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Factors Influencing Consumer's Willingness to Pay for Iot Products in Indonesia: Analysis of Tam and Tri Factors

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Abstract:
The development of technology has emerged positively in these past years and Information Technology (IT) has become one of the potential sectors to have positive development. One of the trends of IT to look out for in 2020 is the Internet of Things (IoT). Globally, IoT has been a trend. The number of IoT connected devices in the world will be 38.5 billion used in 2020, and the market for IoT in Indonesia is expected to grow to 444 Trillion Rupiah in 2022.
However, IoT is considered as a new kind of technology in Indonesia. In some conditions, even though the product has a breakthrough innovative value, but if the consumer is not ready to accept the product, it has a high opportunity to lose its sales. Using the smart garden as the IoT product example to gather the willingness to pay data from the market, this research wants to find out further about the factors that could affect the consumer's willingness to pay (WTP) for IoT products.
To identify the relationship between the readiness and acceptance of IoT products to the willingness to pay, the Technology Acceptance Model (TAM) and Technology Readiness Index (TRI) were used in this research. An external variable (Subjective Norm) is added in this research to test the social influence on people's decisions to use IoT products. Researchers use a quantitative method using purposive sampling and the analysis used is PLS-SEM analysis to test the hypotheses and measure the relationship between one variable to another. Contingent Valuation Method is also used to find out the desirable price of IoT products that the market wants.

Keywords: *Internet of Things (IoT), Technology Acceptance Model (TAM), Technology Readiness Index (TRI), Willingness to Pay*

1. Introduction

The technology industry has been emerging very fast in the past few years. Technology helps people do everything more efficiently and effectively, thus its development is increasing because people's needs become more diverse throughout the year. Information Technology (IT) has become a potential sector of the industry that has a positive development throughout the years. According to a forecast done by Gartner, Inc. in January 2019, the number of global IT Markets was estimated to be $3.76 Trillion US Dollars in 2019, increased by 3.2% from 2018. A report of IT Industry Outlook 2020 from CompTIA mentioned that there are some trends to watch in 2020, some of which are Internet of Things (IoT), artificial intelligence (AI), and 5G.

Internet of Things (IoT) is a system that can be described as a collection of interconnected smart devices and objects that are provided with unique identifiers that can communicate and transfer data without human or computer interaction to fulfill the desired goal (Sicari, 2015). While the major product use is on the smart home system, IoT is reaching wider industries including manufacturing, healthcare, retail, agriculture, energy, security, smart buildings, and smart cities, and all the industries that have device-based systems. IoT provides many benefits for the business including cost reduction, enhanced productivity and customer service, and also the ability to understand consumer behavior. IoT has a huge opportunity in Indonesia. According to the Indonesia Internet of Things Forum 2017, the market for IoT in Indonesia is expected to grow to 444 Trillion Rupiah in 2022.

IoT is considered as a new kind of technology in Indonesia. In some conditions, even though the product has a breakthrough innovative value, but if the customer is not ready to accept the product, it has a high opportunity to lose its sales. Hi!Drops are one of the Indonesian companies that run in the IoT business. Hi!Drops face a huge problem in selling. The company struggled to estimate the right consumers willingness to pay, thus their selling price is considered not suitable according to some customers. They have made no sales up until now and wonder if the customer is ready to accept their innovative product.

IoT products need big production costs and the price for IoT products in Indonesia is not cheap, and there's a constraint for customers to buy the product because there are still many substitute products that can replace it. Thus, their intention to use IoT products is yet questionable considering that they can use substitute products. Intention to use itself is included as one of the factors in technology acceptance. More studies and research need to be conducted to analyze this phenomenon. The market's readiness also has to be analyzed because IoT can be considered as something new in Indonesia and we still don't know about how the market reacts towards this technology. Readiness and acceptance have to be studied more to prove whether or not there is a relationship between these factors and willingness to pay and how we, as the industry players, consider that.

