, Performance Expectancy, Self-Efficacy and Effort Expectancy. In terms of theoretical implications, it underscores the importance of developing ADAS that are not only effective but also user-friendly and safe, enhancing their integration into daily operations. Additionally, the study highlights the crucial role of comprehensive training programs within logistics companies, which are essential for fostering positive attitudes toward the use of ADAS and enhancing user proficiency. Lastly, it advocates for active driver participation in training and feedback processes, which is vital for informing company decisions and ensuring that the systems meet the practical needs of the users, thereby facilitating a smoother transition to new technologies. By examining the unique challenges and characteristics this company faces, the research shed light on the cultural and social factors influencing its digital transformation journey. Although based on a single case, the findings aim to offer valuable perspectives on fostering successful digitalization in the transport sector.

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1. Introduction

Digitalization is one of the main phenomena that is changing society and business (Jabłoński & Jabłoński, 2019). It is a globally relevant topic and critical for the success of companies across all sectors in the upcoming years (Zaoui & Souissi, 2020). Digitalization is driving changes in business models by introducing new technologies within organizations to foster growth and it has received increasing attention (Vial, 2019).

As a core component of Industry 4.0, the business landscape is being transformed by the emergence of new technologies such as big data analytics, artificial intelligence, blockchain, additive manufacturing, and augmented and virtual reality (Kane et al., 2022).

Digitalization distinguishes itself from typical business transformations by necessitating prolonged efforts by executives to fundamentally reshape how an organization adapts and evolves, involving significant shifts in organizational structure to maintain a competitive advantage (Kane et al., 2022). Particularly, it causes environmental turbulences that may result in the breakdown of organizational boundaries and the elimination of established methods for organizing production and creating value. Digitalization encompasses changes in structure, processes, function, and business model to achieve strategic benefit (McKinsey & Company, 2023; Karimi & Walter, 2015).

In this digital age, the transport sector plays a paramount function in the daily lives of individuals, facilitating the movement of people, goods, and services between nations (Da Silva et al., 2008). For the European Commission is holding a crucial and highly important role in today's economy and society, significantly impacting growth and employment.[1] The transportation sector is a significant employer, providing jobs to approximately 10 million individuals. Logistics, transport, and storage constitute 5% of the Gross Domestic Product (GDP) and account for 10-15% of the cost of finished products for European companies (European Commission, 2023). Due to its critical requirements for management automation and enhanced reliability, the transport sector was among the earliest adopters of digital technologies. In an era where significant focus is placed on environmental impact and sustainability, digitalization emerges as a pivotal force driving this transition, especially in

[1]https://european-union.europa.eu/priorities-and-actions/actions-topic/transport_en#:~:text=Transport%20is%20a%20cornerstone%20of,the%20contribution%20to%20the%20economy).

the emerging landscape of Industry 5.0. Digitalization is affecting the transport business, especially in the robotization of human labor-intensive aspects (Jannson et al. 2021). Automation has been used for aviation and maritime freight transport for a while, and nowadays it is spreading also into railway systems and road transport (Theis et al., 2018).

Specifically, within road transportation, digitalization is occurring not only through the integration of technology in vehicles but also via the implementation of sensors directly within the infrastructure (Singh et al., 2021). In the context of digital transformation, which involves not only embracing digital technologies but also implementing fundamental changes in business models, strategies, and culture to thrive in the digital age, the primary agents of this narrative remain the vehicles themselves. Recent years have seen significant advancements in automation within ADAS (Keuchel, 2020), reflecting this broader paradigm shift. Especially in commercial freight logistics, the year 2024 has been a significant turning point as the European Commission implements extensive regulations requiring the integration of various advanced driver assistance technologies throughout the continent with the General Safety Regulation (European Commission, 2022). This is part of a major European project. According to recent studies, 76% of EU member states leverage roads as their prime means for cargo shipment. Future numbers suggest that between now and 2050 demand for transportation by road will triple - but while liner trucks comprise only 1.5% of the road traffic, they are involved in a disproportionate 15% of all accidents. This contrasts with the goal of zero deaths, part of the EU's long-term Vision Zero to eliminate all deaths and serious accidents in Europe before 2050.

In anticipation of these forthcoming regulatory mandates, numerous road transport firms are either installing advanced driving technologies in their existing fleet or acquiring new trucks equipped with these devices. This strategic modernization initiative, however, is not devoid of challenges, most notably the palpable apprehension and resistance amongst the workforce. Due to concerns that digitalization may negatively impact low-skill employees' job positions (Chinoracký & Čorejová ,2019).

Understanding the employee dimension, and their acceptance of new technologies, is essential for effectively managing the complexities of digitalization. The investigation into how employees adapt to an increase in automation at work has not been as extensively pursued as research in other areas (Heijden, 2004). And yet, exploring this area is fundamental to understanding the acceptance of automation by employees (Taherdoost, 2018). The adaptation to new technology was explained by previous literature in the most widely cited models the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The TAM model, created by Davis et al. in 1984, serves as a predictive tool for anticipating how a group or organization will adopt new technology (Tang & Chen, 2011). It posits that the intention to use the technology is influenced by its perceived usefulness and ease of use. UTAUT explains almost 70% of the variance in intention (Venkatesh, 2000).

The numerous studies on technology acceptance in vehicles (Stiegemeier et al., 2024; Madigan et al., 2016; Bellet & Banet, 2023) led to the development of theoretical frameworks from the UTAUT like the Car Technology Acceptance Model (CTAM).

Despite the wealth of research on technology acceptance in cars, studies focusing on acceptance in trucks remain scarce (Xu et al., 2021), and there has been no significant development of models derived from TAM or UTAUT specifically for this context. Firstly, differences in technology acceptance in vehicles can be in the primary users of technology: in the case of trucks, it is often employees, like truck drivers, who utilize the technology in a professional setting, whereas technologies are used by vehicle owners for personal purposes. Secondly, in the context of freight transportation, trucks are required to employ technologies due to legal regulations, company policies or safety protocols. This approach is particularly relevant given that earlier investigations into this subject occurred in contexts where technology use was optional, whereas today, such technologies are often compulsory in vehicles (Xu et al., 2021). This shift has a significant impact on the cultural and legislative factors affecting the adoption of systems (Stiegemeier et al., 2022). Despite new regulations requiring manufacturers to install ADAS systems in trucks, these systems can still be disabled—a frequent occurrence among truck drivers who often do not recognize their benefits (Antich, 2023; Crissey, 2022). This study concentrates on Partial Automation, the present and near-future technology to be implemented in trucks. Acceptance in this scenario may differ from that of fully autonomous vehicles, as the driver remains the primary agent in control (Saravanos et al., 2024) Consequently, the significance of various factors may shift. This also has to consider the specific factors of the sector including vehicle load weight and size (Luce, 2022). Thus, the CTAM would likely require adjustments to aptly address technology acceptance in the context of truck usage. A quantitative approach was chosen because it effectively highlights trends within a population and explains the relationships between different variables (Creswell, 2011).

Therefore, this study aims to explore the effects of UTAUT on the acceptance of technology in trucks. Hence the following research question:

RQ: "What are the factors that influence professional truck drivers' intentions to use ADAS technology?".

Additionally, to reduce the issues of low explanatory power and inconsistencies the inclusion of moderators has been done (Sun & Zhang, 2006). Specifically, the existing literature has proved how inconsistencies can be explained through the identification of situational variations with the role of moderators (Davis, 1989; Taylor & Todd, 1995). Hence, the role of moderators has been added:

Sub- RQ: "What are the effects of moderator factors gender, age, and experience in the intention to use ADAS system by truck drivers?".

By addressing the above research questions, this study contributes to existing literature in two main ways. Firstly, since only a limited number of studies have thoroughly examined employees' acceptance of digital transportation in the transport system, this thesis aims to implement and potentially extend the UTAUT model in a new sector. Specifically, a substantial part of the resources focused on the acceptance of the technologies in cars. A study by Marisda et al. (2020) focused on the acceptance of fully autonomous trucks. However, this quantitative study is limited only to 37-size sample in the exclusive context of Indonesia. Nevertheless, none have focused on the acceptance of technology in the context of road transportation.

This research has also practical implications. This study can assist managers in understanding how to ensure and comprehend the impact of employee involvement during the process of digitalization change. It specifically aims to guide managers in fostering employee engagement to successfully overcome the challenges of digital transformation. The primary goal is to identify success factors, barriers, and the impacts of intervention formats that can be effectively applied in this specific sector.

2. Literature review

The subsequent section digs into a discussion of the relevant literature review. It begins with an exploration of the concept of digitalization, particularly emphasizing its escalating significance in recent years. It then analyses the impact of digitalization on the transportation sector, examining changes driven by advancements in both infrastructure and vehicles. The review highlights the integration of sensors in infrastructure and discusses the technologies and sensors utilized in vehicles. Furthermore, it introduces the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to analyze the factors influencing technology adoption. The review also discusses a tailored version of TAM specifically designed for automotive technology and concludes with a presentation of the proposed model for assessing technology acceptance among truck drivers.

2.1 Digitalization

The business world is entering a new digital era (Brynjolsson & McAfee, 2014). This digital era offers a prime opportunity to boost competitiveness in any sector, whether by launching new businesses or enhancing existing operations (Schwab, 2016). Defined as leveraging technology to significantly enhance the performance or scope of enterprises (Westermann et al., 2011), digitalization is reshaping organizational performance and amplifying value creation (Sommer, 2015).

The worldwide expenditure on digital transformation technologies and services is on an impressive trajectory. In 2022, expenditures on digital transformation have hit 1.6 trillion U.S. dollars. Looking ahead to 2026, global spending in this area is anticipated to grow to 3.4 trillion U.S. dollars (Appendix 1). The acceleration of digital transformation across organizations worldwide in 2020 can be attributed to various factors, with the COVID-19 pandemic playing a significant role. This unprecedented event pushed companies to adopt digital technologies at a faster pace. Additionally, the push to satisfy customer expectations and stay competitive in the market has driven this growth. Embracing digital transformation makes organizations more adaptable to market changes and more innovative, ultimately enhancing their resilience (Statista, 2022).

Initial discussions and writings on the digital economy emerged in ’70, when the technological capabilities for encoding information were primarily limited to computer programming and the transmission of data through analog means (Valenduc & Vendramin, 2017). Today, the real protagonist of digitalization is big data that have become the cornerstone of digitalization, driving an exponential increase in the ability to collect, store, and process digitized information (Brynjolfsson and McAfee, 2015; Cardon, 2015; Valenduc & Vendramin, 2017). The analysis and optimization of this data are achieved through sophisticated algorithms capable of processing gigabytes of information in mere seconds, with machine learning and artificial intelligence playing a pivotal role (Valenduc & Vendramin, 2017; Brynjolfsson and McAfee, 2015).

This way of combining new products and services is providing gains in efficiency and productivity. However, the improved conditions are also impacting the labor market affecting employees, their roles, skills, and job descriptions (Kagermann et al., 2014; Vogelsang, 2019; Schwab, 2017). A paper published in 2013 by two Oxford researchers (Frey & Osborne, 2013) predicted that around 40% of existing jobs could be at risk due to digitalization. Subsequent research has underscored that those most adversely affected are likely to be workers with lower qualifications and earnings (Chinoracký & Čorejová, 2019).

2.2 Digitalization in the road transport system

The road transport system is undergoing comprehensive digitalization globally, due to continuous advancement and the pressing need for developmental strategies (Swedish Transport Administration, 2022). This part aimed to investigate the foremost three areas of digitalization and transport systems: Smart infrastructure, Automation and Autonomous Vehicles, and Data and information management. The initial two areas focus on the aggregation of data, while the third delves into the examination of data utilization. Two main objectives drive digitalization to ensure a safer environment, improved by the technologies and efficiency, and ensure that technologies can assist congested transport systems to operate better (Leviakangas, 2016).

2.2.1 Smart infrastructure and information management

The physical road infrastructure is receiving increasing attention, especially due to technology's role in management, maintenance, and investment in road infrastructure (Swedish Transport Administration, 2022). According to the United Nations 2030 Agenda, the transportation network should be improved to ensure it is safer, more affordable, accessible, and sustainable (Singh et al., 2021). In order to obtain this there must be the implementation for the assistance of digital technologies of the Internet of Things (IoT) and Artificial Intelligence (AI). IoT facilitates the interconnection of various physical devices to share data, enabling the tracking and oversight of traffic flow (Li et al., 2017, Qian et al., 2019). AI is pivotal for accuracy in the forecasting of traffic, potential accidents, and weather conditions (Singh et al., 2021).

The integration of sensors and IoT devices can create a dependable and efficient ecosystem for vehicles and drivers (Singh et al., 2021). An effective method to enhance efficiency is through smart lighting on highways, which optimizes energy use by adjusting the lights based on traffic density (Mustafa et al., 2017) and adjusting the intensity of illumination (Garg et al., 2020) also in the tunnel roads (Singh et al., 2021).

Moreover, sensors play a crucial role in the Internet of Things by transforming information from the physical environment into digital data. Integrating IoT principles within the transportation sector can enhance the systems used to monitor and maintain road infrastructure (Micko et al., 2023). For instance, camera systems, utilizing traditional Computer Vision (CV) techniques and sophisticated artificial neural networks, are adept at handling various monitoring operations. Among sensors, Fiber Bragg Grating (FBG) sensors emerge as the most promising intrusive sensors due to their low-cost manufacturing, long service life, and minimal maintenance costs. They are recognized for their ability to classify various events through machine-learning models, despite needing a calibration system (Al-Tarawneh et al., 2020).

Once digitalized, the system can gather real-time traffic data to minimize social issues caused by road congestion. Data are collected in a database, obtained from digitalization, and are used for the prediction of transport congestion, using also the sensor installed on highways and roads (Gohar et al., 2018). R. Singh et al. (2021) analyzed how the smart traffic and emergency management system will work.

Specifically, with The Vehicle-to-Vehicle (V2V), a communication system that enables vehicles to communicate with each other, the vehicle onboard receives the information and communicates with the road infrastructure that groups the data and shares information with the cloud server. When the real-time cloud server receives traffic data, the traffic authority begins monitoring traffic patterns across various locations. If needed, the authority can issue optimal guidelines for other vehicles to help avoid congestion. The emergency system can also access the information and immediately reply to necessities. Emergency management can effectively improve rescue efficiency. A recent analysis conducted by Juniper Research, a leading authority on technology markets, has revealed that expenditures on smart traffic management will experience a significant increase of 75% by the year 2028, rising from a baseline of $10.6 billion in 2023 (Juniper, 2023).

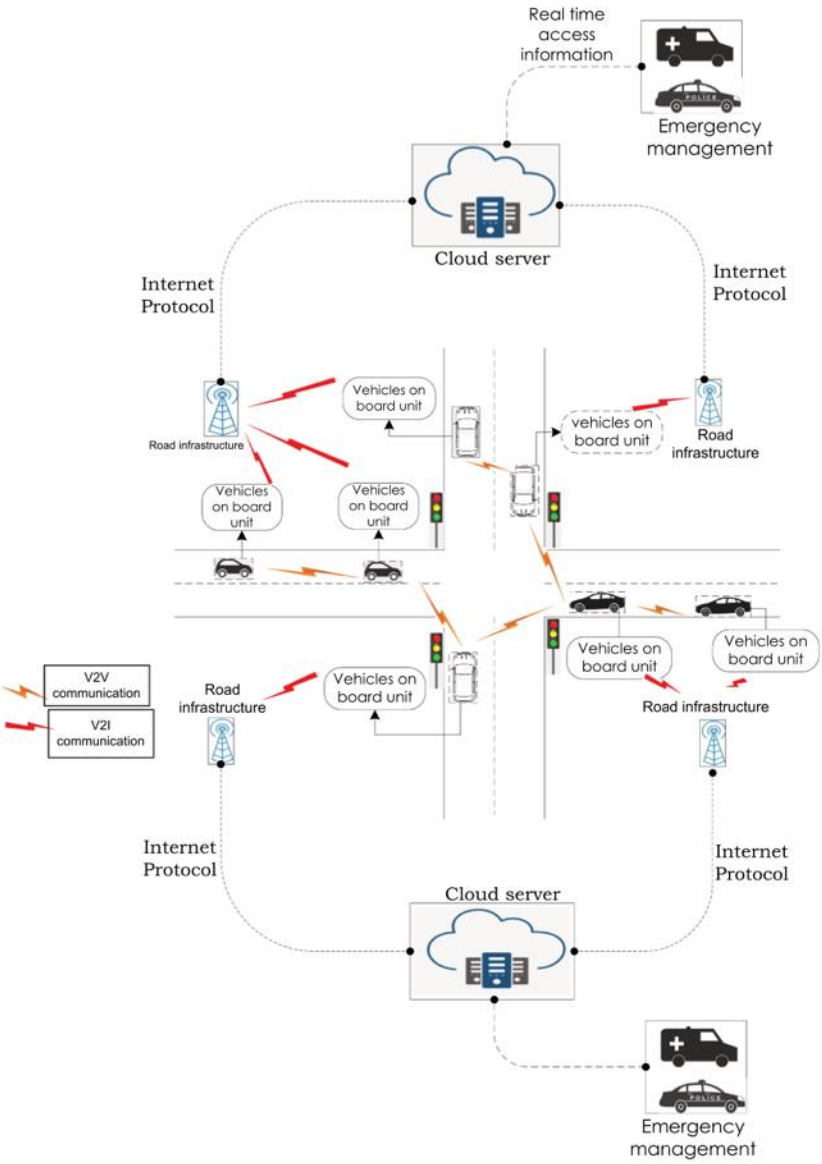

Figure 1 Smart traffic and emergency management (Sing et al., 2021)

2.2.2 Automation and Autonomous Vehicles

The automotive manufacturing industry emerges as a key player in the road sector, with vehicles representing the core services and applications of digitalization alongside emerging technologies (Leviakangas, 2016). Central to vehicle automation are the ADAS, categorized into six levels of automation by the Society of Automotive Engineers (SAE) (Keuchel, 2020). ADAS can offer individualized support in driving situations, yet it may not always consider the capabilities and constraints of older drivers within road environments.

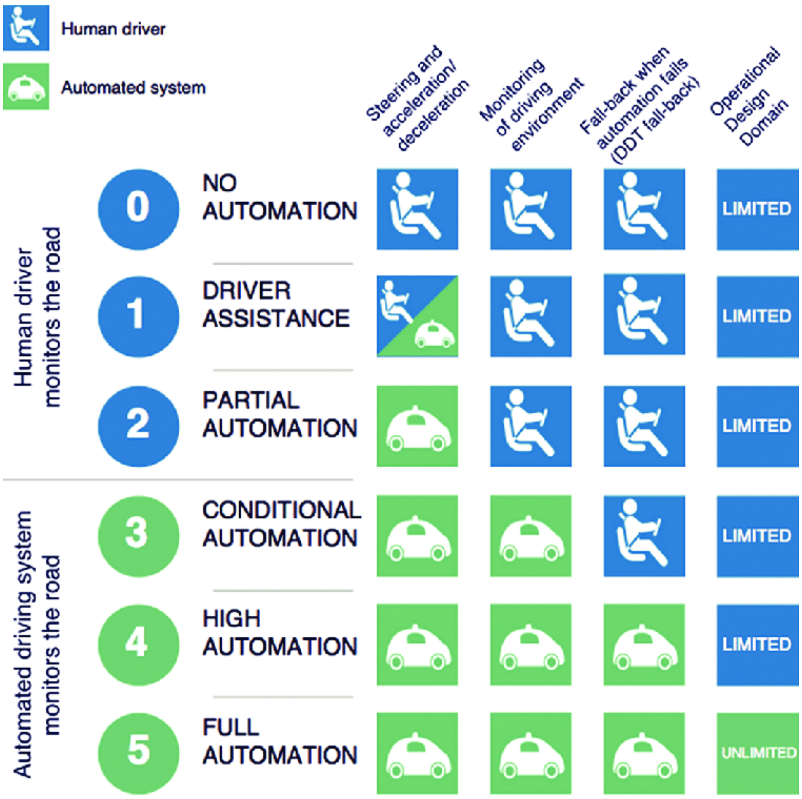

Figure 2. SAE Grade of Automation (Keukel, 2020)

In Level 0 there is no automation. Level 1, or driver assistance, enables the vehicle to manage either acceleration or steering but not simultaneously, with examples including lane-keeping assistance and cruise control (Monolithic Power Systems, 2023). Level 2, also known as partial automation, enables a vehicle to concurrently manage its steering and speed adjustments. Nonetheless, human intervention may be required without warning immediately (Keuchel, 2020). Level 3, or conditional automation, sees the car performing most driving functions and monitoring its environment. An instance of this is Audi's Traffic Jam Pilot system, in which the pilot manages the controls and can start, accelerate, steer, and break until 60 km/h (Audi Media Centre, 2017). At Level 4, known as high automation, the vehicle can independently perform all driving functions in specific scenarios, like restricted areas or designated lanes. Outside of these situations, human intervention becomes necessary. Unlike full automation (Level 5), Level 4 systems may prompt the driver to resume control with some notice, a feature absent in Level 5 automation where no human intervention is required (Keuchel, 2020).

Starting July 2024, all new trucks registered in the European Union must meet the conditions of General Safety Regulations (GSR) for level 2 automation that are currently under development. These regulations were updated in 2019 to incorporate recent advancements in automotive safety technology designed to reduce accidents due to human error (NHTSA,2017). Consequently, a variety of ADAS that assist drivers will be required in all registered new trucks from that date. This initiative supports the EU's long-term 'Vision Zero' aim with the goal of eliminating all fatalities and serious injuries on European roads by 2050 (European Commission, 2022). Potentially saving over 25,000 lives and preventing 140,000 injuries by 2038. The regulation specifies four preventive zones for ADAS in trucks: [2]

1. ADAS breaking. This category encompasses technologies like Automatic Emergency Braking (AEB) and Adaptive Cruise Control (ACC). The new regulations for Automated Emergency Braking Systems (AEBS), effective from 2024, introduce several important enhancements. Previously, the AEBS could be switched off indefinitely, but under the new rules, it can only be deactivated for a maximum of 15 minutes before automatically re-engaging. Additionally, while the earlier regulations required a 1.4 second warning phase before the system would initiate braking, the updated standards allow the system to brake immediately, without alerting the driver beforehand, thereby reducing the time needed to avoid a collision. These new regulations also expand the system's capabilities, requiring trucks to perform emergency stops not only when approaching moving vehicles but also when facing stationary ones—a significant improvement over earlier versions that could only detect moving objects. Furthermore, the updated rules mandate that trucks be able to detect and respond to a single pedestrian crossing in front of the vehicle, although the technology to detect cyclists or groups of pedestrians is not yet included, as such systems are not currently available for trucks according to manufacturers. (DAF truck, 2023).

2. ADAS steering. This category covers technologies designed to help drivers maintain correct vehicle positioning and distance from other vehicles. It includes Emergency Lane Keep Assist (ELKA), which helps keep the vehicle within its lane; Lane Centering (LC) for automatically adjusting steering to keep the vehicle centered in its lane; and Adaptive Steering Control (ASC), which adjusts the steering to help maintain a safe distance from other traffic. Starting from 2024, ELKA will be mandatory in trucks and a supplementary radar will be introduced to support the Drive-off Assist feature,

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[2] https://www.fmcsa.dot.gov/sites/fmcsa.dot.gov/files/202202/ADAS_SAFETY_GUIDE_DRAFT6_081621_508-FINAL.pdf

designed to identify and alert the driver about nearby vulnerable road users, whether stationary or moving. Additionally, a new Rear View Camera will be implemented to provide live visuals of the truck's rear directly to a display inside the cab (DAF truck, 2023).

