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Perception and Intention for Autonomous Vehicle Acceptance in Developing Countries

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***Abstract*—The paper focuses on understanding how people in Ghana perceive autonomous vehicles and whether they intent to use them. Ghana is used as a case study to represent developing countries Many developing countries, including Ghana, lack the advanced infrastructure, technology, and regulatory frameworks that developed countries have for supporting AV adoption. The study's findings in Ghana may provide insights that are relevant to other developing countries facing similar challenges. The study used survey responses from 1,248 people to test a theoretical framework called the Technology Acceptance Model (TAM), which explains how people adopt new technologies. The standard TAM was expanded by adding more factors like: Perceived reliability–how dependable people think AVs are, Perceived risk–concerns about potential failures of AVs. Technological competence–confidence in AV technology's capabilities and Operational environment–the context in which AVs would operate, such as traffic patterns and road conditions. In our findings, all the identified latent constructs—perceived usefulness, perceived ease of use, perceived reliability, perceived risk, and technological competence—influenced whether people intend to use AVs. The study confirmed that user perceptions about usefulness, ease of use, reliability, risk, and competence play important roles in shaping attitudes toward AVs. Among these, perceived reliability emerged as the most influential factor. People's trust in how reliable AVs are was the strongest factor influencing willingness to adopt them. Reliable AVs directly increased the intention to use them. Also, reliable AVs made users see them as more useful and less risky, further increasing the intention to use them. Furthermore, perceived reliability was found to indirectly boost intention to use AVs when accompanied by greater trust in the technological competence and capabilities of AVs. If people believed that AV technology was advanced and capable, their trust in AV reliability increased. These results suggest that raising awareness and educating the public about AV technology could address concerns about safety and reliability, leading to higher acceptance rates. Additionally, in developing countries, road systems often lack organization, with mixed-use lanes shared by regular objects like pedestrians, cyclists, and vehicles and even irregular objects like animals. To make AV adoption feasible, as the governments of developing counties design dedicated AV-friendly lanes and enforce traffic laws to regulate usage, they also need to promote awareness programs to assure people of safety and reliability.**

***Keywords*— Autonomous vehicles, Developing countries, Technology Acceptance Model (TAM)**

I. INTRODUCTION

Autonomous Vehicles AVs are defined as vehicles that can sense their surroundings and operate with minimal or no human involvement. They are also referred to by other names, such as driverless, self-driving, unmanned, or robotic vehicles [1]. This highlights their ability to function autonomously, which distinguishes them from traditional vehicles. These AVs comes with numerous potential benefits. AVs are presented as a future-oriented solution that enhances human mobility and transportation options [2]. Their ability to operate without human drivers opens up new possibilities for transportation systems, improving accessibility and convenience. AVs are associated with shared mobility platforms such as Uber, Lyft, Bike-Share, and Car-Share services [3]. These services leverage AV technology to create shared transportation options, reducing dependency on private vehicles. Also, shared AVs encourage more sustainable resource utilization by reducing the need for private car ownership and associated infrastructure, such as parking spaces [4]. This promotes urban efficiency, reduces congestion, and helps achieve environmental sustainability.

AVs has also improved traffic safety. By removing human control, AVs reduce human errors, which are a major cause of accidents. AVs enhance traffic efficiency by optimizing routes and traffic flow, reducing congestion. Passengers can focus on other tasks during commuting, saving time. AVs can assist

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individuals with limited driving abilities, enabling greater accessibility. Despite these benefits, the adoption of AVs globally has been slower than expected, particularly in developing countries [1]. Developing countries often lack strict traffic enforcement and controlled road usage, making AV adoption more difficult. Deploying AVs in markets with such limited infrastructure and readiness poses significant challenges [5].

AV adoption could transform transportation systems in developing countries as Shared mobility services are gradually emerging [6] and could benefit from AV technologies to enhance convenience and affordability. Most studies on AV adoption focus on developed countries**,** which have better infrastructure and stricter traffic regulations [7]. As use of road are strictly controlled in developed countries, developing countries, by contrast, often have multi-purpose road usage, where roads are used not just for vehicles but also for markets, pedestrians, and informal activities like farm animal crossing unrelated to traffic, creating challenges for AV deployment. Unfortunately, past researchers have not explicitly examined the effect of such contexts on the intention to use AVs. This paper aims to fill the research gap by focusing on Ghana, a developing country in West Africa, as a case study. Ghana represents other developing countries in terms of infrastructure, technology, and regulation readiness for AV adoption. The study uses the Autonomous Vehicles Readiness Index (AVRI) [5] to assess how prepared Ghana is for AV integration.

The study collected data from 1,248 respondents in Ghana**,** It employed a modified Technology Acceptance Model (TAM) to analyze the data and test hypotheses related to perception, reliability, risk, technology trust and intention to use AVs. The study controlled for three critical factors, which are perceived reliability–the respondents' trust in AV technology and its ability to operate safely, perceived Risks–concerns regarding safety, system failures, or accidents associated with AV operations and technology competence–respondents' belief in AV capabilities and technological reliability. The research also examined how these factors associate AV operations under three different traffic environments: Mixed Traffic Environment—AVs operate alongside non-AVs in the same lane, Dedicated AV Lane Environment—AVs are separated from non-AVs in distinct lanes and AV-Only Environment (used as the reference group)—Streets exclusively for AVs with no non-AV traffic.

The key hypothesis is that impact of traffic restrictions on reliability, trust, perceived risk, and technology competence may differ between developing and developed countries due to variations in traffic dynamics. This hypothesis was set because, as earlier discussed, traffic systems in developing countries are often more complex due to heavy reliance on informal transport systems like minibuses, motorcycles, and bicycles. Multi-purpose use of roads for activities such as trading, walking, and parking. The study assumes that these complexities can influence reliability, trust and risk perception related to AV adoption. The findings could provide valuable practical applications for transport planners who can now understanding public attitudes when in designing traffic systems that integrate AVs effectively. Also, the findings provide valuable insights for policymakers when making policies related to traffic regulations and infrastructure planning. Industry practitioners such as developers and manufacturers can address trust issues and perceived risks to promote AV adoption.

II. METHODOLOGY

A. Hypotheses Formulation

This section builds a theoretical foundation by extending the Technology Acceptance Model (TAM), drawing on prior research [8], to investigate factors affecting the intention to adopt autonomous vehicles (AVs) in developing countries and develop hypotheses based on these findings.

