future internet

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Modeling User Acceptance of In-Vehicle Applications for Safer Road Environment

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Abstract: Driver acceptance studies are vital from the manufacturer's perspective as well as the driver's perspective. Most empirical investigations are limited to populations in the United States and Europe. Asian communities, particularly in Southeast Asia, which make for a large proportion of global car users, are underrepresented. To better understand the user acceptance toward in-vehicle applications, additional factors need to be included in order to complement the existing constructs in the Technology Acceptance Model (TAM). Hypotheses were developed and survey items were designed to validate the constructs in the research model. A total of 308 responses were received among Malaysians via convenience sampling and analyzed using linear and non-linear regression analyses. Apart from that, a mediating effect analysis was also performed to assess the indirect effect a variable has on another associated variable. We extended the TAM by including personal characteristics, system characteristics, social influence and trust, which could influence users' intention to use the in-vehicle applications. We found that users from Malaysia are more likely to accept in-vehicle applications when they have the information about the system and believe that the applications are reliable and give an advantage in their driving experience. Without addressing the user acceptance, the adoption of the applications may progress more slowly, with the additional unfortunate result that potentially avoidable crashes will continue to occur.

Keywords: in-vehicle application; driver assistance; technology acceptance; regression analysis; statistical evaluation; significance tests

Citation: Razak, S.F.A.; Yogarayan, S.; Abdullah, M.F.A.; Azman, A. Modeling User Acceptance of In-Vehicle Applications for Safer Road Environment. *Future Internet* **2022**, *14*, 148. https://doi.org/10.3390/fi14050148

Academic Editor: Marco Fiore

Received: 30 March 2022
Accepted: 28 April 2022
Published: 11 May 2022

1. Introduction

Car manufacturers, throughout recent years, have been focusing on delivering new car models equipped with in-vehicle or pre-install applications [1] which support car navigation, maneuver and stabilization. Typically, the applications involve either a camera, sensors or a millimeter wave radar, or a combination of these, to support the driver and ease the driver's driving experience rather than annoy [2,3] which may cause the system to be turned off or its disuse. Human limitations in assessing the current driving context may be lifted via an extension of these in-vehicle applications (see Table 1). Generally, these applications were designed for the global market. However, users' acceptance toward technology has been known to be influenced by cultural differentiation. Overlooking this factor may cause the technology to receive poor attitudes and acceptance rates from the users which eventually may lead to poor or nonactual use of the application [2].

Table 1. In-vehicle applications.

Features	Description
Lane Departure Alert/ Warning (LDW)	Vibrates the steering wheel or emits a warning sound when the car strays off its lane.
Lane-Keep Assist (LKAS)	Applies gentle steering correction when the car is veering off its lane.
360-Degree-Parking Assist (360 cam)	Provides a "bird's eye" view of the car's surroundings.
Rear Cross Traffic Alert (RCTA)	Used when reversing out into the busy street to alert the driver of the approaching vehicle's direction.
Forward Collision Warning (FCW)	Gives a warning buzzer if a frontal collision is imminent. No braking actions.
Autonomous Emergency Braking (AEB)	Applies maximum braking pressure if driver does not respond after warning. Range, speed and detection ability vary.
Adaptive Cruise Controls (ACC)	Maintains a preset highway cruising speed. Brakes and accelerates automatically to maintain a preset safe distance. Some models allow limited (less than 30 s) hands-free driving
Low-Speed Follow/ Traffic Jam Assist (TJA)	Assists in stop–go driving. Follows the vehicle ahead, automatically braking/accelerating. Driver maintains control of steering wheel.
Auto Parking (A-Park)	Automatic steering for parking. Driver maintains control of gear selector (drive or reverse), braking and accelerating. Depending on the model, it may work on both parallel and perpendicular parking.
Head-up Display (HUD)	Projects core driving-related information to driver's view or windscreen.
Blind Spot Monitor (BSM)	Lights up warning on the side mirrors when a vehicle is in the blind spot.
Auto Hold/Brake Hold (A-Hold)	For use in traffic jam/red light. Maintains brake pressure even when driver takes the foot off the brake pedal. Automatically releases when a driver accelerates.
Hill-Start Assist (HSA)	Maintains brake pressure to prevent the vehicle from rolling backward as the driver prepares to drive uphill.
Hill Descent Control (HDC)	Typically used for 4 × 4 vehicles. Maintains safe speed when driving downhill on muddy terrain.
Pedal Misapplication Control (PED)	Prevents accidental reversing/acceleration in the wrong direction, i.e., driver wrongly selected drive instead of reverse.
Auto High Beam (A-BEAM)	Forward-oriented lights that turn brighter and dimmer automatically, depending on the other vehicles and available light on the road.

Driver acceptance studies are vital from the manufacturer's perspective as well as the driver's perspective. Generally, these vehicle manufacturers have included these systems in their manufactured cars to promise an improved and safer driving experience for both vehicle drivers and passengers. Understanding consumers' acceptance is key for effective implementation and the actual use of advanced driver-assistance systems. There is limited research on understanding the acceptance process of in-vehicle applications from the driver's viewpoint [4].

Most empirical investigations are limited to populations in the United States, Europe, Korea, China and Taiwan, with a different culture than Malaysia [5]. The user perspective on new and unfamiliar technology will vary and will normally be driven by personal characteristics and locality. A technology developed based on European culture may not directly fit to users residing in Asian countries [6]. As a result, it is critical to assess the responses of people from a certain background as part of the global market user acceptance studies of the technology [7,8] to acquire the full potential of innovations that cannot be optimally reached until they are well-received by society. Asian communities, particularly in Southeast Asia, which make for a large proportion of global car users, are underrepresented. Even though most modern vehicles nowadays are equipped with in-vehicle applications (see Table 2), these applications are considered new among local drivers. Furthermore, Malaysians generally prefer vehicle-resident features that help them avoid accidents [9], such as collision warnings with auto-braking systems and blind-spot information systems. These vehicle safety features could influence the vehicle buying behavior of urban buyers in Malaysia [10]. However, not all drivers have a propensity or desire to implement the technology. Hence, we intend to explore their acceptance and intention to use the applications should they be made available.

Table 2. Available advanced driver-assistance systems based on vehicle models.

MODEL	LDW	LKAS	360 cam	RCTA	FCW	AEB	ACC	BSM	HUD	A-HOLD	HSA	HDC	PED	A-BEAM	TJA	A-PARK
Perodua MyVi	-	-	-	-	/	/ ^{v}	-	-	-	-	/	-	/	-	-	-
Toyota Rush	-	-	/	/	/	/ ^{vp}	-	/	-	-	-	-	/	-	-	-
Perodua Aruz	-	-	-	-	/	/ ^{vp}	-	-	-	-	/	-	/	-	/	/
Hyundai Ioniq	/	/	-	/	/	/ ^{vp}	/	/	-	/	/	-	-	-	-	/
Proton X70	/	-	/	-	/	/ ^{v}	/	/	-	/	/	/	-	/	/	-
Honda CR-V	/	/	-	-	/	/ ^{vpc}	/ **	/ #	-	/	/	-	-	-	-	/
Mazda CX-5	/	/	/	/ *	/	/	-	/	/	/	/	-	-	/ %	-	-
Nissan X-Trail	/	-	/	/	-	-	-	-	-	/	/	/	-	-	/	/
Toyota Hilux			-	/	-	-	-	/	-	-	-	/	-	-	/	-
Mitsubishi Triton	/	-	-	/	/	/	-	/	-	-	/	/	/	/	-	-
Ford Ranger	/	/	-	-	/	/ ^{vp}	/	-	-	-	/	/	-	-	/	-
Honda Accord	/	/	-	-	/	/ ^{vpc}	/	/ #	-	/	/	-	-	-	-	-
Mazda 3	/	/	/	/ *	/	/	/	/	/	/	/	-	-	/ %	-	-
Mazda 6	/	/	/	/ *	/	/	-	/	/	/	/	-	-	/ %	-	/
Toyota Camry	/	/	-	/	/	/	/	/	/	/	/	-	-	/	-	/

/ = available; - = not available; ** = with low speed; # = lane watch camera; ^{vpc} = vehicle, pedestrian, child above 1 m tall; ^{vp} = vehicle and pedestrian; ^{v} = vehicle only; * = with braking; % = adaptive.