3. ADAS Warning. This category encompasses systems like Lane Departure Warning (LDW), Forward Collision Warning (FCW), and Blind Spot Warning (BSW). These technologies assist drivers by alerting them to potential hazards, such as nearby vehicles, unintended lane changes, or veering off the lane. Beginning in 2024, drivers will be informed of prevailing speed limits by the Intelligence Speed Assist (ISA) system, which also issues alerts upon exceeding these limits. Additionally, the Emergency Stop Signal enhances road safety with lights flashing during rapid deceleration. To further improve driver safety, new features have been introduced, such as the Advanced Driver Distraction Warning (ADDW) in 2026. This system is designed to monitor and assess the driver's level of attention and alertness while operating the vehicle, providing warnings if attention levels fall below a safe threshold (DAF truck, 2023).

4. The ADAS Monitoring. This category features driver-facing and road-facing cameras designed for unseen area detection, along with Camera-based Mirror Systems (CMS) to broaden the driver's field of view. These technologies are aimed at offering feedback to drivers and aiding industry stakeholders in enhancing driver efficiency and safety. Starting in 2024, the Side & Turn Assist feature will notify the driver of pedestrians, cyclists, or other vehicles in the truck's blind spots, extending coverage to the end of the trailer (DAF, 2023). In addition, the new Alcohol interlock installation facilitation (ALC) will be mandatory. In 2029, the Event Data Recorder will document visuals and data upon activation of the AEBS brake warning. This device will record critical data before, during, and after collisions, aiding in accident analysis, and improving future

vehicle safety standards.

Figure 3. Case study firm data of truck technologies devices

There are several devices with mandatory built-in features for the producer that can be disabled by the driver, as represented in the following table. Although ADAS can mitigate human error by providing drivers with additional information and vehicle control, their effectiveness hinges on driver acceptance, especially since drivers can disable some of these systems. For these systems to be widely adopted, drivers must be willing to invest in and utilize them while driving. Acceptance is a crucial factor influencing the adoption of ADAS (Rahman et al., 2019).

Table 1. Disableable ADAS devices (European Commission, 2022)

New ADAS devices that can be disabled by the driver			
Number	Safety feature	Description	Implementation year
1	Intelligence Speed Assist (ISA)	Helps recognize speed limits and alerts driver, when speed limit is exceeded.	2024
2	Emergency Lane Keeping Assist (ELKA)	A system capable of keeping the vehicle within its lane when it crosses the line.	2024
3	Advanced Emergency Braking System (AEBS)	Renewed and expanded with GSR 2024. Technology that monitors the road ahead applying brakes if detect an imminent collision with another vehicle.	2024
4	Advanced Driver Distraction Warning (ADDW)	A system that detects driver fatigue by constantly analyzing through cameras the driver's level of attention.	2026
5	Alcohol interlock installation facilitation (ALC)	Predisposition of alcoholic interlocks (breathalyzers) in vehicles.	2024

In America, there are no specific upcoming federal mandates for 2024, but industry innovation and standardization efforts are driving the adoption and integration of ADAS technologies. More than 60% of registered vehicles in the U.S. will be equipped with ADAS technologies. However, recent reports from the U.S. Department of Transportation (USDOT) show that large truck crashes have increased over the last five years, contrary to the expected benefits of implementing ADAS systems.

Data for the years 2016 to 2020 collected in the "Large Truck and Bus Crash Facts 2020", report from the Federal Motor Carrier Safety Administration (FMCSA), found number of large trucks involved in fatal crashes increased by 6 percent from a total of 4,562 in 2016 to a total of 4,842 over the subsequent four years (Federal Motor Carrier Safety Administration, 2022). However, the rate of fatal crashes among large trucks per 100 million miles traveled by these vehicles increased by 0.3 percent between 2016-2020; from a metric of 1.58 to a record high of 1.61. Large truck overall fatalities have risen during the last five years by 6%. In addition, nearly 2021 data released by the National Highway Traffic Safety Administration (NHTSA) reflects a significant 17 percent increase in large truck-involved fatal crashes versus 2020 (National Highway Traffic Safety Administration, 2021). It is important to appreciate many different variables account for crash incidents. What all ADAS CAN actually do is assist the driver in avoiding a crash throughout many common driving situations. Nevertheless, the performance of these technologies depends on how well they perform and on **acceptance** by drivers (Federal Motor Carrier Safety Administration, 2024).

2.3 Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT) and their evolutions

The integration of technology into the workplace is a critical issue that continues to attract attention not only in the transportation sector. Nearly three decades ago, the research community began to intensively explore the acceptance of technology in both private and organizational settings, as highlighted by Davis in 1989. It is crucial for organizations to leverage existing knowledge to grasp the systems that shape employees' attitudes toward adopting new technologies. The implementation of these technologies in the workplace has transformed both inter- and intra-organizational communication and has streamlined business operations, leading to advantages such as increased productivity, improved employee well-being, and greater consumer satisfaction (Papagiannidis & Marikyan, 2020). According to Venkatesh and Davis (2000), despite the spreading of technology in companies the information technology adoption and use in the workplace remain a central concern. The success rate of implementation is lower than 30%; this is connected to the technology that must be accepted and used by employees in organizations (Venkatesh et al., 2003). This highlights the crucial role of technology acceptance among organizational members for successful implementation. The TAM, originated by Davis in 1989, was developed as a tool to forecast the probability that a new technology will be adopted by a group or within an organization (Tang & Chen, 2011).

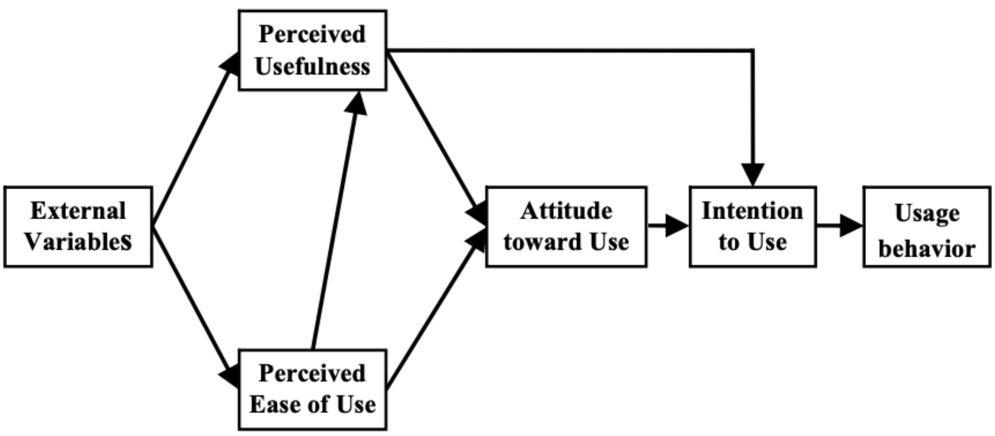


Figure 4. Technology acceptance model (Davis et al., 1989)

At the core, there are the perceived usefulness and the perceived ease of use. The former is the subjective perception of increasing job performance using the specific application system; Perceived ease of use refers to how difficult a prospective user anticipates the technology will be to implement (Venkatesh & Davis, 2000). These two variables influence the intention to use. This influences the usage behavior that is the person's attitude toward using the technology. This theory managed to explain 40% of the variance in usage intention (Davis, 1989). The research underpinning the model was focused on user acceptance in information systems, which meant that when the model was applied more broadly, its explanatory power diminished (Marikyan & Papagiannidis, 2023).

Research continued to accelerate its interest in technology acceptance, numerous models were introduced to understand the acceptance of technology. Many other research models on Information technology acceptance have been yielded (Tang & Chen, 2011). When the UTAUT model was developed, it expanded upon the TAM by including additional elements like social influence and facilitating conditions that were not previously accounted for. This inclusion led to the formulation of the UTAUT model (Venkatesh et al., 2003). The UTAUT was developed by Venkatesh et al. in 2003, unifying multiple theories. This theory managed to arrive at 70% in the explanation of variance being the most predictive model (Tang & Chen, 2011). One of the main advantages of this theory is the fact that with several tests it explained the same variance in user intention of 70% whereas numerous other acceptance models just performed 17-53% (Venkatesh et al., 2003).

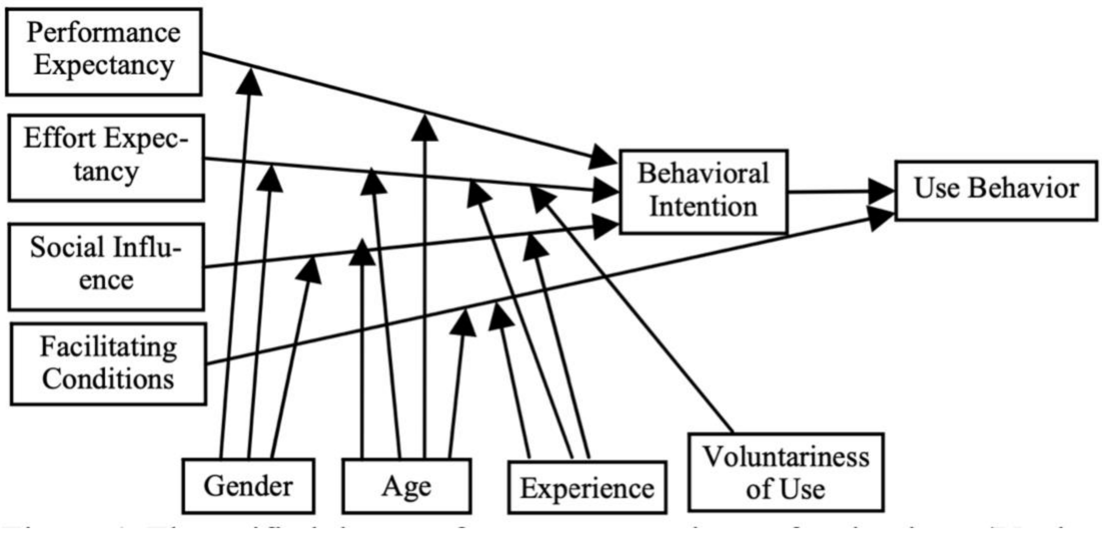


Figure 5. The Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003)

There are now four key constructs: performance expectancy, effort expectancy, social influence, and facilitating condition. These four are mitigated by four variables.

Performance expectancy is “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). It is the strongest predictor of use in intention in both voluntary and mandatory settings (Marikyan & Papagiannidis, 2023). Effort expectancy is “the degree of ease associated with the use of the system” (Venkatesh et al., 2003, p.450) and Social Influence is the degree “to which an individual perceives that important others believe he or she should use the new system” (Venkatesh et al., 2003, p. 451). Social Influence plays a crucial role when the adoption of technology is obligatory. In such scenarios, individuals may use technology because they are required to (Marikyan & Papagiannidis, 2023).

Facilitating Conditions are related to “the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system” (Venkatesh et al., 2003, p. 453). Facilitating the condition will not affect the behavioral intention but, when moderated by age and experience can affect the usage behavior (Venkatesh et al., 2003).

Additionally, there are four moderation variables: age, gender, experience, and voluntariness. Age influences the impact of all four predictive factors, while gender moderates how performance expectancy, effort expectancy, and social influence relate to technology acceptance. Additionally, a user's experience alters the strength of the connections between effort expectancy, social influence, and facilitating conditions. The factor of voluntariness only moderates the link between social influence and the intention to use the technology (Venkatesh et al., 2003; Marikyan & Papagiannidis, 2023).

Another version of Venkatesh et al. in 2012 was published in the UTAUT-2 three new constructs—hedonic motivation, price value, and habit—are integrated into the UTAUT to better adapt it for consumer technology contexts.

Firstly, hedonic motivation is introduced as the enjoyment or pleasure derived from using technology. It has been demonstrated that this type of motivation significantly influences both the acceptance and continued use of technology in consumer settings, thus it is incorporated as a key predictor of behavioral intention (Holbrook & Hirschman 1982; Venkatesh et al. 2012).

Secondly, price value is considered, which reflects the cost-benefit analysis consumers perform when deciding to adopt a technology. Unlike in organizational settings where the cost is typically not borne by individual users, consumers directly handle these expenses. The perceived value, which balances the technology's benefits against its costs, plays a crucial role in shaping consumer behavior and intentions (Dodds et al. 1991).

Finally, habit is acknowledged as a significant factor in technology use. In scenarios where usage extends beyond initial acceptance, habitual use can strongly predict ongoing engagement with technology (Kim & Malhotra, 2005; Limayem et al. 2007).

Together, these additions aim to refine UTAUT by addressing specific dynamics found in consumer technology usage, enhancing the model's applicability and predictive power in these contexts.

Despite UTAUT and UTAUT-2 being a robust model for the acceptance of new technologies, it is a model focused on information and communication technologies in organizations. When applied in the context of vehicles, the result indicated that it could only account for 22% of the intention to use automated vehicles (Bellet & Banet, 2023). Different UTAUT evolutions have been developed to evaluate the specific frame of automation and driverless acceptance in cars. Specifically, Osswald et al. in 2012 predicted information technology usage in cars by developing the Car Technology Acceptance Model (CTAM).

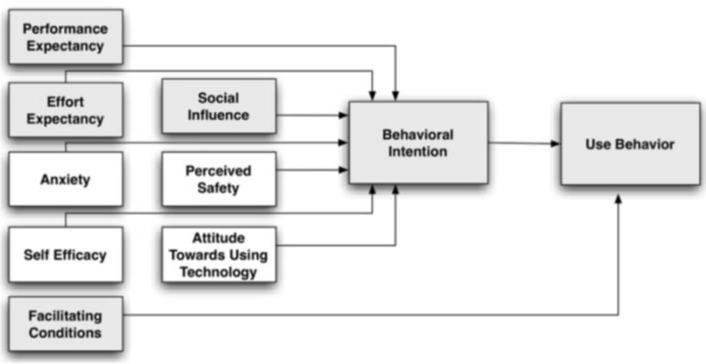


Figure 6. CTAM, the grey determinants are inherited from the UTAUT (Osswald et al, 2012)

In this model, other four determinants are added:

Anxiety: in the car context it refers to the degree to which a person has apprehension, uneasiness, or feeling of arousal. Anxiety was found not significant in the UTAUT model but was found to be significant in the Social Cognitive theory (Osswald et al., 2012).

Self-efficacy: It is an individual's confidence in their capability to use technology effectively to achieve a specific task. It provides insights into how users' personality traits influence their assessment of system-related tasks.

Attitude Towards Using Technology: refers to an individual's emotional response when interacting with a system. This factor didn't significantly influence behavioral intentions in the original UTAUT assessments. However, it is reintroduced because its impact on behavior in automotive contexts cannot be predetermined (Osswald et al., 2012).

Perceived safety: it is the extent to which an individual believes that using a system will impact their well-being. Within the car, this also involves evaluating one's own driving capabilities and the sense of safety felt among other motorists (Osswald et al., 2012).

Bellet and Banet (2023) developed a more sophisticated model to evaluate the acceptance of automated vehicles, enhancing the UTAUT framework originally proposed by Venkatesh et al. (2003). Their model achieved an impressive explanation of 89.1% of the variance in the intention to use automated shuttles, marking a 20-30% improvement over existing models (Bellet & Banet, 2023).

This increased explanatory power likely derives from the inclusion of new variables related to the current transportation methods used by participants, encompassing both their satisfaction with these modes and the perceived enhancements in mobility performance attributed to Automated Systems (AS). Additionally, the integration of individual factors, such as attitudes toward new technologies and innovation, further strengthened the model's explanatory capacity. Moreover, the findings suggest that the UTAUT4-AV model is robust enough to be applicable to other automated vehicle types, including Automated Cars, Robotaxis, and Autonomous Air Mobility Vehicles.

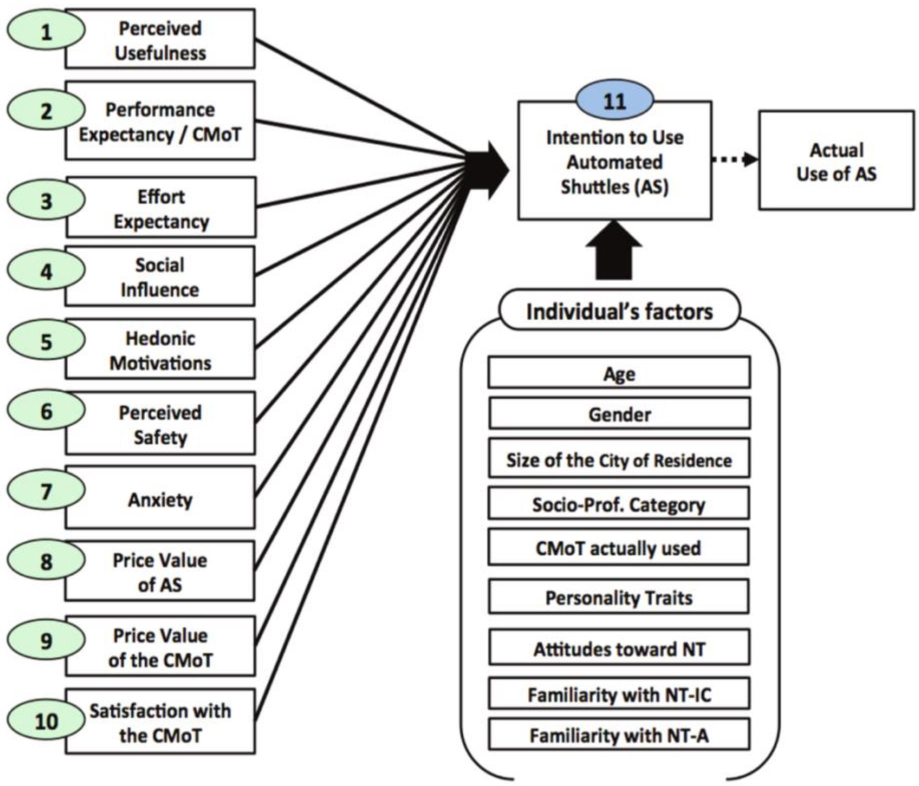


Figure 7. UTAUT4-AV (Bellet & Banet, 2023).

The UTAUT4-AV framework, developed by Bellet and Banet, enhances the comprehension of automated vehicle adoption by integrating several critical variables.

Perceived Usefulness evaluates how automated shuttles might improve user mobility, autonomy, and fulfill specific transportation needs.

Hedonic Motivations focuses on the enjoyment and entertainment derived from utilizing automated vehicles, highlighting the fun aspects of engaging with this technology.

Satisfaction with Current Means of Transport introduces a novel element that evaluates how effectively current transportation methods meet users' needs in efficiency, comfort, and safety, and how this influences their readiness to adopt new automated solutions.

The model also incorporates socio-demographic elements and user profiles such as age, gender, socio-professional status, and urban versus rural residency, which could influence acceptance and usage intentions for automated vehicles. Collectively, these components aim to provide a thorough insight into the factors driving the adoption of automated transportation solutions (Bellet & Banet, 2023).

A key limitation of existing acceptance models is that despite addressing various factors that influence the adoption of new technologies, including automated vehicles, they have not adequately studied the acceptance of partial automation, which is rapidly approaching.

2.4 The Hypothetical Model

The new Vehicle General Safety Regulation, set to become law in July 2024, mandates the installation of these systems in trucks but does not require their active use, as principal ADAS features can still be disabled by drivers (Federal Motor Carrier Safety Administration, 2019). Understanding the factors that influence acceptance is crucial. The proposed model is an adaptation from UTAUT and CTAM for autonomous vehicle technology. CTAM integrates core UTAUT factors such as Performance Expectancy, Effort Expectancy, Attitude Toward Using Technology, Social Influence, Facilitating Conditions, Self-Efficacy, and Behavioral Intention. Additionally, it highlights Perceived Safety as a key factor influencing drivers' intention to use autonomous systems, underscoring the significance of drivers' sense of safety in autonomous vehicles. Building on the enhancements from UTAUT2 by Venkatesh in 2012, the model also incorporates Price Value, which assesses the perceived cost-effectiveness of ADAS technology in influencing the acceptance and intended use by truck drivers.

CTAM has been widely adopted in automotive technology acceptance research as it proposed that the independent variables are direct determinants of Behavioral Intention, unlike UTAUT where only Performance Expectancy, Effort Expectancy and Social Influence are considered direct predictors (Hewitt et al., 2019).

As in CTAM, it is proposed that Performance Expectancy, Effort Expectancy, Social Influence, Price Value of ADAS, Perceived Safety, Self-Efficacy, and Attitude Toward Using Technology and Facilitating Conditions all serve as dependent variables influencing the Driver Intention to Use ADAS technology.

The model proposed also includes key moderating variables: age, gender, and experience.

For age recent research indicates that younger individuals are more receptive to technology in vehicles, Hulse et al. (2018) demonstrated that autonomous cars are likely to be more attractive to younger individuals than older individuals, given that this technology is relatively new and complex. Liu et al. (2019) found that older age is associated with more negative perceptions of Autonomous Vehicles.

Also, gender studies show that men typically exhibit greater interest in Autonomous Vehicles than women. Specifically, Hulse et al. (2018) demonstrated that there was a greater proportion of males exhibited a positive attitude, while females showed more uncertainty; participants with a negative attitude tended to be older on average. Zmud et al. (2016) showed that men were more likely than women to use Autonomous Vehicles, with 18% of men extremely likely to use them compared to 11% of women.

For the experience, the research demonstrated that experienced users might anticipate better performance from a technology if their previous experiences have been positive(Venkatesh et al., 2003). Additionally, familiarity with a technology often diminishes the perceived difficulty of its use. Sun et al. (2020) demonstrated that employees' higher job position levels and work experience increase technology acceptance.

For each independent variable (IV), there are between three and four items. Additionally, it has been hypothesized that the independent variable has a direct effect on driver intention, the dependent variable (DV).

Table 2. Definition of Independent and dependent variables

Variable	Role	Definition
PE: Performance Expectancy	IV	The degree to which a professional truck driver believes that using ADAS can improve their driving performance
EE: Effort Expectancy	IV	The degree of ease associated with the usage of ADAS for professional truck drivers
SI: Social Influence	IV	The degree to which individuals believe that people's opinions about using new Advanced Technology are important
PV. Price Value of ADAS	IV	The degree to which the driver perceives the value for money of ADAS
PS: Perceived Safety	IV	The degree to which professional truck driver trust ADAS technology to increase safety
ATT: Attitude Toward Using Technology	IV	The degree of affective reaction when using a new technology system by professional truck drivers
SE: Self-Efficacy	IV	The degree of competence of the truck driver to use the ADAS technology to accomplish their task
FC: Facilitating Condition	IV	How much professional drivers trust that a technical infrastructure or a person can assist in using ADAS

DI: Driver Intention	DP	The degree to which professional driver aim to use ADAS technology
Age	Mod.	18-29, 30-39, 40-49, 50-59, 60-69, 70+
Experience	Mod.	>5, 5-10, >10

IV: Independent Variable, DP: Dependent Variable, Mod: moderator

Performance Expectancy, in this study, is related to the degree to which a professional truck driver believes that using the ADAS can improve their driving performance. If they hold this belief, they will be more inclined to use ADAS systems. Thus, the first hypothesis, H1, is formulated as follows:

H1: Performance Expectancy has a positive effect on the driver's intention to use ADAS systems.

Effort Expectancy refers to the degree associated with the difficulty with the usage of technology. If the driver thinks that is simple to operate and the interaction is easy, they will be more likely to use that technology. Thus, the second hypothesis, H2, is formulated as follows:

H2: Effort Expectancy has a positive effect on the driver's intention to use ADAS systems.

Social Influence is the degree to which truck drivers perceive technology acceptance by colleagues and the people surrounding them. Truck drivers can be significantly swayed by social influences when deciding whether to use an ADAS system. If fellow drivers and close contacts are using and recommending ADAS systems, they will encourage a driver to adopt the technology as well. Thus, the third hypothesis, H3, is formulated as follows:

H3: Social Influence has a positive effect on the driver's intention to use ADAS systems.

The Price Value of ADAS is tied to how truck drivers perceive the cost of the system in relation to past technology expenses. For the system to be appealing and motivate usage, the higher the Price Value is perceived, the greater the intention to use it will be. Thus, the fourth hypothesis, H4, is formulated as follows:

H4: Price Value has a positive effect on the driver's intention to use ADAS systems.

