

THE APPLICATION OF THE TECHNOLOGY ACCEPTANCE MODEL (TAM) METHOD FOR THE ACCEPTANCE OF AUTONOMOUS TRUCKS AS LOGISTICS DELIVERY SERVICES

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Abstract. Current technological advances have brought new technologies in the field of logistics delivery, and Autonomous Trucks are one of them. New technology must receive special attention from the government, logistics stakeholder, and the public by working together to make it happen. The acceptance of Autonomous Trucks technology by logistic shipping service companies is an important factor in the procurement process of these trucks. In this research, the Technology Acceptance Model (TAM) has been designed to study user acceptance of new technology applications. The purpose of this study was to determine the interest of logistic delivery service companies towards autonomous trucks based on the technology acceptance model questionnaire as the main research methodology. It uses a quantitative approach based on the Technology Acceptance Model (TAM) to be able to become an innovative solution that prioritizes these aspects. Related constructs for evaluation are: Perceptions of Use, Perceptions of Easy Use, Behavioral Intention, and Actual Use. All of these constructions are modified to fit the research context. The results of this study represent a series of approaches that will be applied to examine the suitability of autonomous trucks in the progress of logistics delivery in Indonesia.

Keywords: Technology acceptance model (TAM), technological advancements, autonomous trucks, logistics delivery drivers, new technology

1. Introduction

Community's interest in using technology for work safety increased from 2000 to 2010 with a rate of 270% (Nnaji et al. 2020). Autonomous truck technology – also known as an autonomous vehicle (AV) is characterized as a system that has been developed into a truck vehicle which is capable of making decisions independent on human interference. It relies on artificial intelligence (AI), sensors and big data to analyze information, adapt to changing circumstances, and handle complex situations as a substitute for human judgment, as the latter would no longer be needed for conventional vehicle operations such as lane-changing, parking, collision avoidance and braking (Taeihagh and Lim 2019; West 2021). Automatic vehicle technology (AV) has changed the way a driver operates the vehicle. The biggest change is in the area of division of tasks and controls between drivers and autonomous vehicles (Wilson et al. 2020). Autonomous vehicles are useful in improving safety, comfort, reliability, and equality; increasing empty spaces on the road, reducing parking spaces, and improving the environmental friendliness of the vehicle (if the vehicle is 100% electric) (U.S. Energy Information Administration 2017), (Owczarzak and Zak 2015).

In addition, the adaptation of new technological innovations to society needs to be taken into account to ensure the success of this system (Madigan et al. 2016). For Autonomous Trucks to be successfully implemented in a short time, social acceptance needs to be gained. In addition, the anticipation for the impacts of adopting them from the users' perspective needs to be researched in-depth (Koul and Eydgahi 2018). Significant changes will occur in the internal and external environment of the car and truck business in the future, which results in companies having to prepare themselves and be quick to adapt to new circumstances (Fritschy and Spinler 2019).

The automation in cars driven today has been gradually increasing among consumers of the automobile industry. The automated technologies such as collision avoidance system, park assist, adaptive cruise control, and lane change assist have been implemented in many cars as driver assistance and are available commercially. These systems provide manufacturers collective technologies for supporting the manufacture of AV (Koul and Eydgahi 2018).

The Technology Acceptance Model (TAM) by Davis is a model that is used to predict and explain users' acceptance of information technologies and it has been confirmed to be reliable and valid in several replications and applications of technologies and user populations in original scales measurement. TAM models the system usage of intentions and behavior as a function of perceived usefulness (PU) and perceived ease of use (PEOU) (Davis and Venkatesh 1996). PU defines how big a user believes that using a particular system will enhance the task performance. PEOU defines how strong an individual believes that using a particular system is free of physical and mental efforts.

1.1 Literature Review

Autonomous Truck

The definition of an autonomous vehicle according to the US Department of Transportation (DOT) is "a vehicle that has a safety control function (steering, accelerator and braking) carried out without a driver in the vehicle" (U.S. Energy Information Administration 2017). Autonomous vehicles can reduce drivers' stress and boredom, and increase productivity. These vehicles can be conditioned like a moving office and bedroom, which allow passengers to rest or work while traveling. This reduces the unit cost of travel time (cost per hour) (Todd Litman 2019).