1) Latent Constructs and Dependent Variables

This section categorizes the key latent constructs into two groups: Original and Modified. The Original Constructs, adapted from the conventional Technology Acceptance Model (TAM), include Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). The Modified Constructs, introduced to enhance the model's applicability to AV adoption, include Perceived Reliability (PRel), Technological Competence (TC), and Perceived Risk (PRisk). Since extensive literature exists on the 'Original Constructs', they are only briefly discussed in this section, while more detailed information is provided on the 'Modified Constructs' later.

- Perceived Reliability (PRel) represents the belief that an AV can consistently perform its intended functions without failure, instilling confidence in its safety features and reliability as a mobility service [20].
- Technological Competence (TC) reflects the belief that AV technology is advanced, capable, and trustworthy [9].
- The dependent variable influenced by these latent constructs is Intention to Use (IU) AVs.

The following hypothesized relationships are established.

- PU and PEOU are expected to positively influence IU. Specifically, PU is positively impacted by PEOU, which indirectly affects IU through PU.
- The Modified Constructs—PRel, TC, and PRisk—are hypothesized to influence IU based on prior AV adoption research.
- PRel directly and positively affects IU and indirectly enhances it by improving TC and PU while reducing PRisk.
- PRisk has a direct negative effect on IU and indirectly reduces IU through its impacts on PRel and PU.

The study therefore formulates 10 hypotheses—4 direct and 6 indirect relationships—testing the influences of these constructs on IU.

H_1: PU positively affects IU (direct)
H_{2a}: PEOU positively affects IU (direct),
H_{2b}: PEOU positively affects PU (indirect),
H_{3a}: PRel positively affects IU (direct),
H_{3b}: PRel positively affects PU (indirect),
H_{3c}: PRel positively affects TC (indirect),
H_{3d}: PRel negatively affects PRisk (indirect),
H_{4a}: PRisk negatively affects IU (direct),
H_{4b}: PRisk negatively affects PU (indirect),
H_5: TC positively affects IU (direct),

2) Control Variables

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In addition to the latent constructs and the dependent variable discussed earlier, the influence of control variables was also examined. These control variables were categorized into two groups.

- Sociodemographic and Driving Experience Factors – Data were collected to assess how users' demographic characteristics and prior driving experiences influence their intention to use AVs.
- Operational Environment Factors – Data were gathered to evaluate whether users' understanding of different AV operating environments affects their intention to use AVs [10].

Respondents were divided into three groups and were provided with distinct but interconnected scenarios about AV operations. These groups were defined based on traffic conditions and served to simulate different operational environments for autonomous vehicles (AVs):

- Group 1: Mixed Traffic Environment – Respondents were informed to assume that AVs operate on streets shared with both AVs and human-driven vehicles. This scenario highlights potential challenges arising from interactions between AVs and conventional vehicles.
- Group 2: Dedicated AV Lane Environment – Respondents were instructed to assume that AVs operate on streets with dedicated lanes, separated from human-driven traffic. This setup reduces interaction with conventional vehicles, potentially boosting perceptions of safety and technological competence by emphasizing the AVs' ability to collect data and make autonomous decisions based on lane-specific inputs.
- Group 3: AV-Only Environment (used as the reference group) – Respondents were asked to assume that AVs operate exclusively on roads designed for AV traffic only. This scenario assumes full AV integration, eliminating unpredictable human-driver behaviors and reinforcing confidence in AV safety and technological competence.

A conceptual framework illustrating the influenced of the control variables on the five construct and the hypothesized relationships among these five constructs (PU, PEOU, PRel, TC, and PRisk) and their effects on IU is presented in Figure 1.