Perceived Safety is the degree to which a professional truck driver believes that its safety level will be altered with the usage of ADAS system. The impact of Perceived Safety is crucial in the Driver's Intention to use the system. If they perceive a high level of safety, they will have greater intentions. Thus, the fifth hypothesis, H5, is formulated as follows:

H5: Perceived Safety has a positive effect on the driver's intention to use ADAS systems.

Attitude Toward Using Technology reflects the emotional response of professional truck drivers when they adopt a new technological system. This factor represents the drivers' beliefs about the system's usage and its impact. Essentially, if drivers have a favorable view of technology, they will be more likely to adopt ADAS systems. Thus, the sixth hypothesis, H6, is formulated as follows:

H6: Attitude Toward Using Technology has a positive effect on the driver's intention to use ADAS systems.

Self-Efficacy refers to a professional truck driver's confidence and actual capability to effectively use technology for specific tasks. This belief is closely linked to their external experiences and self-perception. If drivers feel capable of correctly using the systems and believe they can receive assistance when needed, they will have a higher intention to use ADAS systems. Thus, the seventh hypothesis, H7, is formulated as follows:

H7: Self-Efficacy has a positive effect on the driver's intention to use ADAS systems.

Concerning moderators, the user's attributes might influence their intentions to use ADAS in trucks. These personal characteristics encompass factors such as gender, age, and educational attainment. Consequently, hypotheses H8, H9 and H10 are formulated based on these considerations:

H8: Gender plays a moderating role on the driver's intention to use ADAS systems.

H9: Age plays a moderating role on the driver's intention to use ADAS systems.

H10: Experience plays a moderating role on the driver's intention to use ADAS systems.

Facilitating Conditions refer to the degree to which truck drivers believe that support from technical staff or assistance from others can enhance their use of the system. In the context of ADAS, this could include access to educational tools or manuals that assist in understanding and performing specific functions. In the CTAM framework, this concept encompasses the perception of internal and external constraints on behavior. If drivers can acquire the necessary knowledge and skills to operate ADAS, this will greatly affect their intention to use it. Thus, hypothesis H1a is formulated as follows:

H1a: Facilitating conditions has a positive effect on the driver's intention to use ADAS systems.

Based on the hypothesis, the following hypothetical model has been formulated:

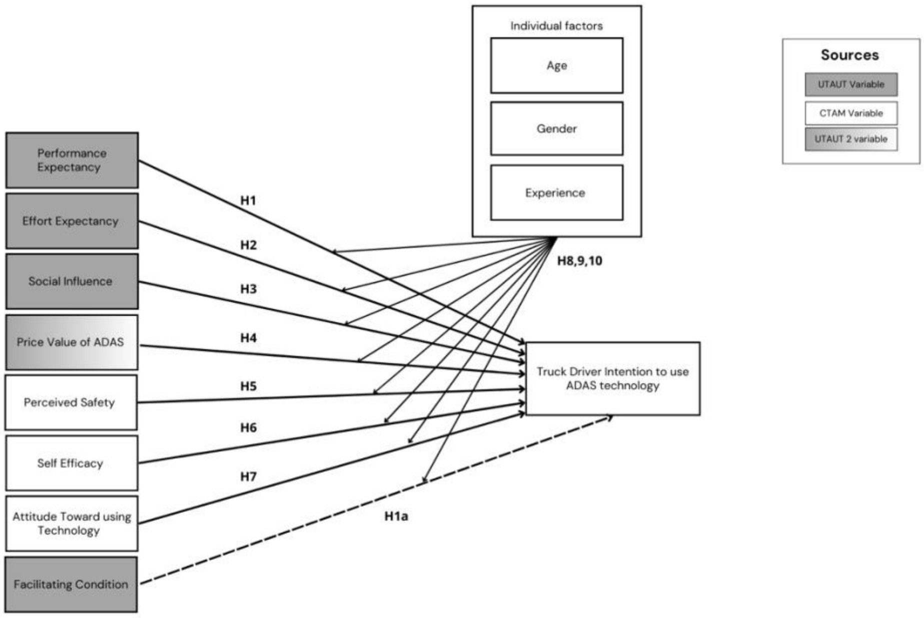


Figure 8. Hypothetical model

3. Method

In this chapter, the research design and methods of data collection are outlined. The study seeks to answer the questions: “What are the factors that influence professional truck drivers’ intentions to use ADAS technology?” and “What are the effects of moderator factors gender, age, and experience in the intention to use ADAS system by truck drivers?”.

The following section provides a detailed explanation of the research design, including the sampling strategy.

3.1 Research design

The focus was particularly on how truck drivers perceive and accept technological advancements. To do so, a quantitative study has been conducted during the research, based on survey research that was utilized to meet the objectives of the study. A quantitative approach was selected for its ability to delineate trends in a population and describe relationships among variables (Creswell, 2011). Quantitative research is valuable because it provides precise, quantifiable evidence for comparing variables and identifying trends, allowing researchers to test hypotheses and draw conclusions from data collected from a large sample, thereby enhancing the reliability and generalizability of the findings (Garbarino & Holland, 2009). Quantitative research explores the interplay and acquisition among various factors (Plonsky & Gass, 2011). It enables the formulation of specific, measurable, and observable research questions and hypotheses, utilizing data collected from a large number of individuals through instruments with predetermined questions and responses (Creswell, 2011). This approach is particularly suitable for assessing the adoption of ADAS in trucks, a context that requires robust analysis of varied variables to understand the dynamics influencing technology acceptance and utilization within the transportation sector, being cost-effective and time-efficient (Abu-Dalbou, 2013).

The power analysis with the G power test has been conducted to detect the number of responses needed to see the necessary sample. Achieving statistical power with R2 values of 0.85 and 0.8, the software estimated that a sample size of 115 and 103, respectively, is required (see Appendix 2). These figures align closely with the anticipated sample size from the transportation company.

Consequently, survey research with quantitative analysis was utilized to investigate the variables in the adoption model and evaluate the acceptance of technology by the truck drivers.

Survey research is a widely used quantitative methodology in educational studies where researchers distribute surveys to a sample to gather insights into their attitudes, opinions, behaviors, or characteristics (Mellinger & Hanson, 2020). This involves the use of surveys to collect quantitative data which can be further analyzed statistically in order to detect patterns and confirm or reject any hypotheses. It describes patterns or trends within the data, in a correlational design of sorts, enabling researchers to examine relationships between variables — although much more towards characterizing a population than predicting outcomes (Creswell, 2011).

Furthermore, a Likert Scale was employed for each set of questionnaires, designed to assess the intensity of respondents' agreement or disagreement with statements on a five-point scale, with the following anchors: (1) Strongly disagree, (2) Disagree, (3) Neutral, (4) Agree, (5) Strongly agree (Chomeya, 2010).

3.2 Data Collection

Purposive sampling was employed to select an organization operating in the transportation sector that has already adopted new technologies in their truck fleets. A food management company, referred to as CoolCarrier Co. (a fictional name), was chosen for this study. CoolCarrier Co. is a medium-sized company with over 130 employees that mainly operates in Italy. They largely transport food at controlled temperatures and operate in Italy with two bases near Rome and Northern Italy.

Over the last years, they have invested in the development and usage of new technologies in trucks, including a system for remote monitoring. Specializing in temperature-controlled transportation, they can conduct remote temperature monitoring, as well as track locations via satellite and oversee the opening and closing of doors. The technology available on all their trucks consists of AEB, Advanced Emergency Brakes; LDW, Line Detection Warning; ACC, Adaptive Cruise Control; ESP, Electronic Stability Program. They are all equipped with older technology compared to the new mandatory standards set by the GSR 2024.

General information about CoolCarrier Co.

Company	CoolCarrier Co.
Industry	Primary- secondary transport of temperature-controlled groceries
Size	Ca. 130
Company age	30 years
Company offices	HQ in Rome, Italy Warehouse in Alba, CN, Italy
Type of technology on trucks	AEB, Advanced Emergency Brakes LDW, Line Detection Warning ACC, Adaptive Cruise Control ESP, Electronic Stability Program
Potential Sample	120
Survey participants	95 (75,8%)

Table 3. Participating organization

On June 18th, 2024, the main location of the company was visited to gain familiarity with the ADAS installed in their trucks. During this visit, a new type of truck compliant with the full GSR and an older model representing the minimum technology level available in trucks were examined (except for less than ten trucks that are used for only local transport).

To the company owner was also presented the survey and discussed the most effective method for disseminating it.

It was decided that the survey link would be shared with specific individuals meeting the following criteria:

- Drivers of Heavy Trucks currently employed at CoolCarrier Co.
- Holders of a type “C” driving license.

This study used a non-probability sampling method in the selection of the respondents. Specifically, purposive sampling has been used, as the above conditions were chosen to detect which drivers were appropriate for the study (Australian Bureau of Statistics, 2023). Purposeful sampling is a strategic method often employed to select particularly insightful cases, optimizing resource use effectively, in choosing individuals or groups who possess significant knowledge or experience relevant to the subject of interest (Cresswell & Plano Clark, 2011). In contrast, probabilistic or random sampling techniques were used in research to enhance the validity of results across a wider population by reducing selection bias and managing the influence of both known and unknown variables (Palinkas et al., 2015).

The questionnaire was divided into three parts. The first part analyzed the personal characteristics of the respondents. The personal characteristics include Age, Education, Years as a Heavy Truck driver. The sensitivity of the topics covered could influence the placement of demographic questions within a survey, the level of privacy assured to participants, and other factors (DeFranzo, 2020). If participants perceive these questions as too intrusive or not directly related to the survey’s main focus, it might lead to discomfort or disengagement. Participants may skip these questions, provide inaccurate or incomplete answers, or even decide to stop taking the survey altogether. Sensitive demographic topics often include questions about religious beliefs, ethnicity, income, and health-related issues (DeFranzo, 2020).

In this scenario, placing demographic questions at the start of the survey was strategically chosen because these questions were not particularly sensitive. Additionally, the last part of this section of the survey focused on the age of the heavy trucks in use. It is important to note that while CoolCarrier Co. retains ownership of the Heavy Trucks, each truck is exclusively assigned to a single driver.

The second part was the center of the project analyzing the factors that can influence the acceptance of the ADAS technology in trucks. This section was grounded in UTAUT model. It was developed from prior studies and delineated eight key factors that influence outcomes. The variables were Performance Expectancy, Effort Expectancy, Social Influence, Price Value of ADAS, Perceived Safety, Attitude Toward Using Technology, Self-Efficacy and Facilitating Condition. Each variable was designed with 3/4/5 measurement items, with a previous analysis of related articles on the topic. Detailed descriptions of each item associated with the influencing factors were provided in Chapter 2. The last part was about the intention in using ADAS technology and specifically, the single systems selected can be deactivated. This was aimed at understanding the potential behaviors and habits of the drivers with the technologies.

Being all attitude questions, the Likert scale has been used. This structure is commonly utilized in research within the social and behavioral sciences and is appropriate for assessing attitudes or evaluating opinions (Bryman, 2013). This research employed a 5-point Likert scale for measurement.

Upon completing the initial draft of the questionnaire aimed at Heavy Truck drivers for the quantitative thesis, it was essential to conduct a pre-test and analyze this preliminary data. The findings from this pre-test would then guide any necessary revisions to enhance the questionnaire's reliability. However, due to the highly specialized and professional nature of the sector, along with concerns regarding sensitivity, comprehensive testing proved challenging. The company permitted only a single distribution of the survey. Additionally, drivers might have lacked the time or been reluctant to repeatedly share potentially sensitive information, as multiple submissions could have generated suspicion.

Consequently, to circumvent these challenges and still validate the questionnaire, an initial test was conducted using a sample of 25 non-professional drivers. These participants were first educated on ADAS technology through a video. This approach was chosen because the ADAS systems in cars, while smaller and less sophisticated, share similarities with the systems used in trucks. This allowed for a preliminary assessment of the survey in a less constrained environment before its actual deployment among professional drivers. An initial Multiple Linear Regression was conducted on the collected data. While the results provided valuable and significant insights, there was room for improvement. To enhance the robustness of the final survey, Confirmatory Factor Analysis (CFA) was introduced to refine the selection of observed variables for each latent construct. This preliminary version was evaluated ensuring that the survey was optimized before its full-scale implementation.

Given that the entire company is Italian, with the majority of the drivers being native Italian speakers and all drivers fluent in Italian, the survey was translated into Italian to improve clarity and understanding among the participants. The initial test was written in English, but to improve comprehension, also the preliminary version was translated. Feedback from non-professional drivers was utilized to refine areas of the survey that were unclear, enhancing overall understanding. The feedback received was generally positive.

In the preliminary version, there were some repetitive measurements which were identified and subsequently removed in the revised draft of the questionnaire. This refinement aimed to streamline the survey and enhance its effectiveness in gathering relevant data.

For this study, the Qualtrics platform was selected, primarily because of the full access provided by the university. The questionnaire was distributed using anonymous links, each sent directly and individually to the drivers. Measures such as IP address tracking, timing, and geolocation checks were implemented to ensure the validity of the responses. The survey remained open for thirty days and was exclusively shared with company employees, in accordance with an agreement with the company's owner. Ultimately, 95 valid responses were collected, resulting in a response rate of 75.8%.

In accordance with the University's GDPR guidelines, all participants consented to voluntary participation. They were informed that they could withdraw from the survey at any time, even at its conclusion.

3.3 Sample

This paragraph provides a description of the participants' general information to better understand the sample.

According to the survey information, the mean age of heavy truck drivers was found to be 44.58 years. None of the heavy truck drivers were female, thus this detail is omitted. Most of the drivers were also found in the 40–60 age group, with 33.0% aged between 40 and 50, and another 22.3% belonging to 51–60. Individuals aged between 21 and 66 years participated in the study. Respondents were on average 45 years of age with just under 15 years of work experience. About 63.9% of the drivers had over 10 years of experience, and 28.5% had five years of experience. Just 12.4% had over 25 years of driving experience.

The survey revealed that the average age of heavy truck drivers was 44.58 years. As all the heavy truck drivers were male, the gender detail was omitted. The majority of the drivers fell within the 40–60 age range, with those aged 40–50 making up 33% of the respondents and those aged 51–60 comprising 22.3%. There were no participants younger than 21 or older than 66 years. The average work experience of the respondents was just under 15 years, aligning with the average age of 45 years. About 28.5% of the drivers had 5 years of experience, whereas 63.9% had over 10 years of experience. Only a small fraction, 12.4%, had more than 25 years of driving experience.

In terms of educational background, over 70% of the drivers had attained more than six years of education beyond elementary school, with 34.7% having more than ten years of education. The average driving work experience of the respondents was just under 15 years, aligning with the average age of 45 years. About 27.8% of the drivers had 5 years of experience, whereas 63.1% had over 10 years of experience. Only a small fraction, 10.4%, had more than 25 years of driving experience.

The remarkable aspect here is the age of the trucks since their registration. Just 4.2% of the trucks are less than a year old, already equipped with the technology that will become mandatory in 2024. However, over 77% of these vehicles are less than five years old; in all these trucks there are previous versions of ADAS technology. These outcomes were anticipated by the company, which had planned multiple new truck purchases for 2024–2025. On a broader scale, these results highlight the substantial investments currently being made in the sector to acquire new trucks that meet upcoming regulatory requirements. Conversely, only 6.3% of the trucks in regular use are over 15 years old and are only equipped with level 0 ADAS. The company continues to use these older trucks for short-range (local) transportation.

Table 4. Demographics of the survey respondents

Descriptive statistics							
Statistic	**Min-max**	**Average**	**Median**	**Item**	**Frequency**	**Percent**	**Cumulative percent**
Age	21-66	44.58	46	21 - 30	17	18.1%	18.1%
				31 - 39	12	14.9%	33.0%
				40 - 50	31	33.0%	66.0%
				51 - 60	21	22.3%	88.3%
				≥ 61	11	11.7%	100,0%
				Total	95	100.0%	
Years as professional truck driver	1-37	14.58	15	≤ 1	5	5.3%	5.3%
				2 - 3	9	9.5%	14.8%
				4 - 6	13	13.7%	28.5%
				7 - 9	8	8.4%	36.9%
				10 - 12	7	7.4%	44.3%
				13 - 15	11	11.6%	55.9%
				16 - 18	12	12.6%	68.5%
				19 - 21	9	9.5%	78.0%
				22 - 24	8	8.4%	86.4%
				25 - 27	3	3.2%	89.6%
				28 - 30	3	3.2%	92.8%
				≥ 31	9	9.5%	100.0%
				Total	95	100,0%	
Year of completed education	0-10			0-2	12	12.6%	12.6%
				3-6	16	16.8%	29.5%
				6-9	34	35.8%	65.3%
				>10	33	34.7%	100.0%
				Total	95	100.0%	
Years of used truck since its registration	0-21	5.35	4.0	≤ 0	4	4.2%	4.2%
				1-2	17	17.7%	21.9%
				2 – 4	28	29.2%	51.0%
				5 –6	24	25.0%	76.0%
				7 –8	4	4.2%	80.2%
				9-10	9	9.4%	89.6%
				11-12	4	4.2%	93.8%
				≥ 13	6	6.3%	100.0%
				Total	95	100.0%	

3.4 Measures

Performance Expectancy, this study was derived from the CTAM model, which is notable for its innovative approach of considering all independent variables as direct predictors. This model recognizes driving performance—particularly in terms of perceived safety, speed, and navigation—as a crucial aspect of professional driving. Additionally, another element was incorporated to potentially influence the acceptance of ADAS technology: the concern that the system might replace the driver's role (PE4). In this context of ADAS, in fact, it is also important to consider not only how the technology enhances performance but also the perception of job security that can impact the driver interaction of ADAS with the resistance to change. This concern can be seen as an inverse or negative reflection of Performance Expectancy, if a driver is afraid of being replaced, he may lower the expectation regarding the benefit of ADAS.

Items	Questions	Sources
PE1	This technology is useful for making safer my job	Osswald et al. 2012
PE2	Using this technology at his fullest will allow me to be faster	Osswald et al. 2012
PE3	Using this technology at his fullest will help me in reaching my destination	Osswald et al. 2012
PE4	I am afraid that this technology will take my place of driver in the future	Author

Table 5. Observed Variables of Performance Expectancy

Effort Expectancy was also derived from CTAM. It is taken that if truck drivers perceive the technology as challenging, they might be more inclined to deactivate the system. It's crucial for drivers to be able to react swiftly and use the system actively and safely. Given that not all ADAS systems are identical, another specific question was included (EE2) about more sophisticated systems like ISA and ELKA. Ultimately, it is essential that the system is user-friendly, with clear and understandable inputs and outputs.

EE1	I think that this technology and ADAS systems are easy to use	Osswald et al. 2012
EE2	Particularly I think that Intelligence speed assistance ISA and Emergency Line Keep Assist ELKA are easy to use	Author
EE3	My interaction with systems is clear and understandable	Osswald et al. 2012

Table 6. Observed Variables of Effort Expectancy

Social Influence was derived from CTAM and UTAUT 4AV. The impact of social factors, well-documented in organizational computer systems, also distinctly affects individual driver behavior. While cars often serve as status symbols and interactive technologies can promote identification and enhance technology acceptance, the context here differs as the focus is on partial automation within a professional setting. Therefore, it is crucial to examine whether social influences persist, whether they come from non-professional acquaintances (SI1) or professional colleagues (SI2 and SI3). Specifically, SI2 was taken from the study of Bellet and Banet as the influence of colleagues can be important. If a driver observes their colleagues using their technology and benefitting from it, they are more likely to intensify their use of the same technology.

SI1	People around me think that I should use this technology	Osswald et al. 2012
SI2	I would use my technology more if my colleagues also use it.	Bellet & Banet, 2023
SI3	If I have ADAS technology available in my truck, I will show it to my colleagues.	Osswald et al. 2012

Table 7. Observed Variables of Social Influence

The Price Value of ADAS, this variable was not included in the CTAM model, the rising cost of technology is likely to influence ADAS acceptance. The cost of new ADAS regulations is esteemed to be in the range between 3,240 and 6340 for trucks[3]. Therefore, it is crucial to evaluate both the current expense associated with the technology (PV1) and future perceptions of ADAS costs (PV3).

[3] https://www.itskrs.its.dot.gov/2021-sc00504

PV1	The expense of this technology, ranging from €3,240 to €6,340, is warranted by the advantages it offers.	Bellet & Banet, 2023
PV2	I want to spend even more on ADAS technology	Bellet & Banet, 2023
PV3	I am afraid that in future the cost of ADAS would be too high	Author

Table 8. Observed Variables of Price Value

Perceived Safety was derived by CTAM model. These variables also encompass the sense of safety at work, such as how they can enhance safety (PS1) and reduce the risk of accidents (PS2). However, these systems might not necessarily prevent drivers from paying less attention (PS4) and could potentially have a negative impact on driving as a profession if they are not perceived as safe. Additionally, it is crucial to investigate whether the use of specific ADAS sensors, like cameras, could be disturbing for drivers who may find them useful for safety but are concerned about their privacy being violated (PS3).

PS1	Thanks to ADAS technology, my trip and work could be safer and risk-free.	Osswald et al. 2012
PS2	ADAS systems minimize the risk of accidents.	Osswald et al. 2012
PS3	It's not a concern for me that the ADAS uses continuously active cameras.	Author
PS4	I am confident that this system would not negatively impact my driving habits.	Osswald et al. 2012
PS5	With this technology, driving demands less attention.	Osswald et al. 2012

Table 9. Observed Variables of Perceived Safety

Attitude Toward Using Technology was also derived from CTAM. The particular nature of trucks, the advanced features of ADAS technology, and the unique responsibilities of professional drivers make it crucial to consider these factors carefully. This approach highlights the drivers' emotional and intellectual reactions to new technologies, showcasing their personal views on how beneficial, user-friendly, and impactful these systems are in their everyday work. Their strong bond with their tools and tasks shapes their will to use new technology that could redefine their roles on the road.

ATT1	Using this technology is a good idea	Osswald et al. 2012
ATT2	These systems make the driving more interesting	Osswald et al. 2012
ATT3	Using these systems is enjoyable, and I want to continue using them.	Osswald et al. 2012

Table 10. Observed Variables of Attitude Toward Using Technology

Self-Efficacy, in the CTAM model is the belief in one's ability to succeed in using the technology. People who have confidence in their skills are more likely to view challenging tasks as opportunities to grow rather than as obstacles to avoid. Specifically, within the context of ADAS and partial automation, it is important to examine the role of support, such as having access to assistance from experts when needed or opportunities to learn quickly. Nonetheless, with partial automation drivers remaining central to truck driving, it is also crucial to explore the impact of the training they receive, possibly through seminars or other educational formats (SE2).

SE1	I would use these systems more if I could receive help from someone	Osswald et al, 2012
SE2	I would use these systems more if someone could explain ADAS technology to me.	Author
SE3	I would use these systems more if I had more time to learn.	Osswald et al., 2012
SE4	I would use these systems more if there were built-in assistance with an expert available.	Osswald et al., 2012

Table 11. Observed Variables of Self-Efficacy

In this study, Driver Intention is the dependent variable, representing the extent to which professional drivers intend to use ADAS systems. This intention is influenced by eight factors identified in the model, with four specific items designed to assess the Driver Intention variable. Derived from the CTAM model, this includes variables related to the overall acceptance of technology and the specifics of the options available in the market. It is also crucial to determine whether systems that are understood will actually be used, and how this connects with the role of training. Additionally, there is a particular focus on the only ADAS that requires direct activation by the driver, the breathalyzer (DI4).

Assuming I had access to the ADAS technology…

DI1	I intend to use this technology to its full potential	Osswald et al., 2012
DI2	I would use the ADAS systems only if I can understand them.	Author
DI3	I would have all the ADAS systems available on the market	Osswald et al., 2012
DI4	I would install a breathalyzer to activate the truck.	Author

Table 12. Observed Variables of Driver Intention

Facilitating Conditions, in the CTAM framework, this concept encompasses the perception of internal and external constraints on behavior. For example, in a car setting, this might depend on the availability of a learning tool. For heavy trucks, it is essential to examine how experts perceive ADAS technology and how drivers can integrate this technology with other systems available in trucks, especially since it involves partial automation that must be coordinated with other truck technologies.

