The Road to Acceptance: a Theory of Planned Behavior Analysis of Indonesian Public Intentions Towards Autonomous Vehicles

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

Auditya Purwandini Sutarto
Department of Industrial Engineering
Universitas Qomaruddin
Gresik, Indonesia
auditya@uqgresik.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 Gadjah Mada
Yogyakarta, Indonesia
achmad.p.rifai@ugm.ac.id

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

***Abstract*—The integration of autonomous vehicles (AVs) into modern transportation systems is an inevitable development, highlighting the need to explore the factors influencing public acceptance of AVs. Although numerous studies have examined user acceptance of AVs in developed nations, the investigation in developing countries remains significantly limited. Drawing upon the theory of planned behavior (TPB), this study investigated the factors influencing individuals' intentions to use two different levels of autonomy: partial (level 2) and full (level 5). Data were gathered from two separate sample sets through an online survey questionnaire, resulting in 640 participants with partial AVs (PAVs) and 593 with fully AVs (FAVs). Partial least squares structural equation modeling (PLS-SEM) analysis indicated moderate predictive power for the TPB models in both cases. All TPB constructs significantly predicted future intentions for both types of AVs. Specifically, the subjective norms construct was the strongest predictor for partial autonomy intention, while perceived behavioral control was the strongest predictor for fully AVs. The findings provide insights into the underlying behavioral and control beliefs that can enhance the public acceptance of AVs within a developing country's context. They also emphasize the similarities and differences in the public's perceptions of the two distinct levels of vehicle automation.**

***Keywords*— autonomy, intelligent system, prediction, modeling, transportation**

I. Introduction

As modern transportation evolves towards a more advanced stage with the help of artificial intelligence (AI), the implementation of autonomous vehicles (AVs) has become inevitable [1]. AI-driven vehicles offer numerous benefits including reduced road-related injuries and fatalities, traffic congestion mitigation, fuel consumption efficiency, decreased greenhouse gas emissions, and increased travel accessibility [1]-[2]. However, the acceptance of AVs among the general public remains uncertain, posing a challenge to their widespread adoption. Therefore, it is essential to investigate the factors that influence public acceptance comprehensively.

Psychological and social concerns often contribute to people's reluctance towards new technologies, including AVs, driven by fears and doubts related to safety, effectiveness, and social impact [3]. Examining people's responses to AVs from a psychosocial perspective is important, as psychosocial factors, including attitudes, beliefs, and perceptions, are potentially changeable compared to demographic traits that tend to remain stable [4]. The theory of planned behavior (TPB) is an established psychosocial framework for understanding and predicting the adoption of AVs [5]. The TPB suggests that attitudes, subjective norms, and perceived behavioral control influence individuals' intentions, which in turn shape their behavior. Understanding and addressing these factors can contribute significantly to enhancing AV acceptance.

Meanwhile, existing research on the acceptance of AVs has primarily focused on developed countries (for example, [6]-[7], presenting a clear research gap. Cultural differences play a significant role in influencing individuals' willingness to adopt AVs, suggesting that the findings from Western studies may not be universally applicable. Variations in attitudes towards AVs have been observed between Europe and Asia [8] as well as between developed and developing nations [9]. Even within developed countries, cultural factors remain influential, as evidenced by varying levels of acceptance reported in Japan (positive), the UK (neutral), and Germany (negative) [10]. Inconsistencies in the factors affecting AV adoption have also been found across countries such as Sweden, Australia, and France using the TPB [6]. Therefore, to gain a comprehensive understanding of the global acceptance of AVs, it is crucial to include developing countries, such as Indonesia.

In terms of market forecasts, it is projected that by 2025, there will be approximately 8 million autonomous or semi-autonomous vehicles on the road [11]. A survey conducted across 109 countries revealed that 69% of respondents projected that AVs would reach a 50% market share by 2050 [12]. However, before AVs can become prevalent, they must progress through the six levels of driver assistance technology advancements defined by the Society of Automotive Engineers (SAE). Currently, the highest level of commercially available driving automation, including in Indonesia, is Level 2, which involves partial autonomous vehicles (PAVs). These PAVs, also known as advanced driver assistance systems

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(ADAS), can control steering and acceleration but still require human monitoring and intervention. Examples of Level 2 systems include Tesla Autopilot, Cadillac's Super Cruise, Ford blue Cruise, and Kia EV6.

