

Literature Review on Acceptance of Technology for Reducing Distracted Driving

Kefira Arviadita Sutantio and Ari Widyanti

Department of Industrial Engineering

Faculty of Technological Industry

Institut Teknologi Bandung

Bandung, Indonesia

kefirasutantio@students.itb.ac.id, widyanti@ti.itb.ac.id

Abstract

Rapid technological development drives the development of technology for reducing distracted driving. Acceptance to such technologies is complex and relatively unknown, as it relies on various constructs and different characteristics of the users. Studies on technology acceptance can contribute to product development and policymaking to minimize driver distraction. This work presents a review of empirical research on technology acceptance for distracted-driving reduction technology, referred from 10 published studies within the past 10 years. Models that are evaluated include behavioral science theory such as the Technology Acceptance Model (TAM) and other proposed variables which influence the acceptance and usage of the technologies. Similarities and differences between studies with potential limitations and gaps are analyzed in this work. The results indicate that TAM is the most common model, proven to be a robust and useful tool. Additional factors added are proven to be insightful to complement the existing constructs in TAM. This work concluded less distraction is proven to improve driving performance, but at the cost of user acceptance. Discrepancy in term of studied location is highlighted in this work. Majority of the empirical studies are conducted in U.S. and European populations. Asian regions, despite largely populated with vehicle users, are severely underrepresented.

Keywords

Distracted driving; distraction; in-vehicle technology; TAM; literature review

1. Introduction

Distracted driving is described as any activity that diverts the driver's attention from driving. Distracted driving has serious consequences towards road safety. NHTSA reported 3.142 fatalities in the United States in 2019 were related to distracted driving, contributing to 15% of all police reported crashes. Razi-Ardakani et al. (2019) studied that distraction-related factors are the most important contributor to severity of car crashes. While Shaaban et al. (2020) stated in-vehicle distractions strongly affect crash likelihood amongst young drivers. It encapsulates any action that diverts one's attention from safe driving, including talking or texting on the phone, eating and drinking, talking to other people inside the vehicle, or interacting with stereo, entertainment, or navigation systems (National Highway Traffic Safety Administration [NHTSA], 2020). Jazayeri et al. (2021) defined these tasks as secondary tasks which encompassed any distraction that does not include tasks that are critical to the driving such as: checking the speedometer, checking for blind spots, activating headlight, etc. Driving distractions could be attributed to internal and external distractions. Internal distractions occur inside the vehicle, for example distraction from mobile phones (Guo et al. 2021), route-guidance systems and navigation technology (Yang et al. 2021; Oviedo-Tres Palacios & Watson 2021), entertainment systems, and nontechnological distractions such as eating and drinking. Radio adjustments, seatbelt adjustments, and other non-critical tasks done in-vehicle are considered part of internal distraction. External distractions occur outside the vehicle, such as road lighting (Robbins & Fotios, 2021) and digital billboards (Sheykhfard & Haghighi, 2020). As distraction needed mental resources to process new information while driving, it claimed further cognitive resources (mental workload). Drivers' attentional capacity decrease as there are more information being processed (Ortega, et al., 2021).

Considering the dangers of distracted driving, efforts have been made to develop prevention and/or reduction technology. Certain car features to prevent and/or reduce distraction have been introduced in cars manufactured within

the last decade, also presented in autonomous vehicles offered exclusively. This technology offer road safety benefit by causes less distraction by reducing the distracting effects when operating in-vehicle secondary control (Ranney et al., 2005), which provides opportunity for drivers to pay better attention on the road while performing secondary tasks. This technology benefits drivers and could increase road safety accidents, yet the overall acceptance of the technology is still relatively unknown. Factors that contribute towards intention to use of such technologies can be optimized to encourage acceptance. Such findings could assist product development and policy making to tackle driver distraction problem.

