Technology Acceptance Model (TAM) For Smart Lighting System in XYZ Company

Teja Laksana[1], Novian Anggis Suwastika[2], Muhammad Al Makky[3]

***Abstract*—This research was conducted to identify and measure the significance of the factors or variables that influence technology acceptance for a smart lighting system built based on the internet of things (IoT) and artificial intelligence (AI) technology implemented in XYZ company. The smart lighting system implemented was a dedicated smart lighting system for office space (more than 20 m^2 to 60 m^2) to sense the conditions and make automatic adjustments to room conditions. Before mass production, the smart lighting system would be reviewed for its technology acceptance by users using the technology acceptance technology model (TAM). TAM is a method used to identify factors that affect the technology acceptance based on the functionality of the smart lighting system. Based on the smart lighting purposes and conditions from the XYZ company, six variables influencing the acceptance of smart lighting systems, namely reliability and accuracy (RA), perceived ease of use (PEOU), perceived usefulness (PU), attitude toward using (ATU), behavior intention (BI), and actual system use (AU) were proposed. These variables influenced each other and formed eight hypotheses, namely H1, H2, H3, H4, H5, H6, H7, and H8. Using the purposive sampling technique, validity test with product-moment correlation, and Cronbach's alpha validity test, five hypotheses had a positive and significant effect, namely H1, H4, H5, H6, and H7. The RA variable influenced the PU variable, the PU variable influenced the ATU variable, the PEOU variable affected the ATU variable, the ATU variable influenced BI, and the PU variable affected BI. Meanwhile, the three hypotheses had negative and insignificant impacts, namely H2, H3, and H8. The RA variable did not affect the PEOU, the PEOU variable did not affect the PU, and the BI variable did not affect the AU variable.**

***Keywords*—Smart Lighting, Technology Acceptance Model, Internet of things, Artificial Intelligence.**

I. INTRODUCTION

According to the IEEE, a system can be called the internet of things (IoT) if it can interconnect "things" (which are connected in the system), communicate things via the internet network, and support implementation in various places (ubiquity); the "things" can also perform sensing/actuating, can be embedded in an intelligent system and knowledge function, has extensive communication support, can perform self-configurability, and has programmability features on its "things" [1]. With these capabilities, IoT is one of the fastest-growing technologies in the last ten years; in 2021, as many as 13.8 billion IoT devices were connected, increasing 12.8% from the previous year. Meanwhile, the growth rate of IoT-connected devices is estimated to amount to 30.9 billion devices by 2025 [2]. One of the most significant capabilities of IoT is the ability to embed programs in both the "things" and the platform. The combination of IoT with artificial intelligence (AI) generates the term "smart" for every system or device applying the two technologies.

The term "smart" is used in many smart definitions in various aspects that implement IoT and AI as essential components. An example is a smart home which refers to a house built with multiple devices that communicate with each other via a communication network (internet). Data obtained from sensing or actuating is stored on the internet to be accessed anytime and anywhere. The system can also automatically adapt to the needs of residents [3]–[5]. It can be applied in smart buildings, namely, buildings that can produce, store, and provide energy efficiently and flexibly [6]–[8].

Smart lighting is one of the "smart" concepts that use IoT and AI to automate and manage lighting efficiency systems [9], improve the effectiveness of energy use by controlling lights automatically to minimize wasted energy, using a technical building management system [10], and enhancing functionality and user-centric lighting [11]. There are many publications on smart lighting used to achieve the goals of smart lighting, especially in technical terms to improve performance, efficiency, effectiveness, develop functionality, reliability, or versatility. Several examples of smart lighting publications to achieve this goal were published by [12]–[16].

Smart lighting developed by [16] is intended explicitly for office buildings. All data are stored on a platform that can only be accessed by the company that owns the office. The development of smart lighting was implemented in the XYZ company, which had a building and workspace size of 45 m^2 with seventeen employees in the office. The functionality of smart lighting was that the system could record the activities of employees in the room. In addition, it could adjust the light's brightness based on the number of people in the room and the bright light around the office environment. All data from sensing people's activities and data from light readings in the office environment were sent to the server via the internet for further processing with AI. Subsequently, they were sent back to the lamp as a response to the condition of the office space and sent to the website to be accessed by people who have access rights.

The development of smart lighting aims to be mass-produced and used by companies that have office space. For this reason, it is necessary to study the technology acceptance. The technology acceptance model (TAM) method has been tested and widely implemented to measure the adoption of new technologies based on user behaviors [17]–[21]. In this study,

[1,2,3] *Program Studi Teknologi Informasi Fakultas Informatika, Telkom University, Jl. Telekomunikasi No. 1, Terusan Buahbatu - Bojongsoang, Kec. Dayeuhkolot, Kabupaten Bandung, Jawa Barat. (telp:(022)-7564108;e-mail:*
[1]*tejalaksana@student.telkomuniversity.ac.id,*
[2]*anggis@telkomuniversity.ac.id,* [3]*malmakky@telkomuniversity.ac.id)*

[Received: 18 February 2022, Revised: 28 February 2022]

TAM was used with six external factors that affect technology acceptance. These six factors were derived from the functionality of smart lighting, namely reliability and accuracy (RA), perceived ease of use (PEOU), perceived usefulness (PU), attitude toward using (ATU), behavior intention (BI), and actual system use (AU). Eight initial hypotheses were revealed from the six factors, namely H1, H2, H3, H4, H5, H6, H7, and H8. Then, the results of these hypotheses were tested with the SPSS application. Several tests were carried out to determine whether the hypotheses made were acceptable; these tests included validity, reliability, normality, and regression tests.

The structure of this research writing consists of five sections. Section 1 is the introduction, which discusses IoT and AI technology as the main components of "smart" systems. This section also describes the selection of TAM as a method for measuring the new technology acceptance and how to obtain external factors from the developed smart lighting functionality. Section 2 presents the literature review, discussing the developed smart lighting and TAM. Section 3 offers the research method, which discusses the stages of the research carried out, starting from defining external factors and hypotheses, TAM design, to calculations (validity testing, reliability testing, normality testing, regression testing) to prove the effectiveness of the proposed hypothesis. Section 4 is the result and discussion, showing the results obtained and discussing the results. The last, Section 5, concludes all stages of the research.

II. Smart Lighting and Technology Acceptance Model (TAM)

A. *Smart Lighting*

1) Smart Lighting Review: There are many publications on the development of smart lighting. In this study, literary studies on smart lighting are grouped into two groups: research on smart lighting applied at home (smart home) and smart lighting installed for industrial purposes in the last five years.