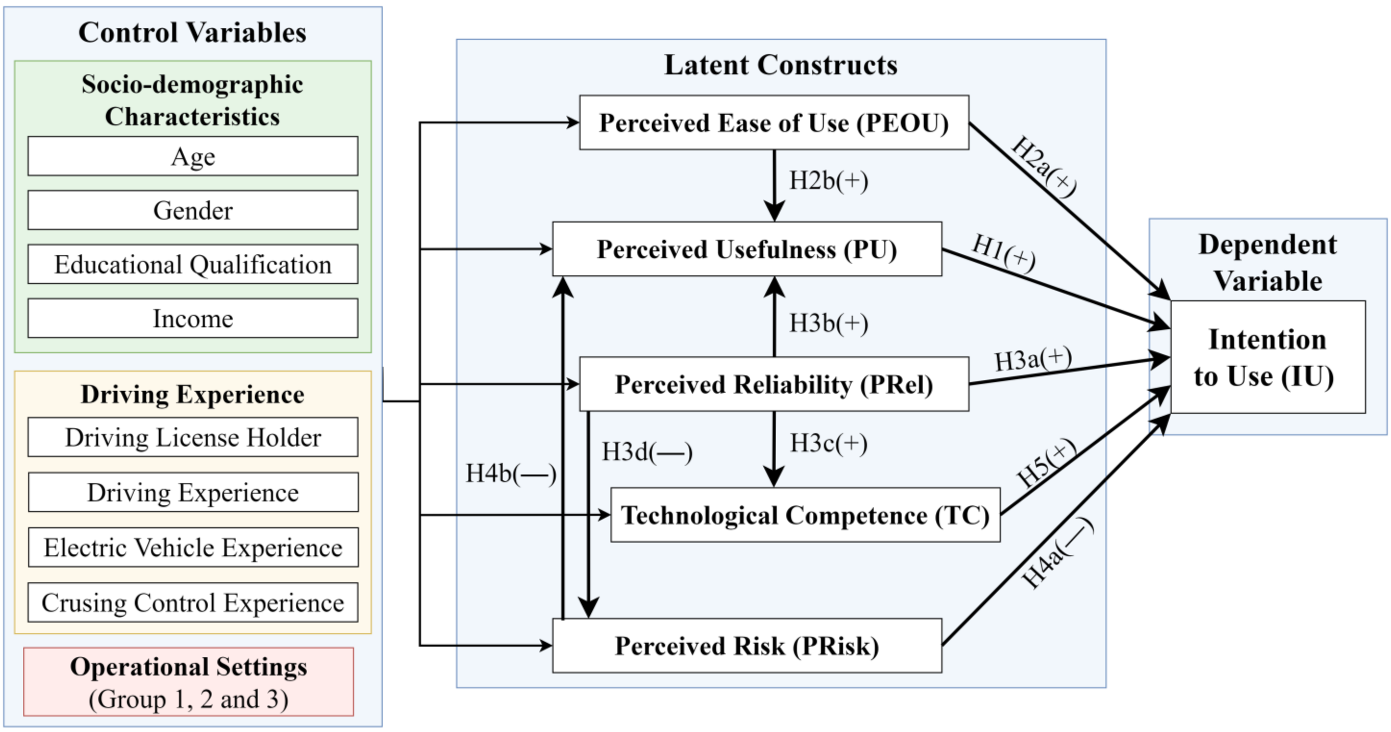

Fig. 1. Hypotheses Formulation

B. Measurement Items Development

To examine the hypotheses regarding the relationships among latent constructs, dependent variables, and control variables, measurement items were carefully designed based on insights drawn from the literature review. Following the application of Confirmatory Factor Analysis (CFA) and the validation of discriminant validity techniques (refer to Section 3.4 for detailed descriptions of these methods), the finalized measurement items, along with their respective references, are presented in Table 1.

C. Data collection

To test the proposed hypotheses, data for this research were collected through face-to-face questionnaire surveys conducted across all 16 regions of Ghana between January 2020 and October 2023. Ghana was selected as the study area due to its emerging potential to adopt autonomous vehicles (AVs), positioned next to Nigeria as one of the most likely West African countries for early AV adoption. This is attributed to the country's growing tech innovations, government initiatives, and infrastructure improvements aimed at smart city development, including drone delivery services. Additionally, Ghana's established ride-hailing platforms like Uber and Bolt provide a strong foundation for piloting and transitioning to AV deployment. The government's investments in public electric vehicles further support the shift, with recent news highlighting the official commissioning of the first fleet of electric buses aimed at enhancing public transportation. Moreover, in 2024, Ghana became home to West Africa's first all-electric Tesla Cybertruck, marking a significant milestone in the country's push towards embracing electric and autonomous vehicle technologies.

Table 1. Measurement items for latent constructs.

Constructs	Variables	Measurement Items
Perceived Usefulness	PU_1	Using autonomous vehicles will boost my productivity.
	PU_2	Automated vehicles will help alleviate traffic congestion.
	PU_3	Automated vehicles will assist with parking.
	PU_4	The use of AVs will lead to a decrease in accidents.
Perceived Ease of Use	$PEOU_1$	Learning to operate an autonomous vehicle would be easy for me.
	$PEOU_2$	I would find it easy to get an autonomous vehicle to do what I want.
	$PEOU_3$	Interacting with an autonomous vehicle would not require much mental effort.
	$PEOU_4$	I would find it easy to become skilled at using autonomous vehicles.
Perceived Reliability	$PRel_1$	Autonomous vehicles are reliable.
	$PRel_2$	I do not have suspicions about automated vehicles.
	$PRel_3$	I would engage in other tasks while riding in an automated vehicle.
	$PRel_4$	I feel hesitant about using an automated vehicle.
Technological Competence	TC_1	I believe autonomous vehicles are equipped with advanced technology that can handle various driving situations.
	TC_2	I trust that the technology behind autonomous vehicles is reliable and efficient.
	TC_3	I feel confident that autonomous vehicles can perform tasks without human intervention.
	TC_4	I am convinced that autonomous vehicle technology is capable of adapting to different road conditions and environments.
Perceived Risk	$PRisk_1$	Autonomous vehicles are more likely to lead me to a fatal accident.
	$PRisk_2$	Autonomous vehicles might not perform well and could crash when faced with small problems.
	$PRisk_3$	Using autonomous vehicles would be risky.
	$PRisk_4$	I am concerned about equipment and system failures in autonomous vehicles.
Intention to use	IU_1	I plan to use an autonomous vehicle in the future.
	IU_2	I expect to use an autonomous vehicle in the future.
	IU_3	I intend to use an autonomous vehicle in the future.
	IU_4	I would recommend that my family members and friends ride in an autonomous vehicle.

The questionnaire was designed as the primary survey instrument and consisted of three sections. The first section collected information on the control variables, including socio-demographic characteristics, while the second section gathered data on driving experiences. The third section included measurement items based on the Technology Acceptance Model (TAM), which collected information on the latent constructs (Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Reliability (PRel), Technological Competence (TC), and Perceived Risk (PRisk)), as well as the dependent variable, Intention to Use (IU).

During the data collection period, a team of ten trained researchers administered questionnaires daily at various locations across Ghana, as shown in Figure 2. Stratified random sampling was employed to recruit participants, ensuring the sample reflected the demographic makeup (age, gender, and education) and geographic distribution of the Ghanaian population. On average, it took 20 minutes to complete a questionnaire. To ensure accuracy and impartiality, participation in the questionnaire was voluntary, and respondents did not receive any form of compensation, whether financial or in-kind, for their contribution.

Before responding to the questionnaire, respondents were provided with basic information about level-5 autonomous vehicle (AV) technology by the researchers. They were also educated on the operations of AVs and grouped accordingly (see Section 3.1.2 for the groupings of respondents). It was observed that after receiving this information, participants found it easier to complete the questionnaire. Many respondents, who found the topic of AVs interesting, were highly motivated and willingly contributed to the survey.

D. SEM estimation procedure

Figure 2 illustrates the procedure used for model estimation in this research, which is divided into three parts, labeled as ①, ②, and ③. The first part, ①, involves the application of five data preprocessing techniques conducted prior to estimating the model. These techniques primarily focus on addressing problematic Likert scale responses to ensure data quality. This process is depicted in Figure 2, with the results provided in Table 1.

1. Identifying Unengaged Responses: Unengaged responses occur when participants provide similar answers across survey questions, indicating they may not be answering thoughtfully. Responses are considered unengaged and removed if the standard deviation (std dev) for a participant's responses is less than 0.3. This threshold ensures variability, suggesting thoughtful engagement.
2. Detecting Multivariate Outliers: The Euclidean distance method is used to measure how far a response is from the average response pattern. Responses are considered an outlier and removed if the Euclidean distance is more than 0.7. This threshold helps ensure that unusual or extreme responses do not skew the analysis.
3. Response Time Analysis: The average timing of questionnaire response is 20 minutes. Removal action is taken for responses completed significantly faster than the

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average response time, indicating possible lack of engagement.