Survey conducted amongst Indonesian drivers (N=50, 31 males, 19 females, mean age= 33.2) resulted in: 76% had knowledge on distraction reducing technology, and 84% had used at least one while driving. This shows the enthusiasm for the technology and the prospects in regards of its acceptance. While an increasing number of studies have been conducted for higher levels of automation, lower levels of SAE is less investigated when they have higher chances to penetrate the market and higher acceptance within current society. Studies in this work have asked respondents how likely they would use the technology and their connections to demographic factors. Distraction reduction and/or prevention technology could serve as transitional technology before diving into acceptance for higher levels of automation. This work presents an overview of demand dimensions currently under investigation and study methods conducted. Results will be compared to detect similarities and differences between studies for distracted-driving reduction technology. To the best of author's knowledge, this is the first study to compare literatures on technology for reducing distracted driving.

The selection criteria and reviewing process would be presented in "Methods" section, scope and methods of the considered experiments are compared in "Scope and methodology comparison" section and the results of literatures would be compared in "Results comparison" section. Summary of findings and gaps identified would be presented in "Conclusion" section.

2. Methods

Google Scholar and Science Direct databases were searched for published articles. The selection criterion includes: any technology that is related to driver distraction reduction and/or prevention (excluding autonomous vehicle), empirical studies with established theories such as Technology Acceptance Model (TAM), description of research methodology, complete research results, and the use of English language. The acceptance criteria are defined as intention to use technology, willingness to use technology, and use or adoption of the technology. This work exclusively considers articles from 2010 onwards for review to maintain relevancy with current technologies. 10 empirical studies are identified and analyzed as shown in Table 1. Table 1 shows the year of publication, the object studied in the publication, model(s) used, main constructs incorporated in the model, and the method of choice.

Table 1 Empirical studies on drivers' acceptance of technology for reducing distracted driving

PU= Perceived usefulness, PEOU = Perceived ease of use, BI = Behavioral intention, ITU= Intention to use, A = Attitude towards technology, PBC= Perceived behavioral control

Reference	Year of Publication	Object studied	Model	Main constructs	Method
Roberts et. al,	2012	Real-time and post-drive distraction mitigation systems	TAM	PU, PEOU, Unobtrusiveness, BI	Driving simulator experiment; post-questionnaire survey; 36 drivers recruited in the U.S.
Normark and Mankila	2013	Personalized in-car HMI	TAM	PU, PEOU, BI, Product attachment,	Cross-sectional online questionnaire survey: 137 respondents recruited in two universities and employees at chemical plants in Finland

Reference	Year of Publication	Object studied	Model	Main constructs	Method
Kervick et al.	2015	Smartphone drivers support systems	TAM, UTAUT	Perceived gains and risks, Delay discounting, social influence, Usability, Perceived accuracy, A, BI	Cross-sectional online questionnaire survey: 333 respondents recruited via national social media campaign in Ireland
Lee et al.	2015	In-vehicle communication interface and smartphone with voice interface	TAM	PU, PEOU, A, BI, External variables	Driving simulator experiment, post-experiment questionnaire, 122 drivers recruited in Boston
Kujala et al.	2016	Mobile phone application	TAM	Trust, Usefulness (PU), Harmfulness, Functioning of circle symbol, Suitability	Glance tracking in driving experiment; post-questionnaire survey; 31 drivers from university mailing list in Finland
Kim et al.	2016	In-vehicle information system (IVIS)	TAM	PU, SN, ITU, Technographics, Prior similar experience, Perceived complexity, Perceived risk, Resistance	Cross-sectional online questionnaire survey: 1070 respondents recruited from survey agency in South Korea
Jung et al.	2019	Infotainment lockout	TAM	PU, PEOU, A, BI, Global satisfaction	Cross-section questionnaire survey, driving simulator experiment; 52 respondents from Opel Automobile GmbH, Germany, 26 drivers for driving data
Graichen et al.	2019	Gesture-based in-vehicle information system (IVIS)	Van der Laan et al. (1997) acceptance questionnaire	"Usefulness" and "Satisfying"	Driving simulator experiment, post-experiment questionnaire, 36 participants recruited in Chemnitz University of Technology in Germany
Oviedo-Trespalacios et al.	2020	Smartphone application to limit driver distraction	TAM, TPB, UTAUT	TAM: BI, A, PU, PEOU TPB: BI, A, SN, PBC UTAUT: BI, Performance expectancy, Effort expectancy, social influence	Cross-sectional questionnaire survey: 731 respondents recruited through Queensland University of Technology in Australia
Stiegemeier et al.	2022	In-vehicle technology	IAM (develop-	PU, PEOU, BI, Need, Context	Cross-sectional online questionnaire survey; 600