Using the results of this study, along with other available information, the decision-makers may decide how to proceed with additional activities involving in-vehicle technologies. To our best knowledge, we have not found any further study investigating drivers' acceptance, specifically addressing Malaysian drivers. The output of this study may also provide input to the implementation of the Malaysia Intelligent Transport System (ITS) Blueprint, which aims to help drivers make informed decisions by outlining three Focus Areas, namely Automated Enforcement, Weigh-in-Motion and Emergency Management [11]. The remainder of this paper is organized as follows. Section 2 describes road safety and advanced driver systems applications focused on Malaysia. The works directly related to this study are discussed in Section 3. Section 4 discusses the methodology approach used for this study. The findings and discussions for this study are provided in Section 5. Finally, Section 6 presents the conclusions.

2. Related Works

User perspectives, attitudes and their actual use of the technology are critical for the continuous development of any new technology. Models and frameworks have been established to explain new technology adoption and to include aspects that can influence the user acceptance [12,13]. This includes the Motivation Model, Innovation Diffusion Theory (IDT), Uses and Gratification Theory, Social Cognitive Theory, Theory of Reasoned Action (TRA), Model of PC Utilization, Unified Theory of Acceptance and Use of Technology (UTAUT) and hybrid models. A summary of the existing ones is illustrated in Figure 1.

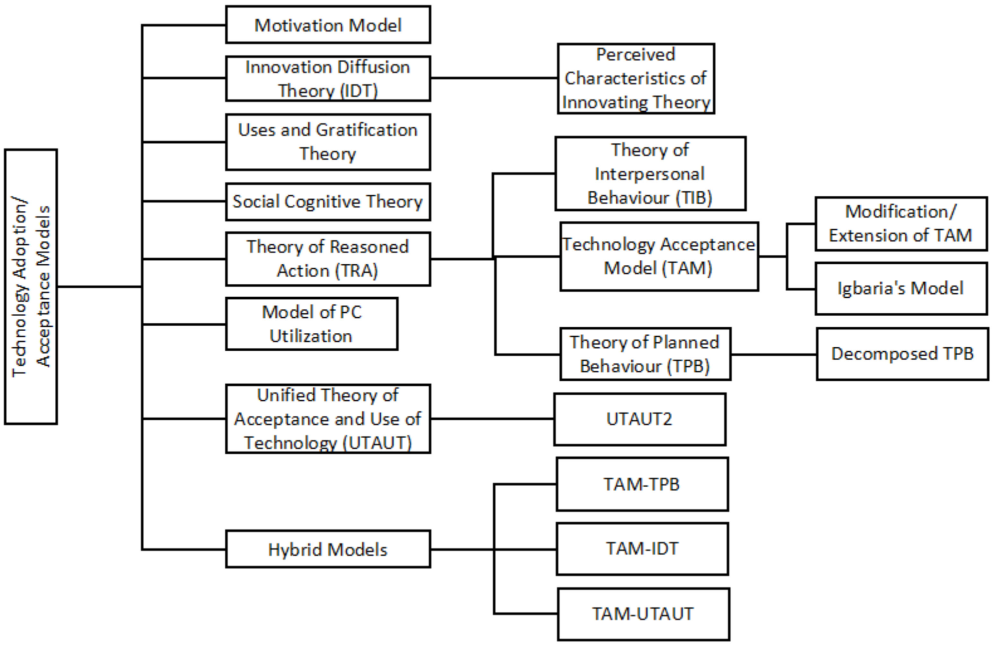

Figure 1. Summary of existing technology adoption models.

2.1. Motivational Models

Motivational models consider intrinsic and extrinsic factors that motivate a user to use a technology. For instance, if the user perceives that the technology will help them to perform better, they will use the technology. This is classified as an extrinsic factor or also referred to as perceived usefulness. Furthermore, if a technology is perceived as easy to use or an entertaining technology, users may also adopt the technology; this is also known as an intrinsic factor or the perceived ease of use (enjoyment) [4]. According to this model, the perceived usefulness and perceived enjoyment directly influence a user's intention to use a technology. When a user perceives a technology as useful and easy to be used, they will use the technology. Previous research has applied this model in various domains to assess the adoption and usage of new technologies. However, these models may require other factors to be customized to specific types of technology.

2.2. Innovation Diffusion Theory (IDT)

The IDT is a generic model proposed by Everett Rogers in 1992 to assess innovation adoption factor rates [14] that focuses on system characteristics and organization based on three core components, i.e., the adopter, innovation characteristics and decision process. Moreover, four factors create technology awareness involving time, communication channels, innovation or social influence. Technology is most adopted when a user sees the technological relative advantages, its compatibility with current technology and that it is less complex and allows trials and observation. The decision to use a technology may be influenced by user classification, i.e., early adopters, the early or late majority, innovators or laggards [13]. A study on the user acceptance of two types of in-vehicle applications which are retro-fit and integrated assumed their respondents are early adopters of the technology based on their high education level, high income and positive attitude toward new technology [15]. However, because this model does not explain the impact of attitude on the user acceptance or the adoption of the innovation, this model is less practical for outcome-based predictions [14]. The authors of [16] integrated the IDT and TAM in their investigation related to autonomous vehicle acceptance.

2.3. Uses and Gratification Theory (U&G)

This model focuses on the user's motivation and satisfaction to use specific communication technologies which are influenced by social and psychological factors. Three main components include satisfaction, behavioral usage and motivations. The behavioral usage component refers to the amount, duration and type of usage. Nevertheless, this model is not only limited to assessing communication media technology. The model may be utilized when the media is used as a part of the work process [13]. No recent publications reported on the use of the U&G model for addressing the user acceptance of in-vehicle applications. This offers a new opportunity which can be explored by future researchers.

2.4. Social Cognitive Theory (SCT)

The SCT predicts information technology usage based on the bi-directional relationship of three factors which reliably and commonly influence one another—behavior, personal and environment. The behavioral factor includes technology usage, performance and adoption issues, while the personal factor considers a user's personal characteristics. Additionally, environmental factors consider external factors such as facilities and social influence. The constructs include self-efficacy, anxiety, outcome expectancy (performance and personal) and preference toward the technology [13,17]. Similar to the U&G, we were not able to find recent publications about the SCT applied for investigating the user acceptance of in-vehicle applications.

2.5. Theory of Reasoned Action (TRA)

The TRA was applied to assess the impact of attitude on technology adoption by Davis et al. in 1989. It was first proposed for social psychology and later used to predict the user acceptance of e-shopping [18]. Besides attitude, the model's core components are the subjective norms/social influence and intention to use the technology. The model does not consider other factors that may influence user attention [19] such as knowledge, experience or likeability, habits or morale consciousness [14]. For instance, the TPB model was developed to explain human behavior in general, whereas the TRA model was first proposed for social psychology and later used to predict the user acceptance of e-shopping [18].

Three well known models, i.e., the Theory of Interpersonal Behavior (TIB), Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB), are derived from the TRA. A less general model compared to the TRA and TPB is the TAM [20]. In relation to our study, the TAM was applied in [21] to assess the user acceptance of the smartphone-based driver assistance in Brasov, Romania. The model removed the original subjective norms component from the TRA. The perceived ease of use and perceived usefulness are proposed as factors influencing a user's attitude toward the technology [20]. If a user perceives that a technology is useful and has a positive attitude toward the technology, the user will have an intention to use the technology which will lead to the actual use of the technology. However, the model does not include an information recency and completeness component which may influence a user's perceived usefulness and the perceived ease of use. On the other hand, the TPB model was developed to explain human behavior in general [18] with the assumption that all actions or behavior are planned. Hence, other factors do not have an impact on user intention and the actual use of a technology [14]. The TPB extends the TRA by adding attitude, subjective norms and a perceived behavioral control. In [20], the authors performed a simulation study to assess the impact of an audio in-vehicle warning for railway level crossings using the TPB.