Technology Acceptance Model (TAM) proposed by Davis (1989) defined a model that is commonly used to understand people's adaptive behavior towards technology. Meanwhile, the basic theory of technology readiness index (TRI) was highlighted as the tendency to embrace and use new technology to achieve goals in work and life (Parasuraman, 2000). Some studies find a correlation between TRI and TAM, which can be said as Technology Readiness and Acceptance Model or TRAM (Lin et al., 2007). Some studies connect the intention of use (one of the TAM factors) to consumer's willingness to pay (Wang et al., 2013). Other factors such as subjective norms also found to be correlated to the intention of use (Hussein, 2018). However, there's not much research that linked all of these factors especially related to IoT products. Hence, this study aims to contribute to gaining more knowledge about the relationship between consumers' acceptance, readiness, and other factors to consumer's willingness to pay in buying IoT products.

2. Literature Review

2.1. Internet of Things (IoT)

Internet of Things (IoT) is a system that can be described as a collection of interconnected smart devices and objects that are provided with unique identifiers that can communicate and transfer data without human or computer interaction to fulfill the desired goal (Sicari, 2015). IoT is a combination of data, web associated items, and integral components of the internet. IoT enables people to connect to the internet and other mobile devices via a central server. By lessening human interactions, IoT gathers the data using sensors and processes it using a controller, then automates it through the actuators (Venkatesan and Tamilvanan, 2017). This enables people to increase their efficiency in working, especially in gathering big data and automating machines. IoT adoption is approved to be the development key of economic and social life in a country (Bessadok et al., 2018). The future of IoT is potentially good, even experts predict that there will be more than 20 billion devices connected to IoT in 2020 (Gartner, 2015).

2.2. Technology Readiness Index

Parasuraman (2000) stated the basic theory of technology readiness Index (TRI) as the tendency of someone to embrace and use new technology to achieve their goals in work and life. There are four dimensions, which are:

- Optimism; a positive belief that technology would increase control, flexibility, and efficiency of your work
- Innovativeness; the tendency of the user to be a technology pioneer.
- Discomfort; the feelings of overwhelmed and lack of control by the technology.
- Insecurity; the distrust and skepticism towards the ability of the technology to work properly.

The four dimensions showed us such contrasting traits. This is not surprising, because there is indeed a paradox of technology to the emotions of its users. Parasuraman classifies the four technology readiness factors into two groups: contributors inhibitors. Optimism and innovativeness bring out positive values, which is why they become the contributor of the readiness index. Meanwhile, discomfort and insecurity show negative values, thus they become the inhibitors in TRI. Research shows a good result of the TRI model's use of IoT products (Bessadok et al., 2018). Although people believe that smart devices will provide them with efficiency in the present and the future, they are still reluctant about the wide use of IoT due to the factor of safety that minimizes the overall TRI score in the research.A study by Pires et al. (2011) analyzes the potential relation between TRI as being the antecedent to TAM and shows that optimism has the most significant influence in making people accept the technology.

2.3. Technology Readiness Acceptance Model (TRAM)

Technology Readiness Acceptance Model is used to explain how the factors in TRI would influence the adoption of new technologies (Lin et al., 2007). Prior experience and knowledge about technology could affect consumer's perception, thus causing acceptance behavior. As there are inhibitors and contributors in TRI factors, they have different effects on two of TAM factors (perceived usefulness and perceived ease of use). Previous studies have explored this topic like the research about the usage of Facebook (Jin, 2013), the adoption of mobile internet service (Oh et al., 2014), and the acceptance of sports wearable technology (Chiu and Kim, 2019). The results from those studies stated that the positive factors of TRI (optimism and innovativeness) have positive effects on both Perceived Usefulness and Perceived Ease Of Use. Meanwhile, the negative factors of TRI (discomfort and insecurity) have negative effects on both Perceived Usefulness and Perceived Ease Of Use. As such, the hypotheses that can be developed from these findings are:

- H1:Optimism has a positive significant correlation to Perceived Usefulness(a) and Perceived Ease of Use(b)
- H2: Innovativeness has a positive significant correlation to Perceived Usefulness(a) and Perceived Ease of Use(b)
- H3: Discomfort has a negative significant correlation to Perceived Usefulness(a) and Perceived Ease of Use(b)
- H4: Insecurity has a negative significant correlation to Perceived Usefulness(a) and Perceived Ease of Use(b)