Reference	Year of Publication	Object studied	Model	Main constructs	Method
			ed from TAM and UTAUT)	and Task, Reliability, Knowledge, Increased effort, Aversion, Anxiety and apprehension, Preference for Own Action, Distrust, Safety, Knowledge, Availability of other systems, Habit, No reason	respondents recruited through online survey platform, respondents are Germans, Austrians, and Swiss.

3. Results and Discussion

Scope and Methodology Comparison

There are two types of technology chosen as research object: (1) in-vehicle system and (2) smartphone-based. Majority of the studies concentrate on one specific object and evaluate its effectiveness and/or acceptance. Such studies include the in-vehicle systems (IVIS): distraction warning system (Roberts et.al, 2012), gesture-based IVIS (Graichen et.al, 2019), lockout system (Jung et.al, 2019), and in-vehicle system (Normark & Mankila, 2013, Kim et.al, 2016). While the smartphone-based studies include smartphone distraction warning (Kujala et.al, 2016) and smartphone driver support system (SDSS) (Kervick et al., 2015). Some compare, such as Oviedo-Trespalcacios & Watson (2021) that compare the performance of two different smartphone blocking application and Lee et.al (2015) that compare voice interface in-vehicle communication feature and smartphone-based interface. Only Stiegemeier et al. (2022) investigated a range of in-vehicle technology to determine which type of systems are more preferred by users. Objects discussed prevent and/or reduce internal distractions proactively, with exception of the distracted warning system studied by Roberts et al. (2012) that tackle external distractions. In the context of the purpose of technology discussed, Jung et al. (2019) differs from the other types of objects as it evaluates the effectiveness of a complete lockout, disabling functionalities in an in-vehicle information system (IVIS). The technology virtually eliminates internal distractions caused by the IVIS, as opposed to the distraction prevention and/or reduction nature of the other studies' objects.

There are similarities in the studies conducted, acceptance is measured by perception of behavioral intention to use the technology such as found in Oviedo-Trespalcacios et al. (2020), Kervick et al. (2015), and Normark and Mankila (2013). Similarly, Kim et al. (2016) measure acceptance as intention to use but with added perception of innovation resistance. Whereas Stiegemeier et al. (2022) is an explorative study that investigates the categories that lead to the behavioral intention to use as measure of acceptance. There are also studies that collect objective data and measured acceptance separately in a self-reported questionnaire. Roberts et al. (2012) and Jung et al. (2019), collected driving performance data and use self reported behavior intention as measures of acceptance. Roberts et al. (2012) collected behavior intention responses from groups that is allowed to use the technology and those who don't. Kujala et al. (2016) and Graichen et al. (2019) both collected glance data. Kujala et al. (2016) collected glance data and measured acceptance as participants finding the warning system acceptable, shown by significance of the four constructs tested against the midpoint. Graichen et al. (2019) collected glance data from both gesture based and touch-based IVIS, but acceptance is measured from subjective acceptance questionnaire. Different from other simulation studies, Lee et al. (2015) did not collect objective data, they allowed participants to test the IVIS and measure its acceptance from behavioral intention via questionnaire.