Smart lighting is an integral part of a smart home. Many studies show that there is always smart lighting or a concept similar to it in a smart home. Several publications on the smart home are presented in this paper, including publications on the topic of smart lighting, which is one part of the smart home topic. Reference [22] implemented a decision tree using kernel density estimation and improvements of Laplace to predict smart home lighting behavior. Reference [23] made a control system based on energy-aware which one of its components focused on optimizing the energy used for lighting. In 2017, [24] categorized energy management in a smart home found in 308 home energy management products. Most of the products classified were smart lighting. In the same year, [25] developed a smart home prototype with an onboard sensor-based intelligent lighting control with computing on mobile devices. Reference [26] built smart lighting for smart homes, focusing on data communication in their system using narrowband-IoT communication. In 2020, [27] designed smart home management by implementing smart lighting. In the same year, [28] built a smart home that focused on energy efficiency with smart lighting-based solutions. One of the latest studies published in 2021 was [29]. Reference [29] developed smart lighting applications for energy saving and user well-being in residential environments. Based on some examples of these studies, it can be concluded that the significance of smart lighting in smart homes is fundamentally to support energy saving.

TABLE I
HARDWARE SPECIFICATIONS

Component	Specification
Power Supply	Perusahaan Listrik Negara (PLN) 110 VAC -220 VAC 50Hz
Mainboard	- System on chip (SoC) with 802.11 communication using ESP8266EX and Espressif - Flash memory external using ESP-12F - Interface serial UART using K1 and over the air (OTA)
Movement Detector	Proximity sensor with RF Doppler
Ambient Sensor	IC BH1730 using interface I^2C
Dimmable LED	Electric current 350 mA and voltage 48 V using PWM duty cycle
PIN mainboard	- UART TTL (3.3 V logic) data in - UART TTL (3.3 V logic) data out - SCL for I^2 C interface with sensor BH1730 - 1 kHz maximum frequency PWM for LED strip brightness adjustment - Versatile LED indicators (active low)

In the second group, smart lighting, which is capable of optimizing energy and automatically adjusting to user needs, is mainly implemented in industrial areas, which have differences in terms of the comprehensive coverage of the room and the number of lighting devices used. A literature review on smart lighting systems implemented in industrial settings has been arranged [30]. In 2021, [31] published research on smart lighting, specifically in warehouse order picking. In the same year, [32] published research on smart lighting to simulate reduced energy costs in warehouses. Meanwhile, another study built smart LED lighting for energy efficiency in industrial and commercial buildings [33]. Compared to smart lighting in a smart home, the application of smart lighting in industrial or office areas is scarce. It is an excellent opportunity for further research.

2) Smart Lighting for XYZ Company: Smart lighting developed has two objectives. The first objective is to sense the presence of people, the light conditions in the room, and the power used by the lamp. Sensing data is stored on the IoT platform. The second one is to process the results of sensing data and adjust the lights based on the processing results. User requirements were created for smart lighting from these two objectives, as translated in the following.

- Functionalities for sensing data include motion data, ambient light data, and electrical power consumption data.
- Functionalities for data communication between smart lighting devices and IoT platforms using local computer networks and internet networks.

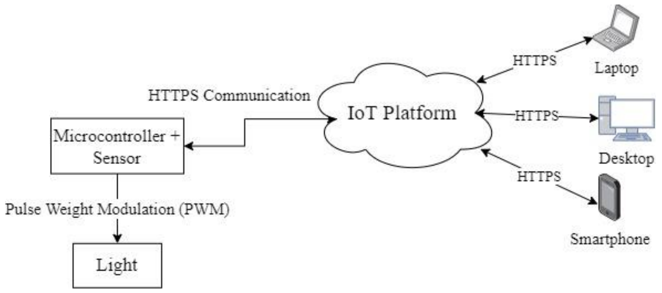

Fig. 1 End node communication.

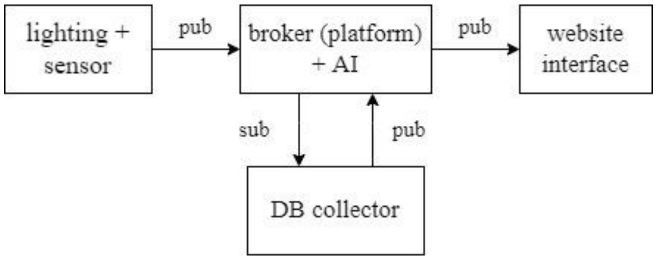

Fig. 2 Data flowchart for smart lighting.

- Functionalities for managing smart lighting system information include database, AI, automatic or manual light management, and system security.

The system specifications to support data sensing functionality are shown in Table I. The components for data communication functionality are end node communication and data flowcharts. The end node communication is shown in Fig. 1; there are three communication components: the smart lighting component (light, sensor, and microcontroller), the IoT platform component, and the user-owned access device component. The three components communicate using the HTTPS protocol. The data transmitted between the smart lighting component and the IoT platform are id_light, id_room, id_building, and light dense. Meanwhile, the data sent between the IoT platforms to the user's device is all data in the systems, such as data on lighting conditions, room conditions, lighting or computing settings, granting access rights, and management data in the systems.

The second component is the data flowchart on the smart lighting; as shown in Fig. 2, the smart device sends the data in the room to the broker. Then, the broker sends the data to the DB collector. The DB collector will check the data transmitted by the broker; if the data is correct, the DB collector will subscribe to the broker. The IoT server will process the data obtained from smart devices and applications. The results of the processed data will be displayed on the web application.

The functionality for managing smart lighting information consists of database components, artificial intelligence, light managing system, and system security. The specifications of this functionality are shown in Table II.

The smart lighting at XYZ company is implemented in a room that has a floor plan, as shown in Fig. 3. There are seventeen lights in the room installed on the employee's desk. During the testing, which coincided with the COVID-19 pandemic, the number of XYZ company employees who came to work varied following local government policies. An

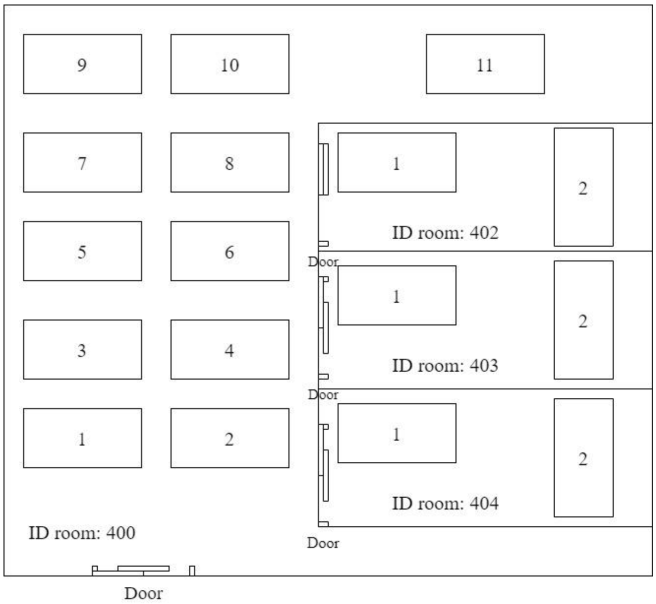

Fig. 3 Floor plan.