In addition, the TIB model incorporates the TRA and TPB. The model adds habits, facilitating conditions and affect or emotion to predict the user's actual use of a technology. The TIB assumed that personal characteristics are shaped by personal beliefs, attitudes, social factors and past experiences. The complexity of the TIB allows only limited previous work compared to the TRA and TAM [13]. The authors of [22] proposed a model of commuter travel behavior performance based on the TIB. The model includes attitude, social factor, affect and habit as the main factors.

2.6. Model of PC Utilization (MPCU)

The MPCU was proposed to predict the actual use of a personal computer (PC). The most influential factors on the actual use of a PC are the user perceptions of the technology complexity and consequences, social influence and job-fit (i.e., if the technology can improve work performance or not). Two other factors, which are facilitating conditions and user affective (i.e., how a user feels about the technology), do not have a strong influence on the actual use of the PC [17]. The model is effective for assessing the voluntary user adoption of a technology. Even so, user adoption may be influenced by how the user perceives the short-term consequences of using the technology [14].

2.7. Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT model was created primarily to explain technology acceptance. The model integrates 32 constructs in accordance with eight well-known adoption theories, including the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), the combined form of the TAM and TPB (C-TAM-TPB), the Model of PC Utilization (MPCU), the Innovation Diffusion Theory (IDT), the Motivational Model (MM) and the Social Cognitive Theory (SCT) [14]. The model highlighted that the actual behavior is highly influenced by user intentions. If a user has a positive intention toward a technology, the user will eventually use or adopt the technology [4,23,24]. The core constructs are performance expectancy, effort expectancy, social influence, facilitating conditions and motivational controls. Users are assumed to have control of their behavior and decisions over the use of technologies [20]. The research on in-vehicle applications that applied the UTAUT includes [20,25,26].

Moreover, in-vehicle applications can be grouped based on the three driving automation standards described by the Society of Automotive Engineers (SAE), the NHTSA in the U.S. and the BASt in Germany [27], as in Table 3. The three main challenges for in-vehicle applications are the user acceptance, safety and security and the development time and cost. In this study, we focused on in-vehicle applications that support driver's driving experience, i.e., level 0 to level 2 to address the user acceptance.

Recognizing drivers' expectations and acceptability of in-vehicle applications would thus help to pave the path for future development, allowing elements that influence drivers' acceptance or rejection of the technology to be addressed. A driver's decision or performance on the road may be influenced by the use of in-vehicle applications [21]. A quantitative study was conducted in Czech Republic to investigate the influence of subjective factors, including the feeling of increased safety, ease of use, increased comfort, trust in the system, previous experience with the system and other aspects such as price, good references, system reliability and functions of the driver-assistance systems [28]. A similar study among Finnish people is presented by [29]. Both studies did not provide any theoretical models for the research design.

We believe that applying a theoretical model is necessary to limit the scope of our study. Even though existing models and frameworks may be considered to explain the drivers' adoption and introduce factors that may affect the drivers' acceptance, these available models and frameworks were not specifically developed to address in-vehicle applications. Previous research by [20] compared the TAM, TPB and UTAUT to assess the validity of these theories in modeling the user acceptance of in-vehicle applications, i.e., a fatigue monitoring system or an adaptive cruise control system combined with a lane-keeping system among users in Boston, MA. The authors concluded that, among the three models, the original TAM performance is the best. Moreover, a few studies apply the TAM to investigate user technology acceptance factors [30], demonstrating that this model can be used to investigate in-vehicle technology adoption. Because the applications are pre-installed in manufactured vehicles, assessing whether drivers accept the applications or not is a relatively new research area [1,31]. In addition, these studies use a few extra study-specific elements (e.g., trust) to better understand the adoption process [30] and investigate public opinion and the willingness to use in-vehicle applications. There are also studies which are limited to a specific age group or criteria [32]. In this study, our respondents are not focused on driver characteristics. Instead, users from various sociodemographic characteristics were included in this study. We reviewed related research that addresses the acceptance of any technology related to in-vehicle applications during the years 2015–2021. A part of our findings is summarized in Table 4.

Table 3. In-vehicle technology applications based on driving automation standards.

Level	SAE	NHTSA	BASt	In-Vehicle Applications
0	No Automation	No Automation	Driver Only	Collision warning, navigation system, lane departure warning, lighting and visibility system.
1	Driver Assistance	Function-specific Automation	Driver Assistance	Night-view assist, blind-spot assist, parking sensors, driver drowsiness detection, adaptive cruise control or lane-keep technology.
2	Partial Automation	Combined Function Automation	Partial Automation	Adaptive cruise control, active lane-keep assist or automatic emergency braking.
3	Conditional Automation	Limited Self-Driving Automation		A vehicle that can manage itself on a freeway journey, excluding on- and off-ramps and city driving, but driver must be alert.
4	High Automation	Full Self-Driving Automation	High Automation	A vehicle that can complete an entire journey without driver intervention may be confined to a certain geographical area (i.e., geofenced) or could be prohibited from operating beyond a certain speed.
5	Full Automation		Full Automation	

Table 4. Summary of previous work related to user acceptance of in-vehicle applications.

Context/Focus	Type of Study	Main Findings
Smartphone-based navigation application with a collision warning system [21]	Real-traffic experiment	Driver's acceptance is attributed to user attitude and perceived usefulness.
Lane-change collision avoidance system using a haptic feedback force [33]	Driving simulator	Driver's acceptance is influenced by corresponding system design with expectations.
Low emission zone and school zone alert system [15]	Real-traffic experiment and questionnaire via email	Experienced drivers have higher satisfaction level and positivity regarding system usefulness.
Adaptive cruise control and lane centering [34]	Controlled road experiment and post-drive survey	Driver acceptance is influenced by system functionalities.
Collision/Risk Alerts (CR); Collision Mitigation (CM); Automatic Driving Tasks (AT); Lighting and Visibility (LV); and Miscellaneous Driving Aids (MA) [32]	Structured live survey	Female drivers are more positive toward collision avoidance features. Features promoting safety are underutilized by drivers.

Table 4. *Cont.*

Context/Focus	Type of Study	Main Findings
Automatic lane-change system [35]	Experimental design with 1823 lane-change events	Driver acceptance of the system was evaluated using performance index.
Parking assistance systems [36]	Survey	Driver acceptance is influenced by the system reliability.
Trust in technology, effect on driving skills and behavior and technology preferences among teens [37]	Standard focus group methodology and purposive sampling methods	Driver acceptance is influenced by trust and reliability of the vehicle technology.
ACC, FCW, LDW, blind-spot monitoring, driver drowsiness detection system, traffic sign recognition system, automatic high beam [29]	Survey	Driver acceptance is influenced by perceived safety benefit of the systems.
Forward collision warning and mitigation (FCWM) [38]	Online survey	Driver acceptance is influenced by knowledge regarding system automation level.
Forward collision warning and lane departure warning [39]	Questionnaire	Driver acceptance is influenced by attitude, perceived usefulness and subjective norms.
Fatigue monitoring system or an adaptive cruise control system combined with a lane-keeping system [19]	Driving simulator and online survey	Driver acceptance can be modeled using TAM and TPB.
Adaptive cruise control (ACC) and lane=keeping assistance (LKA) [40]	Survey	Driver owners have different understanding of ACC and LKA systems and tend to over-estimate the system capabilities. There is no relationship between trust and frequent usage of the systems.
Night-view assist, blind-spot assist, parking sensors, driver drowsiness detection, emergency-brake assist, cruise control and emergency stop system [41]	Online survey	Driver acceptance is influenced by system usefulness, reassurance and trust as well as system level of autonomy.
Vehicle system related to driving convenience and safety [4]	Online survey	Driver acceptance is positively influenced by factors related to driver convenience and trust.

