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Determinants of Autonomous Vehicle Adoption Intention in Jakarta: Extending the UTAUT Model

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Abstract. This research examines factors influencing behavioral intentions to adopt autonomous vehicles in Jakarta, Indonesia, based on an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model. A quantitative study with 400 respondents was conducted using a survey instrument. Independent variables included performance expectancy, effort expectancy, social influence, hedonic motivation, price value, trust in safety, facilitating conditions, and system quality. Results showed that performance expectancy, effort expectancy, price value, trust in safety, and system quality positively influenced behavioral intention, while social influence, hedonic motivation, and facilitating conditions had negative effects. The model explained 64.6% of the variance in behavioral intention. This research validated key UTAUT factors while finding counterintuitive negative effects of social and hedonic aspects on autonomous vehicle adoption intentions in Jakarta, highlighting the importance of emphasizing functional benefits over subjective norms or enjoyment factors in this context.

Keywords: Behavioral Intention, Technology Acceptance, UTAUT Model, Autonomous Vehicle

1. Introduction

In the Economist article and findings obtained by the Boston Consulting Group, 90-94% of accidents are caused by human error (Bendiab et al., 2023). Research Vaezipour et al. (2015) suggests that autonomous vehicles have the potential to improve driving safety by reducing human error, increasing efficiency by reducing congestion and saving fuel, thus becoming a solution for individuals who cannot drive, the elderly, and the disabled because autonomous vehicles are driven by the system, reducing emissions and improve air quality by driving effectively, and increase productivity so that people who use it can carry out other activities in the vehicle.

Autonomous vehicles also known as self-driving cars are vehicles that are capable of operating without a driver. In recent years, advances in Artificial Intelligence (AI) technology have significantly impacted the development of autonomous vehicles. AI allows autonomous vehicles (AV) to collect and analyze data from the driving or street environment, make intelligent decisions, and interact with other pedestrians using a system that detects objects around the vehicle (Ma et al., 2020). One important aspect of the development of autonomous vehicles is safety (Nascimento et al., 2019). Autonomous vehicles must be able to identify and avoid obstacles/obstacles, comply with existing traffic regulations, and be able to interact safely with other drivers. In this case, AI plays a very important role in realizing these things (Cunneen et al., 2019). With the use of AI technology, autonomous vehicles can learn from experience and improve performance over time.

Safety is an important aspect of driving, in the context of autonomous vehicles which are equipped with advanced technology that helps human drivers to control the vehicle independently, without requiring human intervention. However, safety is not the only consideration or factor that influences individuals in accepting autonomous vehicle technology. People also consider comfort, time savings, fuel savings, and other safety features (Shi et al., 2021). Based on the background described above, researchers are interested in examining the factors that will influence the people in Indonesia in particular in accepting this autonomous vehicle technology.

2. Literature Review

2.1 Artificial Intelligence

Artificial Intelligence (AI) is the development of computer-based systems to perform tasks that generally use human intelligence intending to imitate human cognitive processes, such as learning, reasoning, and problem-solving. In the transportation sector, AI has various applications that help overcome challenges related to increasing travel demand, CO2 emissions, safety issues, and environmental degradation (Khayyam et al., 2020). AI methods, such as Artificial Neural Networks (ANN), Genetic algorithms (GA), and Simulated Annealing (SA), can be used to optimize transportation systems and increase efficiency. This algorithm can help in road planning, public transport optimization, traffic incident detection, and traffic condition prediction. Autonomous Vehicles rely on AI algorithms to understand the environment, make decisions, and navigate safely. AI allows these vehicles to analyze sensor data, detect objects, and respond to traffic conditions in real time. AI can also be used to detect incidents in real-time and predict future traffic conditions. By analyzing data from various sources, such as traffic sensors and cameras, AI algorithms can automatically detect accidents and predict future traffic conditions. This information can be used to improve traffic management and reduce congestion (Abduljabbar et al., 2019).

2.2 Autonomous Vehicle

Autonomous technology is a technology that can function and carry out tasks without having to be controlled by humans (Krakul, 2020). According to SAE International (2021) there are 6 levels or levels of automation in vehicles starting with level 0 to level 5. From level 0 to level 2, the driver still has to monitor the driving environment. The self-driving system at level 3 requires the driver to drive if the feature requires it, in other words, level 3 is not yet autonomous because it is limited to the operating environment and requires human involvement. Levels 4 and 5 are the levels where vehicles can drive themselves or are self-driving (S. Chen et al., 2019). According to the National Highway Traffic Safety Administration (NHTSA), an autonomous or self-driving vehicle is a vehicle that can operate without the need for direct control or input from the driver to control steering, acceleration, and braking which is designed in such a way that the driver does not need to monitor continuously when driving a self-driving system running (NAIC, 2022).

2.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT (Unified Theory of Acceptance and Use of Technology) is an acceptance model that synthesizes several theories and models to explain the adoption of information and communication technology (ICT). This model includes four main constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions which influence users' intentions to use technology and their actual use of technology. UTAUT also takes into account individual characteristics, such as gender, age, experience, and voluntariness of use, which may moderate the relationship between constructs and technology adoption. UTAUT has been widely applied in various contexts, such as Internet banking, social networking sites, tourist village websites, and tourist guide applications (Palau-Saumell et al., 2019).