TABLE II
SMART LIGHTING SYSTEM SPECIFICATIONS

Type	Specification
Database	- PostgreSQL for mobile apps - MySQL for web apps
Artificial intelligence algorithm	- Hierarchical hidden Markov model (HHMM) for activity recognition
Lighting management system	- Web apps and mobile apps - Communications using API web services
Security	- Password and access right - Audit trail

example of the application for managing smart lighting is shown in Fig. 4, while a picture of the smart lighting installation process in the XYZ company room is shown in Fig. 5.

B. *Technology Acceptance Model*

TAM is one model that researchers widely used to measure users' technology acceptance and use. The TAM model published in the previous research used the PU and PEOU as the user acceptance's determinant factors [34]. The design of the TAM model in [34] with variables used to identify technology acceptance is shown in Fig. 6. The TAM model continues to evolve from the original model, which impacts external variables in the new model. The second TAM model was proposed in 2000, detailing perceived usefulness and usage intentions on aspects of social influence and cognitive instrumental processes [35]. The subsequent development combined the second TAM model with the unified theory of acceptance and use of technology (UTAUT) model [36].

TAM can also measure user IoT technology acceptance in the IoT field. Several studies on the application of TAM to measure the acceptance of IoT technology were published by [37] in 2017 to understand university students' awareness of using IoT by using two groups of variables, namely perceived

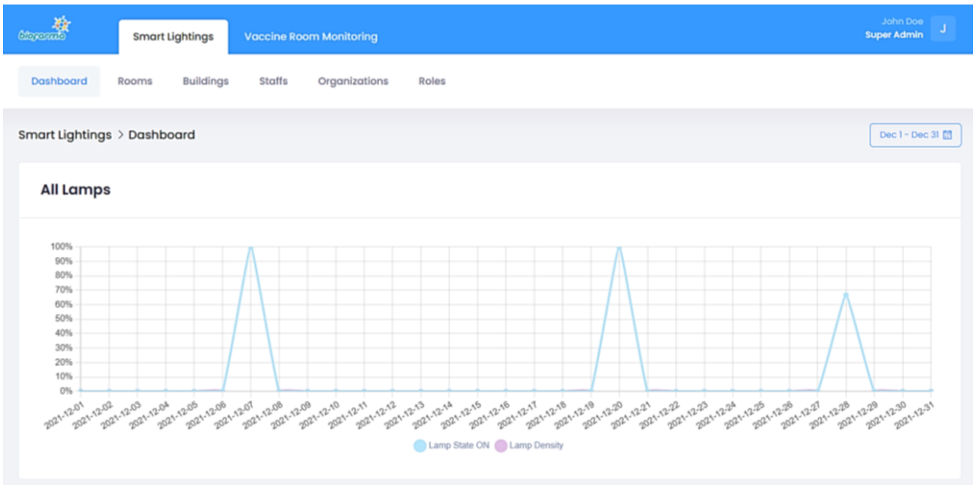

Fig. 4 Interface of smart lighting web applications.

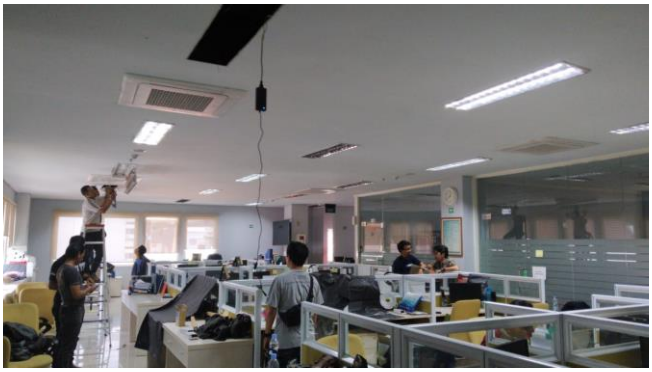

Fig. 5 Installation of smart lighting in XYZ company.

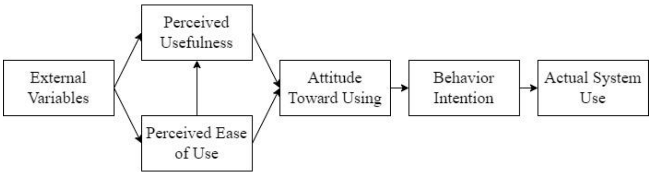

Fig. 6 Technology acceptance model [34].

variables and extended intention of using variables. Reference [38] conducted the following research by investigating the five potential user factors and TAM proposed in the technology acceptance model to determine the significance of the proposed model in the IoT technology acceptance in smart homes. Two other studies that applied TAM to measure IoT technology published in 2017 were the publication by [39] and [40]. Reference [39] conducted user's reuse intention of using TAM with a case study in Korea; meanwhile, [40] investigated the relevance of the technological autonomy of IoT services in the retail sector.

In 2018, research on the application of TAM to IoT technology was published by [41]. It evaluated the intention to use IoT products with TAM. In 2019, [42] implemented TAM to measure the acceptance of IoT technology used for water management in local municipalities. Still, in 2019, [43] reviewed the factors that influence customers receiving IoT services. Reference [44] proposed the real estate stakeholders technology acceptance model (RESTAM) to identify the big nine disruptive technologies in smart real estate, one of which was IoT.

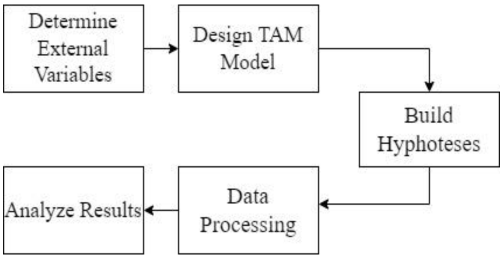

Fig. 7 Research method.

Reference [45] conducted an empirical study on the acceptance of the IoT-based smart meter technology in Malaysia to identify electricity-saving knowledge and awareness. In education, [46] published research on users' intentions to develop IoT using TAM. Reference [47] assessed consumer behavior using IoT products and applications with TAM. Published in 2021, [48] analyzed user behavioral intentions in using TAM-based IoT Smartboard devices. From the search results for publications from various sources, the application of TAM to measure smart lighting products has not been found. This research can be used as a reference for research on the acceptance of smart lighting technology.

III. RESEARCH METHOD

The research method used in this study is shown in Fig. 7. The first stage is to identify the factors of system functionality; the next stage is to discuss the design of the TAM model. Based on the previous stage's results, the next stage is to build a hypothesis, then perform four tests, namely validity, reliability, normality, and regression testing. The last stage of this research method is results & discussion. For details, each stage is explained below.