Kervick et al. (2015) measure acceptance as behavior intention with following questions: "I want to use this app" and "I intend to use this app". Other studies that use similar approach is Jung, et al. (2019) with "I would intend to use

such an infotainment-system, if I had the chance to.” While Oviedo-Trespalcacios et al. (2020) and Normark and Mankila (2013) use this similar approach with more specific questions, addressing perception of price and availability. Roberts et al. (2012) explicitly gave the mark of \$300 as measure of acceptance. All of the studies previously mentioned use Technology Acceptance Model (TAM) as basis for defining acceptance and is the primary model is used to develop questionnaire given. There is only one study that used a different model to measure acceptance which is Graichen et al. (2019). The study uses 9-item questionnaire developed by Van der Laan et al. (1997).

Further look into the research framework used, TAM is the main model used with nine papers citing said model in their research. Some studies such as Oviedo-Trespalcacios et al. (2020) incorporate other models, which are Theory of Planned Behavior (TPB) and Unified Theory of Acceptance and Use of Technology (UTAUT). Graichen et al. (2019) used a different model altogether. “Unobtrusiveness” is added by Roberts et al. (2012), like “Harmfulness” in Kujala et al. (2016). While attitude is part of an older TAM model (Davis, 1985), it is incorporated in Kervick, et al. (2015), Lee et al. (2015), Jung et al. (2019), and Oviedo-trespalcacios et al. (2020). “Trust” is a construct added in Stiegemeier et al. (2022), Kujala et al. (2016), and variable of attitude in Lee et al., (2015). Kim et.al, (2016) is unique from other studies as “Intention to Use” is measured as a negatively correlated function of “Resistance”.

These studies are mostly conducted in developed western countries, with only one study in the Asia region, done by Kim et al. (2016) in South Korea. Cross-sectional questionnaire is also the most used method, with all respondents exceeding 100 people for questionnaire-only studies (Stiegemeier, et al., 2022, Oviedo-Trespalcacios, et al., 2020, Kim et al., 2016, Kervick et al., 2015, Normark & Mankila, 2013). These questionnaire-only studies investigate the users’ perception, while there are studies with driving simulation included hands-on experience on the studied technology. These studies have smaller sample sizes, which is understandable as it requires more resources (Graichen et al., 2019, Jung et al., 2019, Kujala et al, 2016, Lee et al., 2015, Roberts et al., 2012). Some studies recruit through campus network (Oviedo-Trespalcacios et al, 2020, Graichen, et al 2019, Kujala et al., 2016) and others distributed online (Stiegemeier et al., 2022, Kim et al, 2016, Kervick et al., 2015). Jung et al. (2019) differs in their participants came from one company. Normark and Mankila (2013) used a test group from chemical factories to increase the diversity of the test population. However, this decision is not driven from any specific goal aside from preventing the population recruited being too homogenous, as the rest of participants come from universities.

Study Results Comparison

The mentioned studies’ results are going to be discussed in three parts. First, the measure of acceptance response would be examined, second significant constructs will be identified and compared. Lastly socio-demographic variables effects on acceptance will be presented. Table 2 summarizes the result of empirical studies analyzed in this paper. Table 2 presents the behavioral intention measured as mean on one to five Likert type scale unless stated otherwise and the constructs that significantly impact the behavioral intention measured on the previous column.

Table 2 Results of empirical studies on drivers' acceptance of technology for reducing distracted driving

Reference	Year of Publication	Behavioral Intention Mean* (SD)	Significant Constructs Towards Behavioral Intention	Comments
Roberts et al.	2012	3.03 (1.04)	Direct effect: PU, PEOU Indirect effect: <ul style="list-style-type: none"> BI \leftarrow PU \leftarrow Unobtrusiveness BI \leftarrow PEOU \leftarrow Unobtrusiveness 	Only from real-time and post-drive groups.
Normark and Mankila	2013	4.12 (1.10)	Direct effect: PU, PEOU, Product attachment	Product attachment competes with perceived usefulness of the same space
Kervick et al.	2015	-	Direct effect: Perceived gains, social influence Indirect effect:	Higher perceived gains and higher social