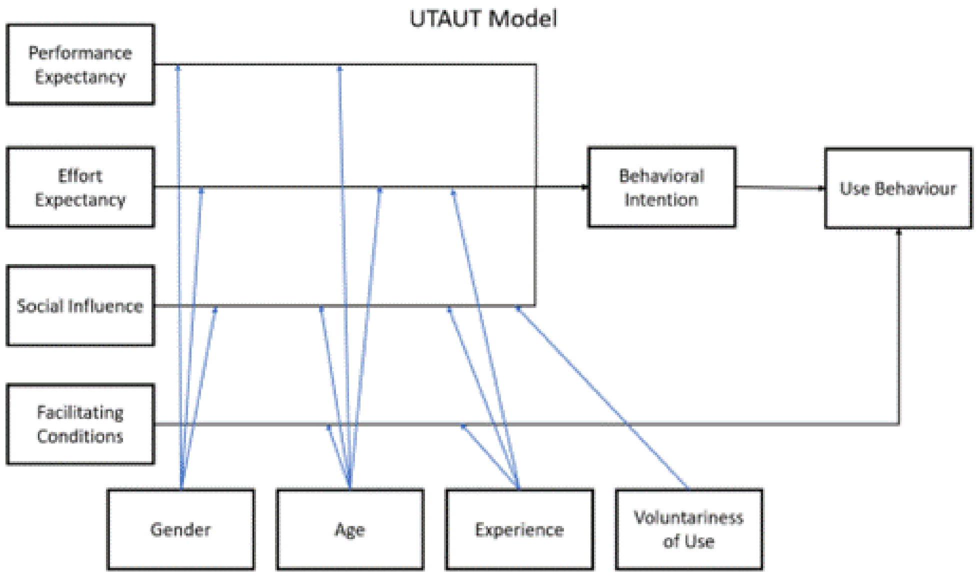

Fig. 1: UTAUT Model

3. Research Methodology

This research follows a systematic methodology consisting of five stages to develop the BCP framework for public sector organizations. Fig. 1 illustrates the research stages, which are problem analysis, literature review, framework analysis and join, data collection and analysis, and the stages construction of BCP Development. The first stage, problem analysis, involves identifying the challenges faced by public sector organizations in managing information systems and the potential disruptions that may impact their business processes.

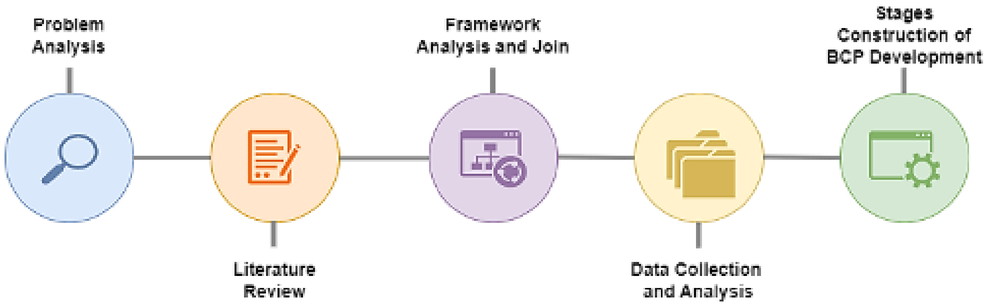

Fig. 2: Research Stage

After doing problem analysis, proceed with the literature review stage to study some theories, previous research, and existing framework concepts related to BCP. The framework analysis and join stage is a critical phase in this research. Two reference framework standards are analyzed and union tocreate a comprehensive BCP framework that suits the needs of public sector organizations. This processinvolves analyzing the components of the standards and integrating them to form a cohesive framework.Data collection and analysis is the subsequent stage, carried out within a specific public sector organizational unit involved in infrastructure management. Various activities such as document collection, interviews with key personnel responsible for information systems, and observations are conducted. Additionally, organizational needs related to BCP are identified and documented at this stage.

The next stage is the construction stage of BCP development. After obtaining information and organizational needs, the next thing to do is to build the BCP stages to get a more structured and effective BCP. The method used at this stage is mapping organizational needs with the components of the new framework. The results of this mapping are the stages used for BCP development based on the needs of public sector organizations. After the BCP development stages are created, it is necessary to evaluate whether the BCP stages proposed in this research can meet the organization’s needs. This assessment is an evaluation process. The evaluation was conducted by mapping the proposed BCP development stages into the PDCA cycle and using a questionnaire distributed to IT staff who manage information systems in public sector organizations. This evaluation assesses whether the proposed BCP stages adequately meet the organization's needs and identifies any necessary improvements or modifications.

3.1. Proposed Method

This research uses a quantitative method using questionnaires and literature studies. To measure the variables studied, researchers use a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The Likert scale is employed to assess constructs such as perceived usefulness, user satisfaction, and intention to use. The research method used in this research is the UTAUT model which has 5 main factors, namely performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention which are then added to additional variables such as hedonic motivation, price value, trust in safety, system quality which is described in Figure 2.

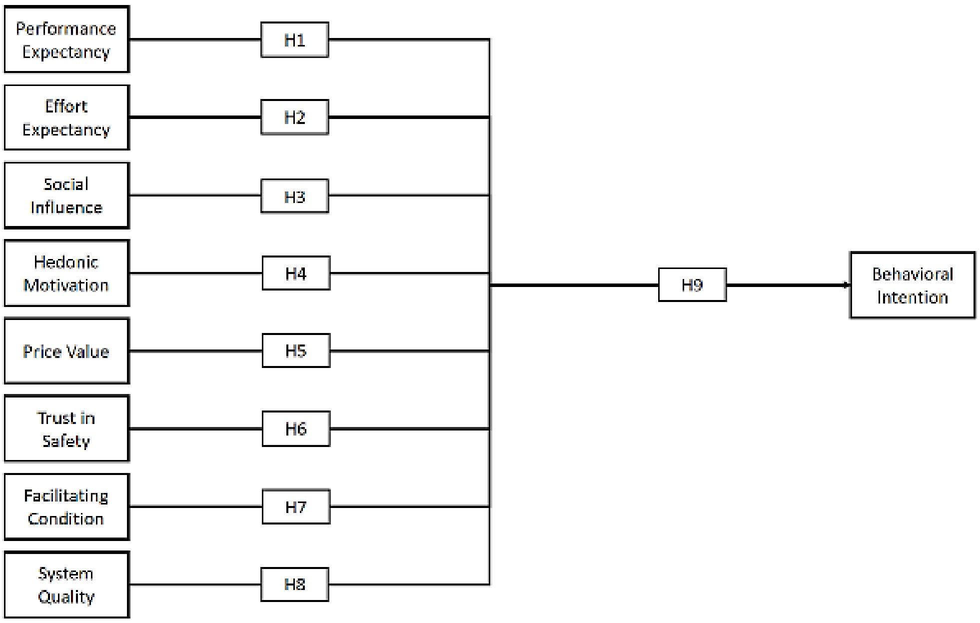

Fig. 3: Research Model

Based on the research method in Figure 3 which was explained previously, each variable in the UTAUT model has a relationship with this research. The independent variables in this research are Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Price Value, Trust in Safety, Facilitating Conditions, and System Quality which influence Behavioral Intention. The following is the hypothesis of this research:

H1: Performance Expectancy influences Behavioral Intention
H2: Effort Expectancy influences Behavioral Intention
H3: Social Influence influences Behavioral Intention
H4: Hedonic Motivation influences Behavioral Intention
H5: Price Value influences Behavioral Intention
H6: Trust in Safety influences Behavioral Intention
H7: Facilitating Conditions Influence Behavioral Intention
H8: System Quality Influences Behavioral Intention
H9: Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Price Value, Trust in Safety, Facilitating Conditions and System Quality simultaneously influence Behavioral Intention.