The mainstream production of AVs beyond Level 2 is still a few years away, primarily because of security concerns rather than technological limitations. Investigating the factors influencing different levels of autonomy is crucial because they offer varying user experiences and expectations from active driving participation to passive passengers. Public reactions to PAVs and fully autonomous vehicles (FAVs) can differ significantly. This study applies the theory of planned behavior to identify factors influencing the intention to use these two levels of automation. Expanding on Kaye's work [10], this study examined the utility of TPB for understanding the intention to use PAVs and FAVs among an Indonesian sample. Conducting research within developing countries' context will facilitate the understanding and addressing of a range of economic, social, and environmental barriers. In specific, this study is expected to be the preliminary study of the feasibility of doing so. Furthermore, by comparing psychosocial factors, this study informs stakeholders, including policymakers, engineers, designers, and society, in planning a smooth AV adoption process with minimal disruption [13].

II. Literature Review

AVs can be considered the most advanced transport technology currently in development. They are able to operate without human intervention, by understanding the world around them through an array of perception sensors, controlled by a computer [5]. These systems provide an end-to-end review of the hardware and software methods required for sensor fusion object detection. Therefore, highlighting some of the challenges to propose possible future research directions for automated driving systems is essential [14].

Advancements in automated driving technology have accelerated since the early 2000s with the introduction of systems such as lane departure warning system (LDWS), adaptive cruise control (ACC), self-parking assistance (SPA), auto-pilot, and traffic sign recognition (TSR) were well introduced for AVs [7][8]. Finally, by 2022 we have intelligent speed adaptation systems and by 2030 fully automated AVs will be predictably available [15][16][17].

By removing the reliance on human drivers, AVs have been predicted to provide several future benefits. These include increasing road safety, lowering infrastructure expenses, and improving human mobility [18]. They promise a large number of benefits like mobility and minimization of energy and emissions [19]. However, for a car to become fully autonomous, these technologies need to be perceived as accurate enough to gain public trust and demonstrate reliability in their approach to solving these problems [20]. AV technologies are grouped into three categories: long-range, medium-range, and short-range [21].

This study focuses on assessing intention as the planned use of autonomous vehicles, which subsequently influences behavior, using the TPB, initially proposed by [5] based on the theory of reasoned action (TRA) [22]. The TPB proposes that attitude, subjective norms, and perceived behavioral control are the antecedents of intention to use a technology, which in turn influences behavior. Attitudes represent an individual's evaluation of a specific behavior. or the feeling of being more or less favorable towards performing a certain activity. Subjective norms refer to the belief that important people and peers support engaging in a particular behavior. Finally, perceived behavioral control represents an individual's perception of how difficult or easy it is to perform a specific behavior. It has been incorporated into the original framework of the TRA [13] as a third predictor of behavioral intentions (and thus behaviors).

In the AVs context, several studies have applied TPB to assess how attitude, subjective norms, and perceived behavioral control influence individuals' intended use using online surveys or driving simulators, as shown in Table I.

TABLE I. Summary of Studies Adopted TPB in the Context of Driver Acceptance

Lead Author, Year	Sample country, Level	Model & Factors / Constructs	Statistical method	R^2, effects found*
Buckley, 2018 [4]	74, USA, Level 3, Experiment	TAM & TPB	Hierarchy Regression	R^2 = 0.49, BI = PBC, ATB, SN, PBC, trust
Dai, 2021 [23]	117, China, Level 4	Extended TPB	PLS-SEM	Adj R^2 = 0.56, IU = ATB, PBC, SN
Zhu, 2020 [24]	355, China, Level 5	TAM, TPB, UTAUT	PLS-SEM	R^2 = 0.54, IU = PU, SE, SN, – PR
Kaye, 2020 [6]	558, Australia, Level 4	TPB & UTAUT	Hierarchy Regression	Australia: R^2 = 0.71, BI = PE, ATB, SN, knowledge
	625, France, Level 4			France: R^2 = 0.58, IU = ATB, PE, SN, PBC, EE
	380, Sweden, Level 4			Sweden: R^2 = 0.74, IU = ATB, PE, PBC
Kaye, 2020 [25]	505, Australia, Level 3 vs 5	TPB	Multiple Linear Regression	Level 3: R^2 = 0.66, IU = ATB, SN Level 5: R^2 = 0.68, IU = ATB, SN
Rahman, 2019 [13]	387, USA, Level 5,	TPB	Multiple Linear Regression	Adj R^2 = 0.80, IU = ATB, SN, PBC
Koul, 2019 [26]	377, USA, Not Assigned	TPB	Multiple Linear Regression	Adj R^2 = 0.51, IU = Perceived safety, SN, # of crashes
Yuen, 2020 [21]	268, Vietnam, Not Assigned	TPB	PLS-SEM	adj R^2 = 0.87, IU = PBC, ATB, SN, PE, EE
Yuen, 2020 [27]	526, South Korea, Level 4 and above	Extended TPB	PLS-SEM	adj R^2 = 0.74, IU = ATB, PBC, SN