4. Attention Check Questions: Dummy questions were intermittently included (e.g., “Select ‘Strongly Agree’ for this statement”) to detect inattentive participants.
5. Self-Reported Engagement: Lastly respondents were asked to rate themselves on how attentively they answered the survey at the end. Only positive rating were included for further analysis

The second part, ②, is the Confirmatory Factor Analysis (CFA). This analysis was performed to ensure the measurement items are actual factors of the constructs and were reliable as well as being accurate representations the TAM framework. Two CFA process are undertaken, which are Reliability Measures and Convergent Validity Assessment

1. Reliability Measures:
- Standardized Factor Loadings: A value of 0.5 or higher indicates that each observed variable strongly relates to its underlying construct.
- Cronbach’s Alpha: A threshold of 0.7 or higher suggests internal consistency among items within a construct.
- Composite Reliability (CR): A CR value of 0.7 or higher confirms that the construct’s items consistently measure the intended concept.

2. Convergent Validity Assessment:
- Average Variance Extracted (AVE): An AVE value of 0.5 or greater indicates that a construct explains at least half of the variance in its observed variables, supporting convergent validity.

The third part, ③, involves evaluating discriminant validity to ensure that the measurement constructs in the model are distinct from one another. The criterion for discriminant validity is that the square root of the Average Variance Extracted (AVE) for each construct must be greater than its correlations with other constructs. If the square root of the AVE exceeds the inter-construct correlations, it confirms that the construct shares more variance with its own items than with items of other constructs, ensuring distinctiveness. Another important consideration in using questionnaires for research is the potential for multicollinearity among the constructs involved. Since each construct represents a variable included in the study, one construct may be heavily influenced by another, which could jeopardize the study’s findings. To address this, it is crucial to minimize the likelihood of multicollinearity through discriminant validity measurement. In this study, AVE correlation is used to establish discriminant validity, while the Heterotrait-Monotrait (HTMT) ratio [11] is used to further verify the validity.

After completing the data preprocessing, Confirmatory Factor Analysis (CFA), and discriminant validity techniques, Structural Equation Modeling (SEM) was conducted as the primary analysis method. SEM was used to test the relationships and hypotheses within the model and to derive findings from the data. This method allows for the evaluation of the direct and indirect effects among the latent constructs and dependent variables, providing insights into the underlying structural patterns and confirming the validity of the proposed model.

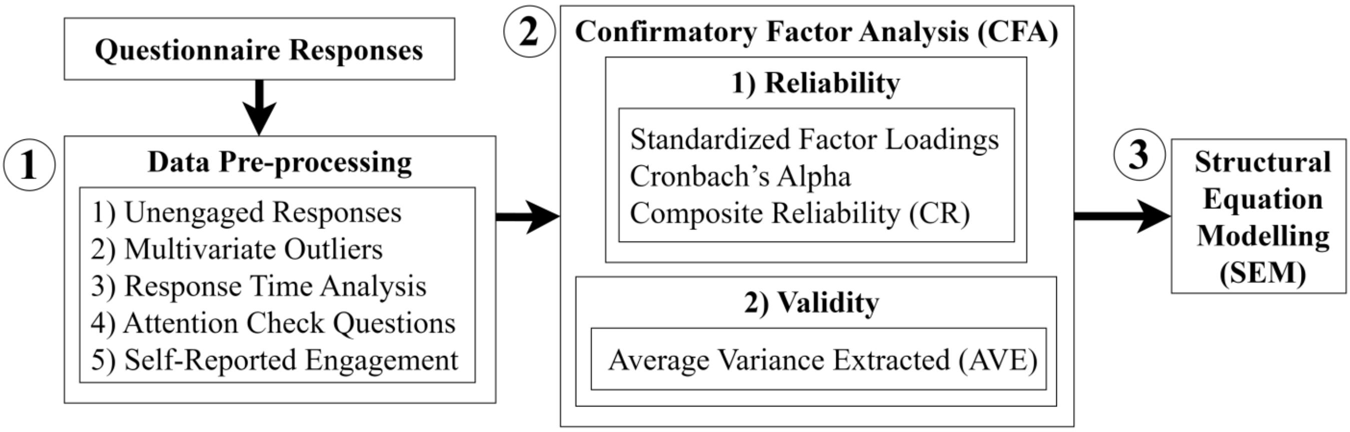

Fig. 2. Modeling procedure.

III. RESULTS

A. Socio-demographic profile of research participants

A total of 1,376 observations were collected, with 1,248 used for further analysis after excluding 21 unengaged responses, 23 outliers, and 28, 32, and 24 responses that failed the response time analysis, attention checks, and self-reported engagement tests, respectively. The final respondent groups were divided as follows: Group 1, with 413 respondents; Group 2, with 428 respondents; and Group 3, with 407 respondents.

Table 1 also summarizes the socio-demographic characteristics of the sample, which is predominantly male (55.53%) and well-educated, with a significant portion holding a Bachelor’s degree (50.32%) and 35.42% having a Master’s or higher. The majority of respondents are aged between 36 and 45 years (36.38%), with an average age of approximately 41 years. The income distribution shows that most respondents fall within the middle-income bracket (Gh₵ 30,001-50,000, 30.93%), with an average income of around Gh₵39,500 (1 USD = 11.49 Gh₵ and 1 CNY = 2.02 as of October 2023). These characteristics suggest a potential user base for autonomous vehicles (AVs) with disposable income and an inclination towards technology adoption.

Regarding driving experience, a significant portion (58.73%) of participants holds a driver’s license, with most having been driving for 7-10 years, and the majority having at least 6 years

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of driving experience. This indicates a high level of driving expertise, and many participants likely rate their driving skills as good or better. However, participants have limited experience with Electric Vehicles (EVs), as only 26.68% have any form of experience with EVs. This lack of experience may lead to misconceptions about EVs and lower trust in AVs, which are often associated with electric propulsion. On the other hand, many participants have experience using cruise control in traditional vehicles. This hands-on experience with vehicle automation, including benefits like reduced driver fatigue and improved fuel efficiency, may increase trust in the potential safety and effectiveness of automation in AVs.

Table 2: Descriptive statistics for control variables.