3. Research Model and Hypotheses Development

According to the literature, Technology Acceptance Model (TAM) is a reliable model for exploring the acceptability of new technologies [20,39] and describing user behavior and technology usage [42]. However, because TAM was commonly explored in the context of other technologies that are different to in-vehicle applications, we aim to investigate other constructs related to driver acceptance by extending the basic TAM model.

The basic independent variables, i.e., perceived usefulness (PU) and perceived ease of use (PE), were first selected from the basic TAM model to represent users' intention to use the in-vehicle applications. We assumed that if user-perceived in-vehicle applications are useful, the user would also perceive that the applications are easy to use and eventually will intend to use the applications. AT and PU are the most important factors influencing the user acceptance [21]. Moreover, if a user perceives that the in-vehicle applications are easy to be used, i.e., users can easily activate the application when they are in the driver's seat, and if the interaction process through the human–machine interface is simple and useful for a driving experience, the user will indicate a positive attitude (AT) and a high probability of accepting the applications. However, we removed the actual use variable because the in-vehicle applications are momentarily not essential components of all vehicle models, and it is beyond the scope of this study. The intention to use in-vehicle applications (BI) is set as the target variable of the model to represent users' or drivers' actual system use.

Three other variables relevant to the context of drivers were included, including trust (T), system characteristics (SCs) and social influence (SI). SC refers to the preferable design or features of the in-vehicle applications, whereas SI represents social factors that influence a user's opinion on aspects of the in-vehicle applications. A study among licensed drivers from United States and Canada revealed that drivers who are not vehicle owners but have better knowledge of system capabilities have lower trust level. However, the trust level of drivers who are also vehicle owners does not seem to be influenced by the knowledge of system capabilities [40]. In another study, Chan et al. studied the effect of trust in the user acceptance of 5G-connected autonomous vehicles. Authors concluded that trust has mediating effect on PU, PE and SI with BI [43]. Apart from that, ref. [35] mentioned that users are more accepting toward the technology if they are certain of the recommendation provided by the system. This may be reflected using T and PU.

In addition, personal characteristics (PCs) of users refer to gender, age, prior knowledge about in-vehicle applications, self-capabilities and involvement in accidents as well as driving distance per week which may influence a user's trust, the expectation of system characteristics and impact of social influence toward the in-vehicle applications. Individuals who are highly educated and earn a good paycheck may be more willing to use the in-vehicle applications [15]. The older a driver is, the more concerned they are regarding the PU, T and SC [41]. Furthermore, ref. [39] concluded that drivers in Jakarta community are positively and significantly influenced by only AT, PU and subjective norms to adopt FCW and LDW. Hence, based on our literature, the research model is designed as in Figure 2 and the research questions of this study are listed in Table 5 with corresponding hypotheses.

Table 5. Research questions and hypotheses.

Research Questions	Hypothesis
Q1: What relationship exists between the PU and EU variables of the research model?	H1: User-perceived ease of use (EU) of in-vehicle applications positively affects perceived usefulness (PU) of the applications.
Q2: What influences exist between PU and EU with the mediating variable (AT) in the research model?	H2: User-perceived usefulness (PU) of in-vehicle applications positively affects their attitude toward the applications (AT). H3: User-perceived ease of use (EU) of in-vehicle applications positively affects their attitude toward the applications (AT).
Q3: How does user attitude (AT) impact the user intention to use the in-vehicle applications (BI)?	H4: User attitude (AT) toward the in-vehicle applications positively affects their intention to use the application (BI).
Q4: What influences exist between PU and EU with the target variable (BI) in the research model?	H5: User-perceived usefulness (PU) of in-vehicle applications positively affects their intention to use the applications (BI). H6: User-perceived ease of use (EU) of in-vehicle applications positively affects their intention to use the applications (BI).
Q5: What is the impact of social influence (SI) on user-perceived usefulness (PU) and perceived ease of use (EU) of the in-vehicle applications?	H7: Social influence (SI) positively influences drivers' perceived usefulness (PU) of the applications. H8: Social influence (SI) positively influences drivers' perceived ease of use (EU) of the applications.
Q6: How does trust (T) influence perceived usefulness (PU) and perceived ease of use (EU) of the in-vehicle applications among users?	H9: Trust (T) positively influences drivers' perceived usefulness (PU) of the applications. H10: Trust (T) positively influences drivers' perceived ease of use (EU) of the applications.
Q7: How do system characteristics (SCs) influence perceived usefulness (PU) and perceived ease of use (EU) of the in-vehicle applications among users?	H11: System characteristics (SCs) positively influence users' perceived usefulness (PU) of the in-vehicle applications. H12: System characteristics (SCs) positively influence users' perceived ease of use (EU) of the in-vehicle applications.
Q8: How do personal characteristics (PCs) influence trust (T), social influence (SI) and system characteristics (SCs) of the in-vehicle applications among users?	H13: Personal characteristics (PCs) positively influence system characteristics (SCs) of the in-vehicle applications. H14: Personal characteristics (PCs) positively influence trust (T) toward the in-vehicle applications. H15: Personal characteristics (PCs) positively influence social influence (SI) toward the in-vehicle applications.

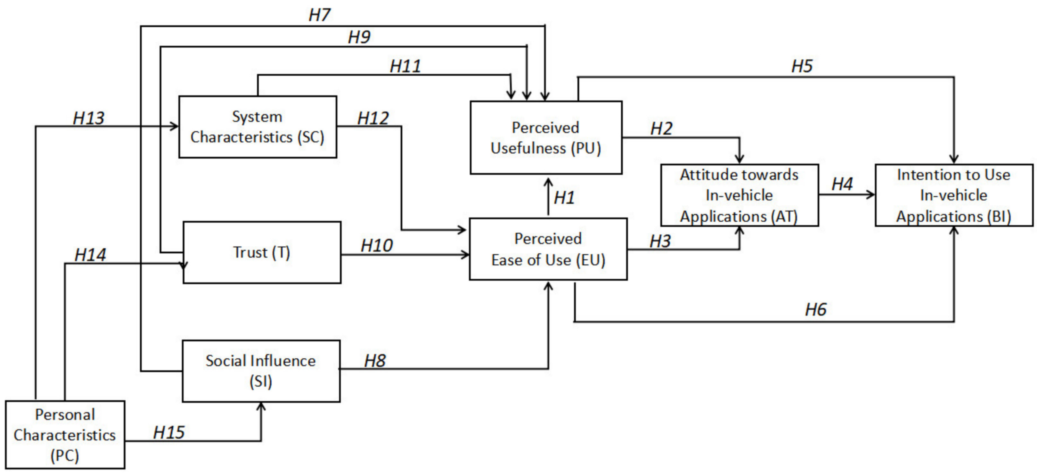

Figure 2. Research model.

4. Questionnaire Design and Data Collection

We collected data from 308 respondents using a questionnaire which was designed based on previous studies. The items in the questionnaire or survey for each construct are shown in Table 6. Respondents are required to rate the items on a scale of 1 (totally disagree) to 7 (totally agree).

Table 6. Survey items.