3.2. Population and Sample

The population in this study was taken from the number of people of productive age, namely the range 15-64 years according to BPS data. In 2022, DKI Jakarta province had 7,667,556 people (Central Statistics Agency, 2022). Then the data on motorized vehicles including passenger cars in 2022 in DKI Jakarta is 3,766,059 vehicles (Central Statistics Agency, 2022). In sampling researchers use the Slovin formula:

$$n = \frac{N}{1+N\varepsilon^2} \qquad (1)$$

Information:
n = number of samples
N = total population
ε = error tolerance

$$n = \frac{3{,}766{,}059}{1 + (3{,}766{,}059)(5\%)^2} = 399{,}95 \cong 400$$

So, the sample that must be obtained or fulfilled is 400 respondents. The individuals used as respondents in this research are residents of Jakarta who know autonomous vehicles.

4. Result and Discussion

4.1 Respondent Profile

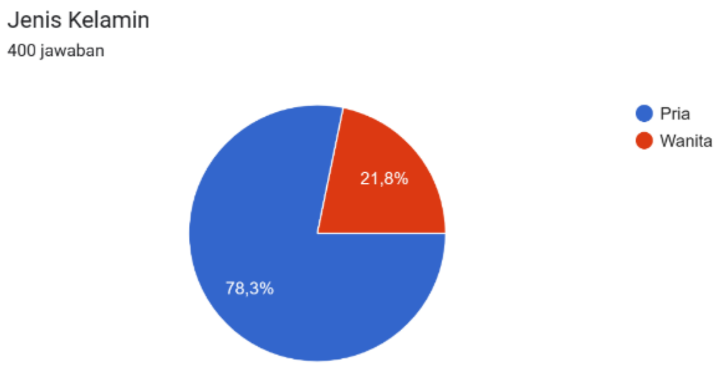

Fig. 4: Respondent Gender

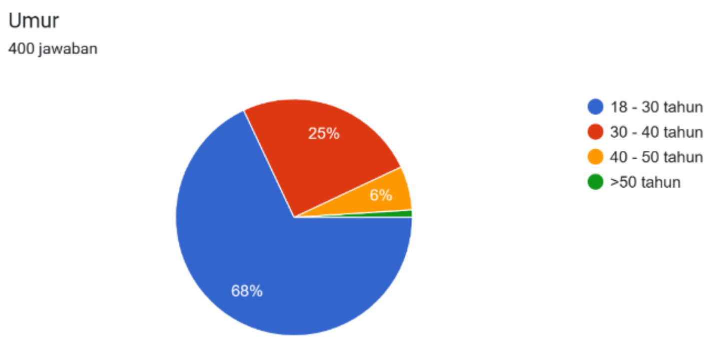

Fig. 5: Respondent Age

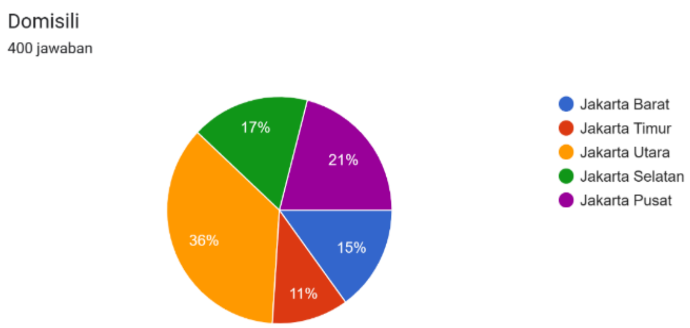

Fig. 6: Respondent Domicile

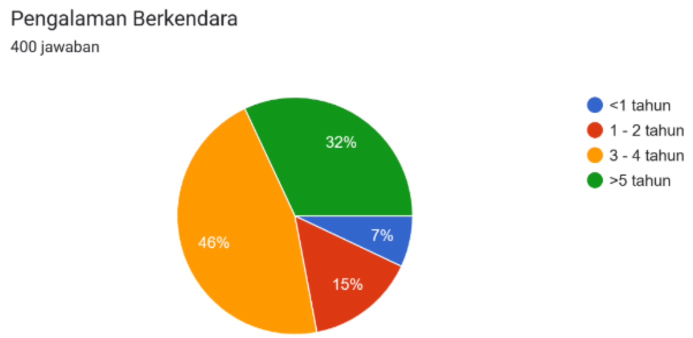

Fig. 7: Respondent Driving Experience

As we can see, the respondents in this study were dominated by men with a productive age of 18-30 years. Then the respondents' domiciles were spread out with 60 people or 15% coming from West Jakarta, while East Jakarta contributed 44 respondents, or 11%. North Jakarta recorded the highest participation with 144 respondents or 36%, South Jakarta with 68 respondents or 17%, and Central Jakarta with 84 respondents or 21%. Of the total respondents, 28 people, or 7% had driving experience of less than 1 year. The 1-2 years driving experience group accounted for 60 respondents or 15%, while the 3-4 years group recorded the highest participation with 184 respondents or 46%. There were also 128 respondents or 32% who had driving experience of more than 5 years.

4.2 Outer Model

Evaluation of the measurement model to test the validity and reliability of the research model.