Variables	**N**	**%**	**Mean(±SD)**
Sample size	*1248*	*100.00*	
Unengaged responses	21	1.68	
Multivariate Outliers	23	1.84	
Responses that failed Response Time Analysis	28	2.24	
Responses that failed Attention Check Questions	32	2.56	
Responses that failed Self-Reported Engagement	24	1.92	
Environmental Context			
Group 1—Mixed traffic environment	413	33.1	
Group 2—Dedicated AV lane environment	428	34.3	
Group 3—AV-Only environment	407	32.6	
Socio-demographic variables			
Gender			1.02±.09
Male	693	55.53	
Female	555	44.47	
Age			3.57±.14
18—25	181	14.5	
26—35	275	22.04	
36—45	454	36.38	
46—55	226	18.11	
56—65	112	8.97	
Educational Qualification			2.96±.33
Senior High School (SHS)	178	14.26	
Bachelor's degree	628	50.32	
≥Master's degree	442	35.42	
Income (GhȻ)			3.95±.18
≤10,000	172	13.78	
10,001—20,000	317	25.4	
20,001—30,000	297	23.8	
30,001—50,000	386	30.93	
≥50,001	76	6.09	
Driving Experience			
Car driving license holder			1.03±.02
Yes	733	58.73	
No	515	41.27	
Years of driving experience			4.08±.36
<1 year	52	4.17	
1—3 years	168	13.46	
4–6 years	287	23	
7–10 years	486	38.94	
>10 years	255	20.43	
Electric Vehicles (EVs) Experience			1.76±.21
Yes	333	26.68	
No	915	73.32	
Cruising Control Experience			0.96±.06
Yes	1002	80.29	
No	246	19.71	

B. Confirmatory factor analysis

The internal consistency check using Cronbach's Alpha reveals that all constructs have alpha values greater than 0.8, indicating high reliability. The alpha values are as follows: Perceived Usefulness (0.884), Perceived Ease of Use (0.975), Perceived Reliability (0.917), Technological Competence (0.867), Perceived Risk (0.929), and Intention to Use (0.983). Additionally, all constructs exhibit Composite Reliability (CR) values above 0.9, demonstrating strong reliability and convergent validity. Specifically, the CR values are: Perceived Usefulness (0.926), Perceived Ease of Use (0.977), Perceived Reliability (0.941), Technological Competence (0.921), Perceived Risk (0.928), and Intention to Use (0.975). Furthermore, the Average Variance Extracted (AVE) values for all constructs exceed the 0.5 threshold, confirming excellent validity. The AVE values are: Perceived Usefulness (0.792), Perceived Ease of Use (0.938), Perceived Reliability (0.883), Technological Competence (0.801), Perceived Risk (0.824), and Intention to Use (0.961). Most items exhibit strong factor loadings (above 0.7), with a few slightly lower but still acceptable (i.e., the factor loadings range from: Perceived Usefulness 0.682–0.913, Perceived Ease of Use 0.742–0.956, Perceived Reliability 0.765–0.932, Technological Competence 0.682–0.941, Perceived Risk 0.732–0.922, and Intention to Use 0.955–0.981). These high factor loadings confirm that the items are strongly associated with their respective constructs. Overall, the results support the reliability and validity of the measurement model, making it suitable for further structural equation modeling (SEM) analysis.

Table 3 CFA through Reliability and Validity for factorizing measurement items of each Constructs.

Constructs	Item	Standardized factor loadings	Cronbach's alpha	CR	AVE
Perceived Usefulness	PU_1	0.682	0.884	0.926	0.792
	PU_2	0.837			
	PU_3	0.853			
	PU_4	0.913			
Perceived Ease of Use	$PEOU_1$	0.742	0.975	0.977	0.938
	$PEOU_2$	0.956			
	$PEOU_3$	0.923			
	$PEOU_4$	0.895			
Perceived Reliability	$PRel_1$	0.868	0.917	0.941	0.883
	$PRel_2$	0.846			
	$PRel_3$	0.765			
	$PRel_4$	0.932			
Technological Competence	TC_1	0.783	0.867	0.921	0.801
	TC_2	0.836			
	TC_3	0.682			
	TC_4	0.941			
Perceived Risk	$PRisk_1$	0.732	0.929	0.928	0.824
	$PRisk_2$	0.922			
	$PRisk_3$	0.901			
	$PRisk_4$	0.881			
Intention to use	IU_1	0.955	0.983	0.975	0.961
	IU_2	0.958			
	IU_3	0.981			
	IU_4	0.978			

C. Discriminant Validity

Additionally, Table 4 presents the correlations between construct pairs, all of which are lower than the square root of AVE (highlighted in bold), confirming the discriminant validity of the constructs. Furthermore, the HTMT ratios for the constructs show excellent values, with the highest ratio observed between Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) at 0.837. While this relatively strong correlation aligns with expectations based on the Technology Acceptance Model [11], it remains slightly below the 0.90 threshold recommended for establishing discriminant validity [11]. Since all HTMT values are below 0.90, the constructs demonstrate strong discriminant validity.

Table 4 Discriminant validity using AVE Correlation and (HTMT)

Constructs	PU	PEOU	PRel	TC	PRisk	IU
PU	**0.882**					
PEOU	0.628 (0.837)	**0.953**				
PRel	0.736 (0.591)	0.812 (0.537)	**0.830**			
TC	0.874 (0.673)	0.803 (0.692)	0.853 (0.707)	**0.908**		
PRisk	−0.451 (0.569)	−0.371 (0.516)	−0.454 (0.537)	−0.547 (0.522)	**0.883**	
IU	0.736 (0.774)	0.831 (0.793)	0.754 (0.763)	0.772 (0.833)	-0.491 (0.587)	**0.983**

Note: Bold values refer to the square roots of AVE.

The establishment of both convergent and discriminant validity confirms that the collected data are suitable for conducting a reliable analysis. This analysis can accurately assess the acceptance of autonomous vehicles (AVs) based on the Technology Acceptance Model (TAM). The next step involves developing a structural model, which incorporates perception and trust into the TAM to evaluate AV acceptance. The complete structural model is depicted in Figure 1, while the model's quality assessment is presented in Table 5.

Table 5 outlines various goodness-of-fit indices used in the confirmatory factor analysis (CFA), alongside their recommended cut-off thresholds and corresponding sources. The results indicate that most indices show a satisfactory model fit, except for the p-value in the chi-square test, which suggests a poor fit. However, this discrepancy is likely attributable to the large sample size [12]. To address this limitation, alternative fit indices—as shown in Table 5—were used. These indices were specifically designed to mitigate the chi-square test's sensitivity to sample size [13], providing a more reliable evaluation of the model's fit.

