Driving the Future: Using TAM and UTAUT to Understand Public Acceptance of Fully Autonomous Vehicles

Auditya Purwandini Sutarto
Department of Industrial Engineering
Universitas Qomaruddin
Gresik, Indonesia
auditya@uqgresik.ac.id

Nachnul Ansori
Department of Industrial Engineering
Universitas Trunojoyo, Madura
Bangkalan, Indonesia
nachnul@trunojoyo.ac.id

Ari Widyanti
Department of Industrial Engineering
Institut Teknologi Bandung
Bandung, Indonesia
ari.widyanti@office.itb.ac.id

Fitri Trapsilawati
Department of Mechanical and Industrial Engineering
Universitas Gadjah Mada
Yogyakarta, Indonesia
fitri.trapsilawati@ugm.ac.id

Achmad Pratama Rifai
Department of Mechanical and Industrial Engineering
Universitas Gajah Mada
Yogyakarta, Indonesia
achmad.p.rifai@ugm.ac.id

Redifa Erlangga
Department of Industrial Engineering
Institut Teknologi Bandung
Bandung, Indonesia
redifaerlangga@gmail.com

Roger Woodman
WMG
University of Warwick
Coventry, United Kingdom
R.Woodman@warwick.ac.uk

***Abstract*—The implementation of fully autonomous vehicles (FAVs) has been proposed to yield societal and environmental benefits. However, there are uncertainties regarding the factors influencing the acceptance of FAVs in developing countries which has been understudied. Therefore, this study aims to examine the factors affecting public acceptance of the adoption of FAVs, applying the Technology Acceptance Model (TAM) and Unified Theory and Acceptance Technology (UTAUT) conceptual frameworks. Data was collected through an online survey (n = 593). The results reveal a moderate predictive ability of both TAM and UTAUT in explaining behavior intention to use FAVs. The most significant predictors of FAVs adoption behavior are perceived usefulness and social influence. This study also identified the perceived ease of use, attitude toward behavior, hedonic motivation, performance expectancy, and effort expectancy as significant predictors. Conversely, facilitating condition is found to exert minimal influence on FAVs acceptance. Finally, none of the demographic factors (age, gender, education, occupations, and residencies) serves as a significant moderator in the relationship between the main factors of TAM and UTAUT. Our findings may help researchers and practitioners to enhance the acceptability of FAV adoption.**

Keywords— autonomous vehicles, behavioral intention, intelligent transport system, PLS-SEM, technology acceptance

I. Introduction

The global shift towards sustainable development necessitates the transformation of transportation systems to favor greater autonomy. SAE International [1], autonomous vehicles (AV) classifies autonomous vehicles into six categories ranging from Level 0 where the human driver does all the driving tasks and no automation is involved, to Level 5 or full driving automation, where the automated system permanently controls all aspects of driving under all conditions [2].

Advanced AVs promise to redefine the future of transportation, potentially reducing traffic-related fatalities and injuries, predominantly attributed to human errors [3], [4]. Fully autonomous vehicles (FAVs) are also expected to improve mobility for individuals with disabilities and the aging populations who may encounter difficulties with conventional vehicles [5], [6], thereby promoting social inclusivity. Moreover, advanced AVs can contribute towards environmental sustainability by reducing greenhouse gas emissions and air pollution. Their development, focused on efficient driving and optimal route selection, promises increased fuel efficiency and reduced traffic congestion, [7], [8], leading to a cleaner, more sustainable environment

While FAV technology promises many benefits, its adoption rate and influencing factors remain uncertain. Public acceptance and intention to use FAVs are essential for successful implementation [9], [10]. As FAVs could significantly impact user mobility behavior and lifestyle, understanding the public acceptance and determinants of user acceptance is essential [8]. Extensive research on public acceptance of partial and fully autonomous vehicles has been done in developed countries [11]–[14], but less is known in developing nations like Indonesia.

Studies into FAV acceptance have been conducted in various developing countries, including Malaysia [15], Tehran [16], and several Middle Eastern countries [17]. In Indonesia, Nurliyana [18] pioneered the investigation of public preference for different levels of vehicle autonomy, focusing on Java Island. The authors found that about 8% preferred FAVs, but attitude and psychological factors were not thoroughly explored. Beyond economic and logistical considerations, cultural factors significantly influence acceptance predictors, potentially leading to different outcomes compared to developed countries [19]–[21].

Meanwhile, the Asia-Pacific region, with Indonesia as a key contributor, held the largest market share for autonomous vehicles [22]. Given Indonesia's rapidly growing middle-class

979-8-3503-3954-3/23/$31.00 ©2023 IEEE

population and the projected emergence of robust economies in Asia position, Indonesia is a potential market for FAVs. Furthermore, the high reliance on personal vehicles, due to a less-developed public transport system, suggests a potential shift towards autonomous transport [23]. Thus, this study aims to explore the degree of public acceptance of FAVs in Indonesia, providing insights into the adoption of this technology in emerging markets. The two widely-used Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) will be employed to understand the influential factors[8], [24].

Given cultural, social, and economic variations, both models will be compared within the Indonesian context. The findings will offer valuable insights into factors impacting public acceptance of AVs, aiding policymakers, researchers, and industry stakeholders, and guiding the optimal adoption of this technology.