Notes. *) Effects found were reported based on a significant beta coefficient and sorted by strength. IU = Intention to Use, ATB = Attitude toward Behavior, SN = Subjective Norms, PBC = Perceived Behavioral Control, PU = Perceived Usefulness, SE = Self-Efficacy, PE = Performance Expectancy, EE = Effort Expectancy, PR = Perceived Risk. UTAUT = Unified Theory of Acceptance and Use of Technology, TAM = Technology Acceptance Model

Based on the aforementioned review, the aim of this research was twofold: (i) to apply the TPB concerning two levels of automation, and (ii) to use an Indonesian sample. This aligns with the model's tenets, which is consistent with previous research [4]. Figure 1 displays the conceptual research framework and formulated hypotheses.

- H1: Attitude toward a behavior (ATB) is a significant predictor of intention to use (IU) PAVs/FAVs
  Research has been conducted in many countries such as the USA, China, Australia, France, Sweden, Australia, Vietnam, and South Korea showed that ATB is the predictor of IU [4][7][25][21][23][25][30]
- H2: Subjective norm (SN) is a significant predictor of intention to use (IU) PAVs/FAVs
  [4][7][25][15][22][23][24][25][30] stated that SN is the significant predictor of IU
- H3: Perceived behavioral control (PCB) is a significant predictor of intention to use (IU) PAVs/FAVs.
  [4][7][15][21][25][30] showed that even though the level of autonomous vehicles is varied, the PCB is proven as the predictor of UI

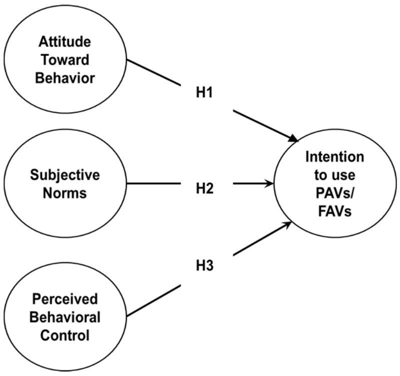

Fig. 1. Conceptual Research Framework and Hypotheses

III. Method

A. Participants

Two sample sets were collected to assess the intention to use PAVs and FAVs through the SurveyMonkey online survey platform Potential participants were initially sourced from the authors' social media networks, followed by encouraging participants to share the survey within their networks. Each set was treated as a distinct dataset. Participation in the study was voluntary, and all participants provided their consent.

Data collection was 3 months starting from February 2023 to May 2023. The data collection areas were extracted from tree areas. There were urban that were observed in Indonesia's New Capital (IKN), suburbs that were observed in big cities, and rural that were observed in 3T areas. Mechanism for data collection through coordinators in each region.

A total of 1380 individuals participated, of which 147 were excluded due to non-response to either PAVs (n = 39) or FAVs (n = 108), resulting in a final sample of 1233 participants (PAVs: n = 640, FAVs: n = 593). Table II presents a similar distribution of participant characteristics between the two sample sets. The majority of participants were male in the PAVs sample (50.2%) and female in the FAVs sample (53.0%). Participants primarily fell within the 17-24 age range (PAVs:72.8%, FAVs:70.7%), had high school education (PAVs:56.6%, FAVs:54.6%), were students (PAVs:63.3%, FAVs:63.1%), and resided in urban areas (PAVs:55.6%, FAVs:40.8%).

B. Measures

Intention to use PAVs and FAVs was measured using the TPB approach [6]. Survey items were adapted from previous TPB-based studies [4][6][25]. The attitude toward behavior shows an individual's positive or negative feelings (evaluative affect) about performing the target behavior [21]. A subjective norm reflects the person's belief to perform the behavior [4]. The perceived behavioral control deals with the perceived ease or difficulty of performing the behavior [28].