A. Determining External Variables

The step to determine the external variables that affect the smart lighting technology acceptance was to explore the external variables according to the type of technology. After obtaining a list of external variables, the next step was to check

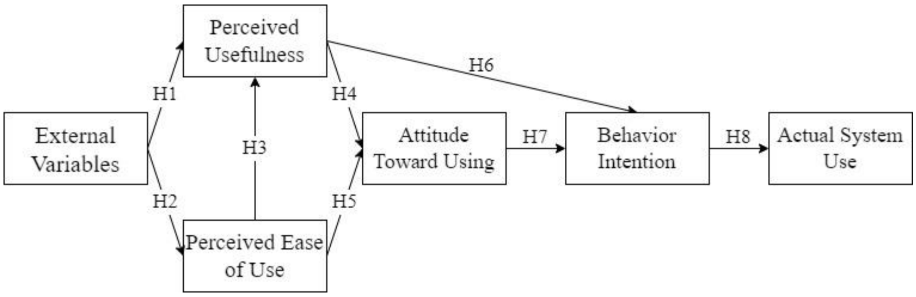

Fig. 8 Design of the TAM model.

the suitability of the variables obtained with the smart lighting functionality. Some of the references used as a reference in this stage were research conducted by [49]–[51].

B. Designing the TAM Model for Smart Lighting

After obtaining the external variables in the previous stage, the relationship between the variables and the form of the hypothesis was determined. This process was taken to build the TAM model.

C. Building Hypothesis

After selecting the variables used to measure smart lighting technology acceptance, the next step was to map between variables to measure the effect of these variables. The mapping of these variables forms hypotheses for the smart lighting technology acceptance.

D. Data Processing

Questionnaires were created and distributed to users of smart lighting technology to prove the hypothesis. Questionnaires were distributed online to sixteen employees of company XYZ who used smart lighting. The results obtained were then processed quantitatively to test the validity, reliability, normality, and regression [52]. Technology acceptance is defined as an attitude towards technology influenced by various factors. After users buy and use a product, acceptance is essential in identifying factors affecting technology use. In this study, to measure the factors that influence the implementation of smart lighting in XYZ company, questionnaires were distributed to employees who used smart lighting with a total population of seventeen people. Using the Slovin formula and with an error margin of 5%, the minimum number of sample sizes was sixteen people.

E. Result Analysis

The last stage was the result analysis. In this stage, data processing results were analyzed to prove the built hypothesis.

IV. Results and Discussion

A. External Variables

Based on the smart lighting functionality and a list of external variables commonly used in TAM, in this study, the selected external variables were variables related to the function of sensing the presence of people in the room and the function of the process of sensing the data and adjusting the lights. The selected variables are RA, PEOU, PU, ATU, BI, and AU. The following is an explanation of each variable used in this study.

1) Reliability and Accuracy (RA): RA is part of the system characteristic, indicating that the system can work reliably and produce accurate output. Smart lighting reliability is measured based on a system that can work according to its function if there are employees, for example, detecting employees, sending data to the IoT platform, and adjusting lighting according to conditions. Meanwhile, smart lighting accuracy is measured based on the suitability of bright light with predetermined requirements and user comfort.

2) Perceived Ease of Use (PEOU): In PEOU, users believe that using the system or technology is effortless [34].

3) Perceived Usefulness (PU): In PU, users believe that using the system or technology can improve their work performance [34].

4) Attitude Toward Using (ATU): ATU is a user’s assessment of the desirability of using a specific information system application [53].

5) Behavior Intention (BI): BI is defined as the strength of a person’s intention to perform a particular behavior [54].

6) Actual System Use (AU): AU is the actual conditions of the use of technology by the user [34].

B. Design of the TAM Model

After completing determining external variable stage, a TAM model design for smart lighting was built. The TAM design was the original TAM design proposed by Davis with external variables, namely reliability, and accuracy. The reason for choosing the original TAM design is research examining TAM’s application for smart lighting implemented in office spaces has not been conducted yet. Meanwhile, the reason for selecting reliability and accuracy as external variables is that the main purpose of building smart lighting is to achieve reliability and accuracy in supporting employee activities in office spaces and leading people to use smart lighting.

The image of the TAM design proposed in this study is shown in Fig. 8. The RA variable influences the PU variable and the PEOU variable. The PEOU variable influences the PU variable. The PU and PEOU variables affect ATU. In addition, the PU variable influences the BI variable. Besides being influenced by the PU variable, the BI variable is also influenced by the ATU variable. The last variable is AU which is

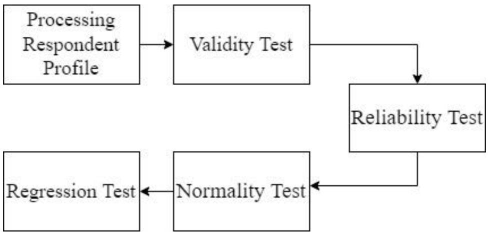

Fig. 9 Data processing.

TABLE III
RESPONDENT BASED ON GENDER

Parameter		Frequency	Percent
Valid	Male	12	75.0
	Female	4	25.0
	Total	16	100.0

TABLE IV
RESPONDENT BASED ON EDUCATIONAL LEVEL

Parameter		Frequency	Percent
Valid	Bachelor	10	62.5
	Master	6	37.5
	Total	16	100.0

influenced by the BI variable. Eight hypotheses were proposed from the relationship between these variables to determine which variables have a significant positive or negative effect.

C. Hypotheses

The list of hypotheses based on the TAM model design discussed in the previous section is as follows:

- H1: The RA variable has a positive and significant effect on the PU variable.
- H2: the RA variable has a positive and significant effect on the PEOU variable.
- H3: the PEOU variable has a positive and significant effect on the PU variable.
- H4: the PU variable has a positive and significant effect on the ATU variable.
- H5: the PEOU variable has a positive and significant effect on the ATU variable.
- H6: the PU variable has a positive and significant BI variable.
- H7: the ATU variable has a positive and significant effect on the BI variable.
- H8: the BI variable has a positive and significant effect on the AU variable.

D. Result of Data Processing

The target population in this study were employees of company XYZ using a smart lighting system in the office space. The number of employees using smart lighting was seventeen people. For the sample data in this study, a random sampling technique was used, which was a random sampling technique regardless of strata and population. In this study, the number of respondents was sixteen people.

The first stage in data processing was processing the profile of respondents who had filled out the questionnaire. The respondent's profile includes gender, education level, and length of time working in the company. The second stage was to test the validity of the questionnaire instrument used in data collection. The next stage tested the reliability utilized to measure the questionnaire's consistency even when the analysis was repeated. The fourth stage was the normality test, which determined whether a dataset was modeled with a normal distribution. The last stage was a regression test to determine the effect between two or many variables. Fig. 9 shows the data processing to calculate the proposed TAM model.