2.4. Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) was introduced by Davis (1989) as the model of how people could accept a technology. The endpoint of the model, which is actual system use is indicated when the person can use the technology. In this model, Behavioral Intention to Use (BI) is influenced by the attitude variable, which defines as the behavior of the person towards the technology. People's positive or negative behavior towards technology or in this case called attitude is affected by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU is interpreted as a degree where people believe that technology will enhance their performance in completing work, while PEOU is interpreted as the degree to which people believe that using technology will free them from putting much effort.TAM is mainly used to explain the user's acceptance of new technology. Research from Karahoca et al.(2017) has successfully explained the acceptance of IoT products in healthcare, showing a positive significant correlation between TAM variables: perceived usefulness, perceived ease of use, attitude, and intention to use. Attitude has the greatest impact on intention to use IoT healthcare products. Chung and Han (2015) analyze the acceptance of Augmented Reality (AR) for tourism application and the results showed an overall positive significant correlation between the TAM factors with attitude as the most influencing factor on the intention to use. From these previous findings, the hypotheses that can be developed are:

- H5: Perceived Ease of Use has positive significant correlation towards user's attitude (a) and Perceived Usefulness of IoT products (b)
- H6: Perceived Usefulness has positive significant correlation towards user's attitude (a) and the intention to use of IoT products (b)

2.5. Subjective Norm to Intention to Use

An external factor that is proven as the factor that could influence one of the factors in TAM (intention to use) is Subjective Norm. Subjective norm defined as the person's belief that is affected by people surrounding them which encourage them to perform a certain behavior (Ajzen and Fishbein, 1980). It is associated with the perceived social pressure that is given by people of importance (Ajjan and Hartshorne, 2008). Subjective norm is an important factor of behavioral intention, it describes the influence of others and how important it is to make others think positively about us (Ndubisi, 2004). It will make us more intent on doing something because it is under what people think we should do.Some previous studiesshowed a significant relationship of subjective norms with the person's intention to use the said technology. Research from Lau et al. (2019) about e-money showed said that users get influence by friends and family when they didn't know how to use mobile payment. Hussein (2018) found out one of the factors that could strengthen someone's intention to use technology is from the significant others believe that technology should be used. Thus, the hypothesis that can be developed from these findings is:

- H8: Subjective norm has a positive significant correlation to the intention to use of IoT product

2.6. Willingness to Pay (WTP)

Willingness to Pay is often used as the criteria to measure the benefit of a customer in exchange for the price or the quality of goods that they paid. Perman and McGilvray (1996) describe the meaning of WTP as the amount of willingness that people want to pay to secure welfare involvement. There are two ways of asking consumer's WTP which can be done directly by asking or indirectly, and it also differs between measuring the hypothetical or actual WTP (Miller et al., 2011). A study about green energy products found that a larger WTP tends to come from families with higher income, higher residence size, and higher awareness of the product (Zografakiset al., 2010).

2.7. Intention to Use to Willingness to Pay (WTP)

This research defines the intention of use as the degree of a person to use IoT products in the present or the future, while the willingness to pay is the degree of a person willing to pay for IoT products in the present or the future. Some previous research that explores willingness to pay in other services like social networking (Hsiao, 2011; Lu and Hsiao, 2010) and information objects (Lopatovska and Mokros, 2008) stated that the customer has to be satisfied and have the intention to use the product or service first before they're willing to pay. Wang et al. (2013) study the acceptance of mobile TV apps and that research discovers that intention to use is the strongest predictor for WTP for mobile TV apps. Anwar et al. (2015) studied the relation from intention to use with the willingness to pay for the MRT system in Jakarta and the result said the model can explain the Intention to adopt MRT and the WTP for MRT fare. From these findings, the hypothesis that can be established is:

- H9: Intention to use has a positive significant correlation on willingness to pay (WTP) of IoT products.