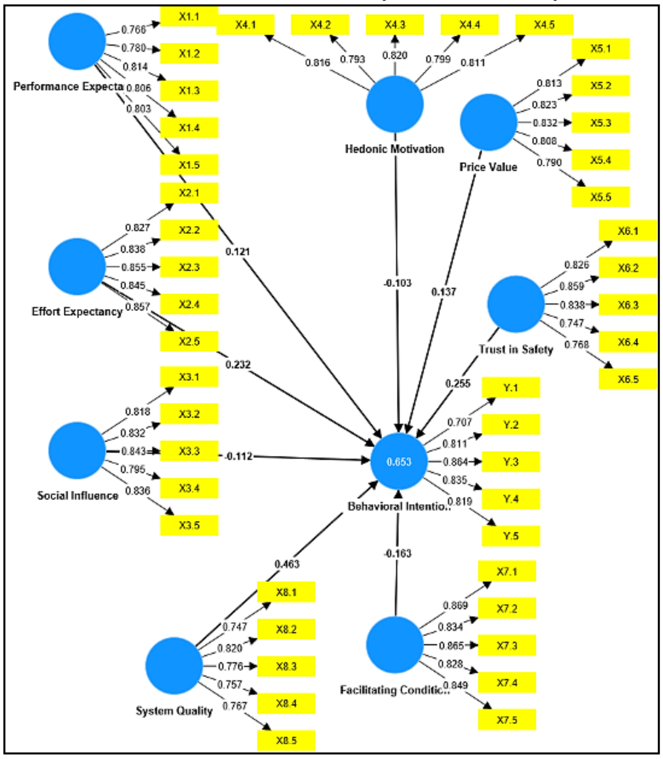

Fig. 8: Convergent Validity Test

The convergent validity test results indicate that each indicator in this study has a loading factor value above the recommended threshold of 0.5, indicating a significant correlation with the measured construct. These indicators meet the criteria for convergent validity, indicating that the measuring tool is reliable and can accurately explain the phenomenon under study. The indicators used in this research create a consistent picture of the construct, demonstrating their adequate level of validity and reliability.

Table 1. Reliability Test

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavioral Intention	0.866	0.869	0.904	0.654
Effort Expactancy	0.899	0.900	0.925	0.713
Facilitating Condition	0.903	0.904	0.928	0.721
Hedonic Motivation	0.867	0.868	0.904	0.653
Performance Expectancy	0.854	0.854	0.895	0.631
Price Value	0.872	0.872	0.907	0.661
Social Influence	0.883	0.888	0.914	0.680
System Quality	0.832	0.834	0.882	0.598
Trust in Safety	0.867	0.873	0.904	0.654

The reliability test results show that all variables in this study have Cronbach's alpha and composite values exceeding 0.6, indicating adequate reliability. High reliability indicates that the measurement instrument is reliable and consistently provides consistent results. The instrument's ability to provide consistent results if repeated measurements are taken is critical to its reliability. Therefore, all variables in this study have a sufficient level of reliability to provide reliable results.

4.3 Inner Model

Evaluation of the structural model in SEM with PLS was carried out by carrying out the R-squared test (R^2) and significance testing by estimating path coefficients.

4.3.1 R Square Test

The output for the R square value using the SmartPLS 4 computer program is obtained:

Table 2. R Square

	R-square	R-square adjusted
Behavioral Intention	0.653	0.646

In this context, the results of the adjusted R square test show the magnitude of the influence of the independent latent variable on the dependent latent variable, behavioral intention. The adjusted R square value obtained is 0.646, which is equivalent to 64.6%. These results indicate that approximately 64.6% of the variation in behavioral intention can be explained by the independent latent variables included in the analysis model. A significant R square value like this indicates the model's level of accuracy and precision in explaining behavioral intention (behavioral intention) in adopting autonomous vehicles. An influence of 64.6% can be interpreted as a substantial contribution from the independent variables to the behavioral intention variable. These findings can provide an in-depth understanding of the factors that significantly influence respondents' behavioral intentions toward adopting autonomous vehicles. Thus, the results of the adjusted R square test provide strong support for the validity and reliability of the analysis model used in this research.

4.4 Significance Test

The significance test in the SEM model with PLS aims to determine the effect of exogenous variables on endogenous variables. Hypothesis testing was conducted using the Structural Equation Modeling Partial Least Squares (SEM PLS) method. This process involved bootstrapping, which was performed using the SmartPLS 4 software. For the bootstrapping process, 5000 bootstrapping samples were generated to estimate the sampling distribution of the model parameters. Ninety-five percent confidence intervals were calculated for these estimates to assess the significance of the relationships between exogenous and endogenous variables. The results of the analysis, detailing the influence of exogenous variables on endogenous variables, are summarized as follows:

4.4.1 Direct Effect Test

The output for the R square value using the SmartPLS 4 computer program is obtained:

Table 3. Direct Effect Test

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Effort Expactancy -> Behavioral Intention	0.232	0.229	0.079	2.943	0.003
Facilitating Condition -> Behavioral Intention	-0.163	-0.164	0.057	2.849	0.004
Hedonic Motivation -> Behavioral Intention	-0.103	-0.103	0.048	2.139	0.033
Performance Expectancy -> Behavioral Intention	0.121	0.122	0.053	2.255	0.024
Price Value -> Behavioral Intention	0.137	0.137	0.066	2.070	0.039
Social Influence -> Behavioral Intention	-0.112	-0.111	0.054	2.086	0.037
System Quality -> Behavioral Intention	0.463	0.466	0.067	6.913	0.000
Trust in Safety -> Behavioral Intention	0.255	0.256	0.073	3.478	0.001

Based on the output results above, the p value of all variables is smaller than 0.05 and the t statistic is greater than 1.96 so there is a significant relationship between the variables. Hypothesis testing for each latent variable relationship is shown as follows:

1. Hypothesis testing of the Effort Expectancy variable on Behavioral Intention

In testing the hypothesis regarding the Effort Expectancy variable on behavioral intention, the output results show a p-value of 0.003, which is smaller than the significance level of 0.05. Apart from that, the t-statistic of 2.943 also exceeds the critical t-statistic value of 1.96. These findings indicate that there is a significant relationship between the variables effort expectancy and behavioral intention, with a positive correlation. With a low p-value, the null hypothesis can be rejected, and these results indicate that effort expectancy has a significant impact on behavioral intention under the proposed hypothesis. Thus, it can be concluded that the positive relationship between the variables effort expectancy and behavioral intention is accepted as significant in the context of this research.

2. Hypothesis testing of the Facilitating Condition variable on Behavioral Intention

The output analysis results show that when testing the hypothesis regarding the Facilitating Condition variable on behavioral intention, the p-value is 0.004, which is less than the significance level of 0.05. Apart from that, the t-statistic reached a value of 2.849, exceeding the critical t-statistic value, which should be 1.96. These findings indicate that there is a significant relationship between the facilitating condition and behavioral intention variables, with a negative correlation. With a low p-value, the null hypothesis can be rejected, and these results indicate that the proposed hypothesis has a significant impact on facilitating conditions in terms of behavioral intention. Thus, it can be concluded that the negative relationship between the facilitating condition and behavioral intention variables is accepted as significant in the context of this research.