II. Literature Review

A. Technology Acceptance Model (TAM)

The TAM, originally developed by Davis [9], was selected as the basic conceptual framework due to its simplicity yet effectiveness in understanding and predicting users' acceptance of technology. Its adaptability was also proven in the context of AVs. From a psychological perspective, the TAM can explain how users' perceptions of the usefulness and ease of use of automated systems can directly impact the adoption of AVs. It posits that three key factors —perceived usefulness (PU), perceived ease of use (PEOU), and attitude towards using a technology (ATT) act as antecedents of technology acceptance (i.e., behavior intention) of FAV.

Perceived Usefulness (PU) represents the belief in an individual that utilizing an AV will improve their performance. AVs are supposed to provide multiple benefits such as improved safety, energy efficiency, and the flexibility to engage in non-driving tasks. These factors could potentially enhance a positive perspective and increase the intention to use AVs [4], [25], [26]. PEOU refers to an individual's belief that using an AV will not require substantial effort. This factor should not be neglected in AV adoption, considering that operating AVs is completely new that may require some learning effort.

In the original TAM framework, the outcome was the users' actual use of a specific technology [9]. However, as the FAV is not yet commercially available and most respondents lack experience with any level of AVs, it is challenging to consider actual use as a measure of public acceptance. As such, we used BI or "intention to use" as the dependent variable when examining the acceptance of early-stage technological systems, instead of actual usage [4].

As depicted in Figure 1, the TAM proposes that PEOU and PU exert direct and positive effects on BI. Previous research has consistently acknowledged PEOU to have a direct effect on PU and attitude [27]. Although PEOU can also influence BI, this typically occurs through the mediation of PU and attitude constructs [9]. Therefore, we hypothesized as follows:

- H1: Perceived ease of use has a positive effect on perceived usefulness.
- H2: Perceived ease of use has a positive effect on positive attitude towards using FAVs
- H3: Perceived usefulness has a positive effect on positive attitudes toward using FAVs
- H4: Perceived usefulness has a positive effect on behavioral intention to use FAVs
- H5: Attitude towards FAVs has a positive effect on behavioral intention to use FAVs

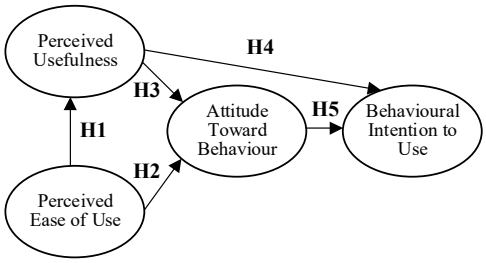

Fig. 1. Proposed Conceptual Model of TAM

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

UTAUT is developed by Venkatesh and colleagues [28] by reviewing and consolidating constructs from eight different acceptance models including the Technology Acceptance Model (TAM). The UTAUT encompasses a more comprehensive set of factors toward a unified view, including Performance Expectancy (PE) (equivalent to PU in TAM), Effort Expectancy (EE) (similar to PEOU in TAM), Social Influence (SI), and Facilitating Conditions (FC).

SI refers to the degree to which an individual perceives significant others (family, colleagues, superiors) endorsing the use of a new system, aligns with subjective norms. FC relates to perceptions of organizational and technical infrastructure supporting system utilization. Subsequently, the authors introduced Hedonic Motivation (HM) as enjoyment derived from using technology. The UTAUT model also posits that these four constructs are moderated by four variables: gender, age, experience, and voluntariness of use, considering various individual and situational factors. In this study, we adapted the original UTAUT framework by introducing new moderator variables: types of residencies education level, and types of occupations to account for disparities between residencies and knowledge background, particularly relevant in the Indonesian context.

Figure 2 displays the proposed path between all factors, leading to the following hypothesis:

- H1: Performance expectancy has a positive effect on behavioral intention to use FAVs
- H1_*i*: demographic factor *i* has a significant moderator effect on the relationship between performance expectancy and behavioral intention to use FAVs (*i* = age/education/gender/occupation/residency)
- H2: Effort expectancy has a positive effect on behavioral intention to use FAVs
- H2_*i*: demographic factor *i* has a significant moderator effect on the relationship between effort expectancy and behavioral intention to use FAVs (*i* = age/education/gender/occupation/residency)

- H3: Social influence has a positive effect on behavioral intention to use FAVs
- H3_*i*: demographic factor *i* has a significant moderator effect on the relationship between social influence and behavioral intention to use FAVs (*i* = age/education/gender/occupation/residency)
- H4: Facilitating condition has a positive effect on behavioral intention to use FAVs
- H4_*i*: demographic factor *i* has a significant moderator effect on the relationship between facilitating conditions and behavioral intention to use FAVs (*i* = age/education/gender/occupation/residency)
- H5: Hedonic motivation has a positive effect on behavioral intention to use FAVs.