Construct	Items
Perceived Usefulness (PU)	In-vehicle application features make driving more convenient. In-vehicle application features would enable me to reach my destination quickly and safely. In-vehicle application features would enable me to reach my destination cost-efficiently. Using in-vehicle application features means extensive internet connectivity is required. Using in-vehicle application features in my vehicle is meaningless if other vehicles are not equipped with in-vehicle application features as well.
Perceived Ease of Use (EU)	I do not need special training to learn how to use in-vehicle application features. I require in-vehicle application features instruction manual to be able to use the features perfectly. It is easy to become skilful in using in-vehicle application features. In-vehicle application features are easy and simple to understand.
Attitude (AT)	I think using in-vehicle application features would be a good idea. I think in-vehicle application features would make my driving experience more interesting and fun. When I drive a vehicle with in-vehicle application features, I feel satisfied. Overall, available in-vehicle application features in my vehicle meet my expectations. I will recommend in-vehicle application features to others.
Intention to Use (BI)	I am willing to use in-vehicle application features in the future. I am willing to use in-vehicle application features frequently and consistently if given the opportunity. If the vehicle with in-vehicle application features becomes available to me, I plan to obtain and use it. I will use in-vehicle application features if required.
Trust (T)	I believe in-vehicle application features are verified professionally. I believe the in-vehicle application features are reliable. I believe in-vehicle application features will perform better as an add-on to my vehicle. I believe my driving experience will be safer with in-vehicle application features. I am worried about using in-vehicle application features.
System Characteristics (SCs)	I am afraid that a mounted dashcam to display alerts from in-vehicle application features will distract my driving. Using in-vehicle application features do not really bother me to drive. I will only use in-vehicle application features with audio when I drive. In-vehicle application features with visuals on the vehicle dashboard will not affect my driving. I prefer in-vehicle application features integrated into a mounted car dashcam.
Social Influence (SI)	I would be proud to show the vehicle with in-vehicle application features to people who are close to me. I would feel more inclined to use in-vehicle application features if it was widely used by others. I would prefer to have someone else as a passenger when I drive a car with in-vehicle application features. Other people will encourage me when I use in-vehicle application features. Other people will think I am wasting money when I purchase a vehicle with in-vehicle application features.

The sociodemographic details of each respondent include their gender and age as other previous work. In addition, we require information whether they are licensed driver or not, involvement in road accidents, driving distance per week, locality as well as knowledge about in-vehicle applications. Respondents were also required to self-declare their hearing, vision and motor skills. The survey items categorized under the personal characteristics' variable are presented in Table 7.

Table 7. Details of respondents (n = 308).

Personal Characteristics (PCs)	Response Category (n)
Gender	Male (113); Female (195)
Age	18–25 years old (152), 26–34 years old (38), 35–54 years old (82), 55–64 years old (25), above 64 years old (11)
Driver's License	Yes (264), No (44)
Accident Experience	Yes (155), No (153)
Locality	Rural (53), Suburban (110), Urban (145)
Knowledge about in-vehicle applications	No (79), Yes (229)
Self-reported capabilities	Limited (141), Not Limited (167)
Driving distance per week	less 100 km (195), 100–200 km (62), 201–300 km (23), 301–400 km (3), more than 400 km (25)

5. Data Analysis and Results

The user responses are made available in Zenodo, an open-access repository under the Creative Commons Attribution 4.0 International license. The data analysis was performed using the Real Statistics Resource Pack software (Release 7.6) for MS Excel [44], including items consistency, correlation analysis, variance inflating factor, regression analysis and mediation analysis. Moreover, the results are presented either in tabular form or figures, and findings are discussed accordingly.

5.1. Construct Items

In this study, a total of seven constructs, i.e., the SC, SI, T, PU, EU, AT and BI, were involved, and the responses were collected based on the survey items as in Table 6. The Cronbach's Alpha tests were performed to assess the reliability of the multiple-question Likert scale used to measure the latent variable structure of psychological measures as single items derived from the respondents. The Cronbach's Alpha value presents how reliable a set of test items are to validate and authenticate the response for the TAM constructs, i.e., 0.91–1.00 (excellent), 0.81–0.90 (good), 0.71–0.80 (good and acceptable), 0.61–0.70 (acceptable) and 0.01–0.60 (not acceptable). We found that the scale system is highly reliable for all constructs where the average is 0.7872. All variables have a value of Cronbach's Alpha higher than 0.7 except for the target variable, i.e., BI, which is 0.6294 (Table 8). Nevertheless, the items for the BI are still acceptable. Increasing the number of items under this construct may increase the internal consistency.

Table 8. Reliability and validity analysis on variables.

Variables	T	SC	SI	PU	EU	AT	BI
Cronbach's α	0.7100	0.8161	0.9733	0.8586	0.7522	0.7712	0.6294

The Kaiser–Meyer–Olkin (KMO) test value of 0.791 indicates that the sample is adequate and has sufficient information to estimate factor solutions. In addition, Bartlett's test *p*-value is less than 0.001 which is significant to reject the null hypothesis. Hence, there exists some level of correlation among the items to estimate the factor loadings. A Confirmatory Factor Analysis was performed using JASP 0.16.1. The factor loadings of each item are shown in Figure 3.

							95% Confidence Interval	
Factor	Indicator	Symbol	Estimate	Std. Error	z-value	p	Lower	Upper
PU	PU1	λ11	0.882	0.037	23.735	<.001	0.809	0.954
	PU2	λ12	0.871	0.036	24.306	<.001	0.801	0.942
	PU3	λ13	0.790	0.040	19.848	<.001	0.712	0.868
	PU4	λ14	0.848	0.038	22.630	<.001	0.774	0.921
	PU5	λ15	0.877	0.037	24.021	<.001	0.805	0.948
EU	EU1	λ21	0.484	0.069	12.459	<.001	0.349	0.619
	EU2	λ22	0.091	0.102	0.898	0.369	-0.108	0.290
	EU3	λ23	0.474	0.070	11.996	<.001	0.338	0.610
	EU4	λ24	0.350	0.080	8.451	<.001	0.193	0.506
T	T1	λ31	0.888	0.040	22.301	<.001	0.810	0.966
	T2	λ32	0.868	0.038	23.028	<.001	0.794	0.942
	T3	λ33	0.891	0.037	24.054	<.001	0.818	0.963
	T4	λ34	0.882	0.038	23.128	<.001	0.807	0.957
	T5	λ35	0.880	0.038	23.541	<.001	0.813	0.960
AT	AT1	λ41	0.869	0.043	20.304	<.001	0.785	0.953
	AT2	λ42	0.895	0.037	23.904	<.001	0.821	0.968
	AT3	λ43	0.882	0.040	22.104	<.001	0.803	0.961
	AT4	λ44	0.889	0.039	23.004	<.001	0.812	0.964
	AT5	λ45	0.884	0.040	22.329	<.001	0.805	0.961
SC	SC1	λ51	0.986	0.042	23.591	<.001	0.904	1.068
	SC2	λ52	0.939	0.044	21.237	<.001	0.853	1.026
	SC3	λ53	0.866	0.042	20.647	<.001	0.783	0.948
	SC4	λ54	0.963	0.043	22.414	<.001	0.847	1.014
	SC5	λ55	0.935	0.041	22.960	<.001	0.855	1.015
SI	SI1	λ61	0.570	0.061	9.389	<.001	0.451	0.690
	SI2	λ62	0.945	0.047	9.971	<.001	0.852	1.038
	SI3	λ63	0.758	0.054	9.680	<.001	0.652	0.864
	SI4	λ64	0.752	0.051	16.175	<.001	0.653	0.852
	SI5	λ65	0.756	0.053	11.304	<.001	0.652	0.861
PC	Distance	λ71	0.267	0.094	2.846	0.004	0.083	0.450
	Age	λ72	0.436	0.096	4.542	<.001	0.248	0.624
	Knowledge	λ73	-0.223	0.039	-5.650	<.001	-0.300	-0.145
	Accidents	λ74	-0.053	0.040	-1.337	0.181	-0.131	0.025
	Gender	λ75	-0.092	0.038	-2.399	0.016	-0.167	-0.017
	Locality	λ76	-0.002	0.028	-0.076	0.940	-0.056	0.052
BI	BI1	λ81	0.877	0.040	22.324	<.001	0.802	0.957
	BI2	λ82	0.832	0.360	11.741	0.247	0.128	1.538
	BI3	λ83	0.778	0.046	18.239	<.001	0.688	0.870
	BI4	λ84	0.787	0.680	1.157	0.247	-0.546	2.119

Figure 3. Factor loadings.