3. Hypothesis testing of Hedonic Motivation variables on Behavioral Intention.

The hypothesis testing results for the hedonic motivation variable on behavioral intention show a p-value of 0.033, which is smaller than the significance level of 0.05. Apart from that, the t-statistic value is 2.139, exceeding the critical t-statistic value, which should be 1.96. These findings indicate that there is a significant relationship between the hedonic motivation and behavioral intention variables, with a negative correlation. With a low p-value, the null hypothesis can be rejected, and these results indicate that the proposed hypothesis has a significant impact of hedonic motivation on behavioral intention. Thus, it can be concluded that the negative relationship between the hedonic motivation and behavioral intention variables is accepted as significant in the context of this research.

4. Hypothesis testing of the Performance Expectancy variable on Behavioral Intention

The results of hypothesis testing regarding the performance expectation variable on behavioral intention show a p-value of 0.024, which is smaller than the significance level of 0.05. Apart from that, the t-statistic value is 2.255, which exceeds the critical t-statistic value, which should be 1.96. These findings indicate that there is a significant relationship between the variables performance expectancy and behavioral intention, with a positive correlation. With a low p-value, the null hypothesis can be rejected, and these results indicate that performance expectation has a significant impact on behavioral intention under the proposed hypothesis. Thus, it can be concluded that the positive relationship between the variables performance expectancy and behavioral intention is accepted as significant in the context of this research.

5. Hypothesis testing of the Price Value variable on Behavioral Intention

According to the results of hypothesis testing regarding the price value variable on behavioral intention, a p-value of 0.039 was obtained, which is smaller than the significance level of 0.05. Apart from that, the t-statistic reached a value of 2.070, exceeding the critical t-statistic value, which should be 1.96. These findings indicate that there is a significant relationship between the price value and behavioral intention variables, with a positive correlation. With a low p-value, the null hypothesis can be rejected, and these results indicate that price value has a significant impact on behavioral intention under the proposed hypothesis.

6. Hypothesis testing of Social Influence variables on Behavioral Intention

The results of hypothesis testing regarding the social influence variable on behavioral intention show a p-value of 0.037, which is smaller than the significance level of 0.05. Apart from that, the t-statistic value reached 2.086, exceeding the critical t-statistic value, which should be 1.96. These findings indicate that there is a significant relationship between the social influence and behavioral intention variables, with a negative correlation. With a low p-value, the null hypothesis can be rejected, and these results indicate that the proposed hypothesis has a significant impact on social influence on behavioral intention.

7. Hypothesis testing of System Quality variables on Behavioral Intention
Based on the results of hypothesis testing regarding the system quality variable and behavioral intention, a p-value of 0.000 was obtained, which is much smaller than the significance level of 0.05. In addition, the t-statistic value reached 6.913, which is significantly greater than the critical t-statistic value, which should be 1.96. These findings indicate that there is a significant relationship between system quality and behavioral intention variables, with a positive correlation.
8. Hypothesis testing of the Trust in safety variable on Behavioral Intention
The hypothesis testing results for the trust in safety variable on behavioral intention show a p-value of 0.001, which is smaller than the significance level of 0.05. Apart from that, the t-statistic value reached 3.478, exceeding the critical t-statistic value, which should be 1.96. These findings indicate that there is a significant relationship between trust in safety and behavioral intention variables, with a positive correlation. With a low p-value, the null hypothesis can be rejected, and the results indicate that trust in safety has a significant impact on behavioral intention under the proposed hypothesis.

4.4.2 F Test

The output for the F Test value using the SmartPLS 4 computer program is obtained:

Table 4. F Test

	Sum square	df	Mean square	F	P Value
Total	4198.578	399	0.000	0.000	0.000
Error	1460.680	391	3.736	0.000	0.000
Regression	2737.897	8	342.237	91.611	0.000

Based on the results of the F test on the output obtained, the p-value recorded was 0.000, clearly smaller than the significance level, which is generally set at 0.05. The findings show that there is a strong connection between the factors Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Price Value, Trust in Safety, Facilitating Conditions, and System Quality on Behavioral Intention in this study. Thus, the hypothesis proposed in this research can be accepted. When the p-value is less than the specified significance level, in this case, 0.05, we can conclude that the difference between the groups of variables is not a mere coincidence but reflects a real and reliable relationship. As a result, these results show that performance expectations, effort expectations, social influence, hedonic motivation, price value, trust in safety, facilitating conditions, and system quality all play a big role in how people plan to act when it comes to adopting self-driving cars. These results not only provide an in-depth understanding of the correlations between variables but also provide strong empirical support for the conceptual framework used in this research. Thus, it can be concluded that these findings provide a significant contribution to the understanding of the factors that influence behavioral intention in the adoption of autonomous vehicles.

4.4.3 Q Square Test

The results of the Blindfolding Q test on the model show a Q2 value of 0.420, which is greater than the generally used significance value, namely 0.05. This statistically significant Q2 value indicates that the model has a fairly high level of predictive relevance. Thus, these results confirm the model's ability to predict accurately beyond the training data that was used to develop the model. In this context, a significant Q2 value indicates that the model has good generalization power and can produce reliable predictions on new data. The significant Q2 value indicates that the model has good predictive relevance for the data. Thus, this positive interpretation of the Q2 value provides empirical support for the predictive ability of the model in the context of this research.

Table 5. Q Square Test

	SSO	SSE	Q^2 (=1-SSE/SSO)
Behavioral Intention	2000.000	1160.562	0.420
Effort Expactancy	2000.000	2000.000	0.000

	SSO	SSE	Q^2 (=1-SSE/SSO)
Facilitating Condition	2000.000	2000.000	0.000
Hedonic Motivation	2000.000	2000.000	0.000
Performance Expectancy	2000.000	2000.000	0.000
Price Value	2000.000	2000.000	0.000
Social Influence	2000.000	2000.000	0.000
System Quality	2000.000	2000.000	0.000
Trust in Safety	2000.000	2000.000	0.000

4.5 Result Interpretation

4.5.1 The Effect of Performance Expectancy on Behavioral Intention

The positive influence of Performance Expectancy on Behavioral Intention is a significant finding in the context of autonomous vehicle adoption. The analysis results show that the higher the performance expectations or anticipated benefits from using autonomous vehicles, the higher the user's intention to adopt them. This finding is in line with the research by Sudirman et al. (2022), which find that performance expectancy has positively and significantly affected behavioral intention. However, this research is not supported by Utomo et al. (2021) research which shows that performance expectations have no effect on behavioral intention. This research shows that when users experience clear benefits from using technology, they tend to have stronger intentions to adopt it. Thus, the positive influence of Performance Expectancy on Behavioral Intention emphasizes the importance of understanding and increasing the perception of anticipated benefits by users to support the adoption of autonomous vehicle technology. The implication is that technology developers can consider marketing strategies that highlight real and expected benefits to users, to increase their acceptance and intention to adopt autonomous vehicles.