			<ul style="list-style-type: none"> • BI \leftarrow Perceived gains \leftarrow Perceived risk 	influence both predicted higher levels of BI
Lee et al.	2015	-	Direct effect: PU, PEOU, A Indirect effect: <ul style="list-style-type: none"> • BI \leftarrow PU \leftarrow PEOU • BI \leftarrow A \leftarrow PU • BI \leftarrow A \leftarrow PEOU • BI \leftarrow A \leftarrow PU \leftarrow PEOU 	Results observed direct correlation between PEOU and BI which was not in the initial model
Kujala et al.	2016	-	Trust, Usefulness (PU), Harmfulness, Trust, Suitability	Measured as significant compared to the midpoint value of 3.
Kim et al.	2016	4.56 (1.10)	Direct effect: Resistance Indirect effect: <ul style="list-style-type: none"> • ITU \leftarrow Resistance \leftarrow PU • ITU \leftarrow Resistance \leftarrow Perceived complexity • ITU \leftarrow Resistance \leftarrow Perceived risk • ITU \leftarrow Resistance \leftarrow PU \leftarrow Technography • ITU \leftarrow Resistance \leftarrow Perceived complexity \leftarrow Technography • ITU \leftarrow Resistance \leftarrow Perceived risk \leftarrow Technography • ITU \leftarrow Resistance \leftarrow PU \leftarrow SN • ITU \leftarrow Resistance \leftarrow Perceived risk \leftarrow SN 	The more resistance increase, the lower intention to use is.
Jung et al.	2019	No Lockout**: 5.49 (1.33) Partial**: 4.33 (1.89) Complete**: 3.29 (2.04)	PU, PEOU, A, Global satisfaction	Differences from varying lockout systems analyzed. No lockout system has significantly higher intent than complete lockout systems.
Graichen et al.	2019	GBI: Usefulness 1.19 (0.64) Satisfying 1.13 (0.77) TBI: Usefulness 0.64 (0.59) Satisfying 0.33 (0.81)	Usefulness, Satisfying	Differences from varying IVIS interaction analyzed. Gesture-based (GBI) has significantly higher intent than touch-based interface (TBI).
Oviedo-Trespalacios, et al.	2020	MPA 1: 4.22 (1.91) MPA 2: 3.67 (1.94)	TAM: PU, PEOU TPB: A, SN, PBC UTAUT: Social influence, Performance expectancy, Effort expectancy, Familiarity	Two different mobile application (MPA) are analyzed. MPA 1 has significantly higher intent than MPA 2.

Stiegemeier, et al.	2022	-	Preference for Own Action, Distrust, Safety, Knowledge, and Habit.	Constructs that are significant precedent for PU and PEOU
---------------------	------	---	--	---

*Five-point scale otherwise stated

** Seven-point scale

Not all studies reported the measure of behavioral intention to use the technology. While there is only one study conducted in Asia region, it has the highest acceptance measured by intention to use (Kim et al. 2016), despite it was reported that South Korea has low penetration of IVIS. This tendency to rate higher seemed to be present in Asian population as opposed to the relatively lower numbers exhibited in the U.S, Australian, and European populations and even lower in simulation studies.

Oviedo-Trespalacios et al. (2020) report stronger "Perceived usefulness" influence on behavior intention to use the technology, while others report stronger "Perceived ease of use" such as in Roberts et.al (2012). Contrary to previously stated hypotheses, past experiences showed to be significant in Roberts et.al (2012) but not significant in Kim et al. (2016). A new construct "Perceived risk" was determined as the most powerful variable to explain resistance (Kim, et al., 2016). Risk should be considered in developing further models especially in Asian populations as it explained more than 50% of the "Resistance" variable. "Perceived risk" was presented as negative statements, which could induce a more realistic outlook on measuring acceptance. Aside from acceptance model, Normark and Mankila (2013) examined technological proficiency and found it had significance, although weak connection towards behavioral intention.