According to the definition of the Society of Automotive Engineers International (SAE), autonomous vehicles are categorized into 5 levels based on the level of drivers' involvement during operation, namely:

Level 0 (Drivers only) - No automation; human drivers do all the driving tasks.

Level 1 (Assisted) - The autonomous system can help human drivers in certain tasks (for example: environment and operating conditions) of driving.

Level 2 (Partial Automation) - The autonomous system performs driving tasks in several parts and humans monitor the driving conditions while carrying out the remaining driving tasks.

Level 3 (Conditional Automation) - The autonomous system performs many predetermined driving tasks and the human drivers do their job to take back the control when the system automatically requests.

Level 4 (High Automation) - The system automatically carries out the tasks of driving and monitoring which have been specified. Humans do not need to take back control when operating. Human drivers assume control outside the specified use case.

Level 5 (Full Automation) - The automatic system performs all driving tasks in all cases that can be carried out by human drivers (U.S. Energy Information Administration 2017).

In this study, **Level 3** Autonomous Trucks were chosen as the study sample.

Technology Acceptance Model (TAM)

TAM was introduced by Davis (1986) (Davis and Venkatesh 1996). Theory of Reasoned Action (TRA) is the basis of the theoretical TAM model. This model is a model that is commonly seen in the actions desired by the user. Users are determined by subjective attitudes and norms associated with agreed actions (Taeihagh and Lim 2019). According to

TAM there are 2 main relevances namely perceived benefits and perceived ease of use (FIGURE 1) (Davis and Venkatesh 1996).

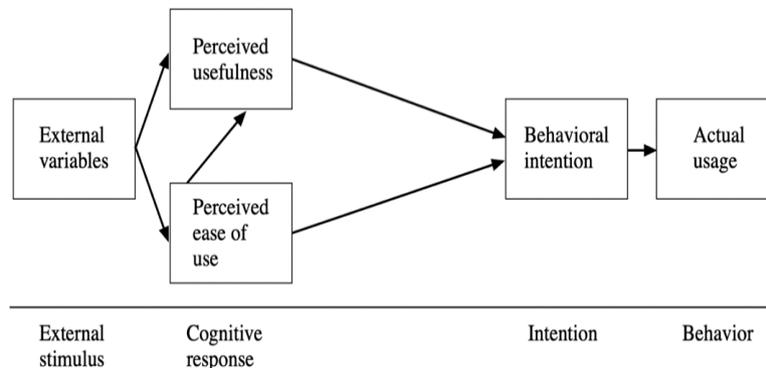


FIGURE 1
TAM model. Adapted from Davis & Venkatesh, 1989

The attitude paradigm from psychology, which specifies how to measure the behavior components of attitudes, distinguishes beliefs and attitude proposed by Fishbein and Ajzen and are adopted by the TAM theory principles (Abu-Dalbouh 2013).

TAM models the system usage of intentions and behavior as the functions of perceived usefulness (PU) and perceived ease of use (PEOU) to determine and explain whether users accept the technology or not (Davis and Venkatesh 1996). These are transferable to different user populations and different kinds of technologies (Abu-Dalbouh 2013).

The success of the acceptance of new technologies depends on the acceptance and the trust of the drivers. Shown by the existence of several frameworks and methodologies, the most prominent one is to assess the usefulness and satisfaction of the system (Revina et al. 2019). Several studies found similar variables related to attitude and usage [10]. The Technology Acceptance Model (TAM) has been in use for more than three decades and has successfully predicted the interest in using technology (Revina et al. 2019).

Behavioral intention of use (BI) is determined by one's attitude towards use (A) and perceived usefulness (U) with regression: $BI = A + U$ (Davis and Venkatesh 1996). All of them make TAM the right choice for a framework to understand how others respond to technological innovations (Davis and Venkatesh 1996).

2. Methodology

This research uses descriptive quantitative research methodology with a Likert scale consisting of 5 answer choices namely SS: Strongly Agree (5), S: Agree (4), RG: Doubtful / Neutral (3), TS: Disagree (2), STS : Strongly Disagree (1) (Revina et al. 2019) to find out and analyze the interests of logistics service delivery companies using autonomous trucks in the future. According to TAM Model, the variable and hypothesis for this research are defined as follows:

Hypothesis H1, Perceived Ease of Use influences toward Perceived Usefulness:

Autonomous Trucks are easy to use so they are useful for logistics distribution.