In addition, we calculated the Average Variance Extracted (AVE) and determined the convergent validity as well as the discriminant validity. We conclude that there is a convergent validity when the AVE is 0.5 and above. Moreover, the discriminant validity exists when the square root of AVE is more that the correlation value. The results are shown in Table 9. Evidence of both the convergent and discriminant validity demonstrates the constructs' validity.

Table 9. Convergent and discriminant validity.

	No. of Indicator	AVE	AVE/Indicator
PU	5	0.7295	0.8541
EU	4	0.5473	0.7398
AT	5	0.7809	0.8837
T	5	0.7778	0.8818
SC	5	0.8808	0.9385
SI	5	0.5859	0.7655
PC	6	0.5537	0.7441
BI	4	0.6717	0.8195

5.2. Correlation Analysis

The Pearson product–moment correlation coefficient *r* was calculated between the variables. The r value is interpreted as 0.0–0.1 (negligible), 0.10–0.39 (weak), 0.40–0.69 (moderate), 0.70–0.89 (strong) and 0.90–1.00 (very strong). Based on Table 10, in general, positive relationships exist among the TAM variables. Strong relationships exist between the PU and T and also the SC and SI with r values more than 0.7. In addition, strong relationships also exist between the AT and BI as well as the SI and T. However, the EU and BI are the only variables with weak relationships compared to the other variables with moderate relationships.

Table 10. Correlation between TAM variables.

	PU	EU	AT	T	SC	SI	BI
PU	1						
EU	0.584278	1					
AT	0.597966	0.400629	1				
T	0.739867	0.603682	0.549366	1			
SC	0.720569	0.664573	0.579474	0.686981	1		
SI	0.749924	0.474516	0.555729	0.84442	0.597722	1	
BI	0.507614	0.334304	0.896483	0.469818	0.416398	0.445437	1

Furthermore, the relationship among the personal characteristic (PC) variables was also assessed and illustrated in Figure 4. There is no correlation (negligible) among most of the variables. However, weak relationships exist between a few variables. This shows that although the response of one variable may change the other correlated variables, the relationship is not strong and can be ignored.

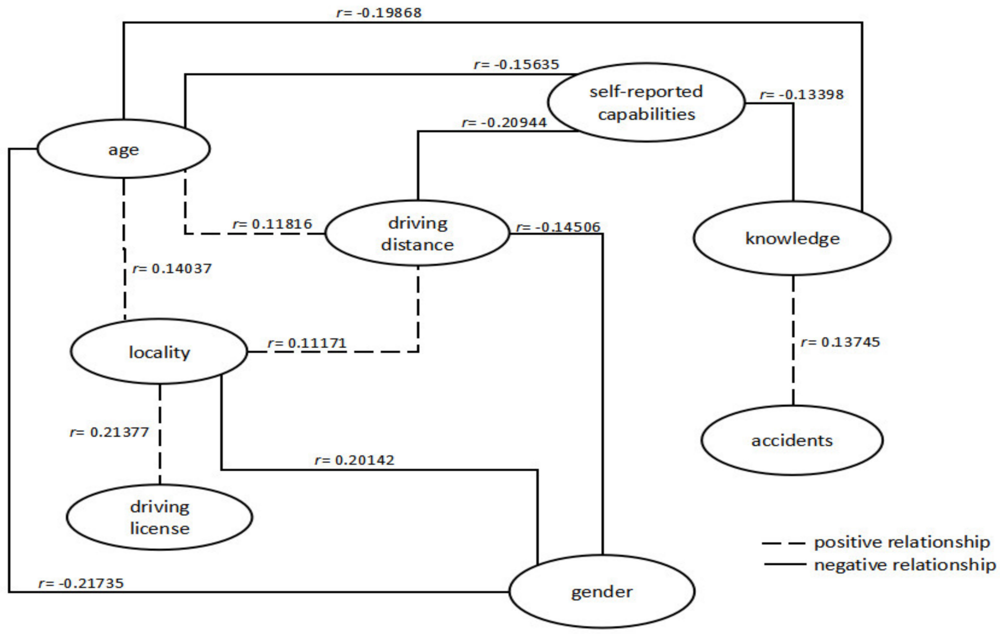

Figure 4. Relationship among PC variables.

5.3. Multicollinearity

When there is a relationship among the exploratory or control variables, there is a possibility of multicollinearity. In regression analysis, the first step is to detect multicollinearity. Generally, a variance inflating factor (VIF) above four indicates that multicollinearity might exist, and further investigation is required. When the VIF is higher than 10, there is significant multicollinearity that needs to be corrected. Because only the VIF for trust (T) is slightly above four, it can be safely ignored without suffering from multicollinearity. The regression coefficients are not impacted and only exist in the control variable but not in the variables of interest (PU, PE and BI). The VIF of each variable is shown in Table 11.

Table 11. Variance Inflating Factor (VIF).

PC Variables	VIF	Exploratory Variables	VIF
Gender	1.1208	Trust	4.2503
Age	1.1637	System characteristics	1.8976
Driving license	1.0660	Social influence	3.4920
Accidents	1.0405	Perceived usefulness	1.5183
Locality	1.1249	Perceived ease of use	1.5183
Knowledge	1.1070		
Self-reporting capabilities	1.1239		
Driving distance per week (km)	1.0926		

5.4. Causal Relationship

The causal relationships between the constructs PU, EU, AT, BI, DC, SC and SI are investigated using regression analysis. The results are shown in Table 12. The hypotheses are validated at 95% confidence level. If the null hypothesis is rejected, it is statistically significant that there is a non-zero correlation among the variables, and it can be modeled with the regression equation. Furthermore, the correlation between the predicted value of Y generated in the equation and the actual Y value for each unit refers to the multiple R. The coefficient values provide the impact or weight of a variable toward the entire regression model.

Table 12. ANOVA results.

X→Y	Multiple R	Coefficient	Std. Error	t Stat	*p*-Value	Hypothesis
EU → PU	0.58428	0.48622	0.03861	12.59397	1.38E-29	H1 rejected
PU → AT	0.59797	0.32618	0.04264	7.64880	2.65E-13	H2 rejected
EU → AT	0.40063	0.32618	0.04264	7.64880	2.65E-13	H3 rejected
AT → BI	0.89648	0.90591	0.02560	35.39342	3.40E-110	H4 rejected
PU → BI	0.50761	0.50186	0.04870	10.30616	1.41E-21	H5 rejected
EU → BI	0.33430	0.27504	0.04433	6.20492	1.78E-09	H6 rejected
T → PU	0.73987	0.75133	0.03906	19.23795	1.29E-54	H9 rejected
SI → PU	0.74992	0.62271	0.03140	19.83043	7.41E-57	H7 rejected
SC → PU	0.72057	0.69049	0.03798	18.17872	1.37E-50	H11 rejected
T → EU	0.60368	0.73669	0.05562	13.24611	5.74E-32	H10 rejected
SI → EU	0.47452	0.473489	0.05021	9.42990	1.06E-18	H8 rejected
SC → EU	0.66457	0.765272	0.04919	15.5580	1.29E-40	H12 rejected

The assumption is that the combination of independent variables will generate a larger multiple R or correlation than any single variable used as a predictor variable. When single predictors were used (T, SC, SI) to predict the PU, the multiple R values were 0.73987, 0.74992 and 0.72057, respectively. The multiple R value increased to 0.82550 when the predictors were combined. Moreover, the Adjusted R2 indicates the amount of variability being explained by the regression model. Any field that attempts to predict human behavior, such as psychology, typically has R-squared values lower than 0.5. For instance, the value of the Adjusted R2 is 0.6783 when the T, SC and SI were assigned to predict the PU. This shows that the explanatory power of trust, system characteristics and social influence to perceived usefulness is 67.83%. Because the value is more than 0.5, the variables are a good fit to predict the perceived usefulness of in-vehicle applications. This means that the combination of the variables has a significant positive effect on the user-perceived usefulness of in-vehicle applications. When trust, system characteristics and social influence have high values, users are much more likely to perceive that an in-vehicle application is useful. The multiple regression analysis results of different models are summarized in Table 13.