4.5.2 The Effect of Effort Expectancy on Behavioral Intention

In the context of autonomous vehicle technology adoption, analysis of the relationship between Effort Expectancy and Behavioral Intention variables provides significant findings. The results of the hypothesis test show that there is a positive and significant relationship between the two variables, so the hypothesis can be accepted. These results consistently support by research Utomo et al. (2021) showed that the effort expectancy can increase the behavioral intention. This reference provides a strong theoretical basis for explaining the positive relationship between ease of use and Behavioral Intention in the context of autonomous vehicle adoption. This research provides a more comprehensive view of technology acceptance by combining several previous models, and the findings can be applied to understanding the relationship between Effort Expectancy and Behavioral Intention in the context of autonomous vehicles. These results provide valuable insights for technology developers and automotive companies. Focusing on improving the ease of use of autonomous vehicles can be an effective strategy in increasing users' intention to adopt this technology. By ensuring that the use of autonomous vehicles becomes easier and more intuitive, the potential for societal acceptance can increase, opening up opportunities for the successful adoption of autonomous vehicles in the future.

4.5.3 The Effect of Social Influence on Behavioral Intention

The finding of a significant relationship between the Social Influence and Behavioral Intention variables, with a negative correlation, shows interesting dynamics in the context of autonomous vehicle adoption. The results of the analysis confirm that the higher the social influence felt by individuals regarding the decision to adopt autonomous vehicles, the lower their intention to adopt them. One study that supports these findings is the work of (Bearden et al., 1989). In this study, they explored consumers' level of vulnerability to interpersonal influence. The results show that social influence can influence consumer behavior, and the existence of a negative relationship may reflect how opinions or pressure from the social environment can moderate an individual's intention to adopt a product or technology. A second reference can be found in research exploring what drives the acceptance of autonomous driving systems and Investigating acceptance factors from the end user's perspective. The findings show that there is a significant relationship between the Social Influence and Behavioral Intention variables, with a negative correlation. This study provides in-depth insight into how social factors can influence individuals' intentions toward autonomous vehicle adoption (Nastjuk et al., 2020). By understanding the negative relationship between Social Influence and Behavioral Intention in the context of autonomous vehicle adoption, developers and marketers can gain valuable insight into the social factors that moderate user decisions. The implication is that marketing and education strategies should consider ways to address or change social perceptions regarding autonomous vehicles to increase user acceptance and intent.

4.5.4 The Influence of Hedonic Motivation on Behavioral Intention

Analysis of the relationship between Hedonic Motivation and Behavioral Intention variables in the context of autonomous vehicle adoption shows interesting findings that there is a significant relationship with a negative correlation. In this context, the negative hypothesis turns out to be accepted, which indicates that there are implications that need to be considered in understanding users' intentions towards autonomous vehicles. References that support these findings can be found in research related to hedonic motivation in technology adoption. For example, The results of Khatimah et al. (2019) research found that hedonic motivation significantly influences payment habits on the behavioral intentions of e-money users. This literature can provide a basis for understanding the concept of hedonic motivation and its implications for behavioral intentions. Keszey (2020) research demonstrates that the behavioral intention of innovative users is impacted by both utilitarian and hedonic motives. In contrast, laggards are mostly driven by hedonic motivation, with utilitarian motivation playing no significant role. By understanding the negative relationship between Hedonic Motivation and Behavioral Intention in the context of autonomous vehicle adoption, technology developers can better understand user preferences and motivations. This understanding can help develop marketing strategies and autonomous vehicle designs that better suit users' needs and desires related to hedonic aspects.

4.5.5 Influence of Price Value on Behavioral Intention

In the context of autonomous vehicle adoption, the analysis results show a significant relationship between the Price Value and Behavioral Intention variables, with a positive correlation. These findings indicate that the more positive users' perceptions of the price value of autonomous vehicles, the higher their intention to adopt them. The main support for these findings can be found in the literature regarding factors influencing consumer behavior in the context of price and usage intentions. For example, Varki & Colgate (cited in Zhong & Moon, 2020) research found that price perception has a significant direct effect on customer satisfaction and behavioral intentions. The second relevant research is the work of Lichtenstein et al. (cited in Bennett et al., 2022) entitled "Price Perceptions and Consumer Shopping Behavior: A Field Study". In this research, they found that perceived price value can influence consumer shopping behavior. Specifically, when consumers perceive positive value regarding the price of a product, they tend to have a higher intention to purchase. Thus, these findings provide valuable insights for autonomous vehicle developers and marketers. Marketing strategies that emphasize positive price value and match the benefits provided by autonomous vehicles can increase users' intention to adopt this technology. Additionally, further understanding how price influences user intent can help make more effective pricing decisions.

4.5.6 The Influence of Trust in Safety on Behavioral Intention

The results of the analysis show that there is a significant relationship between the Trust in Safety and Behavioral Intention variables, with a positive correlation. These findings indicate that the higher the user's level of trust in the safety aspects of autonomous vehicles, the higher their intention to adopt them. This results are not in line with Endah et al. (2017) research which shows that trust has no significant effect on behavioral intention. But there is research that supports the positive relationship between trust in safety and behavioral intention, can be found in the work of Dirsehan & Can (2020) which shows the existence of both direct and indirect effects of trust on behavioral intention. Thus, these findings provide important insight that safety, and the level of user trust in that aspect, is a key factor in shaping users' intention to adopt autonomous vehicles. The implication is that autonomous vehicle developers and manufacturers must continue to improve and emphasize safety features and provide transparent and convincing information to build user trust.