3. Conceptual Framework

This research framework is a combination ofthree previous models. The basis of this concept is from the Technology Readiness Acceptance Model (TRAM) by Lin (2007). TRAM analyzes the extended explanation of acceptance through technology readiness factors. Davis (1989) TAM concept is also adopted in this research to study the correlation of TR factors to perceived usefulness, perceived ease of use, attitude, and intention to use. Anwar et al. (2015) analyze the correlation between subjective norm to intention to useand intention to use to the willingness to pay in Mass Rapid Transport System. The researcher then combines those models and adapted it so that it could be applied to the Internet of Things (IoT) product.Thus, the hypothesis for this research is explained with the graphic below:

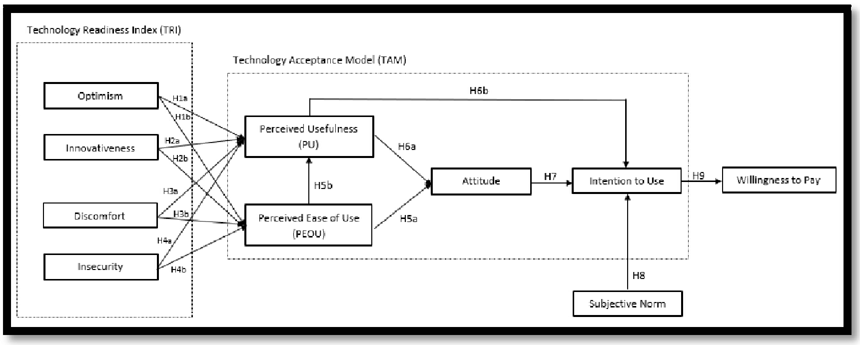

Figure 1: Conceptual Framework
Source: Researchers Analysis

- H1: Optimism has a positive significant correlation to PU (a) and PEOU (b)
- H2: Innovativeness has a positive significant correlation to PU (a) and PEOU (b)
- H3: Discomfort has a negative significant correlation to PU (a) and PEOU (b)
- H4: Insecurity has a negative significant correlation to PU (a) and PEOU (b)
- H5: PEoU has positive significant correlation towards user's attitude (a) and PU of IoT products (b)
- H6: PU has positive significant correlation towards user's attitude (a) and the intention to use of IoT products (b)
- H7: User's attitude toward IoT products gives positive significant correlation to the intention to use
- H8: Subjective norm has a positive significant correlation to the intention to use of IoT product
- H9: Intention to use has a positive significant correlation on willingness to pay (WTP) of IoT products.

4. Methodology

The survey instrument was intended to measure 10 variables: TRI factors (optimism, innovativeness, insecurity, and discomfort), TAM factors (PU, PEOU, attitude, intention to use), subjective norm, and WTP. The measures of TRI factors were developed from Parasuraman (2000) and Parasuraman and Colby (2014). The measures for PU, PEOU, and attitude were developed from Venkatesh and Davis (2000) and Venkatesh (2003). The measures for intention to use were developed by Kimet al. (2017) and Chiu and Kim (2019). The measures for subjective norm were developed from Mitalet al. (2017) and the measures for WTP were developed from Kumar (2014), Kucheret al. (2019). Demographic and behavioral questions were collected, including gender, age, domicile, level of education, occupation, expenditures, and prior experience to IoT products. The original questions are written in English, then the questionnaires were translated to Bahasa Indonesia. The latent variables are measured on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Preliminary research is done to 51 people from the middle to the elite class of economy in Jakarta and Bandung to study their current willingness to pay for Io products. The result is 53.7% of them wouldn't buy the IoT products at the selling price, and most of the middle-class people didn't give positive feedback. Based on that, this research is limited to be conducted to upper-middle to elite economic class Indonesian only. The classification of the economy based on monthly spending from Boston Consulting Group that is used in this research can be described like this:

- Upper Middle: spends between Rp 3.000.000 - Rp 5.000.000 per month
- Affluent: spends between Rp 5.000.000 - Rp 7.500.000 per month
- Elite: spends above Rp 7.500.000 per month

The age of the respondents is also limited to 20 – 55 years old only since those age groups are the largest internet users in Indonesia according to APJII (2018).

This research uses a quantitative approach to collect primary data. After some grammatical improvements, the questionnaire survey was then distributed online to those who meet the requirements. To maintain the robustness of the study, the researcher explains the research purpose and the definition as well as the example of IoT products so the respondents that have no prior experience with IoT could be included in the study. 353 out of 416 respondents answered the questionnaire completely, thus the 353 answers will be analyzed in this study.

To describe more about the findings, the researcher uses Structural Equation Modelling (SEM) and analyzes the data with Smart PLS application.