FC1	In case of necessity I can ask help to some expert	Osswald et al., 2012
FC2	I know how to use ADAS technology	Osswald et al., 2012
FC3	ADAS systems are compatible with other technologies while I drive	Osswald et al., 2012

Table 13. Observed Variables of Facilitating Condition.

3.5 Analysis

The analysis involved several steps. Initially, results from the Likert scale were converted into numerical values for quantitative analysis. Descriptive statistics were then conducted for demographic variables such as gender, age, and experience.

The dataset was subsequently imported into R Studio, Confirmation Factor Analysis (CFA) was utilized to identify latent variables that formed the core of the regression analysis. To validate these constructs, correlation analyses and reliability assessments were performed. The reliability of the scales was evaluated using Cronbach's alpha, while a correlation matrix was generated to explore the relationships between the variables.

To explore the relationship between the independent variables and the dependent variable (Driver Intention), multiple regression models were applied. Multiple linear regression was applied to assess the effect of several independent variables on a single dependent variable.

4. Results

This thesis focuses on examining the acceptance of ADAS technology by professional heavy truck drivers. The findings indicate a significant level of predicted satisfaction among drivers regarding the use of ADAS technology in the future. Out of the 95 surveys analyzed, there is a strong overall intention to adopt ADAS, with an average rating of 7.73 out of 10 and a median score of 8. Only 12.63% of the respondents rated their likelihood of using the system at 5 or lower, while more than 36.84% rated their likelihood as higher than 8.

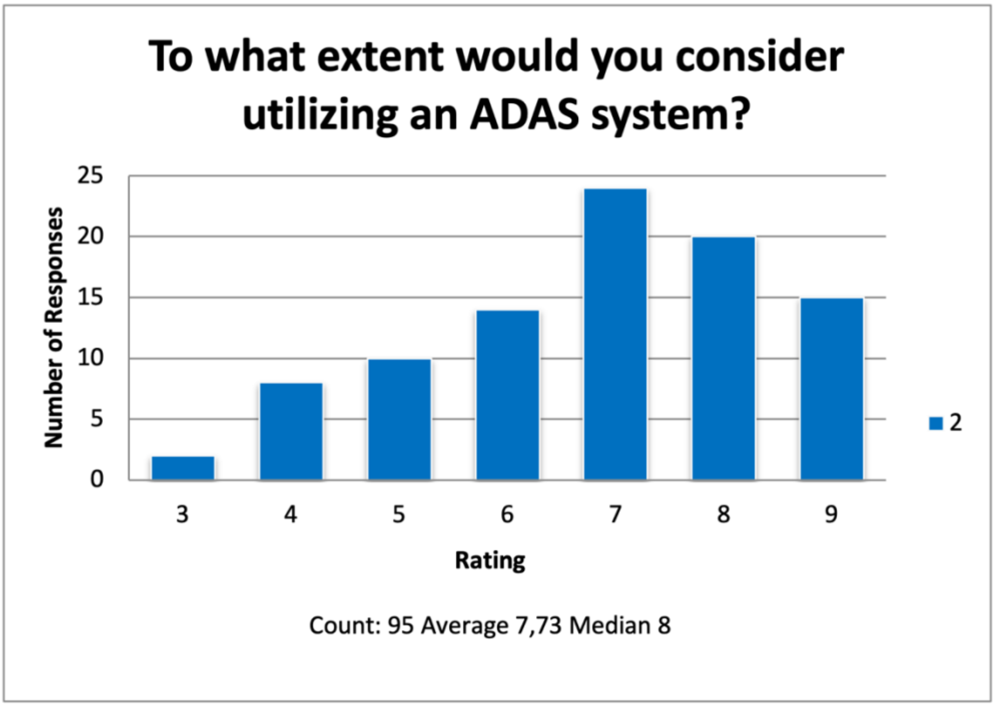


Figure 9. Results of the overall intention to use ADAS systems

It is important to note that drivers have different perceptions about systems that can be disabled. They were specifically asked to indicate their level of agreement with the following statement: "Even though it produces incorrect sounds and lights, I would always keep the Intelligent Speed Assistance (ISA)/ Emergency Lane Keeping System (ELKA)/ Automatic Emergency Braking System (AEBS)/ Advanced Driver Distraction Warning (ADDW) active." For the interlock system, since it requires activation, they were asked, "I would like to have an interlock system with a breathalyzer installed to start the truck." The detailed results are provided in Appendix 7.

Not all ADAS are perceived equally by drivers, with ISA notably receiving lower acceptance rates. The 41.11 % of drivers Strongly Disagree or Disagree with having the system always on and only 42.11% of drivers agree or strongly agree with having ISA always active. Originally it was designed to significantly enhance road safety, reducing deaths by 20%, automatically reducing engine torque, and keeping vehicles within speed limits with a combination of sign-recognition cameras and digital maps face resistance (ETSC, 2022). The European Automobile Manufacturers Association (ACEA) is strongly opposed to the EU's initiative to mandate this technology, advocating instead for a less intrusive system that simply displays a warning on the dashboard when speed limits are exceeded.[4] Thus, the EU approved a reduction to only an audible warning that "was found to be irritating to drivers, and would likely be switched off, effectively destroying the safety potential of the system".[5]

For the ADDW system, the feedback was better. While 24.11% of drivers strongly disagree or disagree with using this system, a larger portion, 60%, agree or strongly agree that it could be beneficial. The system offers numerous advantages, such as promoting healthier driving habits, providing a defense against claims, and reducing insurance costs. However, studies indicate that overall satisfaction among professional drivers is not particularly high, primarily due to concerns about privacy, especially during off-duty hours. Despite the reservations expressed by some drivers, the implementation and use of these cameras will proceed as planned.[6]

For the ELKA system, 23.16% of drivers either strongly disagree or disagree with the idea of having this system always activated. In comparison, for the AEBS, 19.79% of drivers hold the same view. On the other hand, a notable 69.47% of truck drivers either strongly agree or agree with keeping ELKA always on, while 70.84% of drivers support having AEBS constantly activated. It is important to note that all the trucks of CoolCarrier Co. are equipped with the previous version of these systems (LDW and AEB). Lane Departure Warning (LDW) systems provide alerts to the driver when the vehicle starts to drift out of its lane, using visual, audible, or vibration signals to draw attention to the potential hazard. In contrast, ELKA systems not only warn the driver but also take corrective action if the driver fails to respond, automatically ensuring that the vehicle remains within its lane. The 2024 regulations for AEBS introduce key upgrades. The system can now only be switched off for 15 minutes before automatically

[4] https://www.theguardian.com/business/2018/dec/13/car-lobby-opposes-eu-safety-bid-that-would-save-1300

[5] https://etsc.eu/opinion-will-intelligent-speed-assistance-isa-live-up-to-its-promise/ lives-a-year

[6]https://www.insurancethoughtleadership.com/auto-insurance/why-arent-truckers-using-driver-facing-cameras#:~:text=ATRI%20research%20finds%20truckers%20dislike,to%20privacy%20and%20litigation%20issues.&text=Over%20the%20past%20few%20years,issue%20in%20the%20transportation%20industry.

reactivating. Unlike previous rules, which required a warning phase before braking, the new standards allow immediate braking without prior warning to the driver. Additionally, the updated system can now detect and stop stationary vehicles and single pedestrians, though it still lacks the capability to detect cyclists or groups of pedestrians (European Commission, 2022).

A significant majority of drivers in a survey, 64.21%, support the installation of interlock devices, while only 22.11% oppose it. This suggests that the common misconceptions about these devices are not widely held among this group. Contrary to popular belief, interlock devices are not difficult to use; they are designed for simplicity, requiring just a breath and hum to activate the vehicle's ignition. Additionally, while there are initial costs associated with their installation, these are generally reasonable, especially when compared to the severe financial repercussions of a drunk driving incident. Furthermore, interlock devices are reliable and rigorously tested to be tamper-proof, ensuring they function correctly to enhance road safety.[7]

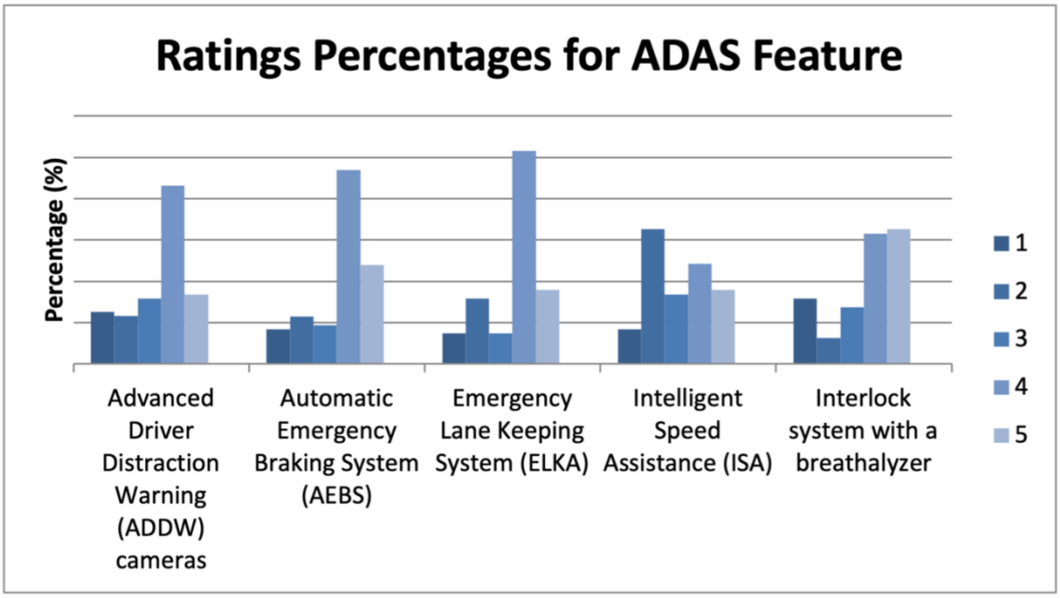


Figure 10. Perception of the specific ADAS systems

[7] https://www.armstronglegal.com.au/traffic-law/vic/drink-driving/alcohol-interlock-devices/

Table 14. Perception of the specific ADAS systems

ADAS system	Average	Median	Rating	Frequency	Percent	Cumulative Percent
Intelligent Speed Assistance (ISA)	3.11	3	1	8	8.42%	8.42%
			2	31	32.63%	41.05%
			3	16	16.84%	57.89%
			4	23	24.21%	82.10%
			5	17	17.89%	100.00%
Emergency Lane Keeping System (ELKA)	3.57	4	1	7	7.37%	7.37%
			2	15	15.79%	23.16%
			3	7	7.37%	30.53%
			4	49	51.58%	82.11%
			5	17	17.89%	100.00%
Automatic Emergency Braking System (AEBS)	3.67	4	1	8	8.33%	8.33%
			2	11	11.46%	19.79%
			3	9	9.38%	29.17%
			4	45	46.88%	76.04%
			5	23	23.96%	100.00%
Advanced Driver Distraction Warning (ADDW) cameras	3.4	4	1	12	12.63%	12.63%
			2	11	11.58%	24.21%
			3	15	15.79%	40.00%
			4	41	43.16%	83.16%
			5	16	16.84%	100.00%
Interlock system with a breathalyzer	3.59	4	1	15	15.79%	15.79%
			2	6	6.32%	22.11%
			3	13	13.68%	35.79%
			4	30	31.58%	67.37%
			5	31	32.63%	100.00%

1, Strongly Disagree; 5, Strongly Agree

In the following section, the discussion begins with a factor analysis conducted on several observed variables to reduce dimensionality and create composite scores for each latent construct. For each construct, initially, all the observed variables were selected, and Cronbach's alpha was calculated to assess the internal consistency and reliability of the items. If Cronbach's alpha indicated sufficient reliability, Confirmatory Factor Analysis (CFA) was performed using one factor. If not, some of the observed variables were dropped to achieve better results. This process helped identify latent variables that formed the core of the subsequent regression analysis. To validate these constructs, correlation analyses and reliability checks were conducted once more.

In the second part, multiple linear regression was used to determine the relationship between the latent variables and Driver Intention. A second linear regression assessed the impact of the moderators Age and Experience. Multiple linear regression has been chosen to assess the impact of the different constructs derived from the factor analysis on the Driver's Intention to use ADAS. The multiple linear regression is a suitable model when the aim is to analyze how multiple independent variables are influencing a continuous dependent variable.

4.1 Reliability

To assess the reliability of the measurements, Cronbach's Alpha was initially calculated for each set of variables related to the latent constructs. If the Cronbach's Alpha result was low, indicating poor reliability, some variables were selectively dropped to enhance the measurement instrument and boost its overall reliability. Following these adjustments, CFA was conducted to validate the structure of the refined constructs. Table 14 details the reliability analysis for each latent variable, each consisting of multiple items. Cronbach's alpha method, used to evaluate the reliability of Likert-scale measurements, assesses the internal consistency of a measurement tool by evaluating the proportion of variance shared among items (covariance) relative to the tool's total variance. The guiding principle is that a higher covariance among items, relative to their total variance, signals a reliable measurement tool (Collins, 2007). The table below includes the ratings for Cronbach's Alpha values, with a benchmark of 0.6 required for reliability to be deemed acceptable.

The analysis reveals robust reliability for constructs such as Attitude Toward Using Technology and Self-Efficacy, with Cronbach's Alpha values well over 0.8. Performance Expectancy also shows good reliability with a value above 0.7. Constructs like Driver Intention and Facilitating Conditions demonstrate acceptable reliability, reaching the threshold of 0.6. However, lower Cronbach's Alpha values around 0.5 for constructs like Social Influence, Perceived Safety, and Effort Expectancy were noted, yet these variables were retained following the confirmatory factor analysis.

Table 15. Reliability result of the latent variables

Reliability of Constructs				
Constructs	N Items	Cronbach's Alpha	Mean	Std deviation
Performance Expectancy	4	0.24	3.75	1.11
Effort Expectancy	3	0.58	4.15	0.42
Social Influence	3	0.52	3.73	0.71
Price Value	3	0.39	3.66	0.82
Perceived Safety	5	0.5	3.34	1.27
Attitude Toward Using Technology	3	0.81	3.78	0.59
Facilitating Condition	3	0.38	3.91	0.71
Self-Efficacy	4	0.8	3.61	0.56
Driver Intention	3	0.45	3.91	0.68

4.2 Confirmation Factor Analysis

First of all, CFA was used to see the relationship between the latent variables and the observed variables.

Factor analysis is a methodical technique used to simplify a group of related variables. Historically, this approach has been employed to investigate the potential inherent organization within a dataset. It does this without assuming any predetermined structure for the results, allowing the data itself to reveal any underlying patterns (Child, 1990).

The factor analysis includes CFA. CFA is a statistical approach used specifically to confirm the factor structure hypothesized for a group of observed variables. In CFA, researchers establish hypotheses based on prior theoretical and empirical knowledge about the expected relationships between observed variables and their latent constructs. These hypotheses are then rigorously tested through statistical methods to verify the proposed structure (Suhr, 2006).

The evaluation of the measurement model emphasized the reliability of its measures and the tool's general internal consistency. Specifically, it is essential that all items on the scale are significant and demonstrate loadings greater than 0.5 on their designated scales. Additionally, the Cronbach's alpha (α), a measure of internal consistency, should not fall below 0.6 (Anderson & Gerbing, 1998; Hair et al., 2014). This approach was taken to maintain the integrity and validity of the constructs, allowing for a reliable factor analysis that accurately represents the underlying theoretical frameworks.

Factor analysis serves to uncover underlying structures in data by condensing a large number of observable variables into fewer latent variables or factors. By carefully selecting and retaining a sufficient number of observed variables, the analysis ensures that the latent constructs are well-defined and supported by the data. Furthermore, even when certain variables consistently perform well, factor analysis can uncover chances to refine the model. It might show that some variables add little value to the factors. By concentrating on the most significant constructs, researchers can simplify their analysis, leading to more solid and trustworthy results. This approach helps in cutting down complexity and enhancing the stability and clarity of the model. This is especially valuable in research environments where both simplicity and precision are crucial. This approach not only simplifies the model, making it easier to interpret and communicate, but it can also improve the overall fit of the model.

In this analysis, factor analysis was conducted on several observed variables to reduce dimensionality and create composite scores representing each latent construct. For each construct, the observed variables were selected, and Cronbach's alpha was recomputed to evaluate the internal consistency and reliability of the items. This process was repeated for all latent constructs in the dataset, ensuring that each construct was adequately represented by its respective factor score in the following regression analysis.

At least two observed variables were retained for each variable to ensure robust measurement. Specifically, the latent variables of Performance Expectancy ($\alpha = 0.74$), Effort Expectancy ($\alpha = 0.65$), Social Influence ($\alpha = 0.57$), Price Value ($\alpha = 0.87$), Attitude Toward Using Technology ($\alpha = 0.85$), Facilitating Condition ($\alpha = 0.51$), and Driver Intention ($\alpha = 0.65$) were each measured using two observed variables. For Perceived Safety ($\alpha = 0.53$) and Self-Efficacy ($\alpha = 0.81$), four observed variables were retained to capture these constructs more comprehensively.

After carrying out the CFA, significant enhancements in the reliability of latent variables were noted. For instance, the Price Value construct saw its Cronbach's alpha rise markedly from 0.39 to 0.87 by reducing items from 3 to 2. The Attitude Toward Using Technology construct continued to show excellent reliability, with Cronbach's alpha improving from 0.81 to 0.85.

Self-Efficacy also demonstrated a slight improvement in reliability from 0.80 to 0.81, with a consistent mean of 3.61 and an increased standard deviation of 0.79. Significant reliability enhancements were seen in Performance Expectancy, with Cronbach's alpha jumping from 0.24 to 0.74 after item reduction. Similarly, Driver Intention notably increased in reliability from 0.45 to 0.65, and Effort Expectancy saw a rise in reliability from 0.58 to 0.65 after reducing the item count. Social Influence experienced a marginal increase in Cronbach's alpha from 0.52 to 0.57 after item reduction. The Perceived Safety construct, after reducing items from 5 to 4, observed a minor increase in reliability from 0.50 to 0.53.

Lastly, Facilitating Condition saw a slight increase in reliability from 0.38 to 0.51 after reducing items. Overall, the CFA process enhanced the reliability of most constructs by concentrating on the most influential items, leading to a more robust measurement model.

Table 16. Results of Confirmation Factor Analysis

Latent variable	**Observed variable**	**α**	**ƛ**
PE: Performance expectancy		0.74	
	PE2: Using this technology at his fullest will allow me to be faster		0.82
	PE3: Using this technology at his fullest will help me in reaching my destination		0.77
EE: Effort Expectancy		0.65	
	EE1: I think that this technology and ADAS systems are easy to use		0.74
	EE3: My interaction with systems is clear and understandable		0.75
SI: Social influence		0.57	
	SI1: People around me think that I should use this technology		0.79
	SI3: If I have ADAS technology available in my truck i will show it to my collogues.		0.81

PV: Price Value		0.87	
	PV1: The expense of this technology, ranging from €3,240 to €6,340, is warranted by the advantages it offers.		0.94
	PV2: I want to spend even more on ADAS technology		0.96
PS: Perceived Safety		0.53	
	PS1: Thanks to ADAS technology, my trip and work could be safer and risk-free.		0.836
	PS2: ADAS systems minimize the risk of accidents.		0.856
	PS3: It's not a concern for me that the Advanced Driver Distraction Warning uses continuously active cameras.		0.789
	PS4: I am confident that this system would not negatively impact my driving habits.		0.765
ATT: Attitude Toward Using Technology		0.85	
	ATT2: These systems make the driving more interesting		0.86
	ATT3: Using these systems is enjoyable, and I want to continue using them.		0.76
FC: Facilitating Condition		0.51	
	FC2: I know how to use ADAS technology		0.79
	FC3.ADAS systems are compatible with other technologies while I drive		0.82
SE: Self-Efficacy		0.81	
	SE1: I would use these systems more if I could receive help from someone.		0.62

	SE2: I would use these systems more if someone could explain ADAS technology to me.		0.67
	SE3: I would use these systems more if I had more time to learn.		0.79
	SE4: I would use these systems more if there were built-in assistance with an expert available.		0.77
DI: Driver Intention		0.65	
	DI1: I will use this technology to its fullest potential.		0,71
	DI3: I would have all the ADAS systems available on the market		0,67

α: Cronbach's Alpha values λ: factor loadings

4.3 Correlation analysis

After exploring the reliability and the CFA, there is the inspection of the correlation among the latent variables in order to test the hypotheses of the research model (see Figure 8).

The correlation matrix reveals that most variables are highly interconnected, suggesting that changes in one latent variable are likely to be reflected in others, indicating a cohesive model. Table 17 presents the correlation matrix, highlighting several key relationships among the constructs.

One of the most notable findings is that all the independent variables exhibit a positive correlation with Driver Intention to use ADAS technology. The variable that shows the least correlation with Driver Intention is Self-Efficacy ($r = .239$, $p < .05$), while Price Value has the next lowest correlation ($r = .358$, $p < .001$). Yet even for others acting as independent variables, variables such as Facilitating Conditions ($r = .478$, $p < .001$), Perceived Safety ($r = .418$, $p < .001$), and Social Influence ($r = .404$, $p < .001$) have correlation coefficients significantly lower than 0.5. Attitude Toward Using Technology has the most significant correlation with Driver Intention at $r = .622$ ($p < .001$), indicating a prominent positive relationship.

Looking at the correlations among the independent latent variables, one of the highest and most significant findings is that Performance Expectancy has a positive correlation with Attitude

Toward Using Technology ($r = .556$, $p < .001$). This suggests that drivers' expectations for the performance of ADAS systems are predictive of their overall attitudes toward advanced technology. In addition, Social Influence is significantly correlated with Performance Expectancy ($r = .452$, $p < .001$) as well as Attitude Toward Using Technology ($r = .484$, $p < .001$), which further confirms that social factors have a significant influence on both performance expectations and attitudes toward technology. Facilitating Condition and Effort Expectancy have a significant positive correlation of $r = .555$ ($p < .001$). Perceived Safety has a significant correlation with all variables.

Some correlations are weaker, as shown. Self-Efficacy is the variable with the highest number of non-significant correlations (with Effort Expectancy, Price Value, and Facilitating Condition). In addition, the link between Performance Expectancy and Facilitating Condition is not statistically significant ($r = .199$, $p > .05$), indicating that individuals' perception of the ease of using technology is not deterministically related to their confidence in being able to do so.

Correlation analysis plays an important role in this study, as it finds that the predicted directions of the research model are indeed present in these statistically significant correlations. Specifically, it demonstrates that the independent latent variables—Performance Expectancy, Effort Expectancy, Social Influence, Price Value of ADAS, Perceived Safety, Self-Efficacy, Attitude Toward Using Technology, and Facilitating Conditions—have a correlation with the dependent variable Driver Intention to use ADAS technologies. These findings align with the proposed model based on CTAM-UTAUT.

This evidence confirms and supports the hypotheses, indicating that these variables may play important roles in shaping the acceptance of drivers toward ADAS. By verifying significant correlations in the expected directions, the correlation analysis prepares the ground for subsequent regression analysis examining direct effects of these variables on Driver Intention to use ADAS. The correlation analysis suggests that all variables are potentially relevant and make useful contributions to explaining the variance of the dependent variable, Driver Intention. Additionally, since there are no pairs of variables with high correlation coefficients (typically above 0.8 or 0.9), the variables do not present multicollinearity issues. To delve more deeply into these relationships, multiple regression models are used. Multiple linear regression was performed to assess the impact of multiple independent variables on the single dependent variable, Driver Intention. Such a method aims at assessing the direct effects of the independent latent variables on the dependent variable. This model is very useful in facilitating the interpretation of regression coefficients: they are the changes that occur in the dependent variable once there is a unit change in the independent variable. Thus, it provides interpretable results for practical and theoretical impact (Souders & Charness, 2016).