  H5_*i*: demographic factor *i* has a significant moderator effect on the relationship between hedonic motivation and behavioral intention to use FAVs

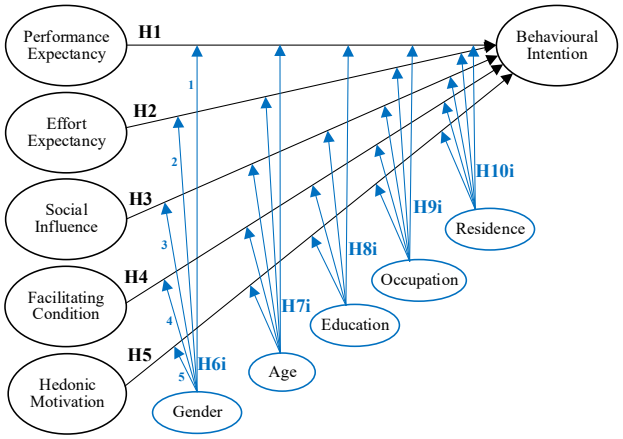

Fig. 2. Proposed Conceptual Model of UTAUT

C. *Summary of Related Work*

Scholars globally have evaluated public acceptance of various levels of AVs using TAM, UTAUT, and/or their adaption and combinations. In a comprehensive survey across 109 countries, Kyriakidis et al., [2] discovered that respondents consider FAVs (Level 5) easier to handle than manual driving, while PAVs, (Level 3) appeared more challenging. Considering, the trend of automation technology is expected to move closer to FAVs through technological advancements in sensing and machine communication, this study focused on FAVs. These vehicles are expected to be commercially available on a large scale in the forthcoming years [11], [23]. To better outline our study's position within the broader context, Table I provides a summary of significant findings of prior FAV studies utilizing TAM and/or UTAUT frameworks.

III. METHOD

A. *Participants and Study Designs*

Participants were invited to take part in the study using convenience and snowball sampling strategies through the authors' networks and social media platforms between March 19 to May 15, 2023. This strategy was employed to encourage participation and to ensure representation from a broad range of demographics within the population [29]. Data collection was conducted via the SurveyMonkey platform. All participants provided informed consent at the beginning of the survey. Participation was voluntary, and the respondents were assured of the anonymity and confidentiality of their responses.

TABLE I. A SUMMARY OF FAV ACCEPTANCE STUDIES BASED ON TAM AND UTAUT AND THEIR MAJOR FINDINGS

Lead Authors (year),	Sample size, population, country	Model	Significant Main Findings
Panagiotopoulos (2018) [11]	583, Greece	- Extended TAM	- BI = PU + Perceived Trust + SI
Hewitt (2019) [12]	200, general, USA	- AVAM (combination TAM & UTAUT)	- BI = PE + EE + Perceived Behavioral Control + PEOU - BI, ATT, and FC tend to decrease as the level of AVs increases - Perceived Safety and Anxiety tend to increase as the level of AVs increases
Zhang (2021) [30]	778, China	Extended UTAUT	- SI the strongest predictor - Risks, performance, traffic conditions, and innovation awareness
Yuen (2021)[14]	274, general, China	TAM IDT (Innovation Diffusion Theory)	- TAM: BI = PU + PEOU - IDT = relative advantage + compatibility + image + result demonstrability + visibility + trialability
Wang (2020) [14]	353, drivers, Singapore	Extended UTAUT	- Technology anxiety and self-identity - Older, female, and lower-income correlate with greater technology anxiety - Male and experienced drivers likely

			to express their self-identity
Farzin (2022) [16]	641, general, Iran	UTAUT	- PE the strongest predictor - BI = EE + SI + Trialability + Observability + Perceived Risk

B. Measures

The survey instrument administered to participants consists of three sections. The initial section introduced a brief description of the survey and basic demographic questions including age, gender, occupation, education, and type of residency. In the second section, participants were asked to provide their agreement level regarding the intention to use FAV based on the TAM model. This evaluation consists of four dimensions: perceived usefulness (three items), Perceived Ease of Use (six items), Attitude Toward Behavior (three items), and Behavioral Intention to Use (four items) [8], [9]. The final section employed constructs derived from the UTAUT model [8], [28], [31]. These include Performance Expectancy (five items), Effort Expectancy (four items), Social Influence (five items), Facilitating Conditions (seven items), Hedonic Motivation (four items), and behavioral intention to use FAVs (four items) were assessed. Both TAM and UTAUT questionnaires were measured using a five-point Likert-type scale (1 = strongly disagree, 5 = strongly agree).

C. Data Analysis

The proposed model and hypothesis testing were evaluated using *Partial Least Squares Structural Equation Modeling (PLS-SEM)* analysis [32] with SmartPLS 3.0. The first stage of the analysis involved an assessment of the measurement model's validity and reliability, through investigation of the convergent validity, internal consistency, and discriminant validity. Cronbach's alpha, a measure of internal consistency, was recommended to be higher than 0.7 [33]. Similarly, factor loadings for items or indicators were expected to exceed 0.6 [32]. The composite reliability values are recommended to be above 0.7, but a lower limit of 0.6 is considered acceptable for exploratory purposes. Moreover, each latent variable's average variance extracted (AVE) should surpass 0.5 with the square root of the AVE should exceed the inter-construct correlations [32]. In the second stage or hypothesis testing, we evaluated the significance of each proposed path using a bootstrapping resampling method with 500 subsamples

IV. Results

A. Descriptive Data

In this study, we collected a total of 701 survey responses. We excluded cases that presented missing or incomplete data across any of the survey items. As such, 103 respondents were excluded, resulting in 593 respondents. Table I shows the distribution of the participants.