Table 13. Multiple Regression Analysis Results.

Model	Multiple R	Adjusted R2	F	p-Value	Sig.
T, SC, SI → PU	0.82550	0.678298	216.7664	3.52E-75	Yes
T, SC, SI → EU	0.69949	0.484246	97.08173	4.3E-44	Yes
T, SC, SI → AT	0.63593	0.398535	68.8067	5.52E-34	Yes
T, SC, SI → BI	0.494563	0.237138	32.81056	2.12E-18	Yes
PU, EU → AT	0.601292	0.357365	86.36036	1.91E-30	Yes
PU, EU → BI	0.509737	0.254979	53.53434	1.18E-20	Yes
PU, EU, AT → BI	0.897264	0.803159	418.5442	1.4E-107	Yes

5.5. Mediating Effect Analysis

This section uses the hierarchical regression method as suggested by [44] to verify the mediating effect of attitude between different factors. First, we analyzed the mediating effect when (i) AT is the mediator between the PU and BI and (ii) AT is the mediator between the EU and BI. The results are shown in Table 14. When the partial correlation analysis is performed i.e., without the AT as the mediator, the correlation value between the PU and BI dropped to −0.0355, and the correlation value between the EU and BI also dropped to −0.0271.

Table 14. Mediation Analysis (PU affects the outcome of BI indirectly through mediator AT).

	Coefficients	Std Error	t-Stat	p-Value	Correlation	Semi-Part
PU → AT	0.5850	0.0448	13.0504	3.00E-31	0.5980	
AT → BI	0.9059	0.0256	35.3934	3.38E-110	0.8965	0.7398
PU → BI	0.5019	0.0487	10.3062	1.41E-21	0.5076	−0.0355
PU	−0.0438	0.0312	−1.4037	0.1614		
AT	0.9327	0.0319	29.2529	1.20E-90		
EU → AT	0.3262	0.0426	7.6488	2.65339E-13	0.4006	
AT → BI	0.9059	0.0256	35.3934	3.3791E-110	0.8965	0.8323
EU → BI	0.2750	0.0443	6.2049	1.77517E-09	0.3343	−0.0271
EU	−0.0438	0.0312	−1.4037	0.1614		
AT	0.9327	0.0319	29.2529	1.20E-90		

Moreover, to determine the significance of the relationship with the mediator AT, the Sobel test was applied. Because the p-value is less than 0.05 (95% confidence level), both paths, i.e., PU→AT→BI and EU→AT→BI, are significant and this confirms that mediating relationships exist between the PU and EU with the BI where the AT is the mediator variable. Additionally, we analyzed the mediating effects considering the EU as the mediator variable between the SI, SC and T with the AT and PU as the mediator variable between the SI, SC and T with the AT as in the research model. Similarly, the semi correlation between the mediator variable and the target variable was weakened by the direct variables. This indicates a mediating effect. We confirm the findings with the Sobel Test as in Table 15. The p-values are significant at a 95% confidence level, ensuring that the PU and EU are the mediator variables for the SC, SI and T, leading to the AT. A user with high values of SC, SI and T will perceive the in-vehicle application as useful and easy to use in their driving experience, which will lead to the user having a positive attitude toward the application and eventually having a high intention to use the application.

Table 15. Results of Sobel Test.

	Coefficients	Std Error	t-Stat	*p*-Value
PU $\rightarrow$ AT $\rightarrow$ BI	0.5361	0.0438	12.2488	2.52E-28
EU $\rightarrow$ AT $\rightarrow$ BI	0.3592	0.0480	7.4791	8.03E-13
SI $\rightarrow$ EU $\rightarrow$ AT	0.190105	0.031894	5.960593	6.94E-09
SC $\rightarrow$ EU $\rightarrow$ AT	0.266247	0.038724	6.875561	3.49E-11
T $\rightarrow$ EU $\rightarrow$ AT	0.241852	0.036435	6.638004	1.45E-10
SI $\rightarrow$ PU $\rightarrow$ AT	0.448429	0.041098	10.91116	1.28E-23
SC $\rightarrow$ PU $\rightarrow$ AT	0.430876	0.040603	10.612	1.34E-22
T $\rightarrow$ PU $\rightarrow$ AT	0.241852	0.036435	6.638004	1.45E-10

5.6. Linear and Non-Linear Relationship

A correlation shows the relationship between two variables, while regression allows us to see how one affects the other. Based on the correlation analysis results, we examine the type of regression involving the personal characteristics variables, including gender, age, locality, involvement in accidents, knowledge about in-vehicle applications, locality, self-reported capabilities (vision, hearing, mobility and dexterity) and driving distance per week as shown in Table 16. Non-linear regressions were found for age and intention to use the in-vehicle application, self-reported capabilities and system characteristics, gender and attitude. We compared the standard error values of linear and non-linear regression models. A lower standard error value indicates a better fit model for the variables.

Table 16. Personal characteristics variable relationships.

	Correlation	Std Error (Linear)	Std. Error (Non-Linear)
Locality $\rightarrow$ PU	-0.12525	0.05677	0.00184
Gender $\rightarrow$ AT	0.15946	0.08532	0.00286
Age $\rightarrow$ AT	-0.1194	0.03490	0.00063
Knowledge $\rightarrow$ AT	0.18236	0.09378	0.00372
Locality $\rightarrow$ T	-0.10759	0.05602	0.00198
Knowledge $\rightarrow$ T	0.14532	0.09498	0.00421
Knowledge $\rightarrow$ SC	0.12307	0.10096	0.00424
Self-reported capabilities $\rightarrow$ SC	-0.11057	0.10396	0.00425
Locality $\rightarrow$ SI	-0.14126	0.06822	0.00234
Knowledge $\rightarrow$ SI	0.14740	0.11612	0.00490
Gender $\rightarrow$ BI	0.14236	0.08645	0.00301
Age $\rightarrow$ BI	-0.13941	0.03518	0.00066
Knowledge $\rightarrow$ BI	0.18607	0.09470	0.00389

Table 17 summarizes our findings when we further investigate the personal characteristics variables, which may have a direct influence or moderate the investigated relationships. Knowledge about in-vehicle applications positively influences trust, social influence and system characteristics, which eventually fosters a positive attitude and higher intention to use the application in their driving experience. Because the paper focuses on individual acceptance, locality and knowledge contribute to social influence. Individuals who reside in sub-urban and urban areas may have more exposure to the automotive changing landscape and information, allowing them to react better toward their social cycle views and comments.

Table 17. Models with personal characteristics variable.

	p-Value	Regression Model	*X* (Not Significant *p*-Value)
Gender, age, knowledge → BI	0.00027	Significant	age (0.17926)
Gender, age, knowledge → AT	0.00024	Significant	age (0.36185)
Locality, knowledge → SI	0.00226	Significant	Significant
Self-reported capabilities, knowledge → SC	0.02361	Significant	knowledge (0.05479) self-reported capabilities (0.09237)
Locality, knowledge → T	0.00845	Significant	locality (0.08158)

6. Discussions

This study investigates the user acceptance of in-vehicle applications where recent vehicle models are equipped with the application and automotive aftermarket service vendors offer the application as a vehicle accessory that can provide advanced driver assistance to users. Due to the variety of vehicle owners and users, this paper aims to answer several research questions by modeling and quantifying the user acceptance of in-vehicle applications based on survey responses. A research model based on the integration of the TAM, trust, system characteristics, social influence and personal characteristics is presented. In addition, the empirical results on the user intention to use in-vehicle applications in a driving experience are provided. Trust and system characteristics are important to Malaysian users. Users will simply turn-off or ignore the warnings from the application which annoy them. They are keener on trusting their instincts then letting technology influence their driving decisions. Their biggest worry is that the application may be faulty and tempered by unauthorized personnel. However, if the users are getting enough information and have seen or observed their close contact using the application before, they have a more positive attitude toward the technology.