Table 5: Model fit to determine the quality of the structural model

Fit indexes	All	Recommended	Sources
Chi-Square (χ^2)	672.818	—	—
Degree-of-freedom (df)	216	—	—
p–value	0.00	>0.05	[14]
χ^2/df	3.115	<5.00	[15]
Root Mean Square Error (RMSE)	0.055	<0.08	[16], [10]
Root Mean Square Residual (RMR)	0.048	<0.50	[10] [17]
Confident Fit Index (CFI)	0.957	>0.90	[10][18]

D. Structural model assessment

The explanatory power of the model is assessed using the R^2 values of each latent construct. As shown in Figure 3, the R^2 values for PEOU (0.152), PU (0.634), PRel (0.166), TC (0.174), PRisk (0.414), and IU (0.676) all exceed the recommended threshold of 0.1 [19]. These results suggest that the latent constructs are adequate for the structural model. The estimation results of the coefficients for the latent constructs in the structural model are also reported in Figure 3. Based on t-tests, the coefficients are all significant at the 0.001 level, supporting all hypotheses concerning the relationships among constructs, as discussed in Section 3.1. Specifically, the key findings are that Perceived Reliability (PRel) exhibits the strongest direct and indirect influence on individuals' intention to use AVs, with the largest standardized coefficient estimate (H_{3a}: 0.593). Technological Competence (TC) follows with the next strongest direct influence on the intention to use AVs, showing a coefficient of (H5: 0.566). Also, Perceived Reliability (PRel) is strongly associated with trust in the Technology Acceptance Model (TAM) which supports the literature of Washburn and Adeleye [20]. Technological Competence (TC) also establishes a positive human-to-technology trust relationship [21]. With this relationship established between Perceived Reliability, Technological Competence and trust, our results align with findings in studies conducted in South Korea [9] and in Thailand [22] where trust and reliability were key determinants of AV adoption. According to KPMG [5], these countries—similar to Ghana—are classified as having low AVRI scores, indicating slower AV adoption rates. The strength of the effect of perceived reliability and trust on intentional to use was followed by those of Perceived Usefulness, (0.248), Perceived Risk (0.153) and Perceived Ease of Use (0.124) respectively. This finding differs slightly from prior research conducted in Thailand [22], which suggested that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) had insignificant relationships with the intention to use AVs. However, this divergence may reflect the unique socio-cultural and economic factors influencing AV adoption in Ghana..

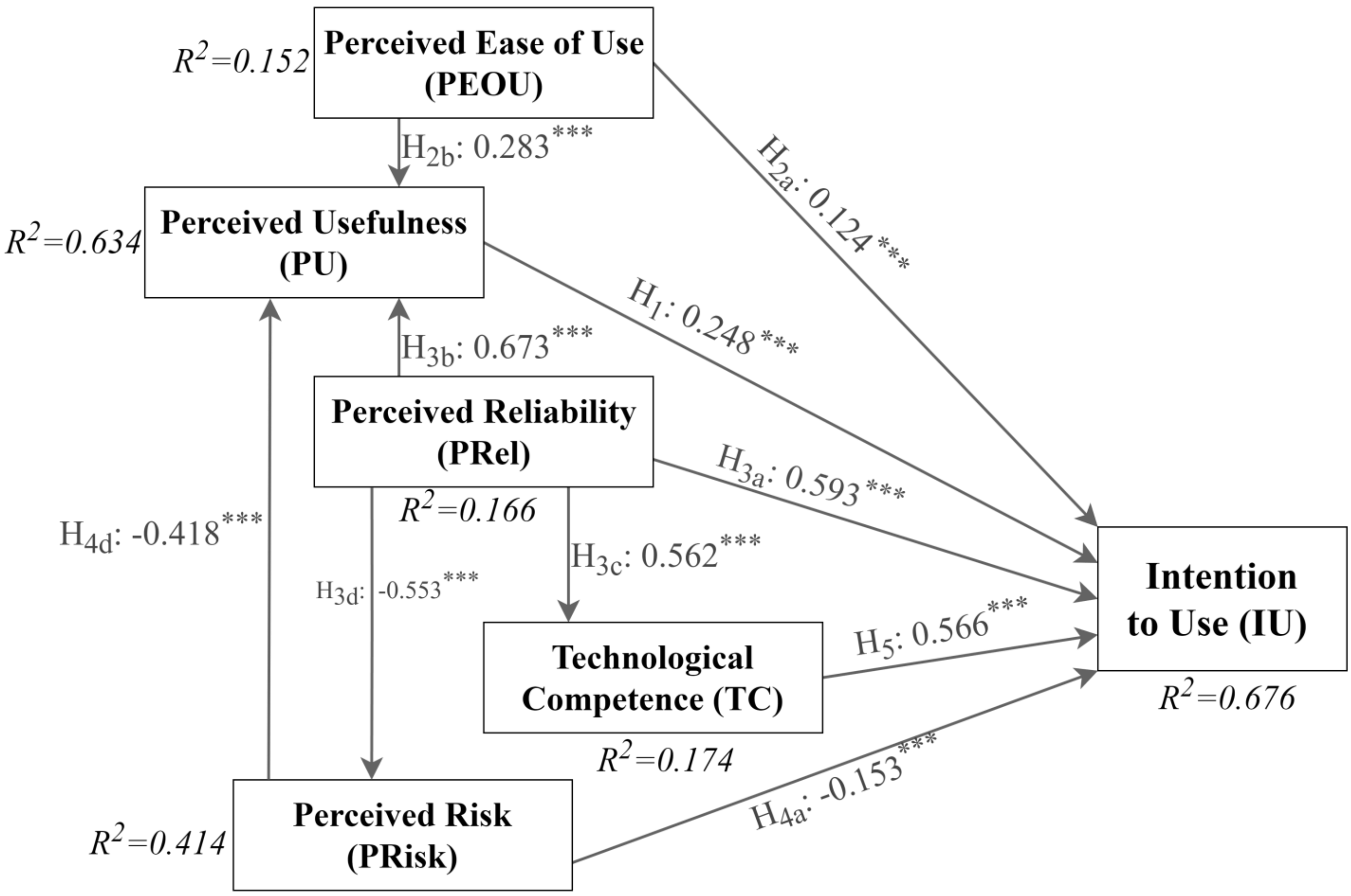

Figure 3 Result of path analysis

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In this study, Perceived Reliability (PRel) was found to have a positive association with Perceived Usefulness (PU) and a negative association with Perceived Risk (PRisk), as hypothesized. These findings suggest that improving individuals' trust in AVs can indirectly boost their intention to use AVs in two ways: (1) By reducing perceived risk, which negatively impacts the intention to adopt AVs and (2) By enhancing perceived usefulness, which positively influences the intention to adopt AVs.