TABLE V
LENGTH OF WORK

Parameter		Frequency	Percent
Valid	1-5 years	14	87.5
	6-10 years	2	12.5
	Total	16	100.0

TABLE VI
VALIDITY OF TEST RESULT

Variable	Item	***R* Counts**	**Table *R***
PEOU (Y1)	PEOU_1	0.834	0.497
	PEOU_2	0.552	0.497
PU (Y2)	PU_1	0.885	0.497
	PU_2	0.935	0.497
	PU_3	0.888	0.497
BI (Y3)	BI_1	0.862	0.497
	BI_2	0.732	0.497
	BI_3	0.834	0.497
ATU (Y4)	ATU_1	0.944	0.497
	ATU_2	0.940	0.497
AU (Y5)	AU_1	0.924	0.497
	AU_2	0.924	0.497
RA (X)	RA_1	0.750	0.497
	RA_2	0.532	0.497

1) Respondent Profiles: Respondents who filled out the questionnaire were employees who worked at company XYZ, with a total of sixteen respondents.

Table III shows the respondents' gender, with the number of male respondents being 75%. Table IV shows the educational level, with the number of respondents who have a bachelor's degree being 62.5%, while the rest have a master's degree. The duration the respondents have worked at company XYZ is shown in Table V; as many as 87.5% have worked for 1 to 5 years, while the rest have worked for a period of 6 to 10 years.

2) Validity Test Result: A validity test is a useful test to determine the validity of the questionnaire instrument used in the data collection [55]. The indicator is valid if (r_{hitung}) > (r_{tabel}), r_{tabel} value was 0.497, taken from the number of respondents, namely 16 and a significance level of 5% or 0.05. The validity test results conducted using the SPSS application are shown in Table VI.

Based on the observation results on (r_{tabel}), the sample value (N) = 16 was 0.497. Referring to the validity test results, the results for all instruments ranging from PEOU (Y1) to AU (Y5)

TABLE VII
RELIABILITY OF TEST RESULT

Cronbach's Alpha	N of Items
0.873	14

TABLE VIII
KOLGOMOROV-SMIRNOV TEST RESULT

One-Sample Kolmogorov-Smirnov Test		
		Unstandardized Residual
N		16
Normal Parameters [a, b]	Mean	0.0000000
	Std. Deviation	0.49073819
Most Extreme Differences	Absolute	0.176
	Positive	0.176
	Negative	-0.122
Test Statistic		0.176
Asymp. Sig, (2-tailed)		0.197[c]
Note: a. Test distribution is normal; b. Calculated from data; c. Lilliefors Significance Correction		

variables were (r_{hitung}) > (r_{tabel}). In addition, the RA (X) variables all generated values of (r_{hitung}) > (r_{tabel}). Hence, it is concluded that all the instruments in this study are valid.

3) Reliability Test Result: A reliability test was used to determine whether the questionnaire still demonstrated good consistency even when the analysis was conducted repeatedly. The questionnaire was reliable if the Cronbach's alpha value had a coefficient value of 0.6 or more. The results of the reliability test are shown in Table VII.

From the results of the reliability test, all values obtained from the results of the variables (X) and (Y) resulted in a Cronbach's alpha > 0.6. Therefore, it can be concluded that the fourteen item indicators of the questionnaire questions in this study are reliable.

4) Normality Test Result: A normality test was used to test whether the research sample was a normal distribution type or not. This test used the Kolmogorov-Smirnov method, which was appropriate for data with various samples [56]. The results of normality testing in this study are shown in Table VIII.

From the normality test results using Kolmogorov Smirnov, a significance impact from the normality test was 0.197, which was greater than the significance level of 0.05. It can be concluded that the normality test in this study is normally distributed.

5) Regression Test Result: A simple linear regression test was used in this study to measure the effect between two variables, namely the independent variable on the dependent variable [57], [58]. The calculation of a simple linear regression test used the SPSS application to calculate the R^2 value, sig value, and beta value of the eight hypotheses. The naming for the variables tested are as follows Y1 = PEOU, Y2 = PU, Y3 = BI, Y4 = ATU, Y5 = AU, X = RA. The results of the simple linear regression test in this study can be seen in Table IX.

TABLE IX
REGRESSION TEST RESULT

Hypotheses	R^2 Value	Sig Value	Beta Value
H1 = X -> Y2	0.110	0.009	0.851
H2 = X -> Y1	0.040	0.195	0.207
H3 = Y1 -> Y2	0.161	0.124	1.000
H4 = Y2 -> Y4	0.537	0.001	0.455
H5 = Y1 -> Y4	0.228	0.010	0.739
H6 = Y2 -> Y3	0.132	0.017	0.388
H7 = Y4 -> Y3	0.406	0.008	1.100
H8 = Y3 -> Y5	0.113	0.203	0.180

TABLE X
T-VALUES

Hypotheses	T-Value
H1 = X -> Y2	1.816
H2 = X -> Y1	0.769
H3 = Y1 -> Y2	1.638
H4 = Y2 -> Y4	4.031
H5 = Y1 -> Y4	2.036
H6 = Y2 -> Y3	2.456
H7 = Y4 -> Y3	3.096
H8 = Y3 -> Y5	1.336

Table IX shows that three hypotheses have a sig value of less than 0.05, including H1, H4, H5, H6, and H7, so the hypothesis has a significant effect. Meanwhile, H2, H3, and H8 have values above 0.05, suggesting that the hypothesis does not have a significant effect. The positive or negative values of the t-values of each hypothesis can be seen in Table X.

From Table X, five hypotheses have a positive or significant effect since the t-value for each hypothesis is greater than t-table (1.745); these hypotheses are H1, H4, H5, H6, and H7. Meanwhile, H2, H3, and H8 have t-values that are less than t-table (1.745), so the effect is negative or not significant.