Table 17. Correlation matrix

Correlation Matrix

	N items	M	SD	1	2	3	4	5	6	7	8	9
1 Performance Expectancy	2	3.78	0.99	(0.74)								
2 Effort Expectancy	3	4.16	0.62	.284**	(0.65)							
3 Social Influence	2	3.82	0.8	.452***	.437***	(0.57)						
4 Price Value	2	3.67	1.01	.407***	.296**	.454***	(0.87)					
5Perceived Safety	4	3.71	0.70	.363***	.471***	.408***	.261*	(0.53)				

6 Attitude Toward Using Technology	2	3.53	0.95	.556***	.361***	.484***	.401***	.444***	(0.85)			
7 Facilitating Condition	2	4.02	0.68	.199	.555***	.385***	.282***	.497***	.302**	(0.51)		
8 Self-Efficacy	4	3.61	0.79	.373***	.166	.376***	.161	.319**	.405***	.022	(0.81)	
9Driver Intention	2	4.01	0.79	.454***	.399***	.404***	.358***	.418***	.622***	.478***	.239*	(0.65)

The correlation is significant at level: *p <0.05, **p<0.01, ***p<0.001.

4.4 Multiple Linear Regression

A linear regression analysis using a one-way procedure was employed to ascertain the predictor of Driver Intention to use ADAS. Specifically, all eight independent variables, generated from CTAM-UTAUT2 model, have been collectively integrated. There is one main point to be highlighted here: based on this model of UTAUT model, 67.3% of variations in driver intent to use ADAS can be explained via a regression model. The overall model is highly significant, with a p-value less than 0.001, confirming its statistical significance. The effect sizes are given in both the graph and the table at a glance, while the details are precise figures for a more thorough analysis.

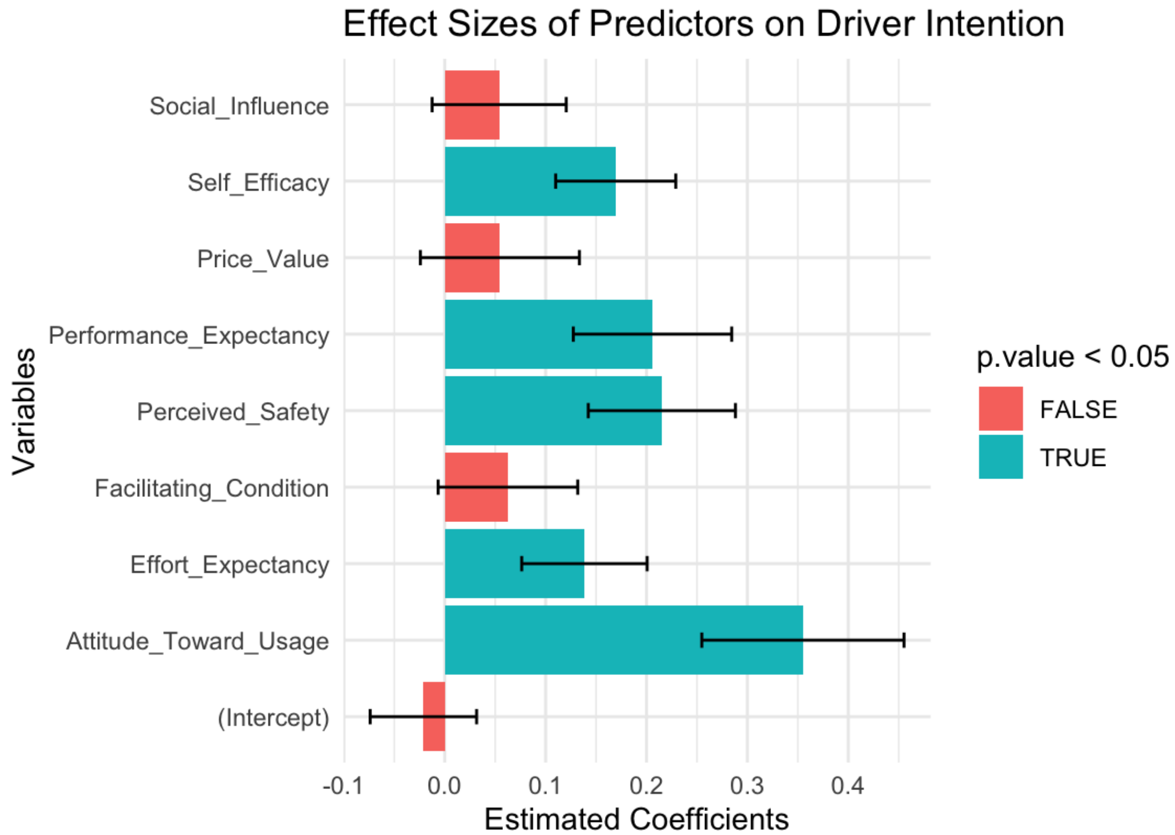


Figure 11. The effect sizes of predictors on Driver Intention ((Multiple linear regression).

The Multiple Regression analysis shows that not all eight constructs significantly contribute to explaining the variance in drivers' intention to use ADAS. Specifically, five constructs emerge as significant predictors: Performance Expectancy, Attitude Toward Using Technology, Perceived Safety, Effort Expectancy, and Self-Efficacy. Among these, **Attitude Toward Using Technolog**y is the most powerful predictor, with a coefficient of 0.355 (SE = 0.100, $t(86) = 3.54$, $p < .001$). Over 85.8% of participants expressed agreement or strong agreement with the statement ATT2, "These systems make the drive more interesting," demonstrating broad support for ADAS technology. Additionally, 58.7% of respondents showed a favorable attitude with ATT3, "Using these systems is enjoyable, and I want to continue using them," indicating that their positive perceptions are strongly influenced by their experiences with the existing ADAS systems in trucks. This data suggests that further education on how to effectively utilize ADAS could significantly enhance their acceptance and enthusiasm for new systems. Hence, H7 is supported.

Perceived Safety is the second most significant predictor, with a coefficient of 0.215 (SE = 0.073, t(86) = 2.95, p = .004). Over 77.1% of respondents agreed or strongly agreed with the statement PS1, "Thanks to ADAS technology, my trip and work could be safer and risk-free." Furthermore, over 84.78% agreed or strongly agreed with PS2, "ADAS systems minimize the risk of accidents." However, lower approval ratings of 52.16% for PS3, "It is not a concern for me that the Advanced Driver Distraction Warning uses continuously active cameras," and 59.17% for PS4, "I am confident that this system would not negatively impact my driving habits," indicate a cautious acceptance of ADAS systems among drivers. While they recognize the potential safety benefits, there is more hesitation regarding constant monitoring and the influence of such advanced technologies on their driving behaviors. Hence, H5 is supported.

Performance Expectancy has a coefficient of 0.206 (SE = 0.079, t(86) = 2.62, p = .010), making it another significant predictor. Specifically, for PE3, "Using this technology at its fullest will help me in reaching my destination," 75% of respondents showed strong agreement or agreement, reflecting confidence in ADAS to aid in efficient navigation. However, a lower percentage, 61.9%, strongly agreed or agreed with the statement PE2, "Using this technology at its fullest will allow me to be faster," suggesting less certainty about ADAS's ability to improve travel time despite its benefits in traffic assistance and navigation. These results demonstrate that a significant portion of drivers view ADAS systems as effective tools in their work, not only for enhancing safety but also for aiding in efficient route planning and time management. Hence, H1 is supported.

Self-Efficacy is the fourth strongest predictor of driver intention, with a coefficient of 0.169 (SE = 0.060, t(86) = 2.85, p = .006). From the survey, the most critical factor identified is education, with 63.04% of drivers agreeing or strongly agreeing with the statement SE2: "I would use these systems more if someone could explain ADAS technology to me." The statements about having more time to learn, having built-in assistance, and receiving personal help to increase ADAS acceptance were agreed upon by approximately 54.3%, 53.3%, and

53.3% of respondents, respectively. Additionally, one comment from the survey pinpointed a notable gap: "The professional role of the driver is lacking. More practical training is needed." This observation emphasizes the need for comprehensive training programs that not only familiarize drivers with ADAS technology but also enhance the professional skills necessary in the evolving landscape of automated driving. Hence, H6 is supported.

Effort Expectancy shows a moderate impact, with a coefficient of 0.138 (SE = 0.062, $t(86) = 2.23$, $p = .029$). In the survey, over 88.0% of respondents strongly agree or agree on EE1, "I think that this technology and ADAS systems are easy to use," indicating that the widespread acceptance of ADAS is largely due to its user-friendly design. Additionally, over 85.8% of drivers find their interaction with the system clear and understandable (EE3: "My interaction with systems is clear and understandable"). Drivers can utilize ADAS systems with minimal effort, which might reduce the cognitive load and help maintain their focus on driving. The user-friendly nature of these systems supports drivers effectively, and if the technology requires more time away from their primary tasks, it could lead to lower satisfaction and reduced adoption. Hence, H2 is supported.

Facilitating Condition has a small coefficient of 0.063 (SE = 0.069, $t(86) = 0.905$, $p = .368$), indicating it is not significant in this study. Over 75.0% of respondents strongly agree or agree with FC2, "I know how to use ADAS technology," highlighting a significant level of familiarity and comfort with these systems, which may be attributed to either effective training or intuitive design. Moreover, over 76.1% of drivers affirm that ADAS systems are compatible with other technologies they use while driving (FC3: "ADAS systems are compatible with other technologies while I drive"), indicating a high level of integration perceived by users. However, H1a is not supported.

Price Value has an even lower coefficient of 0.055 (SE = 0.079, $t(86) = 0.693$, $p = .490$) and is not significant. In this study, over 68.5% of respondents strongly agree or agree that the expense of ADAS technology, which ranges from €3,240 to €6,340, is justified by the benefits it provides (PV1: "The expense of this technology, ranging from €3,240 to €6,340, is warranted by the advantages it offers."). This strong agreement suggests that a majority of users perceive the cost as reasonable given the enhancements in safety and efficiency it brings. Additionally, over 56.5% of respondents express a willingness to spend even more on ADAS technology (PV2: "I want to spend even more on ADAS technology."). This indicates a significant level of satisfaction and trust in the technology's value, with users ready to invest further in advanced features. However, H4 is not supported.

Social Influence has the lowest coefficient value of 0.054 (SE = 0.066, t(86) = 0.812, p = .419) and is not significant. More than 58.7% of respondents are in strong agreement or agreement with SI1, "People around me think that I should use this technology," which suggests that social influences and peer perceptions play a role in the adoption and acceptance of the technology. Furthermore, more than 72.8% of respondents are also personally willing to reveal ADAS technology in their vehicles with others (SI3: "If I have this ADAS technology available in my trucks, I will show to my colleagues"), emphasizing the openness in sharing and communication among staff members. However, H3 is not supported.

This tendency to share and promote ADAS is particularly notable given that professional drivers, whose livelihoods depend on driving, may be less affected by societal influences than the average driver and more focused on the practical and safety enhancements these technologies offer.

The intercept is very close to zero (b = –0.021, SE = 0.053, t(86) = –0.401, p = .689), indicating that when all predictors are at zero, the baseline level of driver intention is nearly zero.

Table 18. Numerical effect sizes of predictors on Driver Intention (Multiple linear Regression)

Predictor	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	–0.021	0.053	–0.401	.689
Performance Expectancy	0.206	0.079	2.623	.010
Effort Expectancy	0.138	0.062	2.227	.029
Social Influence	0.054	0.066	0.812	.419
Price Value	0.055	0.079	0.693	.490
Perceived Safety	0.215	0.073	2.951	.004
Attitude Toward Using Technology	0.355	0.100	3.542	.001
Facilitating Condition	0.063	0.069	0.905	.368

Note. Residual standard error = 0.4905; Multiple R^2 = .6728; Adjusted R^2 = .6413; $F(8, 86) = 21.33$, $p < .001$.

4.4.1 Multiple linear regression and the moderating role of Gender, Age and Experience.

In the regression analysis that assessed the impact of various predictors on Driver Intention, none of the interaction terms demonstrated statistical significance. After data collection, the moderator "Gender" was removed from the analysis because the entire sample consisted only of male drivers, leading to H8 not being supported.

Regarding the Age interaction term, the coefficient was slightly negative ($b = –0.0014$, $t(86) = –0.028$, $p = .978$), indicating a minor decrease in Driver Intention for each additional year of age, assuming all other variables are held constant. However, given the limitations of the sample size, this negative coefficient is not statistically significant ($p = .978$). Appendix 3 includes a scatterplot that illustrates the impact of increasing Age on Driver Intention, leading to the non-support of H9.

For Experience, the coefficient is somewhat larger ($b = –0.0045$, $t(86) = –0.064$, $p = .949$), suggesting a decrease in Driver Intention with each additional year of experience. Yet, this coefficient also lacks statistical significance, with a high p-value of .949. Appendix 4 presents a scatterplot similar to that for Age, showing the effect of Experience on Driver Intention, and likewise, H10 is not supported by the data.

The analysis indicates that the moderating effects of Age and Experience on Driver Intention are similarly inconsequential, likely due to the correlation between being older and having more driving experience. A regression analysis was conducted to confirm that, and the results strongly suggest a significant relationship between Age and Experience among drivers in the dataset (see Appendix 5).

Despite this link, neither Age nor Experience significantly alters Driver Intention. This suggests that other factors have a consistent influence on Driver Intention. Such findings underscore the difficulty in isolating the individual impacts of Age and Experience within groups where these traits often overlap.

Table 19. Table with hypothesis.

Number	Hypothesis	Results
H1	Performance Expectancy has a significant effect on the intention to use.	**Supported**
H2	Effort Expectancy has a significant effect on the intention to use.	**Supported**
H3	Social Influence has a significant effect on the intention to use.	Not supported
H4	Price Value has a significant effect on the intention to use.	Not supported
H5	Perceived Safety has a significant effect on the intention to use.	**Supported**
H6	Attitude Toward Using Technology has a significant effect on the intention to use.	**Supported**
H7	Self-efficacy has a significant effect on the intention to use.	**Supported**
H8	Gender is moderating in the research model concerning drivers' intentions to use ADAS.	Not supported
H9	Age plays a moderating role in the research model concerning driver intentions to use ADAS.	Not supported
H10	Experience plays a moderating role in the research model concerning driver intentions to use ADAS.	Not supported
H1a:	Facilitating condition has a significant effect on Driver Intention.	Not supported

An online survey was distributed among the heavy truck drivers at CoolCarrier Co., specifically targeting those holding a type "C" driving license and employed by the company. The research aimed to address the question: "What factors influence professional truck drivers' intentions to use ADAS technology?". This study significantly advances the understanding of technology acceptance by developing a new model for a previously understudied area. Research on the acceptance of autonomous cars by drivers is extensive, but studies on ADAS are notably fewer. Additionally, the application of UTAUT combined with the TAM in the trucking industry is rare. The only significant research in this context, conducted by Marisda et al. (2020), focused on fully autonomous trucks and was limited to the Indonesian context. This highlights a critical gap in understanding technology acceptance among professional drivers of ADAS technology, an area becoming increasingly important.

Building on the foundations set by Osswald et al. (2012) and UTAUT 2 (Venkatesh et al., 2012), who explored the acceptance of autonomous vehicles, this research applies UTAUT to examine ADAS in partial automation as categorized by SAE. Previous studies did not concentrate on professional drivers, nor did any research specifically target this group. This study fills that void by investigating how professional drivers perceive and accept emerging technologies, particularly as Level 2 autonomous systems become mandatory. This study differs from others primarily in the aspects it explores, such as the type of technology examined, the vehicle types considered, and the specific role of the professional driver. Starting with the technology, while autonomous vehicles are still a developing technology requiring significant investments, they aim to remove the user from the driving process. On the other hand, ADAS has been available for years and is currently under development for future versions. Additionally, while ADAS is designed to assist the driver, especially at this stage, autonomous vehicles aim to take over the driver's role entirely. ADAS is less complex than full automation and is specifically designed to help drivers in their work. Regarding the difference in vehicles, autonomous vehicles are consumer-focused and intended for the general public, where perceived safety is likely the most critical factor in their acceptance. In contrast, ADAS in trucks is much more focused on enhancing efficiency and safety, supporting the driver not taking its place. Finally, there is a difference in professionalism. Non-professional drivers use autonomous vehicles for personal transportation, with their concerns mainly centered around personal safety. In contrast, truck drivers have responsibilities that extend beyond their safety, including the timely and safe delivery of goods, making efficiency and effectiveness critical in their work. This responsibility shapes their acceptance of ADAS, where the focus is on practical benefits rather than personal preferences.

In addition to conducting multiple linear regression analysis, Structural Equation Modeling (SEM) and Partial Least Squares (PLS) regression were deployed to perform a more in-depth examination of the relationships between the independent variables and driver intention. PLS regression is particularly advantageous when predicting multiple dependent variables from a large set of predictors, allowing for the modeling of complex relationships. SEM facilitates the exploration of potential underlying relationships by building latent constructs that encompass indirect effects, and unlike CFA, it utilizes all observed variables to explore these relationships.

However, these sophisticated models encountered limitations in this study. The small sample size adversely affected the reliability of SEM results, and PLS regression did not yield significant findings (results can be found in Appendix 7 and 8). Consequently, these advanced techniques did not provide as robust findings as the multiple linear regression did in this context.

5. Discussion

5.1 Theoretical contribution

The study advances the theoretical understanding of technology acceptance by identifying the key determinants influencing professional truck drivers' intentions to use ADAS. By applying and refining existing models like the TAM and the UTAUT, the research highlights unique factors pertinent to ADAS adoption, distinguishing it from the acceptance of fully autonomous vehicles.

Attitude Toward Using Technology emerged as the most significant predictor of drivers' intention to use ADAS. This finding underscores the critical role of individuals' emotional and affective reactions in technology adoption, as initially theorized by Davis et al. (1989) and further developed by Venkatesh et al. (2003). Attitude has consistently been identified as an important predictor of behavioral intention to use technology across various contexts (Dai et al., 2021; Payre et al., 2014). Similarly, attitudes have been found to significantly influence the adoption of autonomous vehicles. Rahman et al. (2017) and Patel et al. (2023) demonstrated that positive attitudes towards autonomous driving technology increase the likelihood of adoption. Charness et al. (2018) found that drivers with prior knowledge of autonomous vehicles had reduced apprehension and increased readiness to abandon driving control, highlighting the role of familiarity in shaping attitudes. This aligns closely with the findings from this study, as when drivers have positive experiences with the ADAS features they're already using, it can encourage them to adopt more advanced autonomous technologies. In fact, the entire fleet of their company is equipped with AEB, LDW, ACC and ESP. When drivers have recognized the benefits of ADAS, they are more inclined to adopt and utilize these technology increases. The more positive their experiences with these components, the more open they are to adopting more comprehensive and sophisticated ADAS solutions. Furthermore, this research proposes that the relationship between familiarity and adoption may vary depending on the technological maturity of a company's fleet. Future studies could investigate organizations operating older fleets without advanced ADAS features to determine if the absence of prior exposure affects drivers' attitudes and intentions differently.

Perceived Safety was identified as the second most significant predictor. Recognized as a crucial factor in technology adoption, Perceived Safety is not strictly connected with objective safety measurements (Prasetio & Nurliyana, 2023). However it combines actual safety outcomes with socio-psychological perceptions. Previous research has consistently emphasized its significance in the willingness to adopt autonomous vehicles (Xu et al., 2018; Cao et al., 2021). Specifically, Bellet & Banet (2023) found that Perceived Safety was the strongest predictor in the intention to use automated vehicles, emphasizing its paramount importance. Additionally, Pettigrew (2019) highlighted that major concerns for participants regarding autonomous vehicles were associated with a loss of control (cognitive) and feelings of fear (emotional). These findings illustrate that safety perceptions are not solely based on statistical safety records but are also significantly influenced by psychological factors. Perceived Safety is paramount in autonomous vehicles, as control is largely automated, potentially raising concerns about daily driving security. In the ADAS context, the dynamics differ because the driver largely retains control. Although security in ADAS is crucial, the industry is only at the early stages of automation, marked by SAE Level 2 automation. This allows the driver to manage situations directly, especially in emergencies. This aligns with results found by Nees (2019) suggesting that autonomous vehicles would only be widely accepted if perceived as safer than human driving, a threshold that 70% of respondents felt was not yet met. In the context of ADAS, the dynamics differ due to the level of driver control retained. While autonomous vehicles involve high levels of automation with minimal driver intervention, ADAS currently operates at SAE Level 2 automation, allowing drivers to manage situations directly, especially in emergencies. This retained control might mitigate some apprehensions related to loss of control but could also mean that the Perceived Safety benefits are less pronounced in intention compared to fully autonomous systems. Their ability to take immediate control explains the lower prediction of Perceived Safety for intention compared to the study of Autonomous Vehicles.

Performance Expectancy was the third significant predictor, reflecting drivers' beliefs regarding how ADAS can enhance their job performance. This aligns with prior research emphasizing the need for superior system performance to achieve transportation goals efficiently (Sessa et al., 2015; Madigan et al., 2017). Factors such as the reliability of the vehicles and their compatibility with existing transportation services are critical in facilitating broader autonomous adoption. In the research carried out by Bellet and Banet (2023), Performance Expectancy was the fourth strongest predictor, indicating a potential shift in its relative importance across different contexts. In this study, Performance Expectancy is crucial as it reflects the extent to which drivers rely on technology, particularly ADAS, to minimize incidents and increase operational effectiveness. If drivers believe these systems make driving safer, reduce fatigue, or simplify complex driving tasks, they are more likely to use and not disable them. This variation suggests that the role of Performance Expectancy might differ between professional drivers and general consumers. Improved safety not only impacts their well-being but also has professional implications, such as reducing the risk of cargo damage, enhancing delivery timeliness, and minimizing the likelihood of accidents that could lead to loss of work or legal issues. If drivers believe that ADAS systems make driving safer, reduce fatigue, or simplify complex driving tasks, they are more inclined to adopt and consistently use them rather than disable them. Conversely, in the case of autonomous vehicles, Performance Expectancy is less important as they do not have a direct effect on their occupational responsibilities. It suggests that while Performance Expectancy remains a significant predictor, its influence varies depending on whether the user is a professional driver with specific job-related needs or a non-professional driver with different priorities.

Self-Efficacy emerged as the fourth significant predictor, emphasizing the importance of drivers' belief in their ability to effectively use ADAS. Self-Efficacy is about believing in your own ability to handle specific tasks successfully (Bandura, 2002; Marakas et al., 1998). In addition, Self-Efficacy is recognized as a dynamic construct influencing technology adoption (Zhu et al., 2010; Tams et al., 2018). When individuals have low Self-Efficacy, they struggle to manage situations effectively, even when they know the appropriate actions to take

(Bandura, 2002). High Self-Efficacy enables drivers to confidently interact with ADAS, thereby maximizing safety benefits and operational efficiency. In contrast, in the context of autonomous vehicles, the situation shifts since direct interaction and control by the driver are eliminated. A study by Zefreh et al. (2023) showed that Self-Efficacy does not significantly impact the intention to use autonomous vehicles. In fully autonomous cars, the driver’s transition to passenger may diminish the relevance of their confidence in personal driving capabilities. Here, Self-Efficacy might take on a different role, emphasizing the capability to monitor and intervene, when necessary, rather than actively operating the vehicle.

Effort Expectancy was also a significant predictor, representing the perceived ease of using ADAS technology. This includes the simplicity of learning to use these systems and the clarity of interaction with the technology. The context of this study differs significantly from that of autonomous vehicles. In autonomous vehicles, non-professional drivers are not expected to take control of driving, and Effort Expectancy may focus on understanding the system's functionality and trust in automation. Zefreh et al. (2023) also demonstrated that there is no statistical significance of this predictor in autonomous vehicles. In contrast, ADAS are designed as assistive devices rather than replacements. In the context of professional drivers, the need for ADAS to be user-friendly is paramount due to their daily interaction with these systems and the additional responsibilities they bear related to timing, logistics, and vehicle management. They need to understand how to operate these systems effectively to enhance their performance. The study emphasizes that professional drivers require ADAS that are straightforward to comprehend and interact with, minimizing the learning curve and reducing potential disruptions to their workflow. This is consistent with prior research that emphasizes the importance of user-friendly interfaces in facilitating technology acceptance in professional settings (Bhattacherjee & Sanford, 2006).