Hypothesis H2, Perceived Ease of Use and Perceived Usefulness influences toward Behavioral Intention:

The ease of operating the Autonomous Trucks and the benefits gained from them give the Logistics freight forwarding an intention to use the Autonomous Trucks.

Hypothesis H3: Behavioral Intention influences toward Actual Usage:

The interests in using the Autonomous Trucks in logistics distribution makes them the logistics transportation vehicles that are widely used in Indonesia.

The Hypothesis above is depicted on Figure 2 below:

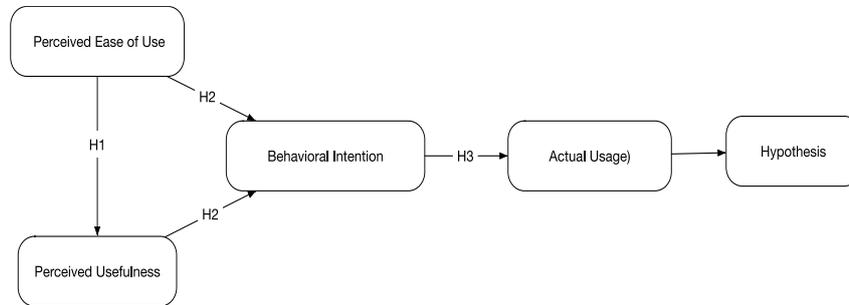


FIGURE 2
TAM hypothesis research framework

2.1 Data Collection

The process of collecting data uses a questionnaire for sampling using Non-Probability Sampling (Non-Random Sample). Participants were obtained by purposive method in accordance with predetermined criteria. Data were randomly drawn from minimum 30 respondents from each group (Gay, Mills 2009). In this research, 37 respondents from a group of logistics distribution service companies were obtained by using the google questionnaire. Questionnaires are data collection techniques done by distributing questions or statements to be answered by respondents, which can be done directly in writing or with applications such as Google forms [14].

3. Discussion and Results

3.1 Discussion

Although many logistical shipping companies in several developed countries have tested autonomous trucks, they are forecast to start operating commercially on the street in 2030. Autonomous trucks will become the new technology that has huge benefits for the world of logistics delivery. However, the existence of these trucks in Indonesia is still not popular enough and it is yet to be accepted by logistic shipping stakeholders. Not many logistic people know about autonomous trucks and they tend to ignore this new technology. This is due to the fact that there are still many uncertainties regarding the development of autonomous trucks including the benefits, costs, impact of travel and consumer demand. Adequate preparation of infrastructure progress must also be prepared through collaboration between governments, logistics delivery stakeholders, and the community. These facts make Indonesia tend to be pessimistic about this technology, in contrast to developed countries who are optimistic about this autonomous truck technology. The biggest consideration for the implementation is the problems related to the fact that many roads in Indonesia need to be fixed. Years of testing and regulatory approval are required before autonomous trucks can be available in a country. Autonomous vehicles will initially be available at high prices with limited options and it will take decades to have a lower model in affordable price.

3.2 Result

3.2.1. Validity

Valid instruments can be used to determine what should be measured to obtain valid data [14]. The number of correlations obtained (r count) must be compared with the critical number of the product-moment correlation table (r table) at the level of 5%. An attribute is said to be valid if the value of r counts $>$ r Table ($r_h > r_t$) and is

positive. To find the r table, we use the formula $dk = N - 2$, then $dk = 35$ and the table at position 35 with a significant level of 5% is 0.3246.

Validity test is performed on variables X1, X2, X3 and X4. Below are the results of the validity test of each variable:

Based on the validity of all variables in the questionnaire statements X1 (Perceived Usefulness), X2 (Perceived Ease of Use), X3 (Behavioral Intention) and X4 (Actual Usage), it can be seen that there are no invalid statements because they have the value of Corrected Item-Total Correlations > 0.3246 . Thus, the number of statements that deserve to be analyzed for variables X1, X2, X3 and X4 is 15.