The attitude toward behavior comprised three items, such as, "PAVs/FAVs, could reduce crashes or accidents". Subjective norms involved five items [28], such as "people who are important to me would think that I should use PAVs/FAVs". Perceived behavioral control consisted of six items, for example, "I have control over using PAVs/FAVs". Intention to Use (IU) was measured using four items, for example, "I plan to buy PAVs/FAVs when they enter the market." Participants rated their agreement on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Factor scores were obtained by averaging participants' ratings for items within each scale.

C. Data Analysis

Descriptive statistics were presented and independent t-tests were conducted to assess the differences between each factor. The partial least squares structural equation modeling (PLS-SEM) technique was used to evaluate the reflective measurement model and structural model [29] using SmartPLS 3.0 [30]. The reliability and validity of the measurement model were assessed using indicator loadings with a recommended threshold of 0.708. Internal consistency was evaluated using Cronbach's alpha, with recommended values between 0.7 and 0.9 [30]. Convergent validity was examined using the average variance extracted (AVE), with a threshold greater than 0.5. Convergent validity was examined through average variance extracted (AVE) with a threshold greater than 0.5. Discriminant validity was assessed using the Fornell-Larcker criterion [31] and Heterotrait-Monotrait (HTMT) ratio of correlations. HTMT ratios below 0.85 indicated no collinearity issues among the latent constructs [29]. Hypothesis testing of the path coefficients was performed using a bootstrapping procedure with 5000 subsamples. Separate PLS-SEM analyses were conducted to determine intention to use PAVs and FAVs. Statistical significance was set at $p < 0.05$.

TABLE II. Demographic Characteristics of Participants

Variables	Categories	PAVs		FAVs	
		N	%	*N*	%
Gender	Female	319	49.8	314	53.0
	Male	321	50.2	279	47.0
Age (year)	17-24	466	72.8	419	70.7
	25-34	78	12.2	40	6.7
	35-44	57	8.9	74	12.5
	45-54	29	4.5	53	8.9
	≥55	10	1.6	7	1.2
Education	High School or less	362	56.6	324	54.6
	Diploma or Certification	28	4.4	27	4.6
	University/Bachelor	223	34.8	167	28.2

	Postgraduate	27	4.2	75	12.6
Occupation	Permanent Worker	148	23.1	144	24.3
	Part-time Worker	25	3.9	17	2.9
	Entrepreneur	47	7.3	28	4.7
	Student/college	405	63.3	374	63.1
	No Work	12	1.9	25	4.2
	Others	3	0.5	5	0.8
Residency	Urban	356	55.6	242	40.8
	Suburbs	81	12.7	100	16.9
	Rural	203	31.7	251	42.3

IV. RESULTS

The descriptive statistics for each construct of the TPB are presented in Table III, which shows the mean and standard deviation for the two levels of autonomy. Participants in both PAVs and FAVs groups exhibited similar levels of agreement or rating towards attitude (ATB), subjective norms (SN), perceived behavioral control (PBC), and intention to use (IU).

TABLE III. DESCRIPTIVE STATISTICS

Factors	PAVs		FAVs		t
	Mean	SD	Mean	SD	
ATB	3.49	0.70	3.55	0.75	- 1.50
SN	3.50	0.66	3.46	0.72	1.04
PBC	3.74	0.61	3.76	0.65	- 0.80
IU	3.68	0.59	3.68	0.64	0.06

A. Evaluation of Measurement Model

PLS-SEM analysis demonstrated satisfactory validity and reliability for both TPB models concerning the intention to use PAVs and FAVs. Most items exceeded the recommended threshold of 0.708 for loading, except for SN3 (0.68), which still falls within the acceptable range of 0.4-0.6 [30]. The AVEs for all constructs (PAV:0.59-0.68, FAV:0.63-0.72) surpassed the 0.5 thresholds, indicating that the constructs explained more than 50% of the item variance. Composite reliability (CR) and Cronbach's alpha exceeded the 0.7 cutoffs. Discriminant validity was confirmed using HTMT ratios, with all values below the predefined threshold of 0.90, signifying no collinearity issues among the latent constructs [29] (see Table IV for details).