For studies that collected objective data, generally, the technologies studies made driving performance significantly better. This shows that the technology is useful in improving road safety and increasing driving performance. Jung et al. (2019) found metrics of lateral control which are considered indicators of distracted driving, significantly improved with locking IVIS functions. As supported by Graichen et al. (2019) that found drivers exhibited more glance time when interacting with touch-based technology. Using technology to help reduce distraction can keep the drivers' eye on the road at more times and increase safety driving behavior. Although this performance is also dependent to how complex the task is and the location of driving (intersection, sharp turn etc.). Kujala et al. (2016) found more complex tasks require more glance time with text messages being the most engaging task.

The differences between technologies used impacted the behavior intention to use the technology. Post-drive system is considered as more acceptable in Roberts et al. (2012) despite not giving warnings during the actual driving experience. As previously mentioned, previous experience significantly impacted acceptance in this study. People that do not try the system directly gave higher acceptance ratings for the real-time feedback that gave alerts during driving compared to those that tested the system. Jung et al. (2019) found that ratings of user acceptance decreased as the number of non-operable system task in IVIS increased. While their driving performance increased, having completely no freedom to personalize or have access to secondary tasks while driving reduces acceptance of the technology. As supported by Normark and Mankila (2013), systems that add more to user experience have a higher acceptance rate.

Some studies investigate the effect of socio-demographic variables towards the acceptance of technology for reducing driver distraction. Oviedo-Trespalacios et al. (2020) found females have lower intention to use for any distraction reducing smartphone application while younger people have lower intention to use smartphone blocking application compared to workload reducing application. Stiegemeier et al. (2022) found that gender only affects the number of in-vehicle technology used but not its usage. Roberts et al. (2012) found older people perceive the technology as more useful. Meanwhile, Kervick et al. (2015) found age did not significantly influence adoption of smartphone application technology, but gender, risk-taking propensity, and adoption likelihood for novel phone app technologies provide significant difference in multilevel analysis. Other studies found that gender and age do not significantly influence acceptance (Lee et al., 2015; Normark & Mankila, 2013). Normark and Mankila (2013) identified demographic data but yield no significance towards acceptance such as: occupation, license by years, and driven km/week. Other studies analyzed in this paper only reported the demographic data collected.

4. Conclusion

With plethora of additional information and entertainment inside of the vehicle, vehicles are now the most sophisticated it has ever been. Minimizing driver distraction proves to be more challenging. From 10 different studies,

it is concluded that TAM is the most popular model, with most studies modifying the constructs to the context of the objects and population observed. Trust is a significant construct in all studies that incorporated it to the original model. Also as suggested by Stiegemeier et al. (2022), safety should be considered in further research as driving is a safety-critical task. Findings in these studies are beneficial in determining ways of interaction that could reduce driver distraction. Users generally prefer non-tactile systems in their driving experience (Graichen et al., 2019, Lee et al., 2015). Rather than reducing workload, users also prefer blocking type of technology (Oviedo-Trespalacios et al. 2020) and clear, less intrusive warnings (Kujala et al. 2015).

Driving performance improved with less distraction, but at the cost of user acceptance. As demonstrated by Jung et al. (2019), full lockout system is less preferred than the partial lock-out. Acceptance decreases when the technology forcibly demanded too much to the users. Users need some freedom for customization to increase their acceptance (Normark & Mankila, 2013). Regarding past experiences, perception-only study and simulator study play a significant role. Past experiences when not specific to the technology tested will not get accurate results on the acceptance measured, as found in Roberts et al. (2012). Minor differences between in-vehicle and smartphone-based technology in the study conducted by Lee et al. (2015) showed both means are equally accepted by users. Conclusion could be drawn that the development of technology for reducing distracted driving could go in any direction; stationary in-vehicle technology and nomadic technology. These findings showed that while initial constructs of TAM are proven to be useful, more detailed research on other contributing factors such as additional constructs and interface design attributes is needed. Closer look upon the specific society the technology is being deployed, as results may vary depending on the socio-demographic condition.