The results of this study are limited to users in Asian countries that are in the early phase of implementing autonomous vehicles, specifically Malaysia. Because previous studies focused mostly on European countries, which have a different culture, there may be a variation of the results when it comes to investigating the user acceptance of the technology. We assumed that in-vehicle applications would be made available to users in recent vehicle models and be available as vehicle accessories to be installed in earlier vehicle models. We did not consider the variety of in-vehicle applications and providers. Hence, the respondents' opinions are based on the general usage of in-vehicle applications.

Additionally, because attitude and behavior are important in marketing in-vehicle applications, the TAM has been adopted to investigate the underlying relationship between attitudes and the behavior or intention to use in-vehicle applications. The attitude–behavior relation is not always straightforward and linear but may display non-linearities. Weak attitude evaluations might not have much of an effect on the user's intention to use the in-vehicle applications. Additionally, an attitude change will not necessarily be followed by an equal change in the user intention or actual application use. Thus, segmenting users based on their attitude extremity before designing a marketing strategy can be valuable.

7. Conclusions

This study presents an implementation of the basic Technology Acceptance Model (TAM) with additional constructs. In addition to the original TAM constructs, we added three variables which are related to driver context, i.e., system characteristic (SC), trust (T) and social influence (SI). We investigated the relationships of the SC, T and SI to the perceived usefulness (PU) and ease of use (EU) which will influence user attitude and lead to the intention to use the in-vehicle application. Moreover, we examined the relationship between the personal characteristic (PC) variable and the SC, T and SI. Compared to a study among Romanian licensed drivers [21] which highlighted perceived usefulness and attitude as the main factors influencing the user acceptance of in-vehicle applications, our results show that other factors such as knowledge about in-vehicle applications can significantly affect trust and social influence, attitude and usage intentions among Malaysians. Similar to the in-vehicle application users in Czech [28], our findings agree that a user will be able to make an informed decision if they are aware of the advantages and limitations of the applications. Applications which are promoted as safety applications will have a higher acceptance rate. Moreover, gender and driving experience also have a moderating effect on the BI [4]. However, in contrast to [45], which investigates user acceptance among users in Rhodes Island, USA, our study shows age and gender do not have a significant influence on the user acceptance. The driving distance per week or driving experience also has no influence on the user acceptance. In addition, the findings show that trust, system characteristics and social influence may also influence the perceived usefulness and perceived ease of use, which in turn positively affects attitude toward using an in-vehicle application, a significant predictor of usage intentions.

Thus, we summarized the findings from our work in relation to each research question in Table 18. Our work fills the gap in the existing research by extending the basic TAM model with variables which are influential on the user acceptance of the in-vehicle applications in a Malaysia context. Even though our study is not designed to study specific in-vehicle applications, vehicle marketers will generally benefit from understanding the factors which positively influence the user acceptance of in-vehicle applications. Consideration of these factors may provide better insight for the developers to ensure the positive response of users toward the advantages of effectively utilizing the in-vehicle applications for a better and safer driving environment. Communications can be strategically planned to educate the users on the benefits of in-vehicle applications to increase the acceptance level in the nation.

Table 18. Findings based on research questions.

Research Question	Findings
Q1: What relationship exists between the independent variables (PU, EU) of the research model?	A user who perceives that the in-vehicle application is easy to be used will also perceive that the in-vehicle application is useful in their driving experience.
Q2: What influences exist between independent variables (PU, EU) and the mediating variable (AT) in the research model?	The higher a user perceives that the in-vehicle application is easy to be used and useful for their driving experience, the more favorable the user attitude toward in-vehicle application.
Q3: How does driver's attitude (AT) impact the driver's intention to use the in-vehicle applications (BI)?	The more positive the attitude of a user toward in-vehicle application, the higher the usage intention of the application.
Q4: What influences exist between independent variables (PU, EU) and the target variable (BI) in the research model?	The higher a user perceives that the in-vehicle application is easy to be used and useful for their driving experience, the higher the usage intention of the application.
Q5: What is the impact of social influence (SI) on drivers' perceived usefulness (PU) and perceived ease of use (EU) of the in-vehicle applications?	The more positive social influence received by a user, the more inclined the user is to perceive that the in-vehicle application is useful and easy to be used.
Q6: How does trust (T) influence perceived usefulness (PU) and perceived ease of use (EU) of the in-vehicle applications among users?	A user who believes that in-vehicle application is safe and provides driving advantages will perceive that the application is useful and easy to be used.
Q7: How do system characteristics (SCs) influence perceived usefulness (PU) and perceived ease of use (EU) of the in-vehicle applications among users?	The higher the perceived relative advantage of in-vehicle applications, the greater the perceived usefulness and ease of use of in-vehicle applications.

Table 18. *Cont.*

Research Question	Findings
Q8: How do personal characteristics (PCs) influence trust (T), social influence (SI) and system characteristics (SCs) of the in-vehicle applications among users?	A user who has been involved in road accidents has greater intention to use in-vehicle application. A user who has limited self-reported capabilities has greater intention to use in-vehicle applications. A user residing in urban or sub-urban area has greater impact on social influence and trust which will influence their intention to use in-vehicle application. There is no sufficient evidence to conclude that age is a factor which positively influences any of the other factors.

Author Contributions: Conceptualization, S.F.A.R. and A.A.; data curation, S.F.A.R. and A.A.; formal analysis, M.F.A.A.; investigation, S.F.A.R.; methodology, S.Y. and M.F.A.A.; resources, S.Y. and M.F.A.A.; supervision, S.F.A.R.; validation, A.A.; writing—original draft, S.F.A.R. and S.Y.; writing—review and editing, S.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Fundamental Research Grant Scheme under the Ministry of Education Malaysia (Grant Number: FRGS/1/2019/TK08/MMU/03/2).

Institutional Review Board Statement: This research obtained ethical approval from the Technology Transfer Office of the Multimedia University (Approval Number: EA0562021).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Abdul Razak, Siti Fatimah; Yogarayan, Sumendra; Abdullah, Mohd Fikri Azli; Azman, Afizan In-vehicle Applications Among Malaysians 2022. https://doi.org/10.5281/zenodo.6393708 (29 March 2022).

Acknowledgments: The authors fully acknowledge the Ministry of Higher Education (MOHE) for the approved fund which makes this important research viable and effective. The authors gratefully acknowledge the use of services and facilities of the Connected Car Services Research Group, Centre of Intelligent Cloud Computing at the Multimedia University. The authors would also like to thank the anonymous reviewers for their constructive comments.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

360 cam	360-Degree-Parking Assist
ACC	Adaptive Cruise Controls
AEB	Autonomous Emergency Braking
A-Hold	Auto Hold/Brake Hold
A-Park	Auto Parking
AT	Attitude
BI	Intention to use the technology
BSM	Blind-spot monitor
C-TAM-TPB	Combination form of TAM and TPB
EU	Perceived Ease of Use
FCW	Forward Collision Warning
HDC	Hill Descent Control
HAS	Hill-Start Assist
HUD	Head-up Display
IDT	Innovation Diffusion Theory
LDW	Lane Departure Alert/Warning
LKAS	Lane-Keep Assist
MM	Motivational Model
MPCU	Model of PC Utilization

PED	Pedal Misapplication Control
PU	Perceived Usefulness
RCTA	Rear Cross Traffic Alert
SC	System Characteristics
SCT	Social Cognitive Theory
SI	Social Influence
T	Trust
TAM	Technology Acceptance Model
TIB	Theory of Interpersonal Behavior
TJA	Low-Speed Follow/Traffic Jam Assist
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
U&G	User and Gratification Theory
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflating Factor

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