An analysis of the demographic characteristics of the participants showed that most of the participants were female (53%) and 71% fell within the 17-24 years age group. The mean age of the participants was 26.23 (SD = 10.27 years). Our sample was composed primarily of students (63.1%). The participants' residential backgrounds indicated a nearly equal representation of urban (41%) and rural (42%) residencies, indicating a balanced composition from both urban and rural settings.

TABLE I. DEMOGRAPHIC DATA OF PARTICIPANTS

Variables	**Categories**	***N***	**%**
Gender	Female	314	(53)
	Male	279	(47)
Age (year)	17-24	419	(71)
	25-34	40	(7)
	35-44	74	(12)
	45-54	53	(9)
	≥55	7	(1)
Education	No Formal Education	1	(0.2)
	Elementary School	0	(0)
	High School (Junior/Senior)	318	(53.6)
	Certification Program	1	(0.2)
	Diploma	26	(4.4)
	University (Bachelor)	167	(28.2)
	University (Master)	68	(11.5)
	University (Doctoral)	7	(1.2)
	Others	5	(0.8)
Occupation	Permanent Worker	144	(24.3)
	Part-time Worker	17	(2.9)
	Entrepreneur	28	(4.7)
	Volunteer	4	(0.7)
	Student/college	374	(63.1)
	Retired	1	(0.2)
	No Worker	25	(4.2)
Residency	Urban	242	(41)
	Suburbs	100	(17)
	Rural	251	(42)

B. Technology Acceptance Model

As shown in Table II and Table III, the TAM shows good validity and reliability. All items or indicators' loadings surpassed the recommended threshold of 0.7. All AVEs for all constructs meet the recommendation criteria, larger than 0.5. The composite reliability, as indicated by Cronbach's alpha, is greater than 0.7 for all factors.

TABLE II. OUTER LOADING OF INDICATORS (TAM)

Indicators	**Factors**			
	PEU	**PU**	**ATB**	**BIU**
PEOU1	0.825			
PEOU2	0.857			
PEOU3	0.865			
PEOU4	0.881			
PEOU5	0.803			
PEOU6	0.864			
PU1		0.729		
PU2		0.812		
PU3		0.873		
ATB1			0.888	
ATB2			0.804	
ATB3			0.677	

BIU1				0.798
BIU2				0.847
BIU3				0.803
BIU4				0.840

TABLE III. RELIABILITY OF FACTORS (TAM)

Factors	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Attitude toward behavior	0.703	0.835	0.631
Behavioral intention to use	0.840	0.893	0.676
Perceived ease of use	0.923	0.939	0.721
Perceived usefulness	0.731	0.847	0.651

The empirical model evaluation results are provided in Table IV. The model accounts for 42.5 % of the variance in Behavioral Intention (BI). Perceived Ease of Use (PEOU) was found to significantly influence Perceived Usefulness (PU) ($\beta = 0.132, p < 0.001$) and Attitude Toward Behavior ($\beta = 0.197, p < 0.001$). PU was also a significant determinant of ATB ($\beta = 0.531, p < 0.001$). Moreover, the strongest predictor of BI was PU ($\beta = 0.490, p < 0.001$), followed by ATB ($\beta = 0.217, p < 0.001$).

TABLE IV. RESULT OF STRUCTURAL MODEL (TAM)

Hypothesis	Path	β	*t* statistics
H1	Perceived ease of use → Perceived usefulness	0.573	16.203^{***}
H2	Perceived ease of use → Attitude toward behavior	0.197	4.663^{***}
H3	Perceived usefulness → Attitude toward behavior	0.531	12.952^{***}
H4	Perceived usefulness → Behavioural intention to use	0.490	9.516^{***}
H5	Attitude toward behavior → Behavioural intention to use	0.217	3.896^{***}

Note: β = path coefficient, $^{***}p<0.001$

C. Unified Theory and Acceptance Technology

The evaluation of the UTAUT measurement model is displayed in Table V and Table VI, exhibiting good validity and reliability. Most of the indicators manifest factor loadings exceeding 0.7. There are a few indicators, namely PE1 and FC, which demonstrate factor loadings below the 0.7 thresholds, although not lower than 0.6. As this study is exploratory in nature [32], we decided to retain all items for further analysis. All AVEs are larger than 0.5, indicating the convergent validity of the constructs. The composite reliability Cronbach's alpha is greater than 0.7 for all factors, confirming the internal consistency and reliability of the measurement model.

The hypothesis test evaluation of each path in the UTAUT model is displayed in Table VII. Analysis reveals that the UTAUT model accounts for 57.2% of the variance. Significant positive relationships were observed between behavioral intention to use FAVs and factors such as Performance Expectancy (PE) ($t = 3.316, p < 0.001$), Social Influence (SI) ($t = 4.625, p < 0.001$, and Hedonic Motivation (HM) ($t = 6.776, p < 0.001$). In contrast, the effect of Facilitating Condition (FC) was not significant ($t = 1.414, p = 0.157$).