4.5.7 Effect of Facilitation Conditions on Behavioral Intention

Analysis of the relationship between the Facilitating Condition and Behavioral Intention variables in the context of autonomous vehicle technology adoption shows interesting results. The results of the hypothesis test show that there is a significant relationship between Facilitating Conditions and Behavioral Intention with a negative correlation. These findings contribute to the understanding of factors influencing users' intention to adopt autonomous vehicles, particularly through the Facilitating Conditions dimension. The first reference that supports these findings is Nahla Aljojo (2020) research, which shows that facilitating conditions were significant and directly influenced students' behavioral intention to use mobile learning. The negative relationship between facilitating conditions and behavioral intention in the context of autonomous vehicles may be caused by the complexity or obstacles that arise due to conditions that facilitate such use. However, there are references that are not relevant to these findings, namely research by Tusyanah et al. (2021), which indicates a positive relationship between facilitation conditions and behavioral intention, which means that when facilitation conditions increase, so does behavioral intention. Thus, these findings suggest that conditions that facilitate autonomous vehicle use may negatively influence user intentions. The implication is that technology developers and autonomous vehicle manufacturers need to pay attention to and overcome obstacles that may arise in implementing facilitating conditions, to increase user acceptance and intention towards autonomous vehicle technology.

4.5.8 The Influence of System Quality on Behavioral Intention

The results of the analysis show that there is a significant relationship between the System Quality and Behavioral Intention variables, with a positive correlation. These findings indicate that the more positive users' perceptions of the quality of an autonomous vehicle system, the higher their intention to adopt it. A study that supports these findings can be found in the work of H.-K. Chen & Yan (2019) research findings indicate that if individuals see autonomous vehicles system as trustworthy and have no concerns regarding their operational control, they are more likely to have a strong intention to employ autonomous vehicles. In addition, Keszey (2020) study demonstrates that the behavioral intentions of innovative users to adopt autonomous vehicles (AVs) are affected by particular technology anxieties, such as concerns about data privacy. On the other hand, less progressive users are influenced by more general concerns, such as overall apprehension about technology. This implies the significance of system quality in dealing with these challenges. The quality of the AV system, encompassing safety features and overall usability, significantly impacts user acceptance in various segments. Thus, understanding that system quality has a positive influence on Behavioral Intention provides an important insight for autonomous vehicle technology developers. Focusing on improving system quality, user interface, and overall performance of autonomous vehicles can be an effective strategy to increase user acceptance and intent to adopt this technology.

4.5.9 The Influence of Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Price Value, Trust in Safety, Facilitating Conditions, and System Quality on

Behavioral Intention

Research on autonomous vehicle adoption has become a major focus in understanding consumer preferences and intentions towards this technology. Two relevant studies highlight the significant relationship between various factors and Behavioral Intention in adopting autonomous vehicles. The first reference presents a comprehensive approach by integrating the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). The findings show that anticipated performance, the effort required, social influence, hedonic motivation, price value, confidence in safety, facilitating conditions, and system quality together have a positive and significant impact on consumer's intention to adopt autonomous vehicles. This study provides a solid and comprehensive theoretical foundation for understanding the factors that influence Behavioral Intention (Nordhoff et al., 2020). The second reference uses a Structural Equation Modeling (SEM) approach to explore the factors that influence consumer intentions. The results of the analysis confirmed that the integrated theoretical model of acceptance and use of technology 2 (UTAUT2) was modified to include variables such as performance expectations, effort expectations, social influence, facilitating conditions, hedonic motivation, price value, habits, trust and security, perceived benefits, risk perception, and behavioral intention construct (Korkmaz et al., 2021). These two studies consistently support the idea that various factors, ranging from technology usability to aspects of trust and hedonic motivation, play an important role in shaping Behavioral Intention toward autonomous vehicles. The implication is that stakeholders in the development of autonomous vehicles can use these findings as a guide to increase the adoption of this technology among consumers.

5. Conclusions and Further Works

The findings reveal several significant factors influencing behavioral intention towards autonomous vehicle adoption in Jakarta. Emphasizing performance expectancy, ease of use, price value, safety assurances, and system quality can positively impact adoption intentions. Surprisingly, social influence, hedonic motivation, and facilitating conditions had negative effects, suggesting that subjective norms and enjoyment aspects are less critical drivers compared to functional benefits in this context.

These insights make valuable contributions by applying and validating an extended UTAUT model to understand technology acceptance factors specifically for autonomous vehicles in Jakarta. The counterintuitive negative effects also highlight unique characteristics of this market, diverging from previous studies. For autonomous vehicle developers and marketers, these findings suggest prioritizing demonstrations of vehicle performance, safety features, and cost-value propositions over social desirability or hedonic appeals.

However, this study faced certain limitations such as the use of a general population sample versus targeted groups like existing vehicle owners. Future research could explore additional factors like government policies, infrastructure readiness, and cultural influences on autonomous vehicle acceptance. Overall, this study provides a robust empirical analysis offering key theoretical and practical implications for stakeholders in autonomous vehicle development and adoption strategies for the Jakarta market.

References

Abduljabbar, R., Dia, H., Liyanage, S., & Bagloee, S. A. (2019). Applications of artificial intelligence in transport: An overview. *Sustainability*, *11*(1), 189. https://doi.org/https://doi.org/10.3390/su11010189

Bearden, W. O., Netemeyer, R. G., & Teel, J. E. (1989). Measurement of consumer susceptibility to interpersonal influence. *Journal of Consumer Research*, *15*(4), 473–481. https://doi.org/https://doi.org/10.1086/209186

Bendiab, G., Hameurlaine, A., Germanos, G., Kolokotronis, N., & Shiaeles, S. (2023). Autonomous vehicles security: Challenges and solutions using blockchain and artificial intelligence. *IEEE Transactions on Intelligent Transportation Systems*, *24*(4), 3614–3637. https://doi.org/https://doi.org/10.1109/TITS.2023.3236274

Bennett, D. H. S., Anaza, N. A., & Andonova, Y. (2022). Big names and small price tags: an analysis of celebrity endorsement on consumers' perceptions of price, quality, and intent to purchase. *Journal of Marketing Theory and Practice*, *30*(2), 154–171. https://doi.org/10.1080/10696679.2021.1896952

Chen, H.-K., & Yan, D.-W. (2019). Interrelationships between influential factors and behavioral intention with regard to autonomous vehicles. *International Journal of Sustainable Transportation*, *13*(7), 511–527. https://doi.org/10.1080/15568318.2018.1488021

Chen, S., Kuhn, M., Prettner, K., & Bloom, D. E. (2019). The global macroeconomic burden of road injuries: estimates and projections for 166 countries. *The Lancet Planetary Health*, *3*(9), e390–e398. https://doi.org/https://doi.org/10.1016/S2542-5196(19)30170-6

Cunneen, M., Mullins, M., & Murphy, F. (2019). Autonomous vehicles and embedded artificial intelligence: The challenges of framing machine driving decisions. *Applied Artificial Intelligence*, *33*(8), 706–731. https://doi.org/https://doi.org/10.1080/08839514.2019.1600301

Dirsehan, T., & Can, C. (2020). Examination of trust and sustainability concerns in autonomous vehicle adoption. *Technology in Society*, *63*, 101361. https://doi.org/10.1016/j.techsoc.2020.101361

Endah, P. E., Umar, N., Suharyono, S., & Andriani, K. (2017). Study on destination image, satisfaction, Trust and Behavioral Intention. *Russian Journal of Agricultural and Socio-Economic Sciences*, *61*(1), 148–159.