3.2.2 Reliability

A reliability test is used to measure a research questionnaire which is an indicator of a variable. Instruments are considered reliable if they can be used repeatedly to measure the same object with the same results [14]. Reliability test is done by using the retest test technique (retesting), with reference to Cronbach's alpha, namely the level of reliability or the price of r (alpha) reaching 0.80. If the alpha is > 0.866 , then reliability is perfect. If the alpha is between 0.80-0.866, then reliability is high. If the alpha is 0.80 - 0.866, then the reliability is moderate. If the alpha is < 0.80 , then the reliability is low. If the alpha is low, it is possible that one or more items are not reliable. From the output table, the reliability test results above show that the Cronbach Alpha value for the statements X1 (Perceived Usefulness), X2 (Perceived Ease of Use), X3 (Behavioral Intention) and X4 (Actual Usage), which are used in this study is greater than 0.80. So, it can be concluded that X1, X2, X3 and X4 are of high reliability.

3.2.3 Central Tendency and Variability

		Statistics			
		x1	x2	x3	x4
N	Valid	37	37	37	37
	Missing	0	0	0	0
Skewness		-1.948	-.569	-1.301	-1.210
Std. Error of Skewness		.388	.388	.388	.388
Kurtosis		4.704	.302	1.402	1.078
Std. Error of Kurtosis		.759	.759	.759	.759

TABEL 1

Statistics Technology acceptance model (TAM): Processed Data SPSS Version 1.0.0.1461

3.2.3.1 Perceived Ease of Use influences toward Perceived Usefulness

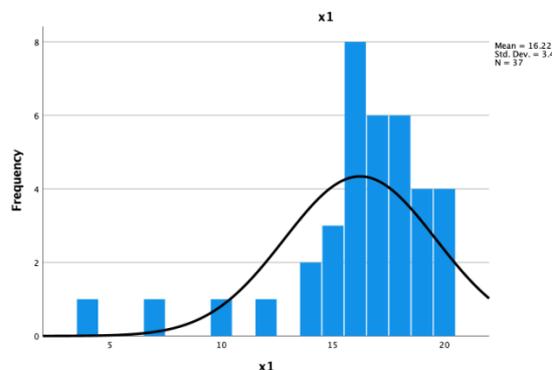


FIGURE 3

Histogram Technology acceptance model: Processed Data SPSS Version 1.0.0.1461

Figure 3 shows the histogram for the Tracking Perceived Usefulness (X1). The calculation of skewness and kurtosis from the data gives the following results: The skewness of -1.948 gives the meaning that the distribution curve has a negative slope that the tail protrudes or enlarges to the right. Kurtosis of 4.704 means that it tends to be greater than 1. This gives the meaning that the curve is a moderate or Leptocurtic distribution.

Table 2
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.827 ^a	.684	.675	1.940

a. Predictors: (Constant), x2

R Square result dependency PU to PEOU T-test result

Table 3

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
x1.1	37	4.00	.972	.160
x1.2	37	4.35	.857	.141
x1.3	37	3.95	1.129	.186
x1.4	37	3.92	1.140	.187

T-Test Mean Result of X1

One-Sample Test

Test Value = 3

	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
x1.1	6.259	36	.000	1.000	.68	1.32
x1.2	9.593	36	.000	1.351	1.07	1.64
x1.3	5.096	36	.000	.946	.57	1.32
x1.4	4.905	36	.000	.919	.54	1.30

Table 4

T-Test Significant Value Result of X1

3.2.3.2 Perceived Ease of Use and Perceived Usefulness influences toward Behavioral Intention

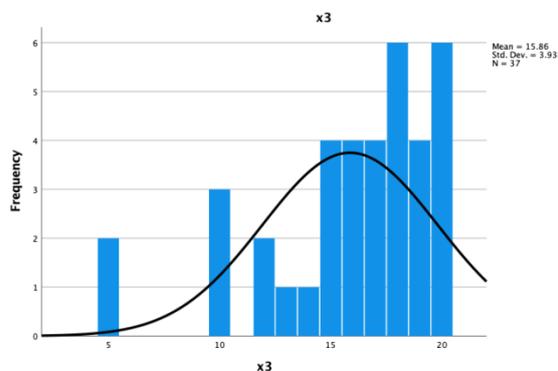


FIGURE 4

Histogram Technology acceptance model: Processed Data SPSS Version1.0.0.1461

Table 5

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.830 ^a	.689	.670	2.261

a. Predictors: (Constant), x1, x2

R Square result dependency BI to PU and PEOU

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
x3.1	37	3.76	1.234	.203
x3.2	36	4.03	1.055	.176
x3.3	37	4.03	1.013	.167
x3.4	37	4.16	1.041	.171