TABLE V. OUTER LOADING OF INDICATORS (UTAUT)

Indicator	Factor Loading					
	PE	EE	SI	FC	HM	BI
PE1	0.690					
PE2	0.617					
PE3	0.737					
PE4	0.692					
PE5	0.644					
EE1		0.595				
EE2		0.717				
EE3		0.668				
EE4		0.763				
SI1			0.823			
SI2			0.850			
SI3			0.794			
SI4			0.763			
SI5			0.808			
FC1				0.780		
FC2				0.603		
FC3				0.650		
FC4				0.751		
FC5				0.739		
FC6				0.728		
FC7				0.667		
HM1					0.903	
HM2					0.902	
HM3					0.923	
HM4					0.808	
BI1						0.804
BI2						0.853
BI3						0.792
BI4						0.839

TABLE VI. RELIABILITY OF FACTORS (UTAUT)

Factors	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Behavioral Intention	0.840	0.893	0.676
Effort Expectancy	0.628	0.781	0.474
Facilitating Condition	0.830	0.873	0.497
Hedonic Motivation	0.907	0.935	0.783
Performance Expectancy	0.705	0.809	0.459
Social Influence	0.867	0.904	0.653

Interestingly, the significant moderator effect of occupation was observed in the relationship between PE and BI ($t = 2.054, p < 0.05$). However, no significant impact was found for other demographic variables, including age, education, gender, and residential status. Moreover, the examination of other paths within the model revealed no significant influences from any of the demographic factors (see Table VII). This indicates that the magnitude of the

influence exerted by each factor within the UTAUT model is not contingent upon these demographic variables.

V. Discussion

This study aims to explore the public acceptance of FAVs in Indonesia employing two widely applied theoretical frameworks: the TAM and UTAUT models. Empirical validation demonstrates that both models manifest good validity and reliability, making them appropriate for modeling public acceptance. Hypothesis testing evaluation reveals that both TAM and UTAUT models significantly account for most of the proposed paths on the relationship between each factor to behavioral intention to use FAVs.

TABLE VII. RESULT OF STRUCTURAL MODEL (UTAUT)

Hypothesis	Path	β	t Statistics
H1	PE → BI	**0.137**	**3.316*****
H7_1	PE*Age → BI	0.049	0.797
H8_1	PE*Education → BI	0.008	0.153
H6_1	PE*Gender → BI	0.018	0.457
H9_1	PE*Occupation → BI	**0.113**	**2.054***
H10_1	PE*Residency → BI	-0.032	0.741
H2	EE → BI	**0.180**	**4.625*****
H7_2	EE*Age → BI	0.089	1.295
H8_2	EE*Education → BI	-0.051	1.040
H6_2	EE*Gender → BI	0.057	1.538
H9_2	Eff*Occupation → BI	-0.038	0.898
H10_2	Eff*Residency → BI	0.010	0.253
H3	SI → BI	**0.324**	**6.776*****
H7_3	SI*Age → BI	-0.039	0.500
H8_3	SI*Education → BI	-0.032	0.560
H6_3	SI*Gender → BI	-0.046	1.037
H9_3	SI*Occupation → BI	-0.051	0.902
H10_3	SI*Residency → BI	0.045	0.929
H4	FC → BI	0.061	1.414
H7_4	FC*Age → BI	-0.036	0.629
H8_4	FC*Education → BI	0.067	1.410
H6_4	FC*Gender → BI	0.003	0.086
H9_4	FC*Occupation → BI	0.004	0.062
H10_4	FC*Residency → BI	0.025	0.614
H5	HM → BI	**0.254**	**5.585*****
H7_5	HM*Age → BI	-0.110	1.517
H8_5	HM*Education → BI	0.058	0.963
H6_5	HM*Gender → BI	-0.036	0.781
H9_5	HM*Occupation → BI	-0.007	0.124
H10_5	HM*Residency → BI	-0.054	1.172

Note: β = path coefficient, $^{***}p$ <0.001, $^{*}p$ <0.05

Our findings support prior studies [11], [12], [14], [34] that perceived usefulness (as per TAM) and performance expectancy (as per UTAUT) play significant roles in shaping adoption behavior. Both these constructs, sharing analogous concepts, are significant predictors of behavioral intention. Perceived ease of use was also a significant determinant of behavioral intention, mediated by attitude toward behavior. Similarly, there were also significant effects of effort expectancy and hedonic motivation of the UTAUT which align with findings from studies [17], [20], [24]. However, facilitating conditions exhibited a very weak effect on behavioral intention, as also evidenced in prior studies [30], [35]. This might be attributed to respondents' insufficient understanding of the transportation infrastructure to assist autonomous driving.

Furthermore, the TAM approach revealed that perceived usefulness was demonstrated to be the strongest predictor of the individuals' intentions to use FAVs. This finding corroborates the findings of [11], [36]. In recent systematic reviews focusing on various levels of Autonomous Vehicles (AVs) and TAM-based research (whether fully or partly implemented), how individuals perceive FAVs to be useful as expected has been also shown as the most determinant of its adoption [8], [19], [37].