Conversely, Social Influence, Price Value of ADAS, and Facilitating Conditions were not significant predictors of drivers' intention to use ADAS in this study. This contrasts with findings in autonomous vehicle research, where these factors often play more substantial roles (Bellet & Banet, 2023).

Price Value is the economic value of using technology, managing perceived benefits with monetary cost (Venkatesh et al., 2012). This connects with earlier research like that from Seuwou et al. (2020) and Bellet and Banet (2023) that discovered that Price Value is positively related to the intention of adopting autonomous vehicle technology in cars, which involves high financial investment. Autonomous vehicles require a substantial capital investment, including purchase price, maintenance, and technology updates, making Price Value a critical consideration for consumers. In contrast, for ADAS in trucks, the cost is relatively limited, often up to 6000 euros. The benefits of improved safety and operational efficiency may outweigh any perceived costs, rendering Price Value less influential in their adoption decision. Furthermore, in scenarios like at CoolCarrier Co., where the trucks are company property, the direct cost to the individual driver is virtually non-existent. Therefore, Price Value may not be a significant predictor for this sample of professional truck drivers. Future research could explore whether this finding is specific to this study sample, or a broader trend related to differing technology costs.

Social Influence encompasses the impact of subjective norms and social pressure on behavioral intentions (Venkatesh et al., 2003). It has been a key factor in technology adoption, influencing individuals through the opinions and behaviors of peers, family, and societal trends. Social Influence has been incorporated into models like the CTAM by Osswald et al. (2012) and the UTAUT-4AV by Bellet and Banet (2023). Research by Liu et al. (2018) and Panagiotopoulos and Dimitrakopoulos (2018) demonstrated how the experiences and opinions of peers significantly influence an individual's acceptance of automated vehicles.

However, in this study, Social Influence was not statistically significant. Non-professional drivers tend to be influenced by the opinions of family and friends when adopting new technologies on vehicles. The decision to fully accept autonomous vehicles is closely related to the behaviors and choices of those in their immediate peers, with social acceptance playing a significant role. On the other hand, ADAS systems are relatively low-cost, have been available for many years, and are integrated into the professional context of trucking. They are not viewed as innovative or groundbreaking technology by professional drivers, having already undergone extensive testing and usage in the industry. Consequently, the adoption of ADAS is less influenced by the opinions of others, with drivers placing greater emphasis on the functionality, reliability, and safety benefits of the systems rather than on social considerations. This suggests that in professional contexts, Social Influence may have a diminished impact compared to consumer markets.

The lack of significance of Social Influence suggests that professional drivers prioritize the functionality and security of ADAS over the opinions of peers or social pressures. The insignificance of price value may be attributed to the relatively lower cost of ADAS in trucks and the fact that some companies cover these expenses, reducing the financial consideration for drivers.

Facilitating Conditions, defined as the degree to which an individual believes that organizational and technical infrastructures exist to support the use of a system (Venkatesh et al., 2003), were included in the initial model, although it was anticipated they might not significantly predict the intention to use ADAS. Furthermore, in this study they had no statistically significant impact on intention to use. Thus, these conditions do not have a meaningful impact on whether professional drivers intend to adopt these systems. In other words, factors like organizational support, infrastructure, or resources available to assist with using ADAS are not significantly influencing drivers' intentions to use the technology.

This research contributes to the theoretical framework by refining existing technology acceptance models in the context of ADAS among professional truck drivers. It highlights the necessity of considering the unique characteristics of ADAS and partial automation—such as the importance of drivers and the professional heavy truck context—that influence the relative importance of various predictors. The findings suggest that while traditional factors like Attitude Toward Using Technology, Perceived Safety, Performance Expectancy, Self-Efficacy, and Effort Expectancy remain significant, their impacts may vary compared to those in autonomous vehicle contexts.

By demonstrating that factors like Social Influence, Price Value, and Facilitating Conditions have no effects in this specific setting, the study encourages a reevaluation of these constructs within technology acceptance models when applied to ADAS. This tailored approach provides a more accurate understanding of the determinants influencing professional drivers' acceptance of ADAS technologies.

In this model, however, age was found not to have reached a statistical significance in moderating the acceptance of ADAS technology. A relatively small tendency was observed for intention to decrease as age increases (See Appendix 3). This interpretation is in line with the mixed results from the literature on the acceptance of self-driving cars. For instance, in their article on the acceptance of fully autonomous cars, Bellet and Banet (2023) identified age as a statistically significant factor that diminishes acceptance. Souders and Charness (2016), in complete contrast, argued that acceptance increases with increasing age in autonomous cars. Thus, this project makes a novel contribution to the ongoing discussion. By showing that age does not statistically influence acceptance of partially automated driving, it is shown that the relationship between age and technology acceptance may be context-dependent, influenced by factors such as the level of automation and the professional experience of the users.

With regards to Experience, in the UTAUT, it was detected as one of the pivotal moderators in technology acceptance (Venkatesh et al., 2003). According to Youen et al. (2022), the findings show that good experiences increase acceptance by building trust in and knowledge of technology institutes. In contrast, poor experiences or limited exposure reduce acceptance. This dual impact of experience is consistent with the findings of this thesis, indicating that acceptance is connected with the personal perceived experience with technology. This perspective could also be applicable to the findings of this study.

5.2 Updated conceptual model

Building on these insights, a revised conceptual model is proposed, incorporating the identified key determinants. This model offers a refined framework for predicting and enhancing the adoption of ADAS among professional truck drivers, contributing to theoretical advancement in the field of transportation technology.

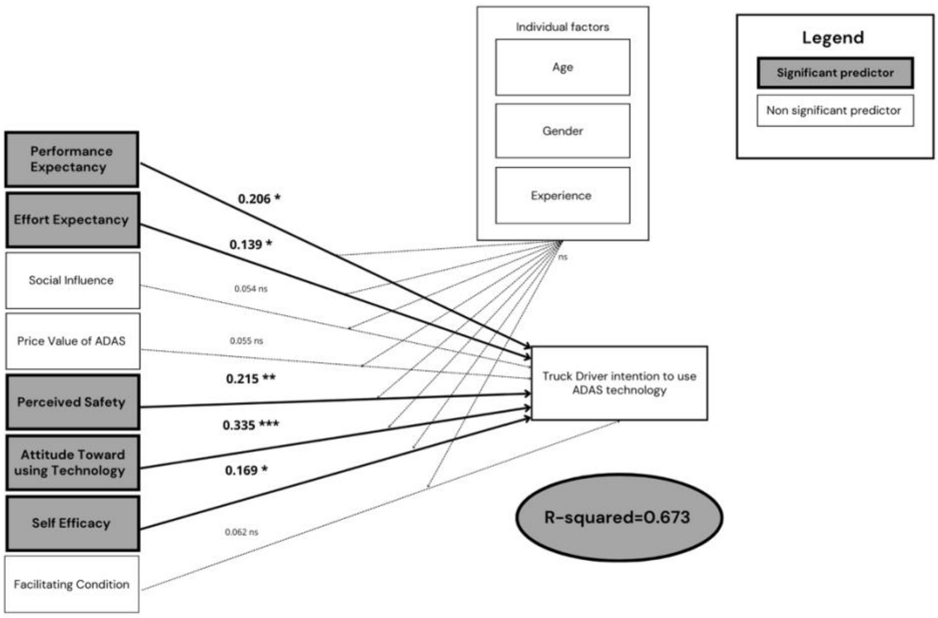


Figure 12. Updated conceptual model

5.3 Practical Contributions

This study aims to emphasize the significance of ADAS, which is expected to advance toward partial automation in the coming years, particularly within the trucking industry. The practical contributions of this research are manifold. For the Transportation Regulation Authority, the results offer valuable insights on how to implement ADAS systems: gradually. As drivers, particularly professional ones, become familiar with and gain experience using one device, they are more likely to adopt new systems. This is highlighted by the fact that attitude is the primary predictor of acceptance. For example, ADAS systems like AEBS and ELKA, which are advancements of AEB and LDW, are the most accepted by truck drivers. In contrast, newer systems like ISA and ADDW receive less acceptance. The study also highlights that truck drivers value the option to install specific ADAS devices, such as an alcohol breathalyzer, which positively influences their acceptance.

Secondly, the Transport Regulation Authority, should have a stronger stance on maintaining the autonomy of ADAS systems. The original ISA was designed to automatically reduce speed using sign-recognition cameras and digital maps. However, this system faced resistance from the ACEA (European Automobile Manufacturers' Association), which pressured regulators to reduce the system's functionality to simply provide a speed warning indicator. This change is likely to annoy drivers and lead to the system being disabled, rather than fulfilling its intended purpose of saving lives. It is vital to uphold the system's initial objective to ensure the effective improvement of road safety.

Lastly, infrastructure updates should be synchronized with advancements in ADAS technology. Typically, urban environments present more challenges for ADAS systems, requiring continual improvements to infrastructure with each technological update. Often, ADAS features are deactivated when the systems fail to detect imperfections in the road, such as missing lane markings or poor-quality asphalt. In these scenarios, drivers must turn off the ADAS systems to prevent incorrect signals and warnings. On the contrary, highways, which typically receive more maintenance, offer optimal conditions for ADAS systems to operate effectively.

For truck manufacturers, the acceptance of ADAS by professional drivers is high. However, it is crucial to pay attention to the ongoing evolution of ADAS, as these systems are becoming more efficient and complex each year. It is particularly important to maintain the emphasis on enhanced safety, as perceived safety is a key predictor of ADAS usage. If truck drivers perceive these systems as safe, they will be more likely to continue using them.

Similar to the approach recommended for Transport Regulatory Authorities, manufacturers are encouraged to implement these devices gradually. In fact, they can equip trucks with more advanced ADAS beyond those required by transport regulations. Ensuring the technology is user-friendly and simple to operate is crucial, as a decrease in ease of use (connected with increased Effort Expectancy) could lead to a decline in the intention to use these systems. If the technology becomes too complex, drivers may be less inclined to use it. Moreover, clear communication on the ADAS functioning is necessary for understanding the ADAS technology and emergency management.

Finally, special attention should be given to the future role of Self-Efficacy. While the need for assistance or built-in help features is currently limited, as ADAS systems evolve and become more complex, the role of assistance could become crucial in increasing Driver Intention to use the systems. This factor is already significant and is likely to become even more important as the technology advances.

For truck logistics companies, firstly, to obtain effective implementation is vital to have a strong emphasis on the role of training for drivers' companies. This training is essential for building the capabilities and confidence needed to enhance their Attitude Toward Using Technology. Additionally, Self-Efficacy plays a significant role; over 60% of truck drivers indicated they would be more likely to use these devices if they received more training on their proper use.

Secondly, selecting the right trucks is crucial. The perceived safety of ADAS is fundamental, shaped by both the selection of trucks and the potential addition of extra ADAS features, which often come at a significant additional cost from the manufacturer. It is vital to make well-informed decisions regarding the type of truck and the technology that can best assist drivers in ensuring a safer journey. Conducting interviews and surveys with drivers using new ADAS technology can provide valuable insights into whether a particular system is perceived as useful or not. Additionally, while consulting with different transport companies can be beneficial, it is important to recognize that each company and each driver has unique needs based on their specific routes and the goods they transport. Furthermore, it is critical to assess the impact ADAS might have on their work ensuring that these systems yield tangible gains connected to performance expectations. ADAS should not only enhance safety but also contribute positively to the overall efficiency and effectiveness of the driver's role. Effort Expectancy is an important factor for the future. Currently, it remains significant but has a relatively low impact, largely due to the simplicity of the ADAS systems in use at the moment and those expected to be implemented in the near future. However, as more complex ADAS systems are introduced and conditional automation advances to levels like SAE Level 3, greater attention will need to be paid to this parameter. Ensuring that drivers can easily and effectively interact with these more advanced systems will become increasingly critical.

Lastly, for truck drivers, it is crucial to actively participate in their training, striving to thoroughly understand how ADAS systems function and their benefits. This training should foster full adaptability to the evolution of new ADAS technologies, which may alter the available technology in the coming years. Moreover, drivers should also provide active feedback to their transport companies. This immediate feedback helps the company understand which aspects are important for current operations, and it also aids in long-term planning for the future acquisition of new trucks.

6. Limitation and future studies

This study represents a pioneering effort in analyzing the intention of truck drivers to use ADAS systems. Despite previous attempts involving autonomous trucks in a logistics company, which garnered only 37 responses, this analysis marks a significant first. Here are some potential improvements for future research:

Initially, incorporating qualitative research at the outset could provide a deeper understanding of the relationship between drivers and ADAS systems. This approach would be beneficial in formulating more insightful survey questions. Ideally, a pre-test could be conducted with a sample of professional drivers rather than non-professionals. However, due to the specific context and limited availability within the company, this was not feasible.

Secondly, the sample size of 95 was notably restrictive, yet the challenge of engaging with more companies was compounded by the highly specialized and sensitive nature of the sector. Factors that appeared non-significant in this study may need to be reassessed with alternative analytical models to determine their impact, as they may indeed be less relevant for the studied demographic.

For future research, expanding the sample size and involving additional companies would enhance sample diversity. Although the company in this study operates nationwide in Italy, the findings may not generalize to drivers under different operational conditions. A larger sample size would also facilitate analyses of moderating factors like age and experience and enable the use of more sophisticated statistical approaches, which were not feasible in this study due to sample constraints.

Moreover, comparisons between professional and non-professional drivers could highlight the influence of professional experience on the acceptance of ADAS. Future studies could also include comparisons across different levels of ADAS sophistication, types of vehicles, and the professional status of drivers. These comparative analyses would offer a more comprehensive view of how various factors interact with Driver Acceptance and utilization of ADAS technologies, providing valuable insights into their applicability and effectiveness across different segments of road users.

It would be worthwhile to explore the actual usage of ADAS technology in trucks, especially as upcoming regulations will mandate ADAS systems in all new trucks by 2024. This analysis would align with the second phase of technology acceptance studies, commonly explored in models like TAM and UTAUT. As UTAUT evolves and conditional automation advances, repeating this study could provide valuable insights into how perceptions and attitudes shift with technological progression. Qualitative analyses could offer deeper insights into driver experiences, attitudes, and the evolving dynamics of ADAS use.

These enhancements would not only refine the methodological robustness of the research but also enrich the understanding of how ADAS technologies are integrated into and impact the professional lives of truck drivers.

7. Conclusion

This study aimed to explore a context that has not been previously addressed within the frameworks of UTAUT and TAM. While a significant amount of research on TAM and UTAUT has focused on the acceptance of fully autonomous vehicles, little attention has been given to the acceptance of ADAS systems by drivers, particularly in the context of trucks and professional drivers. Despite challenges in accessing and studying specific, often difficult-to-approach contexts, solutions have been obtained for the research question posed. Truck transportation remains the primary method for moving goods in Europe, a trend expected to continue until at least 2050. Unfortunately, trucks, which constitute only 1.5% of road vehicles, are involved in 15% of road accidents. With goals set to achieve zero road fatalities by 2050, emphasizing safety in goods transportation is paramount. Additionally, the role of ADAS is pivotal in preventing car crashes, with ADAS implementation expected to increase and become more efficient.

The UTAUT model has proven to be a reliable indicator of individual factors that determine technology adoption. In this study, the model was applied within the context of professional heavy truck transport, focusing on a lower level of technology compared to the models tested for fully autonomous cars. The aim was to answer the question:

“What are the factors that influence professional truck drivers’ intentions to use ADAS technology?”

This research analyzed the differences and similarities in the application of UTAUT for the acceptance of autonomous vehicles. Similarities were found in the roles of Performance Expectancy, Effort Expectancy, Perceived Safety, Attitude Toward Using Technology, and Self-Efficacy in predicting the Driver’s Intention to use ADAS. However, the study did not find any significant influence from one of the core elements of other UTAUT studies, Social Influence, nor from the Price Value of ADAS, which is a key factor in models applied to autonomous vehicles. Additionally, no significance was observed in the Facilitating Conditions.

In a world committed to enhancing road safety, this study offers an innovative contribution. As Vision Zero aims to drastically reduce fatalities, it is essential to include the heavy transportation sector and consider drivers' perspectives. Understanding how truck drivers perceive ADAS, which is crucial for advancing automation, increasing road safety, and reducing fatalities, is vital. If drivers are not fully on board with these changes, some may legally deactivate systems or engage in unauthorized modifications. Without their support, achieving the Vision Zero goal will continue to be out of reach.

References

Abdi, H. (2010). Partial least squares regression and projection on latent structure regression (PLS Regression). Wiley Interdisciplinary Reviews Computational Statistics, 2(1), 97–106. https://doi.org/10.1002/wics.51

Abu-Dalbouh, H. M. (2013). A questionnaire approach based on the technology acceptance model for mobile tracking on patient progress applications. J. Comput. Sci., 9(6), 763-770.

Al-Tarawneh, M., Huang, Y., Lu, P.& Bridgelall, R.(2020).Weigh-In-Motion System in Flexible Pavements Using Fiber Bragg Grating Sensors Part A: Concept. IEEE Trans. Intell. Transp. 21, 5136–5147.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin, 103, 411–423.

Antich, M. (2027, April 27). ADAS saves lives, but the technology has limitations. Automotive Fleet.

Audi Media Centre, (2017). TechDay piloted driving – The traffic jam pilot in the new Audi A8 – Press information.

Australian Bureau of Statistics, (2023). Census and Sample.

Avdeenko, T.V. & Aletdinova, A.A. (2017). Digitalization of the economy on the basis

of improving expert knowledge management system. Scientific and Technical Journal

of St. Petersburg State Polytechnic University. Economic sciences, 10, 47-55.

Bandura, A. (2002), Social Cognitive Theory in Cultural Context. Applied Psychology, 51: 269-290.

Bartlett, L., & Vavrus, F. (2017). Comparative case Studies: an innovative approach. Nordic Journal of Comparative and International Education, 1(1). https://doi.org/10.7577/njcie.1929

Baomar, H.& Bentley, P. J. (2016). An Intelligent Autopilot System that learns piloting skills from human pilots by imitation. International Conference on Unmanned Aircraft Systems (ICUAS),. 1023-1031. doi: 10.1109/ICUAS.2016.7502578.

Bellet, T., & Banet, A. (2023). UTAUT4-AV: An extension of the UTAUT model to study intention to use automated shuttles and the societal acceptance of different types of automated vehicles. Transportation Research. Part F, Traffic Psychology and Behaviour, 99, 239–261.

https://doi.org/10.1016/j.trf.2023.10.007

Bhattacherjee, A., & Sanford, C. (2006). Influence Processes for Information Technology Acceptance: An Elaboration Likelihood model. AIS Electronic Library (AISeL).

Blanka, C., Krumay, B., & Rueckel, D. (2022). The interplay of digital transformation and employee competency: A design science approach. Technological Forecasting and Social Change, 178,121575.

Bryman, A. (2015). Social Research Methods (5th ed.). Oxford University Press.

Brynjolsson, E. & Mcafee, A. (2014). The Second Machine Age, WW Norton & Company, New York, NY, London

Burnes, B. (2004). Managing Change: A Strategic Approach to Organisational Dynamics, 4th edn (Harlow: Prentice Hall).

Butollo, F., Gereffi, G., Yang, C. & Krzywdzinski, M. (2022). Digital transformation and value chains: introduction. Global Networks, 22, 585-594.

Cao, J., Lin, L., Zhang, J., Zhang, L., Wang, Y., & Wang, J. (2021). The development and validation of the perceived safety of intelligent connected vehicles scale. Accident; analysis and prevention, 154, 106092.

Cardon D. (2015). What do Algorithms Dream of? Our Lives in the Age of Big Data Paris: Seuil, coll. République des idées.

Cetindamar Kozanoglu, D., & Abedin, B. (2020). Understanding the role of employees in digital transformation: Conceptualization of digital literacy of employees as a multi-dimensional organizational affordance. Journal of Enterprise Information Management, 34(6), 1649–1672.

Charness, N., Yoon, J. S., Souders, D., Stothart, C., & Yehnert, C. (2018). Predictors of attitudes toward autonomous vehicles: The roles of age, gender, prior knowledge, and personality. Frontiers in Psychology, 9, 2589. https://doi.org/10.3389/fpsyg.2018.02589

Child, D. (1990). The essentials of factor analysis, second edition. London: Cassel Educational Limited.

Chinoracký, R., & Čorejová, T. (2019). Impact of digital technologies on labor market and the transport sector. Transportation Research Procedia, 40, 994–1001.

Cho, Y., Park, J., Park, S., & Jung, E.S. (2017). Technology Acceptance Modeling based on

User Experience for Autonomous Vehicles. Journal of The Ergonomics Society of Korea, 36, 87-108.

Chomeya, R. (2010). Quality of psychology test between likert scale 5 and 6 points. J. Soc. Sci., 6: 399-403.

Collins, L. (2007). Research design and methods. In Elsevier eBooks, 433–442.

Creswell, J.W., (2011). Educational Research: Planning, Conducting and Evaluating Quantitative and Qualitative Research. 4th Edn., Pearson Education, Boston, ISBN-10: 0132613948, 650.

Creswell, J.W., & Plano Clark, V.L. (2011). Designing and Conducting Mixed Methods Research. 2nd Edition, Sage Publications.

Crissey, A. (2022). What's now, and what's next, for truck ADAS. Fleet Équipement. https://www.fleetequipmentmag.com/advanced-truck-driver-assistance-systems/

Dai, J. D., Li, R., & Liu, Z. (2021). Does initial experience affect consumers' intention to use autonomous vehicles? Evidence from a field experiment in Beijing. Accident; Analysis and Prevention, 149, Article 105778. https://doi.org/10.1016/j.aap.2020.10577

Da Silva, A. N. R., Da Silva Costa, M., & Macêdo, M. H. (2008). Multiple views of sustainable urban mobility: The case of Brazil. Transport Policy, 15(6), 350–360.

DAF Trucks (2023). DAF introduces full range of enhanced safety features.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319–340.

DeFranzo, S. E. (2020). What's the Difference between Qualitative and Quantitative Research? Snap Surveys Blog.

Dodds, W. B., Monroe, K. B., & Grewal, D (1991). Effects of Price, Brand, and Store Information on Buyers, Journal of Marketing Research 28(3), 307-319.

Elizondo-Montemayor, L., Hernández-Escobar, C. E., Ayala-Aguirre, F., & Aguilar, G. M. (2008). Building a sense of ownership to facilitate change: the new curriculum. International Journal of Leadership in Education, 11(1), 83–102. https://doi.org/10.1080/13603120701663486

Emelyanov, N.V. (2019). Digitalization of the economy as a factor in ensuring the national security of Russia. Economic growth: problems, patterns, prospects, 5, 89-93

European Transport Safety Council. (2022). Opinion: Will Intelligent Speed Assistance (ISA) live up to its promise?.

European Commission (2023). Transport sector economic analysis. EU Science Hub.

European Environment Agency (2024). Transport and mobility.

Everitt, T. & Hutter, M. (2018). Universal artificial intelligence. In Foundations of Trusted Autonomy; Springer: Cham, Switzerland, 15–46

Federal Motor Carrier Safety Administration (2022). Large truck and bus crash facts 2020.

Federal Motor Carrier Safety Administration (2024). Accelerating the Adoption of Advanced Driver Assistance Systems (ADAS): “Tech-Celerate Now” Phase 1.

Federal Motor Carrier Safety Administration (2019). Bring it Home Safely . . . How You Can Use Technology to Prevent Crashes.

Frey, C.B. & Osborne M.A. (2013). The Future of Work: How Susceptible are Jobs to Computerisation?.Working paper of the Programme on the impacts of future technology. Oxford: Oxford University.

Garson, G. D. (1993). Human factor in information systems. R.T. Golembiewski, Handbook of organizational behavior.