There is also room for further improvements identified through this review. The studies presented are mostly done in developed western countries. While there are different levels of knowledge and familiarity, these countries generally have high awareness for road safety and in-vehicle technology. This indicates discrepancy, with lack of studies in Asia-Africa regions and other developing countries. Social-demographic variables would also impact results in different countries, as demonstrated by Roberts et al. (2012). Aside from the choice of country, it will be interesting to see the study in populations that are generally more unfamiliar with in-vehicle technology and more resistant to be introduced to in-vehicle technology. Location (intersection, tight turns etc.) are found to have significant difference on objective data (Kujala et al. 2015), acceptance of such technologies might differ when tested on countries with different driving terrain and situational conditions.

Most of the studies conducted were cross-sectional. Safety features in IVIS and smartphone might increase the interaction between users and the technology due to false sense of security. There would be a need for longitudinal study in different populations across the world to see whether the benefits of technology for reducing distraction outweigh its negative effects in prolonged usage. The glance studies deployed while useful is still limited by the reliability of the equipment used outside of laboratory setting. Subsequently, Widyanti et al. (2017) concluded that eye blink rate is appropriate for assessing visually demanding task rather than mentally demanding task, which both are the nature of driving. When more advanced technological breakthrough regarding glance tracking got introduced, this technology and appropriate real-world scenarios could be leveraged to conduct more accurate analyses and for other studies in different countries.

Indonesia is one of the developing countries with surprisingly high acceptance of distracted driving reducing technology, despite the general population having lower knowledge and interest in such technologies. Simultaneously, Indonesia also has high prevalence of mobile phone and generally exhibit unsafe driving behavior (Widyanti et al., 2020). As distraction is related to mental workload, objective studies measuring mental workload has been performed in Indonesia (Widyanti et al., 2017; Widyanti, et al., 2017) and another assessed acceptance for a variety of technology such as Bluetooth audio systems, cellphone blocking application, and phone mirroring. In the future, multiple assessment methods should be combined (objective and subjective studies). In addition, further study should consider broader range of technology and verify whether the acceptance level was connected to built-in features available in recent car models circulating in Indonesia. Consideration is to be made on performing longitudinal studies to observe drivers' behavior in longer periods of time and measure objective data regarding driving performance.

Reference

Davis, F., A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results. Diss. Massachusetts Institute of Technology, 1985.