On the other hand, consistent with prior studies [14], [34], the UTAUT model identified social influence as the primary determinant of behavioral intention, followed by hedonic motivation. However, other research has found that performance expectancy, a similar concept to perceived usefulness in the TAM, is the strongest predictor of behavioral intention [11], [16]. These differences might be partly explained that the FAVs assessed in our study have not been commercialized yet. Since participants did not obtain first-hand usage experience, their perceived evaluation of FAVs might be substantially influenced by media reports or opinions from friends.

Furthermore, the socio-cultural context of Indonesia, where the study was carried out may have affected the results. Given the collectivistic culture, public opinions tend to be influenced by group conformity [34]. A similar phenomenon has been found in other collectivistic countries such as China, Egypt, Iraq, Jordan, and Lebanon [17], [34], resulting in differing impacts on technology acceptance compared to Western cultures [20]. This socio-cultural dynamic also offers a plausible explanation for why hedonic motivation is the second strongest predictor of behavioral intention. Individuals in Indonesia believe that their future use of FAVs is supported in their social network (i.e., social influence) [17] and they are more likely to perceive FAVs as enjoyable.

Among the demographic factors, only occupation significantly moderated the relationship between performance expectancy and behavioral intention. Surprisingly, no significant effects of age, gender, occupation, and residential type were observed on other paths. These findings are inconsistent with prior studies which identified the significant effects from age [14], [38], gender [14], [39], and education level [2] (for review, see [8], [19]). A potential reason for this inconsistency could be the homogeneity of our study's participants. Primarily, they were from the latter segment of Gen Z, aged 18-24, and predominantly students. However, other studies demonstrated the opposite results which led to inconclusive findings regarding the moderator role of certain demographic factors in the public acceptance of AVs across both developed and developing countries [17], [19], [21], [35]. Further studies need to clarify this issue.

Furthermore, the UTAUT model performed slightly better in explaining the variance of behavioral intention (Adjusted R^2 = 0.572), compared to the TAM (Adjusted R^2 = 0.490), suggesting a stronger predictive power of the UTAUT [28]. The inclusion of more constructs within the model demonstrates the complexity of the technology acceptance process [31]. Nonetheless, both R^2 values are considered moderate [33], falling within [11], [16], [17] or slightly below the range reported in prior AV studies [14]. This suggests the possible underrepresentation of influential factors in the current TAM and UTAUT models with regard to individuals' behavioral intention to use FAVs. Therefore, it is needed to

introduce additional variables to increase the prediction accuracy regarding FAVs usage intention

This paper has several limitations. Firstly, the sample is composed predominantly of students and young adults, hence caution should be considered when generalizing these findings. Further studies need to involve more heterogenous or diverse sample compositions, such as the elderly, people with disabilities, and millennials. Secondly, despite being informed about FAVs and their potential uses, our participants did not have direct experience with such vehicles. This can lead to potential misconceptions and hinder them from constructing an accurate mental model about FAVs. This concern has also been highlighted in previous studies, which observed inconsistencies in the literature regarding the predictors of user acceptance and adoption preferences for FAVs. Lastly, due to the cross-sectional nature of our study, the identified paths may vary over time. Thus, longitudinal studies are recommended to further clarify FAVs acceptance dynamics, either using the same models or extended versions.

Notwithstanding these limitations, the theoretical models validated herein provide information to researchers studying AV adoption, guiding them in selecting constructs for future research, particularly in developing countries. Furthermore, considering the most significant roles of perceived usefulness and social influence among other factors, strategies to enhance the acceptability of autonomous vehicles should focus on harnessing these factors. This could involve informational campaigns informing potential users about the benefits and utilities of AVs, offering test drives, and promoting public advocacy, community engagement, and partnership influencer. Importantly, these strategies should not aim to force the acceptance of AVs. Rather, they should strive to provide accurate information, facilitate constructive dialogue, and allow people to form their own opinions based on the experiences and viewpoints of others within their social network and viewpoints of others within their social network

VI. Conclusion

Considering highly/fully autonomous vehicles are expected to be made commercially available in the next few years, it is critical to evaluate public acceptance in favor of using FAVs as this will determine the successful implementation and shape the future of AVs. In this study, we propose and empirically validate FAVs acceptance models using TAM and UTAUT frameworks. Our results showed that both models have moderate predictive power in explaining individuals' intention to use FAVs. Of the numerous determinants within the TAM and UTAUT, perceived usefulness (TAM) and social influence (UTAUT) acted as the most influential in determining users' intentions to use FAVs or not. Significant influences on the FAV's adoption intentions were also observed for perceived ease of use, attitude toward behavior, performance expectancy, effort expectancy, and hedonic motivation. Finally, the relationship between each main factor of TAM and UTAUT is not moderated by any of the demographic variables. Despite the study's limitations, our results provide valuable insights for researchers and practitioners aiming to increase the usage intention of FAVs. This can be accomplished by extending the theoretical models and focusing on leveraging the perceived usefulness and social influence.

Acknowledgment

This research was funded by UK-Indonesia Consortium for Interdisciplinary Sciences (UKICIS)

References

[1] SAE International, "Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles," 2021. https://www.sae.org/standards/content/j3016_202104/ (accessed May 20, 2023).