Garbarino, S., & Holland, J. (2009). Quantitative and Qualitative Methods in Impact Evaluation and Measuring Results. Discussion Paper. University of Birmingham.

Gohar, M., Muzammal, M., & Rahman, A. U. (2018). SMART TSS: Defining transportation system behavior using big data analytics in smart cities. *Sustainable Cities and Society*, *41*, 114–119. https://doi.org/10.1016/j.scs.2018.05.008

Hair, J., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). Multivariate analysis. Harlow, Essex: Pearson New International Edition.

Hammarberg, K., Kirkman, M., & de Lacey, S. (2016). Qualitative research methods: when to use them and how to judge them. Human reproduction, 31(3), 498-501.

Heijden, H. (2004). User Acceptance of Hedonic Information Systems. MIS Quarterly, 28(4), 695–704.

Hewitt, C., Theocharis A., Sarkar, A., & Ioannis, P. (2019). Assessing Public Perception of Self-Driving Cars: the Autonomous Vehicle Acceptance Model.

Holbrook, M. B., & Hirschman, E. C. (1982). The Experiential Aspects of Consumption: Consumer Fantasies, Feelings, and Fun. Journal of Consumer Research 9(2), 132-140.

Hulse, L., Xie, H., & Galea, E. R. (2018). Perceptions of autonomous vehicles: Relationships with road users, risk, gender and age. Safety Science, 102, 1–13.

Hussain, S.T., Lei, S., Akram, T., Haider, M.J., Hussain, S.H. & Ali, M. (2016). Kurt Lewin's change model: a critical review of the role of leadership and employee involvement in organizational change. Journal of Innovation and Knowledge, 3, 123-127.

Im, I., Hong, S. & Kang, M.S. (2011). An international comparison of technology adoption.

Information & Management, 48 (1), 1-8.

Jabłoński, M., & Jabłoński, A. (2019). Social factors as a basic driver of the digitalization of the business models of railway companies. Sustainability, 11(12), 3367.

Jansson, E., Olsson, N. O., & Fröidh, O. (2023). Challenges of replacing train drivers in driverless and unattended railway mainline systems—A Swedish case study on delay logs descriptions. Transportation Research Interdisciplinary Perspectives, 21, 100875.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jiang, Y., Li, X., Luo, H., Yin, S., & Kaynak, O. (2022). Quo vadis artificial intelligence? Discover Artificial Intelligence, 2(1).

Juniper (2023). Smart Traffic Management to Generate Revenue of $18.5 Billion Globally by 2028; Accelerated by Smart Cities' Investment. Smart Cities & IoT.

Kagermann H., Wahlster W. & Helbig J. (2013). Recommendations for Implementing the strategic initiative industries 4.0. National academy of science and engineering.

Kane, G. C., Phillips, A. N., Copulsky, J., & Andrus, G. R. (2022). The technology fallacy. The MIT Press.

Kaplan, A. & Haenlein, M. (2019). Siri, siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Bus. Horiz. 62 (1), 15–25.

Karimi, J. & Walter, Z., (2015). The role of dynamic capabilities in responding to digital disruption: a factor-based study of the newspaper industry. Journal of Management Information

Systems 32(1), 39–81.

Katsaros, K. K., Tsirikas, A. N., & Bani, S. N. (2014). Exploring employees' perceptions, job-related attitudes and characteristics during a planned organizational change. Int. Journal of Business Science and Applied Management, 9(1).

Kaynack, O., (2021). The golden age of Artificial Intelligence. Discov Artif Intell. 1(1),

Keuchel, S. (2020). Digitalisation and automation of transport: A lifeworld perspective of travellers. Transportation Research Interdisciplinary Perspectives, 7, 100195.

Kim, S. S. & Malhotra, N. K. (2005). A Longitudinal Model of Continued IS Use: An Integrative View of Four Mechanisms Underlying Post-Adoption Phenomena, Management Science 51(5), 741-755.

Nikitas, A., Michalakopoulou, K., Njoya, E.T. & Karampatzakis, D. (2020). Artificial Intelligence, Transport and the Smart City: Definitions and Dimensions of a New Mobility Era. Sustainability12, 2789.

Langton, N., & Robbins, S. (2006). Organizational Behaviour. Toronto: Pearson Prentice Canada.

Leviäkangas, P. (2016). Digitalisation of Finland's transport sector. *Technology in Society*, *47*, 1–15.

Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How Habit Limits the Predictive Power of Intentions: The Case of IS Con- tinuance. MIS Quarterly 31(4), 705-737.

Liu, P., Zhang., Y., & He, Z. (2019). The effect of population age on the acceptable safety of self-driving vehicles. Reliab. Eng. Syst. Safety, 185, 341-347.

Luce, T. Benefits of Advanced Driver Assistance Systems. ATZ Heavy Duty world (2022).

Luecke, R. (2003) Managing Change and Transition. Harvard Business School Press..

Li, Z., Al Hassan, R., Shahidehpour, M., Bahramirad, S. &Khodaei, A. (2017). A hierarchical framework for intelligent traffic management in smart cities. IEEE Trans. Smart Grid. 10, 691–701.

Madigan, R., Louw, T., Wilbrink, M., Schieben, A., & Merat, N. (2017). What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of automated road transport systems. Transportation Research Part F Traffic Psychology and Behaviour, 50, 55–64.

Marakas, G. M., Yi, M. Y., & Johnson, R. D. (1998). The multilevel and multifaceted character of computer Self-Efficacy: toward clarification of the construct and an integrative framework for research. Information Systems Research, 9(2), 126–163. https://doi.org/10.1287/isre.9.2.126

Marikyan, D. & Papagiannidis, S. (2023) Unified Theory of Acceptance and Use of Technology: A review. In S. Papagiannidis (Ed), TheoryHub Book. Available at https://open.ncl.ac.uk / ISBN: 9781739604400

Matt, C., Hess, T. & Benlian, A. (2015). Digital transformation strategies, Business & Information Systems Engineering, 57, 339-343.

Marikyan, D. & Papagiannidis, S. (2023) Unified Theory of Acceptance and Use of Technology: A review. In S. Papagiannidis (Ed), TheoryHub Book.

Marisda, M., Keke, Y., Pratiwi S., Irenita N (2020). The application of the Technology Acceptance Model (tam) method for the acceptance of autonomous trucks as logistics delivery services

McKinsey &Company (2023, June 14). What is digital transformation?

Mellinger, C. D., & Hanson, T. A. (2020). Methodological considerations for survey research:

Validity, reliability, and quantitative analysis. Linguistica Antverpiensia, New Series: Themes inTranslation Studies, 19, 172–190.

Montoro, L., Useche, S. A., Alonso, F., Lijarcio, I., Bosó-Seguí, P., & Martí-Belda, A. (2019). Perceived safety and attributed value as predictors of the intention to use autonomous vehicles: A national study with Spanish drivers. Safety Science, 120, 865–876.

Moore, G. C., and Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information technology Innovation, Information Systems Research Moran, Leading organizational change', Career Development International,6(2), 111–118.

Murawski, M., & Bick, M. (2017). Digital competencies of the workforce – a research topic? Business Process Management Journal, 23(3), 721–734. https://doi.org/10.1108/BPMJ-06-2016-0126.

Nees, M. A. (2016). Acceptance of self-driving cars: An examination of idealized versus realistic portrayals with a self-driving car acceptance scale. In Proceedings of theHuman

Factors and Ergonomics Society (Vol. 60, pp. 1448–1452). Lafayette College, Easton, PA, United States: Human Factors an Ergonomics Society Inc.

Nees, M. A. (2019). Safer than the average human driver (who is less safe than me)? Examining a popular safety benchmark for self-driving cars. Journal of Safety Research, 69, 61–68.

Nelson, L. (2003) ‘A case study in organizational change: implications for theory’, The Learning Organization,10(1),18–30.

NHTSA: U.S. DOT Announces (2017). Roadway Fatalities Down.

Nikitas, A., Michalakopoulou, K., Njoya, E.T. & Karampatzakis, D. (2020). Artificial Intelligence, Transport and the Smart City: Definitions and Dimensions of a New Mobility Era. Sustainability, 12, 2789.

Okumus, F. & Hemmington, N. (1998) Barriers and resistance to change in hotel firms: an investigation at unit level, International Journal of Contemporary Hospitality Management, 10(7), 283–288.

Osswald, S., Wurhofer, D., Trösterer, S., Beck, E., & Tscheligi, M. (2012). Predicting information technology usage in the car. AutomotiveUI ’12: Proceedings of the 4th International Conference on Automotive User Interfaces and Interactive Vehicular Applications.

Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2015). Purposeful Sampling for Qualitative Data Collection and Analysis in Mixed Method Implementation Research. Administration and policy in mental health, 42(5), 533–544.

Panagiotopoulos, I., & Dimitrakopoulos, G. (2018). An empirical investigation on consumers’ intentions towards autonomous driving. Transportation Research Part C Emerging Technologies, 95, 773–784.

Papagiannidis, S. & Marikyan, D. (2020). Smart offices: A productivity and well-being perspective. International Journal of Information Management, 51, 102027.

Payre, W., Cestac, J., & Delhomme, P. (2014). Intention to use a fully automated car: Attitudes and a priori acceptability. Transportation Research Part F, 27, 252–263.

Pettigrew, S., Worrall, C., Talati, Z., Fritschi, L., & Norman, R. (2019). Dimensions of attitudes to autonomous vehicles. Urban, Planning and Transport Research, 7(1), 19–33.

Phusakulkajorn, W., Núñez, A., Wang, H., Jamshidi, A. A., Zoeteman, A., Ripke, B., Dollevoet, R., De Schutter, B., & Li, Z. (2023). Artificial intelligence in railway infrastructure: current research, challenges, and future opportunities. Intelligent Transportation Infrastructure, 2.

Plonsky, L. and Gass, S. (2011), Quantitative Research Methods, Study Quality, and Outcomes: The Case of Interaction Research. Language Learning, 61: 325-366.

Prasetio, E. A., & Nurliyana, C. (2023). Evaluating perceived safety of autonomous vehicle: The influence of privacy and cybersecurity to cognitive and emotional safety. IATSS Research, 47(2), 160–170

Qian, Y., Wu, D., Bao, W. & Lorenz, P. (2019). The internet of things for smart cities:

Technologies and applications. IEEE Netw. 33, 4–5.

Rahimi, M., Liu, H., Cardenas, I.D., Starr, A.; Hall, A. & Anderson, R. (2022). A Review on Technologies for Localisation and Navigation in Autonomous Railway Maintenance Systems. Sensors, 22, 4185.

Rahman, M. M., Lesch, M. F., Horrey, W. J., & Strawderman, L. (2017). Assessing the utility of TAM, TPB, and UTAUT for advanced driver assistance systems. Accident Analysis & Prevention, 108, 361–373.

Robertson, R., Meister, S. R., VanLaar, W., & Hing, M. M. (2017). Automated vehicles and behavioural adaptation in Canada. Transp. Res. Part A Policy Pract., 104, 50–57.

Robbins, S.P. (2004). Organizational behavior 10th ed., New Jersey: Prentice-Hall Inc.

Saravanos, A., Pissadaki, E. K., Singh, W. S., & Delfino, D. (2024). Gauging public acceptance of conditionally automated vehicles in the United States. Smart Cities, 7(2), 913–931

Schwab, K., (2017). The Fourth Industrial Revolution, Crown Business, New York ISBN 9781524758868

Schraeder, M., Swamidass, P., & Morrison, R. (2006). Employee involvement, attitudes and reactions to technology changes. Journal of Leadership & Organizational Studies, 12(3), 85–100.

Sessa, C., Pietroni, F., Alessandrini, A., Stam, D., Delle Site, P., & Holguin, C. (2015). Results of the On-Line DELPHI Survey. CityMobil2 Deliverable 27.2: European Commission Seventh Framework Programme.

Seuwou, P., Chrysoulas, C., Banissi, E., & Ubakanma, G. (2020). Measuring consumer behavioural intention to accept technology: towards Autonomous Vehicles Technology Acceptance Model (AVTAM). In Advances in intelligent systems and computing (pp. 507–516).

Shachak, A., Kuziemsky, C., & Petersen, C. (2019). Beyond TAM and UTAUT: Future directions for HIT implementation research. Journal of Biomedical Informatics, 100, 103315.

Singh, R., Sharma, R., Akram, S. V., Gehlot, A., Buddhi, D., Malik, P. K., & Arya, R. (2021). Highway 4.0: Digitalization of highways for vulnerable road safety development with intelligent IoT sensors and machine learning. Safety Science, 143, 105407.

Sommer, L. (2015). Industrial revolution – industry 4.0: are German manufacturing SMEs the first victims of this revolution?, Journal of Industrial Engineering and Management, 8(5), 1512-1532.

Souders, D., & Charness, N. (2016). Challenges of older drivers' adoption of advanced driver assistance systems and autonomous vehicles. In Lecture notes in computer science (pp. 428–440).

Statista. (2022). Spending on digital transformation technologies and services worldwide from 2017 to 2026 (in trillion U.S. dollars) [Graph]. In Statista. Retrieved March 09, 2024.

Stiegemeier, D., Kraus, J., & Baumann, M. (2024). Why drivers use in-vehicle technology: The role of basic psychological needs and motivation. *Transportation Research Part F Traffic Psychology and Behaviour*, *100*, 133–153. https://doi.org/10.1016/j.trf.2023.11.014

Suhr, D. (2006). Exploratory or Confirmatory Factor Analysis. University of Northen Carolina paper, 200, 31.

Sun, H., Lee, P., Law, R., & Hyun, S. S. (2020). An investigation of the moderating effects of current job position level and hotel work experience between technology readiness and technology acceptance. International Journal of Hospitality Management, 90, 102633.

Sun, H., & Zhang, P. (2006). The Role of Moderating Factors in User Technology Acceptance. International Journal of Human-Computer Studies. 64. 53-78. 10.

Swedish Transport Administration, 2022. Roadmap – Digitalisation of the Road Transport System Publication number: 2022:030.

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia Manufacturing*, *22,* 960-967. https://doi.org/10.1016/j.promfg.2018.03.137

Takele, Y., & Kiltu. (2015). Employees’ perception of organizational climate and its implications for organizational effectiveness in Amhara National Regional State, Ethiopia. The Ethiopian Journal of Business and Economics, 4(1), 116.

Tang, R., De Donato, L., Bešinović, N., Flammini, F., Goverde, R. M., Lin, Z., Liu, R., Tang, T., Vittorini, V., & Wang, Z. (2022). A literature review of Artificial Intelligence applications in railway systems. Transportation Research Part C: Emerging Technologies, 140, 103679

Tang D., & Chen L. (2011). A review of the evolution of research on information Technology Acceptance Model. IEEE Conference publication 588-591

Taylor, S., Todd, P.A., 1995b. Understanding information technology usage: a test of competing models. Information Systems Research 6 (2), 144–176.

Theis, J., Ossmann, D., Thielecke, F., & Pfifer, H. (2018). Robust autopilot design for landing a large civil aircraft in crosswind. Control Engineering Practice, 76, 54–64.

Todnem B. R. (2005) Organisational change management: A critical review, Journal of Change Management, 5(4), 369-380.

Ullrich, A., Reißig, M., Niehoff, S., & Beier, G. (2023). Employee involvement and participation in digital transformation: a combined analysis of literature and practitioners’ expertise. Journal of Organizational Change Management, 36(8), 29–48.

Valenduc, G., & Vendramin, P. (2017). Digitalisation, between disruption and evolution. Transfer: European Review of Labour and Research, 23(2), 121-134.

Van Dun, D. H., & Kumar, M. (2022). Social enablers of Industry 4.0 technology adoption: transformational leadership and emotional intelligence. International Journal of Operations & Production Management, 43(13), 152–182.

Venkatesh V. & Davis F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal fields studies. Management Science, 46, 186-204.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly 27(3), 425-478.

Venkatesh, V. & Thong, J. & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly. 36. 157-178.

Venkatesh, V., Thong, J. & Xu, X. (2016). Unified Theory of Acceptance and Use of

Technology: A Synthesis and the Road Ahead. Journal of the Association for InformationSystems, 17 (5), 328-376.

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems, 28(2), 118–144.

Vogelsang, K., Packmohr, S. & Hoppe, U. (2019). Barrier to digital transformation in Manufacturing: Development of a Reasearch Agenda. Proceedings of the 52nd Hawaii International Conference on System sciences.

Younkin, J., Chuck, B. J., Stewart, S., Frank, S., Farquhar, E., & Shuler, J. (2018). Advancing the Authenticatable Container Tracking System (ACTS). In Oak Ridge National Laboratory (ORNL), Oak Ridge, TN (United States).

Wang, D., Ozden, M., & Tsang, Y. P. (2023). The impact of facilitating conditions on electric vehicle adoption intention in China: An integrated unified theory of acceptance and use of technology model. International Journal of Engineering Business Management, 15.

Yuen, K. F., Choo, L. Q., Li, X., Wong, Y. D., Ma, F., & Wang, X. (2022b). A theoretical investigation of user acceptance of autonomous public transport. Transportation, 50(2), 545–569.

Weber, P. S., & Weber, J. E. (2001). Changes in employee perceptions during organizational change. Leadership & Organization Development Journal, 22(6), 291–300.

Westerman, G., Calméjane, C., Bonnet, D.; Ferraris P. & McAfee A. (2011). A. Digital Transformation: A Roadmap for Billion-Dollar Organizations. MIT Sloan Manag, 1, 1–68.

Williams, M. D., Rana, N. P. and Dwivedi, Y.K. (2015). The unified theory of acceptance and use of technology (UTAUT): a literature review, Journal of Entreprise Information Management, 28(3), 443-488.

Wold, H. Estimation of principal components and related models by iterative least squares. In: PR Krishnaiah, ed. Multivariate Analysis. New York: Academic Press; 1996; 391–420.

Wu, J., & Lederer, A. (2009). A Meta-Analysis of the Role of Environment-Based Voluntariness in Information Technology Acceptance. MIS Quarterly, 33(2), 419–432.

Xu, Y., Zhirui Y., & Wang C. (2021). Modeling commercial vehicle drivers' acceptance of advanced driving assistance system (ADAS). Journal of intelligent and connected vehicles, 4(3), 125-135.

Xu, Z., Zhang, K., Min, H., Wang, Z., Zhao, X., & Liu, P. (2018). What drives people to accept automated vehicles? Findings from a field experiment. Transportation Research Part C: Emerging Technologies.

Zanon, G. N., Szejka, A. L., & De Freitas Rocha Loures, E. (2021). Towards an integrated MCDM and BSC method to support the digital transformation strategy in railway companies. In IOS Press eBooks.

Zaoui, F., & Souissi, N. (2020). Roadmap for digital transformation: A literature review. Procedia Computer Science, 175, 621–628.

Zaoui, F., Saliha A., & Nissrine S. (2019). What Are the Main Dimensions of Digital Transformation? Case of an Industry. International Journal of Recent Technology and Engineering (IJRTE) (8)4: 9962-9970.

Zefreh, M. M., Edries, B., Esztergár-Kiss, D., & Torok, A. (2023). Intention to use private autonomous vehicles in developed and developing countries: What are the differences among the influential factors, mediators, and moderators? Travel Behaviour and Society, 32, 100592.

Zhu, G., Sangwan, S., & Lu, T. (2010). A new theoretical framework of technology acceptance and empirical investigation on self-efficacy-based value adoption model. Nankai Business Review International, 1(4), 345–372.

Zhu, G., Zheng, J., & Chen, Y. (2021). Acceptance of free-floating car sharing: A decomposed self-efficacy-based value adoption model. Transportation Letters, 14(5), 524–534.

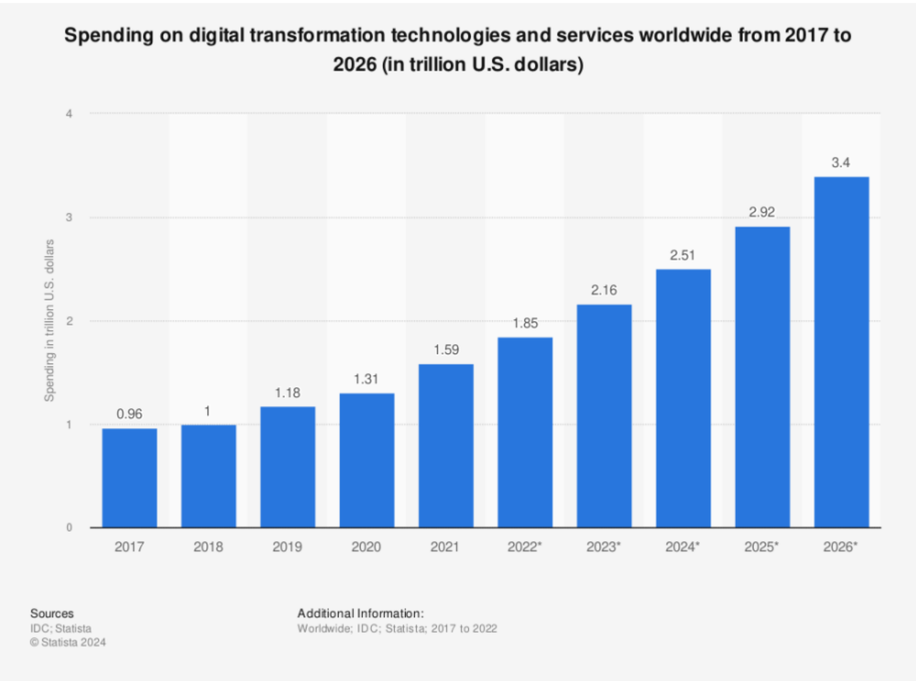
Zhu, Y., Corbett, J., & Chiu, Y. (2020). Understanding employees' responses to artificial intelligence. Figshare.

Zhu, W., Zhang, T., Ying, Z., Liao, Z., Luan, X., & Meng, L. (2023). Real-time high-speed train rescheduling based on a Human-Computer Interaction framework. High-Speed Railway, 1(2), 130–140.

Zmud, J., Sener, I.N., & Wagner J.(2016). Self-Driving Vehicles: Determinants of Adoption and Conditions of Usage Transportation Research Record, 2565, 57-64.

Appendix

Appendix 1. Spending on digital transformation



Note: Spending on digital transformation technologies and services worldwide from 2017 to 2026.

Appendix 2. Results from the G Power test on sample size

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[1] -- Thursday, June 06, 2024 -- 12:17:47
F tests - Linear multiple regression: Fixed model, R² deviation

Analysis:   A priori: Compute required sample size
Input:      Effect size f²                  =   0,15
            α err prob                      =   0,05
            Power (1-β err prob)            =   0,85
            Number of predictors            =   7
Output:     Noncentrality parameter λ       =   17,2500000
            Critical F                      =   2,0963214
            Numerator df                    =   7
            Denominator df                  =   107
            Total sample size               =   115
            Actual power                    =   0,8532116

[2] -- Thursday, June 06, 2024 -- 12:17:55
F tests - Linear multiple regression: Fixed model, R² deviation

Analysis:   A priori: Compute required sample size
Input:      Effect size f²                  =   0,15
            α err prob                      =   0,05
            Power (1-β err prob)            =   0,80
            Number of predictors            =   7
Output:     Noncentrality parameter λ       =   15,4500000
            Critical F                      =   2,1075065
            Numerator df                    =   7
            Denominator df                  =   95
            Total sample size               =   103
            Actual power                    =   0,8004218
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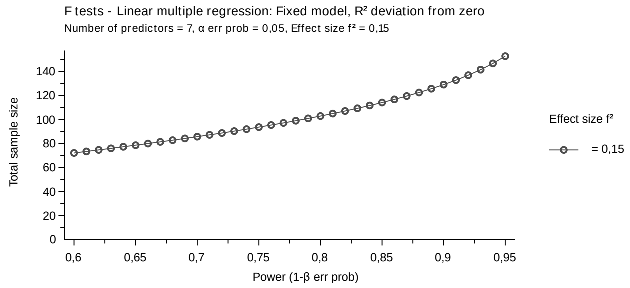


Note: 2Power Plot with Sample size with G plot.