Table 6 summarizes the relationships between socio-demographic control variables and each latent construct. The findings reveal noteworthy insights into how these control variables impact the intention to use AVs. Highly educated individuals, those who hold a driver's license, and those with experience using electric vehicles (EVs) are more likely to adopt AVs. More specifically, young and well-educated respondents tend to perceive higher usefulness and ease of use, which positively influences their intention to use AVs. Our findings on the significant effects of education on the intention to use AVs aligns with findings from European countries [23]. However, this contrasts with studies conducted in Beijing, China [24], which reported no significant effect of education on AV adoption.

Furthermore, individuals with high household incomes are more inclined to perceive AVs as useful, particularly because they often rely on vehicles for daily commuting, shopping, social visits, and attending events. Interestingly, the insignificant relationship between income and AV adoption observed in this study is consistent with findings from China and the USA [25, 26]. General driving experience also emerged as a key factor influencing perceptions of AVs. Specifically, longer driving experience, holding a driver's license, sing cruise control in traditional vehicles, and experience with EVs, all contribute to higher perceived usefulness and ease of use, further supporting positive attitudes toward AV adoptionIn summary, highly educated respondents and those holding driving licenses may possess a better understanding of the real-world operating environment for autonomous vehicles (AVs). Consequently, they may be more capable of assessing the readiness of local conditions for AV deployment, which could lead to a greater hesitation to adopt them. The findings also highlight the significant influence of several control variables on the latent constructs. Specifically, age, education, and gender influenced perceived usefulness, ease of use, technological competence, and intention to use AVs. Household income affected perceived usefulness, perceived reliability, technological competence, and intention to use AVs. Factors such as holding a driving license, years of driving experience, and experience with cruise control systems impacted perceived usefulness, ease of use, reliability, risk, and intention to use AVs.

Additionally, the environmental context emerged as a critical factor in shaping individuals' acceptance of AVs. Notably, participants in Group 1 (Mixed AV Traffic Environment) and Group 3 (AV-Only Traffic Environment) reported higher perceived usefulness and trust in AV technology compared to those in Group 2 (Dedicated AV Lane Traffic Environment). The overall implication after considering all results together is that, when considering all the results, the effects of the latent constructs (as hypothesized in this study) were more impactful on intention to use AVs than the influences of socio-demographic control variables and environmental contexts.

IV. CONCLUSION

The intention to adopt new technologies often varies across individuals and regions, particularly when socio-demographic factors and environmental conditions differ significantly. For autonomous vehicles (AVs), people in developing-country cities may exhibit different levels of willingness to adopt compared to those in developed nations due to disparities in infrastructure, technology readiness, and regulatory frameworks. In this study, we analyzed survey data on the intention to use AVs in Ghana by employing a modified Technology Acceptance Model (TAM). The findings confirmed a significant intention to adopt AVs in Ghana, irrespective of the automation level of AVs or the urban context in this developing African country. We extended the traditional TAM by incorporating perceived reliability, perceived risk, and trust in technological competence as new latent constructs to explore their influence on AV adoption in developing countries. Our results revealed that Perceived reliability and trust in the technological competence of AVs emerged as the strongest predictors of intention to use AVs, directly and positively influencing adoption—aligning with findings from previous studies. The study's results also revealed that Perceived risk, although significant, exerted a negative direct effect on the intention to adopt AVs. These findings highlight the importance of addressing trust and risk perception in promoting AV adoption, particularly in developing countries with lower readiness levels for advanced technologies.

Our findings also highlighted the significance of perceived usefulness and perceived ease of use in shaping individuals' intention to adopt AVs. The modeling results further suggested that enhancing perceived usefulness and reducing perceived risk could indirectly boost willingness to adopt AVs. Additionally, we observed that individuals' understanding of environmental contexts, such as mixed-AV and AV-only traffic environments, positively influenced their perceived usefulness and trust in the technological capabilities of AVs. This outcome suggests that a deeper understanding of AV technologies may be key to improving adoption rates, particularly in developing countries. To promote AV adoption in developing countries, the study emphasizes the importance of well-designed, regulated, and promoted operating environments in areas where AVs are introduced. Such measures can help build public confidence and foster trust in AV technologies. Moreover, the intention to adopt AVs may differ across socio-demographic groups. Specifically, individuals with experience in cruise control systems and electric vehicles (EVs) were more inclined to adopt AVs. This finding suggests that familiarizing the public with related technologies could serve as an effective strategy to encourage broader acceptance of AVs.

Table 6 Standardized estimates of each control variables towards each construct.