- H1: The relationship between X and Y2 has a value of sig (0.009) < 0.05 and a t-value of (1.816) > 1.745, which means that X has a significant and positive impact on Y2. So, **H1 is accepted.**
- H2: The relationship between X and Y1 has a sig value of (0.195) > 0.05 and a t-value of (0.769) < 1.745, meaning that X has an insignificant and not positive impact on Y1. So, **H2 is not accepted.**
- H3: The relationship between Y1 and Y2 has a sig value of (0.124) > 0.05 and a t-value of (1.638) < 1.745, meaning that Y1 has an insignificant and not positive impact on Y2. So, **H3 is not accepted**.
- H4: The relationship between Y2 and Y4 has a sig value of (0.001) < 0.05 and a t-value of (4.031) > 1.745, meaning that Y2 has a significant and positive impact on Y4. So, **H4 is accepted.**
- H5: The relationship between Y1 and Y4 has a sig value of (0.061) < 0.05 and a t-value of (4.031) > 1.745, meaning that Y2 has a significant and positive impact on Y4. So, **H5 is accepted.**
- H6: The relationship between Y2 and Y3 has a sig value of (0.017) < 0.05 and a t-value (2.456) > 1.745, meaning

that Y2 has an insignificant and not positive impact on Y3. So, **H6 is accepted.**

- H7: The relationship between Y4 and Y3 has a sig value of (0.008) < 0.05 and a t-value of (3.096) > 1.745, meaning that Y4 has a significant and positive impact on Y3. So, **H7 is accepted.**
- H8: The relationship between Y3 and Y5 has a sig value of (0.203) > 0.05 and a t-value (1.336) < 1.745, meaning that Y3 has an insignificant and not positive impact on Y5. So, **H8 is not accepted.**

From Table IX, the R^2 value on H1 has a value of 0.110 which can be concluded that 11% of the X variable affects the Y2 variable, while the remaining 89% is influenced by other variables.

- R^2 on H2 has a value of 0.040, which can be concluded that 40% of the X variable affects the Y1 variable, while the remaining 60% is influenced by other variables.
- R^2 on H3 has a value of 0.161, which can be concluded that 16.1% of the Y1 variable affects the Y2 variable, while the remaining 83.9% is influenced by other variables.
- R^2 on H4 has a value of 0.537, which can be concluded that 53.7% of the Y2 variable affects the Y4 variable, while the remaining 46.3% is influenced by other variables.
- R^2 on H5 has a value of 0.228, which can be concluded that 22.8% of the Y1 variable affects the Y4 variable, while the remaining 77.2% is influenced by other variables.
- R^2 on H6 has a value of 0.132 which can be concluded that 13.2% of the Y2 variable affects the Y3 variable, while the remaining 86.8% is influenced by other variables.
- R^2 on H7 has a value of 0.406, which can be concluded that 40.6% of the Y4 variable affects the Y3 variable, while the remaining 59.4% is influenced by other variables.
- R^2 on H8 has a value of 0.113, which can be concluded that 11.3% of the Y3 variable affects the Y5 variable, while the remaining 88.7% is influenced by other variables.

E. Discussion

Based on the results of the calculation of the regression test on the proposed hypotheses, it was found that the reliability and accuracy variables had a positive and significant impact on the PU variable. The respondents feel confident that reliable and accurate system performance can help and be useful in employee work activities; it is shown that H1 is positive and significant. The other significant hypotheses are H4, H5, H6, and H7. H4 indicates that the PU variable has a positive and very significant impact (the largest t-value) on the ATU variable. In H5, the PEOU variable positively and significantly impacts ATU variable. In H6, the PU positively and significantly impacts the behavior intention variable. Likewise, attitude toward using has a positive and significant impact on the behavior intention variable, as shown in H7.

Three hypotheses have a negative and insignificant impact; these three hypotheses are H2, H3, and H8. The reliability and accuracy variables have no impact on the PEOU variable, which is a statement from H2. In H3, the PEOU variable has no impact on PU. It happens because the operation of smart lighting is done automatically, so there is only little user involvement. In H8, the BI variable has no significant impact and positively impacts AU; this finding suggests that, besides BI, other variables influence the AU variable.

Based on the calculation results of the proposed TAM model, it can be concluded that the selected external variables, namely the reliability and accuracy variables, have a positive and significant impact on the PU variable, which has a positive and significant impact on the ATU variable and BI variables. The technology tested for acceptance in this study was smart lighting that was applied according to the company's needs so that the proposed TAM model was specific to a particular organization. The proposed TAM model will also be different if smart lighting is implemented in different companies with different needs. However, based on the testing results and initial implementation of smart lighting, the external variables that must be used are the reliability and accuracy variables.

V. Conclusion and Suggestion

This study aims to measure the acceptance of the smart lighting system implemented in the XYZ company using the TAM method. The steps taken in calculating technology acceptance were identifying external variables that produce six external variables affecting smart lighting acceptance. Of the six selected external variables, the TAM model was successfully designed, and eight hypotheses were built based on the built model. From the calculation results of hypothesis testing, five hypotheses have a positive and significant effect: the RA variable influences the PU variable, the PU variable influences the ATU variable, the PEOU variable affects the ATU variable, the ATU variable affects BI, and the PU variable affects BI. Meanwhile, the RA variable does not affect the PEOU, the PEOU variable does not affect the PU, and the BI variable does not affect the AU variable.

In this study, TAM was applied to measure the acceptance of smart lighting products developed according to the user organization or company (XYZ company). The use of external variables was limited to the characteristics of the system. The following research on the acceptance of smart lighting explores external variables from aspects of organizational characteristics (e.g., competitive environment, management support, etc.) or other external variables. Opportunities to research the acceptance of smart lighting products at-home scale and mass-market products are still open.

Conflict of Interest

The authors of the article entitled "Technology Acceptance Model (TAM) For Smart Lighting System in XYZ Company" declare no conflicts of interest.

Author Contributions

Conceptualization by all authors; goals and problem statements Teja Laksana and Novian Anggis S.; data collection and data analysis Teja Laksana and Muhammad Al Makky; writing and drafting Novian Anggis S. and Muhammad Al Makky, review and editing Novian Anggis S. and Muhammad Al Makky.

REFERENCES

[1] R. Minerva, A. Biru, and D. Rotondi, "Towards a Definition of the Internet of Things (IoT)," *IEEE Internet Initiative*, Vol. 1, No. 1, pp. 1–86, 2015.

[2] L.S. Vailshery (2021) "Internet of Things (IoT) and non-IoT Active Device Connections Worldwide from 2010 to 2025," [Online], https://www.statista.com/statistics/1101442/iot-number-of-connected-devices-worldwide/, access date: 3-Jan-2022.

[3] D.J. Cook, A.S. Crandall, B.L. Thomas, and N.C. Krishnan, "CASAS: A Smart Home in a Box," *Comput.*, Vol. 46, No. 7, Jul. 2013.

[4] N. Balta-Ozkan, O. Amerighi, and B. Boteler, "A Comparison of Consumer Perceptions towards Smart Homes in the UK, Germany and Italy: Reflections for Policy and Future Research," *Technol. Anal., Strategic Manage.*, Vol. 26, No. 10, pp. 1176–1195, Nov. 2014.

[5] B.L.R Stojkoska and K.V. Trivodaliev, "A Review of Internet of Things for Smart Home: Challenges and Solutions," *J. Clean. Prod.*, Vol. 140, pp. 1454–1464, Jan. 2017.