TABLE IV. THE RESULTS OF CONVERGENT VALIDITY

Item	Loading		Cronbach Alpha		CR		AVE	
	PAV	FAV	PAV	FAV	PAV	FAV	PAV	FAV
ATB1	0.81	0.88	0.68	0.70	0.82	0.84	0.61	0.63
ATB2	0.78	0.78						
ATB3	0.78	0.71						
SN1	0.79	0.82	0.83	0.87	0.88	0.90	0.59	0.65
SN2	0.84	0.85						
SN3	0.68	0.79						
SN4	0.76	0.76						
SN5	0.78	0.81						
PBC1	0.79	0.83	0.91	0.92	0.93	0.94	0.68	0.72
PBC2	0.85	0.86						
PBC3	0.88	0.86						
PBC4	0.83	0.88						
PBC5	0.80	0.89						
PBC6	0.80	0.86						
IU1	0.76	0.80	0.80	0.84	0.87	0.89	0.63	0.68
IU2	0.85	0.85						
IU3	0.77	0.79						
IU4	0.79	0.84						

Notes. Data are reported to two decimal points due to formatting restrictions of the paper

TABLE V. THE RESULTS OF DISCRIMINANT VALIDITY TESTS

Factors	**PAVs**			
	ATB	**SN**	**PCB**	**IU**
ATB	**0.779**	*0.588*	*0.465*	*0.666*
SN	0.499	**0.771**	*0.512*	*0.733*
PBC	0.373	0.446	**0.826**	*0.652*
IU	0.448	0.602	0.557	**0.795**
Factors	FAVs			
	ATB	SN	PCB	IU
ATB	**0.793**	*0.728*	*0.616*	*0.687*
SN	0.571	**0.808**	*0.576*	*0.764*
PBC	0.503	0.518	**0.849**	*0.769*
IU	0.535	0.652	0.680	**0.822**

Notes. The lower left diagonal indicates correlation. The diagonal elements in bold are the square roots of AVE. The Heterotrait-Monotrait (HTMT) ratio is shown in the upper right diagonal in italics.

B. Hypotheses Testing

Figure 2 shows the proposed models and their path coefficients. Adjusted R^2 values reveal that 50.3% of the variance in intention to use PAVs can be explained by three constructs and 59.2% by FAVs. Path coefficients demonstrated that attitudes toward behaviors, subjective norms, and perceived behavioral control were all significant predictors of intention to use PAVs and FAVs. For PAV, the strongest predictor was subjective norms (β = 0.365), followed by perceived behavioral control (β = 0.312). In contrast, for FAV, perceived behavioral control had the most substantial effect on intention to use (β = 0.437), followed by subjective norms (β = 0.364). Attitude toward behavior plays the least important role in predicting intention to use in either the PAVs (β = 0.107) or FAVs models (β = 0.219).

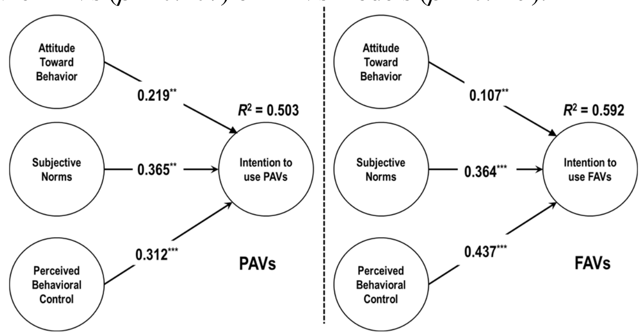

Fig. 2. Parameter estimation of the proposed model. ** indicates that the path estimate is significant (p<0.01), *** p<0.001.

V. DISCUSSION

Drawing upon the TPB, this study examines beliefs and feasibility factors that predict individuals' intentions to use PAVs and FAVs. The TPB, consisting of attitudes toward behavior, subjective norms, perceived behavioral control, and intention to use, displayed moderate predictive power for both PAVs and FAVs usage. However, the model was more effective for FAVs (R^2 = 0.592) than for PAV (R^2 = 0.503), in line with the findings of Kaye's [25] findings. However, other prior studies have demonstrated mixed predictive powers, either similar to our results [4][23][24][26] or higher predictive abilities [13][27][32]. Despite the moderate predictive power of our model [30], this suggests the need for additional variables to explain the variance in usage intention.

When considered separately, PAVs and FAVs exhibited different magnitudes for each predictor. For PAVs, intention to use was mostly influenced by subjective norms, followed by perceived behavioral control, corroborating prior studies (for example, [3][9][33]. Subjective norm, a concept similar to social influence [23], has the most significant effect on an individual's intention to adopt AVs, particularly in traditional collectivist countries such as China [33] and Middle Eastern countries [9]. The dominant role of subjective norms indicates that the public's understanding of AVs may still be in its early stages. Consequently, individuals are more likely to depend on the opinions of their social circle or trusted influencers, rather than making decisions based on their understanding or evaluation.