[2] P. Bazilinskyy, M. Kyriakidis, and J. de Winter, "An International Crowdsourcing Study into People's Statements on Fully Automated Driving," *Procedia Manufacturing*, vol. 3, no. Ahfe, pp. 2534–2542, 2015, doi: 10.1016/j.promfg.2015.07.540.

[3] P. Jing, G. Xu, Y. Chen, Y. Shi, and F. Zhan, "The determinants behind the acceptance of autonomous vehicles: A systematic review," *Sustainability (Switzerland)*, vol. 12, no. 5, 2020, doi: 10.3390/su12051719.

[4] T. Zhang, D. Tao, X. Qu, X. Zhang, R. Lin, and W. Zhang, "The roles of initial trust and perceived risk in public's acceptance of automated vehicles," *Transportation Research Part C: Emerging Technologies*, vol. 98, pp. 207–220, Jan. 2019, doi: 10.1016/j.trc.2018.11.018.

[5] F. Janatabadi and A. Ermagun, "Empirical evidence of bias in public acceptance of autonomous vehicles," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 84, no. September 2021, pp. 330–347, 2022, doi: 10.1016/j.trf.2021.12.005.

[6] J. Meyer, H. Becker, P. M. Bösch, and K. W. Axhausen, "Autonomous vehicles: The next jump in accessibilities?," *Research in Transportation Economics*, vol. 62, pp. 80–91, Jun. 2017, doi: 10.1016/j.retrec.2017.03.005.

[7] K. Othman, *Public acceptance and perception of autonomous vehicles: a comprehensive review*, vol. 1, no. 3. Springer International Publishing, 2021. doi: 10.1007/s43681-021-00041-8.

[8] F. Golbabaei, T. Yigitcanlar, A. Paz, and J. Bunker, "Individual Predictors of Autonomous Vehicle Public Acceptance and Intention to Use: A Systematic Review of the Literature," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 6, no. 4, p. 106, Dec. 2020, doi: 10.3390/joitmc6040106.

[9] F. D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly*, vol. 13, no. 3, p. 319, Sep. 1989, doi: 10.2307/249008.

[10] H. Liu, R. Yang, L. Wang, and P. Liu, "Evaluating Initial Public Acceptance of Highly and Fully Autonomous Vehicles," *International Journal of Human-Computer Interaction*, vol. 35, no. 11, pp. 919–931, 2019, doi: 10.1080/10447318.2018.1561791.

[11] I. Panagiotopoulos and G. Dimitrakopoulos, "An empirical investigation on consumers' intentions towards autonomous driving," *Transportation Research Part C: Emerging Technologies*, vol. 95, no. January, pp. 773–784, 2018, doi: 10.1016/j.trc.2018.08.013.

[12] C. Hewitt, I. Politis, T. Amanatidis, and A. Sarkar, "Assessing public perception of self-driving cars," in *Proceedings of the 24th International Conference on Intelligent User Interfaces*, New York, NY, USA: ACM, Mar. 2019, pp. 518–527. doi: 10.1145/3301275.3302268.

[13] T. Leicht, A. Chtourou, and K. Ben Youssef, "Consumer innovativeness and intentioned autonomous car adoption," *Journal of High Technology Management Research*, vol. 29, no. 1, pp. 1–11, 2018, doi: 10.1016/j.hitech.2018.04.001.

[14] X. Wang, Y. D. Wong, K. X. Li, and K. F. Yuen, "This is not me! Technology-identity concerns in consumers' acceptance of autonomous vehicle technology," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 74, pp. 345–360, 2020, doi: 10.1016/j.trf.2020.06.005.

[15] N. Adnan, S. Md Nordin, M. A. bin Bahruddin, and M. Ali, "How trust can drive forward the user acceptance to the technology? In-vehicle technology for autonomous vehicle," *Transportation Research Part A: Policy and Practice*, vol. 118, no. October, pp. 819–836, 2018, doi: 10.1016/j.tra.2018.10.019.

[16] I. Farzin, A. R. Mamdoohi, and F. Ciari, "Autonomous Vehicles Acceptance: A Perceived Risk Extension of Unified Theory of

Acceptance and Use of Technology and Diffusion of Innovation, Evidence from Tehran, Iran," *International Journal of Human-Computer Interaction*, vol. 0, no. 0, pp. 1–10, 2022, doi: 10.1080/10447318.2022.2083464.

[17] M. M. Zefreh, B. Edries, D. Esztergár-Kiss, and A. Torok, "Intention to use private autonomous vehicles in developed and developing countries: What are the differences among the influential factors, mediators, and moderators?," *Travel Behaviour and Society*, vol. 32, no. December 2021, p. 100592, Jul. 2023, doi: 10.1016/j.tbs.2023.100592.

[18] C. Nurliyana, Y. D. Lestari, E. A. Prasetio, and P. F. Belgiawan, "Exploring drivers' interest in different levels of autonomous vehicles: Insights from Java Island, Indonesia," *Transportation Research Interdisciplinary Perspectives*, vol. 19, no. April, p. 100820, 2023, doi: 10.1016/j.trip.2023.100820.