[6] B. Morvaj, L. Lugaric, and S. Krajcar, "Demonstrating Smart Buildings and Smart Grid Features in a Smart Energy City," *Proc. 2011 3rd Int. Youth Conf. Energetics (IYCE)*, 2011, pp. 1–8.

[7] T. Weng and Y. Agarwal, "From Buildings to Smart Buildings—Sensing and Actuation to Improve Energy Efficiency," *IEEE Des. Test Comput.*, Vol. 29, No. 4, pp. 36–44, Aug. 2012.

[8] W. Xu et al., "The Design, Implementation, and Deployment of a Smart Lighting System for Smart Buildings," *IEEE Internet of Things J.*, Vol. 6, No. 4, pp. 7266–7281, Aug. 2019.

[9] A.K. Sikder et al., "IoT-Enabled Smart Lighting Systems for Smart Cities," *2018 IEEE 8th Annu. Comput., Commun. Workshop, Conf. (CCWC)*, 2018, pp. 639–645.

[10] L. Martirano, "A Smart Lighting Control to Save Energy," *Proc. 6th IEEE Int. Conf. Intell. Data Acquisition, Adv. Comput. Syst.*, 2011, pp. 132–138.

[11] I. Chew, D. Karunatilaka, C.P. Tan, and V. Kalavally, "Smart Lighting: The Way Forward? Reviewing the Past to Shape the Future," *Energy Build.*, Vol. 149, pp. 180–191, Aug. 2017.

[12] M. Castro, A.J. Jara, and A.F.G. Skarmeta, "Smart Lighting Solutions for Smart Cities," *2013 27th Int. Confer. Adv. Inf. Netw., Appl. Workshops*, 2013, pp. 1374–1379.

[13] J. Higuera et al., "Smart Lighting System ISO/IEC/IEEE 21451 Compatible," *IEEE Sens. J.*, Vol. 15, No. 5, pp. 2595–2602, May 2015.

[14] N.K. Kandasamy et al., "Smart Lighting System Using ANN-IMC for Personalized Lighting Control and Daylight Harvesting," *Build. Environ.*, Vol. 139, pp. 170–180, Jul. 2018.

[15] B. Sun, Q. Zhang, and S. Cao, "Development and Implementation of a Self-Optimizable Smart Lighting System Based on Learning Context in Classroom," *Int. J. Environ. Res. Public Health*, Vol. 17, No. 4, Feb. 2020.

[16] M. Abdurohman, R. Nugraha, and A.G. Putrada, "An Improvement of LED Lighting System Accuracy with Voltage Control System," *2020 Fifth Intl. Confer. Inform., Comput. (ICIC)*, 2020, pp. 1–5.

[17] S.-C. Chen, S.-H. Li, and C.-Y. Li, "Recent Related Research in Technology Acceptance Model: A Literature Review," *Australian J. Bus., Manage. Res.*, Vol. 1, No. 9, pp. 124–127, Apr. 2012.

[18] P. Surendran, "Technology Acceptance Model: A Survey of Literature," *Int. J. Bus., Social Res.*, Vol. 2, No. 4, pp. 175–178, 2012.

[19] N. Marangunić and A. Granić, "Technology Acceptance Model: A Literature Review from 1986 to 2013," *Univers. Access in the Inf. Soc.*, Vol. 14, No. 1, pp. 81–95, Mar. 2015.

[20] M.J. Mortenson and R. Vidgen, "A Computational Literature Review of the Technology Acceptance Model," *Int. J. Inf. Manage.*, Vol. 36, No. 6, pp. 1248–1259, Dec. 2016.

[21] A. Granić and N. Marangunić, "Technology Acceptance Model in Educational Context: A Systematic Literature Review," *Brit. J. Educ. Technol.*, Vol. 50, No. 5, pp. 2572–2593, Sep. 2019.

[22] I.B.P.P. Dinata and B. Hardian, "Predicting Smart Home Lighting Behavior from Sensors and User Input Using Very Fast Decision Tree with Kernel Density Estimation and Improved Laplace Correction," *2014 Int. Confer. Adv. Comput. Sci., Inf. Syst.*, 2014, pp. 171–175.

[23] M. Khan, B.N. Silva, and K. Han, "Internet of Things Based Energy Aware Smart Home Control System," *IEEE Access*, Vol. 4, pp. 7556–7566, 2016.

[24] R. Ford, M. Pritoni, A. Sanguinetti, and B. Karlin, "Categories and Functionality of Smart Home Technology for Energy Management," *Build. Environ.*, Vol. 123, pp. 543–554, Oct. 2017.

[25] S. Tang, V. Kalavally, K.Y. Ng, and J. Parkkinen, "Development of a Prototype Smart Home Intelligent Lighting Control Architecture Using Sensors Onboard a Mobile Computing System," *Energy Build.*, Vol. 138, pp. 368–376, Mar. 2017.

[26] Y.S. Chang, Y.H. Chen, and S.K. Zhou, "A Smart Lighting System for Greenhouses Based on Narrowband-Iot Communication," *2018 13th Int. Microsystems, Packag., Assem., Circuits Technol. Confer. (IMPACT)*, 2018, pp. 275–278.

[27] T.A. Khoa et al., "Designing Efficient Smart Home Management with IoT Smart Lighting: A Case Study," *Proc. Int. Wirel. Commun. Mob. Comput. Conf.*, Vol. 2020, Nov. 2020.

[28] O. Ayan and B. Turkay, "IoT-Based Energy Efficiency in Smart Homes by Smart Lighting Solutions," *2020 21st Int. Symp. Elect. App. Technol. (SIELA)*, 2020, pp. 1–5.

[29] M. Soheilian, G. Fischl, and M. Aries, "Smart Lighting Application for Energy Saving and User Well-Being in the Residential Environment," *Sustain. Sci. Pract. Policy*, Vol. 13, No. 11, pp. 1–17, May 2021.

[30] M. Füchtenhans, E.H. Grosse, and C.H. Glock, "Use Cases and Potentials of Smart Lighting Systems in Industrial Settings," *IEEE Eng. Manage. Rev.*, Vol. 47, No. 4, pp. 101–107, 2019.

[31] M. Füchtenhans, E.H. Grosse, and C.H. Glock, "Smart Lighting Systems: State-of-the-Art and Potential Applications in Warehouse Order Picking," *Int. J. Prod. Res.*, Vol. 59, No. 12, pp. 3817–3839, Jun. 2021.

[32] M. Füchtenhans, C.H. Glock, E.H. Grosse, and S. Zanoni, "Using Smart Lighting Systems to Reduce Energy Costs in Warehouses: A Simulation Study," *Int. J. Logist. Res. Appl.*, to be published, Jun. 2021.