Conversely, the usage intention of FAVs was most significantly determined by perceived behavioral control, implying the need for user confidence in technology. This finding confirms the results of a prior study on FAVs [32]. It seems that, when asked about FAVs, participants have a clearer understanding of the features of FAVs. This might explain why perceived behavioral control emerged as the most influential factor in explaining FAVs usage intention. Participants acknowledged their lack of control over the vehicles and relied on the system, implying a need for user empowerment when using FAVs. Users must be confident in their ability to operate and interact with technology.

Interestingly, attitude toward behavior was the least significant predictor for both PAVs and FAVs. This finding conflicts with previous studies [4][14][18][19][21][22][25], which highlighted the importance of attitude in the acceptance of AVs. This inconsistency suggests potential cultural differences in the significance of attitudes, warranting further research.

A. Implications

This study contributes to the existing literature by examining the feasibility of TPB in understanding the public intention to use PAVs and FAVs, providing insights into strategies to promote their usage. By emphasizing subjective norms and perceived behavioral control, marketing strategies can leverage testimonials from early adopters, influencers, and opinion leaders to influence potential users. Improving the user interface and control, and incorporating user-activated safety measures, such as emergency stop functions and manual override options, can enhance users' sense of control and comfort with AVs.

Policymakers can launch public awareness campaigns to educate and inform the public about the ease of using AVs, highlighting the level of control that users have over vehicles. These campaigns can feature influential figures endorsing the technology, aiming to increase understanding and alleviate any fear or concerns. Policymakers should also ensure that guidelines and regulations concerning AVs allow users to maintain a reasonable degree of control over vehicles. Additionally, it is important to consider other factors that may interact with and influence user acceptance to obtain a comprehensive understanding of AV adoption.

B. Limitations and Future Study's Recommendations

This study was limited by social desirability bias due the nature of self-report measures [34]. Participants may not offer accurate evaluations of their perceptions. The use of convenience sampling, given the time and resource constraints, also introduces another limitation in this study [35]. Although we were able to collect relatively large sample sizes for each level of AVs in order to reduce these biases, the reliability and generalizability of the study may be affected. Thus, findings should be interpreted with caution. While the TPB is a prevalent framework for understanding AV user acceptance, it does not encompass all influential factors. Comparison of TPB with models such as the Technology Acceptance Model (TAM) [36] and Unified Theory of Acceptance and Use of Technology (UTAUT) [28] as well as the incorporation of additional variables, such as trust and perceived risk [3][37] are important. Several studies have utilized both TAM and UTAUT to study public acceptance of different AV levels (e.g., [7][37][38]. The TAM proposes that technology acceptance (or behavioral intention) towards a particular technology is primarily influenced by perceived usefulness, perceived ease of use, and an attitude towards using the technology. The UTAUT provides a more comprehensive perspective, considering performance expectancy (analogous to TAM's perceived usefulness), effort expectancy (equivalent to perceived ease of use in TAM), social influence (similar to TPB's subjective norms), and facilitating conditions. Additionally, the UTAUT suggests that these constructs' effects are moderated by gender, age, experience, and voluntariness of use, acknowledging various individual and situational factors. Furthermore, the study of ethics in AVs warrants attention due to the prospective ethical dilemmas faced by future users. In particular, these users could face unavoidable collision scenarios, prompting the vehicle to make a decision on the most acceptable and moral actions [39]. Finally, the TPB may not capture the dynamic nature of user acceptance as individuals gain experience or new information, warranting longitudinal studies. Our focus was on pre-acceptance rather than post-acceptance, neglecting the potential influence of the direct AVs experience, which may yield different acceptance outcomes.

VI. CONCLUSION

With the emergence of AV technology, it is important to understand the nature of public perception and intention to adopt these vehicles. In this study, we employ the TPB as a theoretical framework to explain the factors influencing public acceptance of AVs at two different levels. Our findings revealed the significant predictive power of all TPB constructs in determining future intentions for both PAVs and FAVs. Specifically, subjective norms exhibited the highest influence on PAVs acceptance, whereas perceived behavioral control was the primary predictor of FAVs acceptance. These results contribute to an enhanced understanding of public acceptance of distinct levels of autonomy in AVs and provide valuable insights for designing effective public education campaigns in the future.

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