Table 6

T-Test Mean Result of X3

One-Sample Test

Test Value = 3

	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
x3.1	3.731	36	.001	.757	.35	1.17
x3.2	5.844	35	.000	1.028	.67	1.38
x3.3	6.164	36	.000	1.027	.69	1.36
x3.4	6.789	36	.000	1.162	.82	1.51

Table 7

T-Test Significant Value Result of X3

Figure 4 shows the histogram for the Behavioral Intention (X3). The calculation of skewness and kurtosis from the data gives the following results: The skewness of -1.301 gives the meaning that the distribution curve has a negative slope that the tail protrudes or enlarges to the right. Kurtosis of 1.402 means that it tends to be greater than 1. This gives the meaning that the curve is a moderate or Leptocurtic distribution.

3.2.3.3 Behavioral Intention influences toward Actual Usage

FIGURE 5

Histogram Technology acceptance model: Processed Data SPSS Version 1.0.0.1461

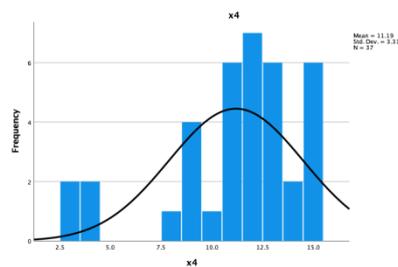


Figure 5 above shows the histogram for the Behavioral Intention (X4). The calculation of skewness and kurtosis from the data gives the following results: The skewness of -1.201 gives the meaning that the distribution curve has a negative slope that the tail protrudes or enlarges to the right. Kurtosis of 1.078 means that it tends to be greater than 1. This gives the meaning that the curve is a moderate or Leptokurtic distribution.

R Square result dependency AU to BI:

Table 8

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.751 ^a	.564	.551	2.220

a. Predictors: (Constant), x3

T-Test Significant Value Result of X3

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
x4.1	37	3.51	1.146	.188
x4.2	37	4.08	1.299	.214
x4.3	37	3.59	1.189	.196

Table 9

T-Test Mean Result of X4

One-Sample Test
Test Value = 3

	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
x4.1	2.727	36	.010	.514	.13	.90
x4.2	5.062	36	.000	1.081	.65	1.51
x4.3	3.041	36	.004	.595	.20	.99

Table 10

T-Test Significant Value Result of X4

From the above calculation we get the RSquare values from each of variable which are shown in the table below:

Variables	R Square
Perceive Usefulness (PU)	0,675
Perceived Ease of Use (PEOU)	0.0000
Behavioral Intention (BI)	0,689
Actual Usage (AU)	0,564

Table 11

RSquare of PU, PEOU, BI and AU

Based on the Table 11, PU has an RSquare value of 0.65, which means that PEOU is able to influence the PU variable by 67.5%. RSquare value is also found in BI which is influenced by PU and PEOU of 0.689 or 69.9%. Finally, the AU with a value of 0.564 or 56.4% is influenced by BI.

Furthermore, the T-test results from each variable obtained Mean and Significant value with test value of $\Pi = 3$ (Neutral Response) and Significant rule of $p = 0,05$ as shown in the table below:

Hypothesis	Mean	Sig. Value
PEOU influences toward PU	4,055	0,000
PEOU and PU influence toward BI	3,965	0,00025
BI influences toward AU	3,74	0,00466

Table 12
Mean and Significant value of PU, PEOU, BI and AU

Table 12 shows that Mean value of each variable is above Π (neutral response) and Significant value of each variable is smaller than p . So, it can be concluded that the test result is significant and the survey result gives positive values.

4. Conclusion

Based on the results of research that has been done, it can be concluded that Autonomous trucks provide benefits and are useful for Logistics freight forwarders and they are considered easy to implement. Logistics freight forwarders intends to use Autonomous Truck, so they will be widely used as a means of transportation logistics delivery in Indonesia.

Indonesian logistics stakeholders can start preparing themselves with Autonomous Truck technology that has been developed in various developed countries so that the Indonesian logistics world is more advanced and can benefit the community, especially the logistics stakeholders.

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