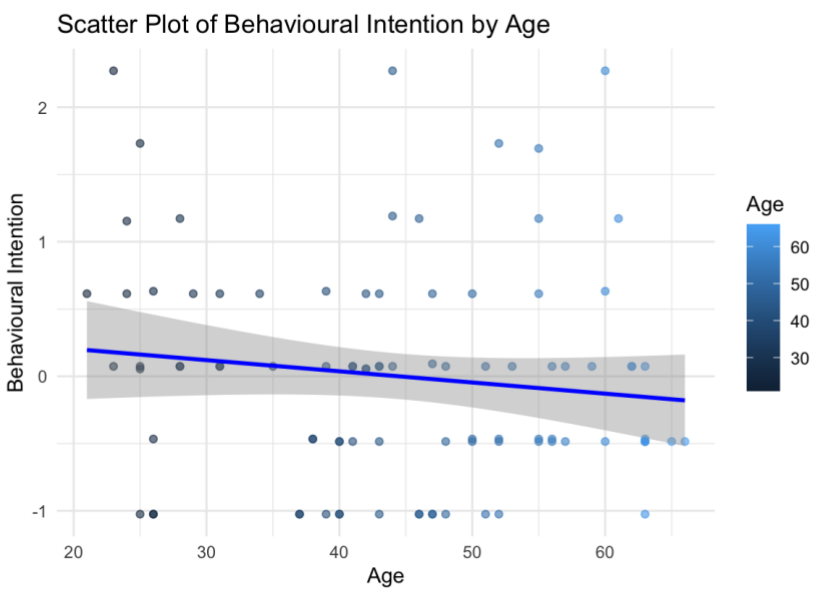
Appendix 3. Results from Initial Cronbach's alpha

Reliability result of the latent variables

		Cronbach's		
Constructs	N Items	Alpha	Mean	Std deviation
Price Value	2	0.87	3.67	1.01
Attitude Toward Using Technology	3	0.85	3.53	0.95

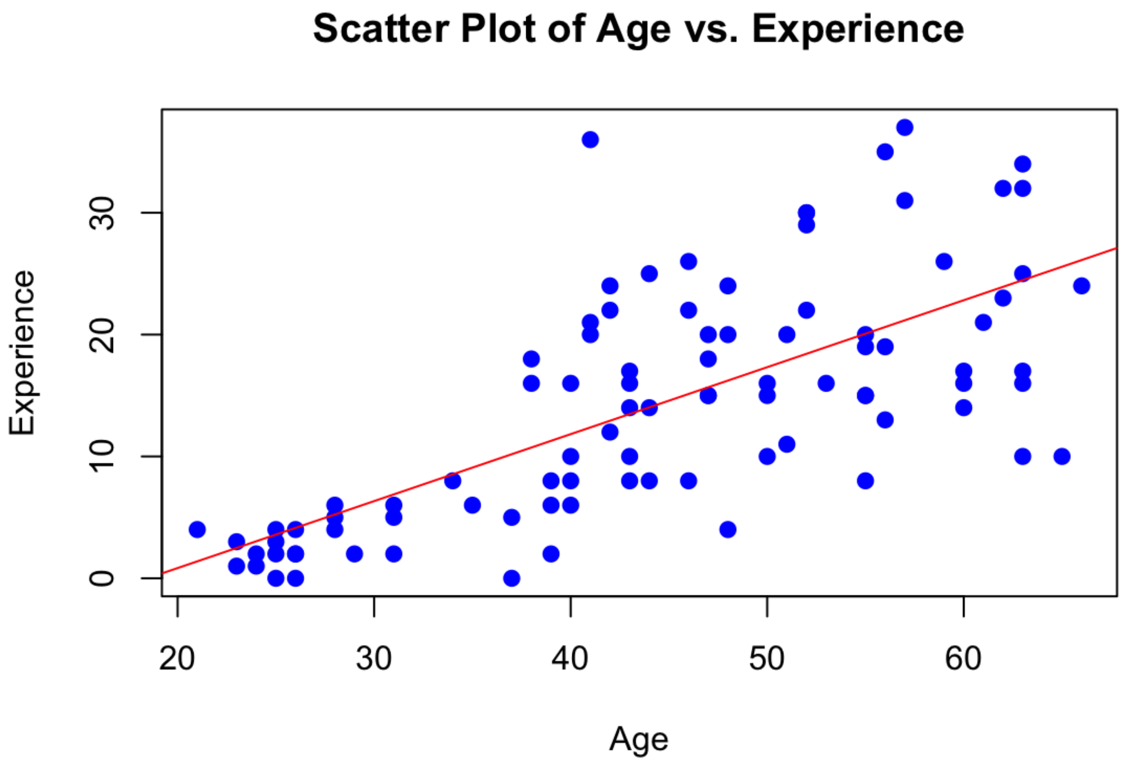
Self Efficacy	4	0.81	3.61	0.79
Performance Expectancy	2	0.74	3.78	0.99
Driver Intention	2	0.65	4.01	0.79
Effort Expectancy	2	0.65	4.16	0.62
Social Influence	2	0.57	3.82	0.8
Perceived Safety	4	0.53	3.71	0.7
Facilitating Condition	2	0.51	4.02	0.68

Appendix 4. Impact of age on Driver (Behavioral in the graph) intention



Appendix 5. Impact of Experience on Driver (Behavioral in the graph) Intention

Appendix 6. Relationship of Moderators Age and Experience



Appendix 7. Partial Least Square (PLS) analysis

Partial Least Squares Path Modeling (PLS-PM) was deployed to analyze the relationships among the latent variables and Driver Intention. This advanced technique, which builds upon the principles of Principal Component Analysis (PCA) and multiple linear regression, offers a more sophisticated approach for examining complex relationships. This technique is designed to predict a group of dependent variables based on a collection of independent variables, or predictors. The prediction process involves extracting a set of orthogonal factors, known as latent variables, which possess the strongest predictive capabilities. These latent variables serve as the foundation for generating visual representations similar to those produced by PCA (Abdi, 2010).

The effectiveness of the predictions made by a PLS regression model is typically assessed using cross-validation methods, such as the bootstrap or jackknife techniques. PLS regression is especially advantageous when predicting multiple dependent variables from a very large set of predictors. Originally developed within the social sciences, it has since found applications across various fields due to its robustness in handling complex data sets (Wold, 1996).

The PLS-PM analysis was conducted to examine the interactions among nine latent variables, which were constructed from 22 observed variables previously selected using Confirmatory Factor Analysis (CFA). The analysis was based on a sample of 95 cases. To ensure that each variable contributed equally to the model's construction, all variables were standardized. The centroid weighting scheme was employed for determining the weights.

PLS-PM is known for its iterative nature. In this particular analysis, convergence was achieved quickly, requiring only four iterations out of a typical maximum of 100. This rapid convergence indicates that the model was efficiently optimized and is stable. The tolerance level was set at 1e−6, as defined by the PLSR package.

The PLS-PM model is divided into two parts: the inner model and the outer model. The inner model describes the relationships between the latent variables, testing the hypothesized paths and connections between the constructs to validate the causal relationships and the model's overall structure. On the other hand, the outer model defines the relationships between the latent variables and the observed variables, essentially linking the observed data to the constructed latent variables.

In the outer model analysis, manifest variables associated with Price Value (e.g., Price Value

1 and Price Value 2) exhibit particularly high loadings of 0.947 and 0.933 respectively, translating into communalities of 0.8963 and 0.8697, illustrating strong individual contributions to the latent construct. Only Perceived Safety's variable 4 shows a notably poor loading of 0.290, resulting in a low communality of 0.0843, pointing to significant measurement or representational gaps.

In the inner model, significant paths are centered around the relationship between Attitude Toward Usage and Driver Intention. This path has a coefficient of 0.392, with a standard error of 0.1051, and a highly significant p-value of 0.000347, highlighting its substantial influence on the endogenous variable. Additionally, Facilitating Condition emerges as the second strongest predictor, exerting a positive and significant impact on Driver Intention with a p-value of 0.002811, confirming its statistical significance. On the other hand, while the path from Performance Expectancy to Driver Intention has a coefficient of 0.1006, it does not achieve statistical significance, as indicated by its p-value of 0.334582. Both Effort Expectancy (Estimate = -0.00632, p = 0.951523) and Social Influence (Estimate = 0.000628, p = 0.995024) exhibit very small coefficients and high p-values, signifying their statistically insignificant and negligible effects. Similarly, Price Value (Estimate = 0.0398, p = 0.662463) and Self-Efficacy (Estimate = 0.0468, p = 0.619674) do not demonstrate statistical significance, despite having slightly higher coefficients.

The model's goodness-of-fit index is calculated at 0.5835, indicating a moderate fit and suggesting that the model captures a substantial portion of the variance in Driver Intention. Driver Intention is explained for the 51% of its variance ($R^2 = 0.51$). The most influential predictors in this model are Attitude Toward Usage and Facilitating Condition. While Performance Expectancy, Perceived Safety, and Price Value exhibit positive effects, these effects are not statistically significant. Effort Expectancy and Social Influence have minimal effects and lack statistical significance.

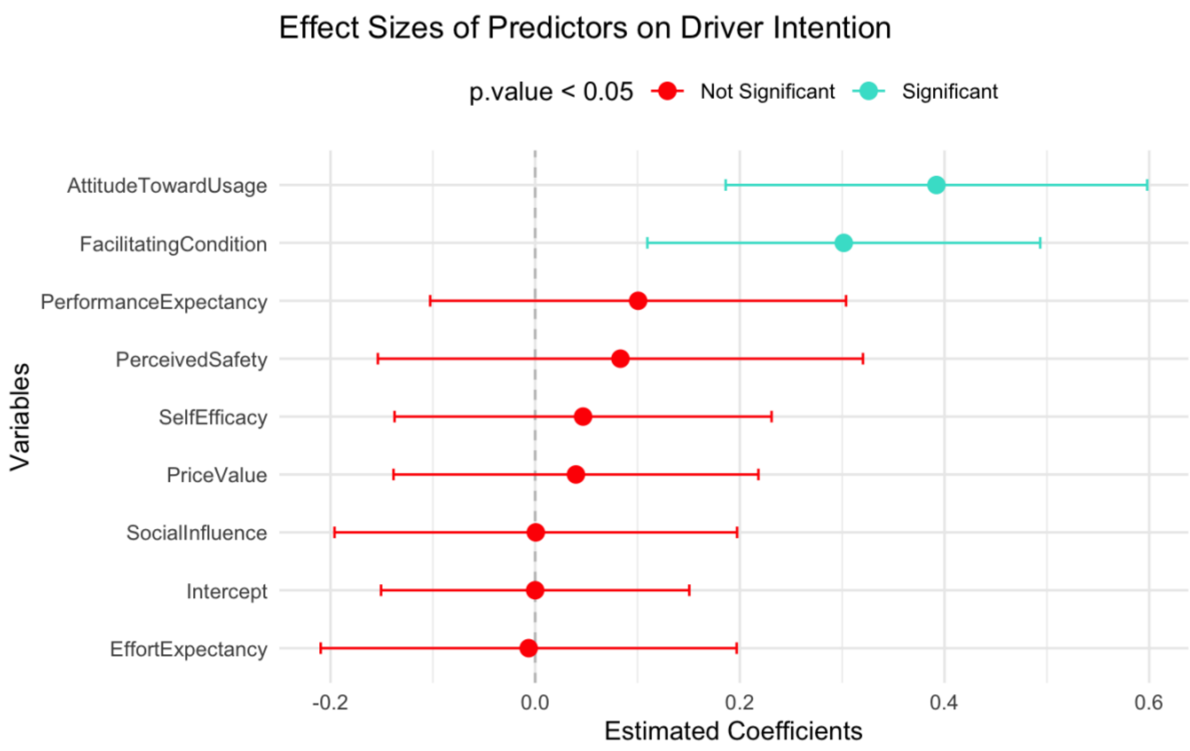


Figure The effect size of the predictors on Driver intention

Partial Least Square and the Moderating Role of Gender, Age, and Experience

The findings reveal that age has a direct negative effect on driver intention, suggesting that older individuals are less likely to intend to use the system. However, the interaction effects provide a more nuanced understanding of this relationship, highlighting additional factors that may influence the impact of age on intention. As users age, the importance of ease of use (Effort Expectancy) becomes more significant, with the highest positive interaction effect, followed closely by Social Influence and Performance Expectancy, indicating that older users place greater emphasis on these factors when considering system usage. Conversely, factors like Attitude Toward Usage, Perceived Safety, and Facilitating Condition show negative interaction effects with Age, suggesting that their influence on Driver Intention diminishes as users get older.

When considering Experience, Social Influence has the strongest positive interaction effect, indicating that more experienced users are increasingly influenced by social factors. Performance Expectancy and Self Efficacy also positively interact with Experience, suggesting that these factors become more influential as users gain experience. However, the influence of Facilitating Condition, Price Value, and Perceived Safety on Driver Intention decreases as Experience increases, with the smallest interaction effect observed between Experience and Attitude Toward Usage, indicating that Experience has little to no impact on this relationship.

Table. The moderating role of Age and Experience results from PLS.

Variable	Effect on driver intention	Variable	Effect on driver intention
Performance Expectancy * Age	0,054708	Performance Expectancy * Experience	0,055159
Effort Expectancy * Age	0,057258	Effort Expectancy * Experience	0,010941
Social Influence * Age	0,056057	Social Influence * Experience	0,143711
Price Value * Age	0,009545	Price Value * Experience	-0,02177
Perceived Safety * Age	-0,02314	Perceived Safety * Experience	-0,00911
Attitude Toward Usage * Age	-0,03534	Attitude Toward Usage * Experience	-0,00045
Facilitating Condition * Age	-0,02319	Facilitating Condition * Experience	-0.11639
Self Efficacy * Age	0,01727	Self Efficacy * Experience	0,039095

Appendix 8. Structural Equation Modelling (SEM) analysis

A comprehensive analysis was conducted using the Lavaan package in R to explore the relationship between observed variables and latent constructs, with a detailed examination of the constructs themselves. From an overall perspective, several results warrant discussion.

The model yielded a Chi-Square (χ^2) of 430.011 with 271 degrees of freedom, indicating the model's sensitivity; the low p-value highlights significant discrepancies between the observed data and model predictions. Regarding the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI), which are measures that compare the model against a baseline null model, optimal values are generally above 0.90. However, the model scores 0.816 and 0.779, respectively, which are slightly below the desired threshold.

The Root Mean Square Error of Approximation (RMSEA) indicates the model's fit to the population data and, with a value at the upper limit of acceptability, suggests room for improvement. The Standardized Root Mean Square Residual (SRMR), which quantifies the discrepancy between observed correlations and those predicted by the model, also shows a value slightly above the preferred maximum of 0.094.

In summary, while the model demonstrates potential, certain key indicators such as CFI and TLI fall below the benchmarks for a robust model, indicating that further refinements are necessary to enhance model fit and reliability.

Table 20.. Table of the relationship of the variables from SEM

Metric	**User Model Results**	**Accepted Benchmarks**
Chi-square (χ^2)	430.011	Lower is better
Degrees of freedom	271	N/A
P-value (Chi-square)	0	> 0.05 (not significant)
CFI	0.816	> 0.90
TLI	0.779	> 0.90
RMSEA	0.08	<= 0.05 excellent, <= 0.08 good
SRMR	0.094	< 0.08

For the construction of the latent variables, some observed variables (parameters) are well represented. Specifically, for the construct Performance Expectancy (PrE), all standardized loadings are above 0.6, and for Self Efficacy (SlE), they are over 0.630. Effort Expectancy (EfE) has only the second measurement with a lower loading of 0.507. Social Influence (ScI) shows a reduced loading of 0.66 for its second measurement. Additionally, there is an issue with Price Value (Prv); the second construct has a negative loading of -0.178. Perceived Safety (PrS)shows lower loadings of 0.48 for Perceived Safety 3 and 0.33 for Perceived Safety 4. Lastly, for Driver Intention (DrI), the loadings are not above 0.7 only for Behavioural Intention 4, Behavioural Intention 8.

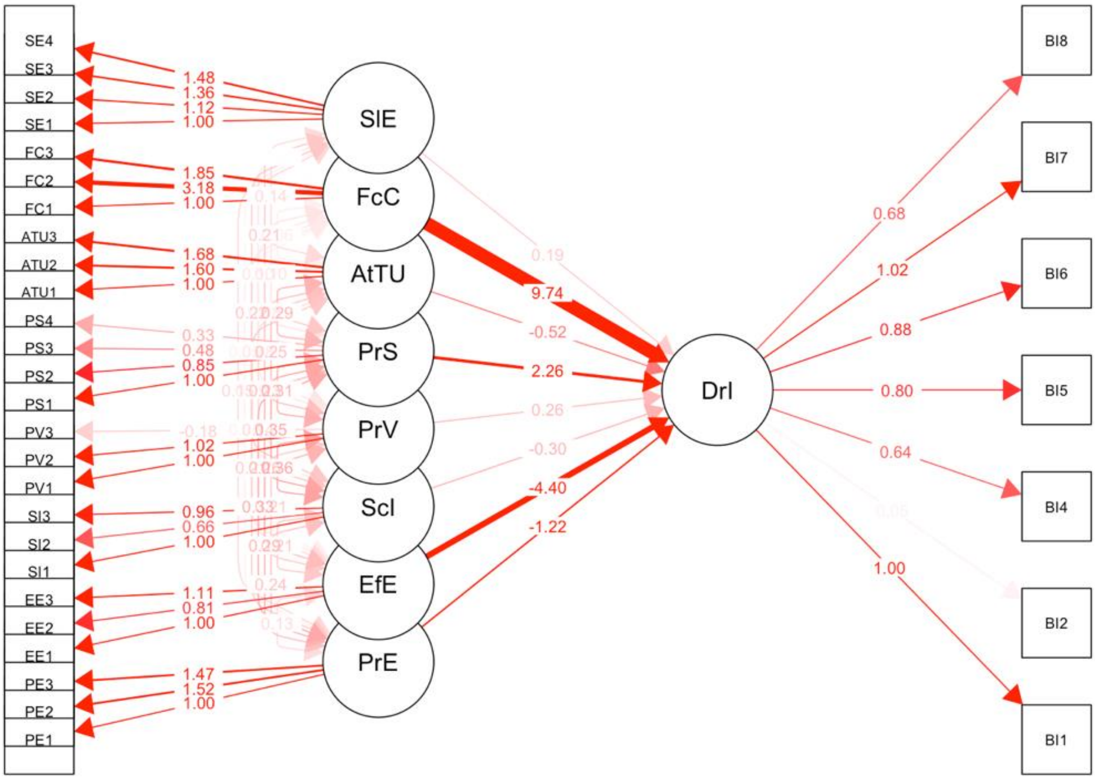


Figure 13. Results of Structural Equation Modeling (Lavaan from R)

In analyzing the regression among the latent variables, is observed the following order of influence on Driver Intention (DrI), although none show statistical significance. The variable Facilitating Condition (FcC) exhibits the highest coefficient at 9.74, indicating the most substantial positive influence, despite is not statistically significant. Effort Expectancy (EfE) follows but with a substantial negative coefficient of -4.40. Perceived Safety (PrS) is the third strongest positive predictor with a value of 2.26. Conversely, Performance Expectancy (PrE) shows a negative impact with a coefficient of -1.22. The other four latent variables have coefficients below 1. Self Efficacy (SIE) and Price Value(PrV) contribute positively with coefficients of 0.19 and 0.26, respectively, while Attitude Toward Usage (AtTU) and Social Influence (ScI) negatively affect with coefficients of -0.52 and -0.30, respectively. However, it is important to note the lack of statistical significance for these values, suggesting that the relationships might not be reliable predictors of DrI within this model.

Table 21. Results of coefficient and p-value from SEM

Variable Name	**Coefficient**	**Significance (p-value)**
Performance Expectancy	-1.224	0,9
Effort Expectancy	-4.401	0.755
Social Influence	-0.297	0.939
Price Value	0.263	0.858
Perceived Safety	2.263	0.865
Attitude Toward Usage	-0.516	0.903
Facilitating Condition	9.741	0.752
Self Efficacy	0.195	0.955

Structural Equation Model with Moderators

This additional SEM analysis focused on the impact of the moderators age (Age) and experience (Experience), the results indicate that neither variable has a statistically significant impact on Driver intention, with coefficient values of -0.000 for Age and -0.001 for Experience, and p-values of 0.937 for Age and 0.854 for Experience respectively. This suggests that, although included as moderators in the model, they do not significantly modify the relationship between the latent variables and Dehavioral Intention.

Furthermore, the value of 83.65, likely representing a correlation measure, indicates a strong association between Age and Experience.

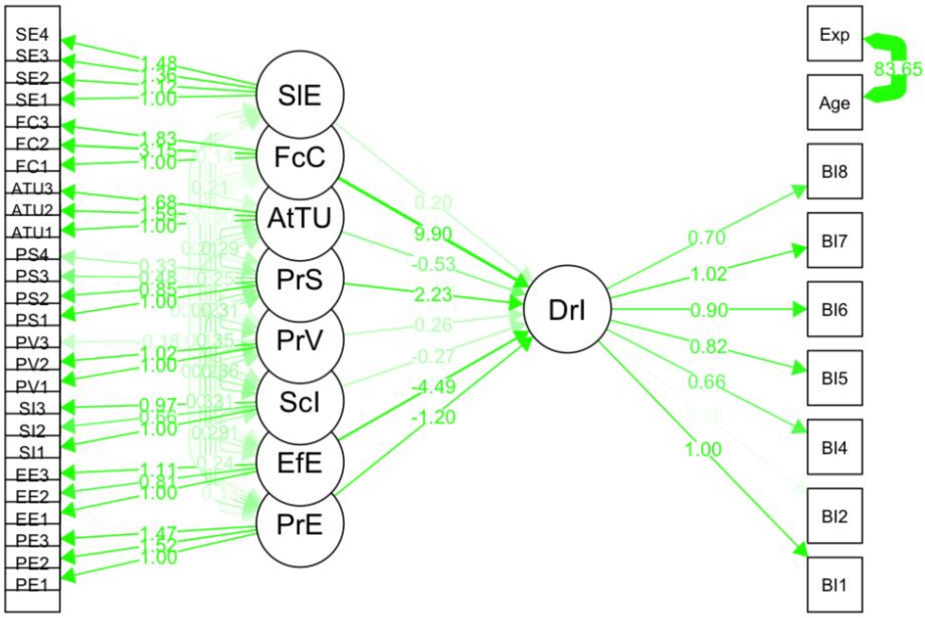


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Figure 14. Results of Structural Equation Modeling with Moderators (Lavaan from R)

To enhance model performance, the number of observed variables contributing to each latent variable was reduced, as previously done in Confirmatory Factor Analysis (CFA). However, this modification did not result in improved fit indices. Several factors could explain this outcome. Notably, both linear regression and CFA concentrate on more narrowly defined pathways, whereas Structural Equation Modeling (SEM) entails a higher level of complexity. SEM not only involves pathways among latent variables but also requires constructing measurement models for each latent variable. Given the relatively small sample size, SEM might be underpowered, particularly when the ratio of variables to observations remains high. Furthermore, SEM is generally more sensitive to the reduced number of observations compared to linear regression, which tends to be more resilient to such conditions.

Given the complexities and challenges associated with Structural Equation Modeling (SEM) in a small sample context and only two statistically significant results in Partial Least Squares (PLS) regression considering that the most favorable results were obtained through linear regression, the next discussion will primarily focus on the linear regression analysis. This approach offers a more robust and reliable foundation for interpreting the data within the given constraints. The table below presents the proposed hypotheses along with the results obtained.

Results of coefficient from reduced SEM

Variable (Full Name)	**Coefficient**	**P-Value**
Performance Expectancy	-1,484	0,865
Effort Expectancy	2,843	0,776
Social Influence	1,872	0,834
Price Value	-0,144	0,903
Perceived Safety	1,027	0,898
Attitude Towards Usage	1,827	0,581
Facilitating Conditions	-12,135	0,802
Self Efficacy	-1,643	0,801