International, S. (2021). *SAE Levels of Driving Automation™ Refined for Clarity and International Audience*. Society of Automotive Engineers (SAE).

Keszey, T. (2020). Behavioural intention to use autonomous vehicles: Systematic review and empirical extension. *Transportation Research Part C: Emerging Technologies*, *119*, 102732. https://doi.org/10.1016/j.trc.2020.102732

Khatimah, H., Susanto, P., & Abdullah, N. L. (2019). Hedonic motivation and social influence on behavioral intention of e-money: The role of payment habit as a mediator. *International Journal of Entrepreneurship*, *23*(1), 1–9.

Khayyam, H., Javadi, B., Jalili, M., & Jazar, R. N. (2020). Artificial intelligence and internet of things for autonomous vehicles. In *Nonlinear approaches in engineering applications: Automotive Applications of engineering problems* (pp. 39–68). Springer.

Korkmaz, H., Fidanoglu, A., Ozcelik, S., & Okumus, A. (2021). User Acceptance of Autonomous Public Transport Systems (APTS): Extended UTAUT2 Model. *Journal of Public Transportation*, *23*(1). https://doi.org/10.5038/2375-0901.23.1.5

Krakul. (2020). *Understanding Autonomous Technology and its Uses*. Krakul.Eu.

Lichtenstein, D. R., Ridgway, N. M., & Netemeyer, R. G. (1993). Price perceptions and consumer shopping behavior: a field study. *Journal of Marketing Research*, *30*(2), 234–245. https://doi.org/https://doi.org/10.1177/002224379303000208

Ma, Y., Wang, Z., Yang, H., & Yang, L. (2020). Artificial intelligence applications in the development of autonomous vehicles: A survey. *IEEE/CAA Journal of Automatica Sinica*, *7*(2), 315–329. https://doi.org/https://doi.org/10.1109/JAS.2020.1003021

Nahla Aljojo, B. A. (2020). Investigating effort expectancy and facilitating conditions affecting behavioral intention to use mobile learning. *Journal Of Southwest Jiaotong University*, *55*(5).

https://doi.org/10.35741/issn.0258-2724.55.5.14

NAIC. (2022). *Autonomous Vehicles*. National Association of Insurance Commissioner (NAIC).

Nascimento, A. M., Queiroz, A. C. M., Vismari, L. F., Bailenson, J. N., Cugnasca, P. S., Junior, J. B. C., & de Almeida, J. R. (2019). The role of virtual reality in autonomous vehicles' safety. *2019 IEEE International Conference on Artificial Intelligence and Virtual Reality (AIVR)*, 50–507. https://doi.org/https://doi.org/10.1109/AIVR46125.2019.00017

Nastjuk, I., Herrenkind, B., Marrone, M., Brendel, A. B., & Kolbe, L. M. (2020). What drives the acceptance of autonomous driving? An investigation of acceptance factors from an end-user's perspective. *Technological Forecasting and Social Change*, *161*, 120319. https://doi.org/https://doi.org/10.1016/j.techfore.2020.120319

Nordhoff, S., Louw, T., Innamaa, S., Lehtonen, E., Beuster, A., Torrao, G., Bjorvatn, A., Kessel, T., Malin, F., Happee, R., & Merat, N. (2020). Using the UTAUT2 model to explain public acceptance of conditionally automated (L3) cars: A questionnaire study among 9,118 car drivers from eight European countries. *Transportation Research Part F: Traffic Psychology and Behaviour*, *74*, 280–297. https://doi.org/10.1016/j.trf.2020.07.015

Palau-Saumell, R., Forgas-Coll, S., Sánchez-García, J., & Robres, E. (2019). User acceptance of mobile apps for restaurants: An expanded and extended UTAUT-2. *Sustainability*, *11*(4), 1210. https://doi.org/https://doi.org/10.3390/su11041210

Shi, X., Wang, Z., Li, X., & Pei, M. (2021). The effect of ride experience on changing opinions toward autonomous vehicle safety. *Communications in Transportation Research*, *1*, 100003. https://doi.org/https://doi.org/10.1016/j.commtr.2021.100003

Sudirman, A., Butarbutar, N., & Lie, D. (2022). Analysis of the effect of performance expectancy, effort expectancy, and lifestyle compatibility on behavioral intention QRIS in Indonesia. *International Journal of Scientific Research and Management*, *10*(11), 4203–4211.

Tusyanah, T., Wahyudin, A., & Khafid, M. (2021). Analyzing factors affecting the behavioral intention to use e-wallet with the UTAUT model with experience as moderating variable. *Journal of Economic Education*, *10*(1), 113–123. https://doi.org/10.15294/JEEC.V9I2.44824

Utomo, P., Kurniasari, F., & Purnamaningsih, P. (2021). The effects of performance expectancy, effort expectancy, facilitating condition, and habit on behavior intention in using mobile healthcare application. *International Journal of Community Service & Engagement*, *2*(4), 183–197.

Vaezipour, A., Rakotonirainy, A., & Haworth, N. (2015). Reviewing in-vehicle systems to improve fuel efficiency and road safety. *Procedia Manufacturing*, *3*, 3192–3199. https://doi.org/https://doi.org/10.1016/j.promfg.2015.07.869

Zhong, Y., & Moon, H. C. (2020). What drives customer satisfaction, loyalty, and happiness in fast-food restaurants in China? Perceived price, service quality, food quality, physical environment quality, and the moderating role of gender. *Foods*, *9*(4), 460. https://doi.org/10.3390/foods9040460