- Graichen, L., Graichen, M., & Krems, J. F., Evaluation of Gesture-Based In-Vehicle Interaction: User Experience and the Potential to Reduce Driver Distraction, *Human Factors: The Journal of the Human Factors and Ergonomics*, pp. 1-19, 2019.
- Guo, X., Wu, L., Kong, X., & Zhang, Y., Inclusion of phone use while driving data in predicting distraction-affected crashes, *Journal of Safety Research*, vol. 79, pp. 321-328, 2021.
- Jazayeri, A., Martinez, J. R., Loeb, H. S., & Yang, C. C., The Impact of driver distraction and secondary tasks with and without other co-occurring driving behaviors on the level of road traffic crashes, *Accident Analysis & Prevention*, vol. 153, pp. 106010, 2021.
- Jung, T., Kaßa, C., Zapf, D., & Hecht, H., Effectiveness and user acceptance of infotainment-lockouts: A driving simulator study, *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 60, pp. 643-656, 2019.
- Kervick, A. A., Hogan, M. J., O'Hara, D., & Sarma, K. M., Testing a structural model of young driver willingness to uptake Smartphone Driver Support Systems. *Accident Analysis & Prevention*, vol. 83, pp. 171-181, 2015.
- Kim, J., Kim, S., & Nam, C., User resistance to acceptance of In-Vehicle Infotainment (IVI) systems. *Telecommunications Policy*, vol. 40, no. 9, pp. 919-930, 2016.
- Kujala, T., Karvonen, H., & Mäkelä, J., Context-sensitive distraction warnings – Effects on drivers' visual behavior and acceptance, *International Journal of Human-Computer Studies*, vol. 90, num. 39-52, 2013
- Lee, C., Reimer, B., Mehler, B., & Coughli, J. F., User Acceptance of Voice Interfaces in the Automobile, *Proceedings of the Human Factors and Ergonomics Society 59th Annual Meeting*, vol. 59, num. 1, pp. 1641-1645, 2015
- National Highway Traffic Safety Administration. Distracted Driving 2019, *Traffic Safety Facts Research Notes*, 2020
- Normark, C. J., & Mankila, J. P., Personalisable in-vehicle systems, technology acceptance and product attachment, *International Journal of Human Factors and Ergonomics*, vol. 2, num. 4, pp. 262-280, 2016.
- Ortega, C. A., Mariscal, M. A., Boulagouas, W., Herrera, S., Espinosa, J. M., & García-Herrero, S., Effects of Mobile Phone Use on Driving Performance: An Experimental Study of Workload and Traffic Violations, *International Journal of Environmental Research and Public Health*, vol. 18, num. 13, pp. 7101, 2021
- Oviedo-Trespalacios, O., & Watson, B., Navigation apps are becoming a threat to road safety (beyond distraction). *Injury Prevention*, vol. 27, num. 2, pp. 103, 2021.
- Oviedo-Trespalacios, O., Briant, O., Kaye, S.-A., & King, M., Assessing driver acceptance of technology that reduces mobile phone use while driving: The case of mobile phone applications. *Accident Analysis & Prevention*, vol. 135, pp. 105348, 2020
- Ranney, T. A., Harbluk, J. L., & Noy, Y. I., Effects of Voice Technology on Test Track Driving Performance: Implications for Driver Distraction, *Human Factors*, vol. 47, num. 2, pp. 439-454, 2005.
- Razi-Ardakani, H., Mahmoudzadeh, A., & Kermanshah, M., What factors results in having a severe crash? a closer look on distraction-related factors, *Cogent Engineering*, vol. 6, num. 1, pp. 1708652., 2019.
- Robbins, C., & Fotios, S., Road lighting and distraction whilst driving: Establishing the significant types of distraction, *Lighting Research & Technology*, vol. 53, num. 1, pp. 30-40, 2021.
- Roberts, S. C., Ghazizadeh, M., & Lee, J. D., Warn me now or inform me later: Drivers' acceptance of real-time and post-drive distraction mitigation systems, *International Journal of Human Computer Studies*, vol. 70, num. 12, pp. 967-979, 2012
- Shaaban, K., Gaweesh, S., & Ahmed, M., Investigating in-vehicle distracting activities and crash risks for young drivers using structural equation modeling, *PLoS ONE*, vol. 15, num. 7, pp. e0235325, 2020.
- Sheykhsfard, A., & Haghighi, F., Driver distraction by digital billboards? Structural equation modeling based on naturalistic driving study data: A case study of Iran. *Journal of Safety Research*, vol. 72, pp. 1-8, 2020.
- Stiegemeier, D., Bringeland, S., Kraus, J., & Baumann, M., "Do I really need it?": An explorative study of acceptance and usage of in-vehicle technology. *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 84, pp. 65-82, 2022.
- Widyanti, A., Hanna, M. K., & Sutalaksana, I., The sensitivity of Galvanic Skin Response for assessing mental workload in Indonesia, *Work*, vol. 56, num. 1, pp. 111-117, 2017.
- Widyanti, A., Pratama, G., Anindya, A., Yamin, P., & Soetisna, H., Mobile phone use among Indonesian motorcyclists: prevalence and influencing factors, *Traffic Injury Prevention*, vol. 21, num. 7, pp. 459-463, 2020
- Widyanti, A., Sofiani, N., Soetisna, H., & Muslim, K., Eye blink rate as a measure of mental workload in a driving task: Convergent or divergent with other measures? *International Journal of Technology*, vol. 8, num. 2, pp. 283-291, 2017

Yang, L., Bian, Y., Zhao, X., Liu, X., & Yao, X., Drivers' acceptance of mobile navigation applications: An extended technology acceptance model considering drivers' sense of direction, navigation application affinity and distraction perception, *International Journal of Human-Computer Studies*, vol. 145, pp. 102507, 2021