Constructs →	PU		PEOU		PRel		TC		PRisk		IU	
Control Variables↓	**S.E**	**p-val**	**S.E**	**p-val**	**S.E**	**p-val**	**S.E**	**p-val**	**S.E**	**p-val**	**S.E**	**p-val**
Age	***-0.0482***	***0.279***	***-0.061***	***0.5038***	***-0.05***	***0.2314***	***-0.139***	***0.2166***	***-0.035***	***0.5998***	***-0.0182***	***0.2754***
18—25	-0.071	0.268	-0.002	0.726	-0.024	0.276	-0.062	0.301	-0.006	0.902	-0.022	0.371
26—35	-0.056	0.174	-0.019	0.716	-0.082	0.114	-0.015	0.517	-0.021	0.152	-0.032	**0.051**
36—45	-0.036	0.361	-0.277	**0.003**	-0.012	0.132	-0.213	**0.001**	-0.013	0.731	-0.028	0.518
46—55	-0.026	0.319	-0.003	0.817	-0.086	0.214	-0.317	**0.001**	-0.038	0.383	-0.025	0.163
56—65	-0.052	0.273	-0.004	0.257	-0.044	0.421	-0.088	0.263	-0.097	0.831	0.016	0.274
Gender	***-0.002***	***0.277***	***-0.2***	***0.1005***	***-0.054***	***0.399***	***-0.0465***	***0.462***	***-0.003***	***0.161***	***-0.0305***	***0.079***
Male	-0.001	0.376	-0.369	**0.047**	-0.032	0.277	-0.067	0.183	-0.001	0.101	-0.038	**0.003**
Female	-0.003	0.178	-0.031	0.154	-0.076	0.521	-0.026	0.741	-0.005	0.221	-0.023	0.155
Edu. Qualification	***-0.1487***	***0.14633***	***-0.127***	***0.2047***	***-0.044***	***0.5097***	***-0.0333***	***0.2947***	***-0.0147***	***0.2913***	***-0.030333***	***0.495***
SHS	-0.017	0.116	-0.017	0.331	-0.013	0.632	-0.019	0.173	-0.019	0.522	-0.043	0.757
Bachelor's	-0.016	0.316	-0.077	0.279	-0.076	0.476	-0.014	0.184	-0.017	0.231	-0.022	0.651
≥Master's	-0.413	**0.007**	-0.287	**0.004**	-0.043	0.421	-0.067	0.527	-0.008	0.121	-0.026	**0.001**
Income	***-0.1132***	***0.257***	***0.0362***	***0.4212***	***-0.108***	***0.0286***	***-0.178***	***0.1646***	***-0.0026***	***0.5718***	***-0.0274***	***0.4219***
≤10,000	-0.011	0.742	-0.077	0.581	0.032	0.083	-0.024	0.187	0.088	0.919	-0.001	0.9673
10,001—20,000	-0.073	0.358	0.087	0.411	-0.412	**0.001**	-0.061	0.216	0.029	0.273	-0.035	0.531
20,001—30,000	-0.163	**0.001**	0.083	0.258	0.066	0.031	-0.476	**0.001**	-0.031	0.692	-0.016	0.431
30,001—50,000	-0.272	**0.001**	0.066	0.572	-0.219	**0.001**	-0.311	**0.001**	-0.087	0.862	-0.061	**0.017**
≥50,001	-0.047	0.183	0.022	0.283	0.034	0.027	-0.018	0.418	-0.012	0.113	-0.024	0.163
Car driving license	***-0.082***	***0.1415***	***-0.1165***	***0.009***	***0.3525***	***0.012***	***-0.031***	***0.822***	***-0.0215***	***0.1775***	***-0.0855***	***0.122***
Yes	-0.091	**0.066**	-0.167	**0.001**	0.418	**0.001**	-0.018	0.681	-0.045	0.154	-0.098	**0.006**
No	-0.073	0.217	-0.066	0.017	0.287	**0.023**	-0.044	0.963	0.002	0.201	-0.073	0.238
Driving Experience	***0.0378***	***0.6536***	***-0.1928***	***0.0722***	***0.3334***	***0.0156***	***-0.0628***	***0.3756***	***-0.0566***	***0.1824***	***0.0532***	***0.3932***
<1 year	0.013	0.631	-0.008	0.269	0.458	**0.038**	-0.036	0.279	-0.041	0.173	0.073	0.681
1—3 years	0.027	0.871	-0.317	**0.033**	0.398	**0.018**	-0.073	0.277	-0.029	0.651	0.062	0.438
4–6 years	0.061	0.651	-0.121	**0.051**	0.273	**0.001**	-0.053	0.318	-0.191	**0.001**	0.022	**0.033**
7–10 years	0.017	0.274	-0.297	**0.007**	0.281	**0.019**	-0.079	0.612	-0.211	**0.086**	0.061	0.428
>10 years	0.071	0.841	-0.221	**0.001**	0.257	**0.002**	-0.073	0.392	0.189	**0.001**	0.048	0.386
EVs. Experience (Exp)	***0.049***	***0.2015***	***-0.1025***	***0.4815***	***0.175***	***0.209***	***-0.0455***	***0.5715***	***0.1655***	***0.0275***	***-0.0305***	***0.196***
Yes	0.086	**0.016**	-0.178	0.351	0.287	**0.047**	-0.018	0.631	0.128	**0.004**	-0.027	**0.001**
No	0.012	0.387	-0.027	0.612	0.063	0.371	-0.073	0.512	0.203	**0.051**	-0.034	0.391
Cruising Control Exp.	***-0.025***	***0.2475***	***-0.231***	***0.131***	***0.0455***	***0.589***	***0.1955***	***0.09***	***0.1455***	***0.0575***	***0.0075***	***0.3315***
Yes	0.044	0.111	-0.481	**0.001**	0.073	0.651	0.328	**0.001**	0.173	**0.086**	0.001	0.187
No	-0.094	0.384	0.019	0.261	0.018	0.527	0.063	0.179	0.118	**0.029**	0.014	0.476
Environment. Context	***0.37033***	***0.32667***	***0.01333***	***0.625***	***0.017***	***0.4967***	***0.117***	***0.1867***	***-0.0493***	***0.2793***	***0.021***	***0.365***
Group 1	0.722	0.551	0.018	0.623	0.033	0.263	0.081	0.283	-0.151	**0.001**	-0.021	0.313
Group 2	-0.192	0.418	0.001	0.531	0.002	0.478	0.198	**0.001**	0.017	0.122	0.061	0.371
Group 3	0.581	**0.011**	0.021	0.721	0.016	0.749	0.072	0.276	-0.014	0.715	0.023	0.411

Notes: S.E. refers to standardized estimate, p-values refers to *p*-value.

While this study offers valuable insights into consumers' behavioral intention to adopt AVs in developing countries, several areas warrant further investigation. For instance, our findings suggest that knowledge of AV technological competencies and operational environments can enhance trust and, consequently, intention to use AVs. Building on this, future research could explore the role of explainable AI (XAI) in improving technology acceptance by offering clearer explanations of AV operations. A key limitation of this study is its reliance on a modified TAM model to examine the determinants of intention to use AVs. Although the model incorporates new constructs, it may still be constrained by the basic TAM framework. Future studies should therefore consider more advanced models, potentially extending TAM to include additional constructs relevant to XAI exposure. Specifically, research could investigate how XAI influences latent constructs such as trust, perceived usefulness, and risk perception, comparing these findings with the results of the current study. Such studies could offer deeper insights into the psychological mechanisms underlying AV adoption and help refine strategies to promote technology acceptance in developing regions

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