[33] A. Shankar, K. Vijayakumar, B.C. Babu, and A. Durusu, "Smart LED Lighting System for Energy Efficient Industrial and Commercial LVDC Nanogrid Powered Buildings with BIPV," *2020 Int. Confer. Smart Energy Syst., Technl. (SEST)*, 2020, pp. 1–6.

[34] F.D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quart.*, Vol. 13, No. 3, pp. 319–340, Sep. 1989.

[35] V. Venkatesh and F.D. Davis, "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies," *Manage. Sci.*, Vol. 46, No. 2, pp. 186–204, Feb. 2000.

[36] V. Venkatesh, M.G. Morris, G.B. Davis, and F.D. Davis, "User Acceptance of Information Technology: Toward a Unified View," *MIS Quart.*, Vol. 27, No. 3, pp. 425–478, Sep. 2003.

[37] T. Saenphon, "An Analysis of the Technology Acceptance Model in Understanding University Student's Awareness to Using Internet of Things," *Proc. 2017 Int. Confer. E-Commerce, E-Bus., E-Government*, 2017, pp. 61–64.

[38] E. Park, Y. Cho, J. Han, and S.J. Kwon, "Comprehensive Approaches to User Acceptance of Internet of Things in a Smart Home Environment," *IEEE Internet of Things J.*, Vol. 4, No. 6, pp. 2342–2350, Dec. 2017.

[39] S.-H. Jang and C.H. Yu, "A Study on Internet of Things (IoT): Users' Reuse Intention Using Technology Acceptance Model in Korea," *Int. J. of Bus., Manage. Sci.*, Vol. 7, No. 2, 2017.

[40] E. Constantinides, M. Kahlert, and S.A. de Vries, "The Relevance of Technological Autonomy in the Acceptance Of IoT Services in Retail," *2nd Int. Confer. Internet of Things, Data and Cloud Comput. (ICC 2017)*, 2017, pp. 1-7.

[41] E. Pazvant and F. Emel, "Evaluation of the Intention of Using Products with Internet of Things within the Context of Technology Acceptance

Model," *J. Manage. Marketing and Logistics*, Vol. 5, No. 1, pp. 41–54, Mar. 2018.

[42] L.D. Morienyane and A. Marnewick, "Technology Acceptance Model of Internet of Things for Water Management at a local Municipality," *2019 IEEE Technol. Eng. Manage. Confer. (TEMSCON)*, 2019, pp. 1–6.

[43] A.M. Al-Momani, M.A. Mahmoud, and M.S. Ahmad, "A Review of Factors Influencing Customer Acceptance of Internet of Things Services," *Int. J. Inf. Syst. Service Sector*, Vol. 11, No. 1, pp. 54–67, Jan. 2019.

[44] F. Ullah, P.S. Sepasgozar, and T.H. Ali, "Real Estate Stakeholders Technology Acceptance Model (RESTAM): User-Focused Big9 Disruptive Technologies for Smart Real Estate Management," *Proc. 2nd Int. Confer. Sustain. Develop. Civil Eng. (ICSDC 2019)*, 2019, pp. 5–7.

[45] G.A. Alkawsi, N. Ali, and Y. Baashar, "An Empirical Study of the Acceptance of IoT-Based Smart Meter in Malaysia: The Effect of Electricity-Saving Knowledge and Environmental Awareness," *IEEE Access*, Vol. 8, pp. 42794–42804, 2020.

[46] R.B. Ab Rahman, R.B. Ab Rahman, and A.B.M. Amirruddin, "Users' Intention in Developing Internet of Things in Education Context using the Technology Acceptance Model: A Case Study," *J. Social Sci., Tech. Educ. (JoSSTEd)*, Vol. 1, No. 1, pp. 98–104, Sep. 2020.

[47] M. Tsourela and D.-M. Nerantzaki, "An Internet of Things (IoT) Acceptance Model. Assessing Consumer's Behavior toward IoT Products and Applications," *Future Internet*, Vol. 12, No. 11, pp. 1–23, Nov. 2020.

[48] R. Agustina, D. Suprianto, and R. Ariyanto, "Technology Acceptance Model Analysis of User Behavioral Intentions on IoT Smart Board Devices," *2021 1st Confer. Online Teaching for Mobile Educ. (OT4ME)*, 2021, pp. 89–92.

[49] F. Abdullah, R. Ward, and E. Ahmed, "Investigating the Influence of the Most Commonly Used External Variables of TAM on Students' Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of E-Portfolios," *Comput. Human Behav.*, Vol. 63, pp. 75–90, Oct. 2016.

[50] S.H. Hong and J.H. Yu, "Identification of External Variables for the Technology Acceptance Model(TAM) in the Assessment of BIM Application for Mobile Devices," *IOP Conf. Ser. Mater. Sci. Eng.*, Vol. 401, No. 1, pp. 1–6, Oct. 2018.

[51] I.A. Castiblanco Jimenez et al.,"Commonly Used External TAM Variables in e-Learning, Agriculture and Virtual Reality Applications," *Future Internet*, Vol. 13, No. 1, pp. 1–21, Dec. 2020.

[52] D. Priyatno, *Mandiri Belajar SPSS: untuk Analisis Data dan Uji Statistik*. Yogyakarta, Indonesia: MediaKom, 2008.

[53] I. Ajzen and M. Fishbein, "Attitude-behavior Relations: A Theoretical Analysis and Review of Empirical Research," *Psychological Bull.*, Vol. 84, No. 5, pp. 888–918, Sep. 1977.

[54] I. Ajzen and M. Fishbein, "Attitudinal and Normative Variables as Predictors of Specific Behavior," *J. Pers. Soc. Psychol.*, Vol. 27, No. 1, p. 41-57, 1973.

[55] R. Alfian and A.M.P. Putra, "Uji Validitas dan Reliabilitas Kuesioner Medication Adherence Report Scale (Mars) terhadap Pasien Diabetes Mellitus," *J. Ilm. Ibnu Sina*, Vol. 2, No. 2, pp. 176–183, Oct. 2017.

[56] M.A. Oktaviani and H.B. Notobroto, "Perbandingan Tingkat Konsistensi Normalitas Distribusi Metode Kolmogorov-Smirnov, Lilliefors, Shapiro-Wilk, dan Skewness-Kurtosis," *J. Biometrika dan Kependudukan*, Vol. 3, No. 2, pp. 127–135, Dec. 2014.

[57] I.M. Yuliara. (2016). Regresi Linier Sederhana [Online], https://simdos.unud.ac.id/uploads/file_pendidikan_1_dir/321812643899 0fa0771ddb555f70be42.pdf, access date: 3-Jan-2022.

[58] D. Kurniawan (2008) "Regresi linier," [Online], https://ineddeni.files.wordpress.com/2008/07/regresi_linier.pdf, access date: 3-Jan-2022.