[19] T. Keszey, "Behavioural intention to use autonomous vehicles: Systematic review and empirical extension," *Transportation Research Part C: Emerging Technologies*, vol. 119, no. June, p. 102732, 2020, doi: 10.1016/j.trc.2020.102732.

[20] K. Gopinath and G. Narayanamurthy, "Early bird catches the worm! Meta-analysis of autonomous vehicles adoption – Moderating role of automation level, ownership and culture," *International Journal of Information Management*, vol. 66, no. May, p. 102536, 2022, doi: 10.1016/j.ijinfomgt.2022.102536.

[21] A. Taniguchi, M. Enoch, A. Theofilatos, and P. Ieromonachou, "Understanding acceptance of autonomous vehicles in Japan, UK, and Germany," *Urban, Planning and Transport Research*, vol. 10, no. 1, pp. 514–535, 2022, doi: 10.1080/21650020.2022.2135590.

[22] T. B. R. Company, "Autonomous Cars Global Market 2023," 2023. https://www.thebusinessresearchcompany.com/report/autonomous-cars-global-market-report (accessed May 15, 2023).

[23] IESR, "Indonesia Electric Vehicle Outlook 2023," 2023.

[24] J. Smyth, H. Chen, V. Donzella, and R. Woodman, "Public acceptance of driver state monitoring for automated vehicles: Applying the UTAUT framework," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 83, pp. 179–191, Nov. 2021, doi: 10.1016/j.trf.2021.10.003.

[25] Z. Xu, K. Zhang, H. Min, Z. Wang, X. Zhao, and P. Liu, "What drives people to accept automated vehicles? Findings from a field experiment," *Transportation Research Part C: Emerging Technologies*, vol. 95, pp. 320–334, Oct. 2018, doi: 10.1016/j.trc.2018.07.024.

[26] J. K. Choi and Y. G. Ji, "Investigating the Importance of Trust on Adopting an Autonomous Vehicle," *International Journal of Human-Computer Interaction*, vol. 31, no. 10, pp. 692–702, 2015, doi: 10.1080/10447318.2015.1070549.

[27] S. Y. Yousafzai, G. R. Foxall, and J. G. Pallister, "Technology acceptance: a meta-analysis of the TAM: Part 2," *Journal of Modelling in Management*, vol. 2, no. 3, pp. 281–304, Nov. 2007, doi: 10.1108/17465660710834462.

[28] Venkatesh, Morris, Davis, and Davis, "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly*, vol. 27, no. 3, p. 425, 2003, doi: 10.2307/30036540.

[29] R. D. Fricker Jr., "Sampling methods for online surveys," in *The SAGE Handbook of Online Research Methods*, N. G. Fielding, R. M. Lee, and G. Blank, Eds., London: SAGE Publications Ltd, 2017, pp. 162–183. doi: 10.4135/9781473957992.n10.

[30] S. Zhang, P. Jing, and G. Xu, "The acceptance of independent autonomous vehicles and cooperative vehicle-highway autonomous vehicles," *Information (Switzerland)*, vol. 12, no. 9, 2021, doi: 10.3390/info12090346.

[31] Venkatesh, Thong, and Xu, "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology," *MIS Quarterly*, vol. 36, no. 1, p. 157, 2012, doi: 10.2307/41410412.

[32] J. F. Hair Jr., G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Thousand Oaks*, 3rd ed. SAGE Publications, Inc., 2022.

[33] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *European Business Review*, vol. 31, no. 1, pp. 2–24, 2019, doi: 10.1108/EBR-11-2018-0203.

[34] T. Zhang *et al.*, "Automated vehicle acceptance in China: Social influence and initial trust are key determinants," *Transportation Research Part C: Emerging Technologies*, vol. 112, no. September 2019, pp. 220–233, 2020, doi: 10.1016/j.trc.2020.01.027.

[35] R. Madigan, T. Louw, M. Wilbrink, A. Schieben, and N. Merat, "What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of automated road transport systems," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 50, pp. 55–64, Oct. 2017, doi: 10.1016/j.trf.2017.07.007.

[36] K. F. Yuen, L. Cai, G. Qi, and X. Wang, "Factors influencing autonomous vehicle adoption: an application of the technology acceptance model and innovation diffusion theory," *Technology Analysis and Strategic Management*, vol. 33, no. 5, pp. 505–519, 2021, doi: 10.1080/09537325.2020.1826423.

[37] S. A. Kaye, K. Somoray, D. Rodwell, and I. Lewis, "Users' acceptance of private automated vehicles: A systematic review and meta-analysis," *Journal of Safety Research*, vol. 79, pp. 352–367, 2021, doi: 10.1016/j.jsr.2021.10.002.

[38] P. Liu, Y. Zhang, and Z. He, "The effect of population age on the acceptable safety of self-driving vehicles," *Reliability Engineering & System Safety*, vol. 185, pp. 341–347, May 2019, doi: 10.1016/j.ress.2019.01.003.

[39] R. A. Acheampong, F. Cugurullo, I. Dusparic, and M. Guériau, "An Examination of User Adoption Behavior of Autonomous Vehicles and Urban Sustainability Implications," *Transportation Research Procedia*, vol. 41, no. 2016, pp. 187–190, 2019, doi: 10.1016/j.trpro.2019.09.037.