5. Analysis and Result

There are three types of analysis performed in this research. Descriptive analysis was performed first to describe the demography and the behavior of the respondents. The PLS-SEM analysis began with model fit test (SMRM, CMIN/DF, NFI) and reliability and validity test including indicator reliability, internal consistency reliability, convergent validity, discriminant validity. Then, a collinearity test was performed to make sure there's no multicollinearity in the data. The structural model was evaluated by R2 and Q2, and the hypothesis testing was measured by the path coefficients, T-Value, and the total effect of the data. Contingent Valuation Method is used to find out the appropriate WTP for IoT products from the data.

5.1. Descriptive Analysis

The description in the table I showed the characteristics of the answers from 353 respondents.

Characteristics		n	%
Gender	Male	117	33.1%
	Female	236	66.9%
Age	20-31 years old	171	48.4%
	32-43 years old	93	26.3%
	44-55 years old	89	25.2%
Domicile	Jabodetabek	102	28.9%
	West Java	115	32.6%
	Central and East Java	83	23.5%
	Outside Java	36	10.2%
Level of Education	Elementary School	1	0.3%
	High School	97	27.5%
	Diploma	33	9.3%
	Bachelor	185	52.4%
	Magister	37	10.5%
Occupation	Students/College Students	102	28.9%
	Employees	29	8.2%
	Freelancer	82	23.2%
	Entrepreneur	96	27.2%
	Housewife	5	1.4%
	Others	39	11.0%
Expenditures	Rp 3.000.000 - Rp 5.000.000	202	57.2%
	Rp 5.000.000 - Rp 7.500.000	65	18.4%
	> Rp 7.500.000	86	24.4%
Have known about IoT products before	Have	248	70.3%
	Have not	105	29.7%
Have used IoT products before	Have	135	38.2%
	Have not	218	61.8%
Have ever bought IoT products before	Have	109	30.9%
	Have not	244	69.1%

Table 1: Descriptive Analysis
Source: Researchers Analysis

The sample was dominated by females (66.9%) aged 20 -31 years old (48.4%) domiciled in West Java (32.6%). 248 (70.3%) have known about IoT products before and 135 (38.2%) of the respondents have used it. Meanwhile, 109 respondents (30.9%) have ever bought IoT products and 244 respondents haven't (69.1%). This answer then takes them to different sections of questionnaires asking the reason for purchase and reasons for not purchasing IoT products.

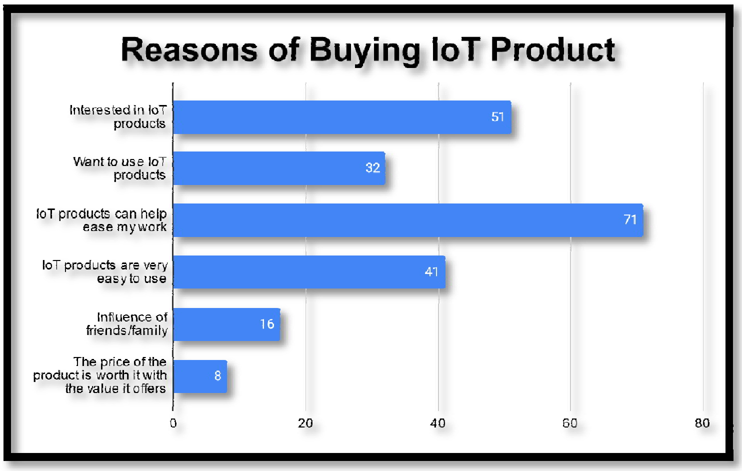

Figure 2: Reasons for Buying IoT Product
Source: Researchers Analysis

109 respondents were asked about the reasons for buying IoT products. From figure 2, We can see that most of the respondents said they bought IoT product because it can help them ease their work (71 respondents), followed by their interest in IoT product (51 respondents), the ease of use from IoT product (41 respondents), their willingness/intention to use IoT product (32 respondents), the influence from friends and family to buy IoT product (16 respondents), and the value that IoT product offers is worth to the price (8 respondents). The majority of the answers indicate that people who have bought IoT products tend to pay attention to the usefulness of the product to buy.

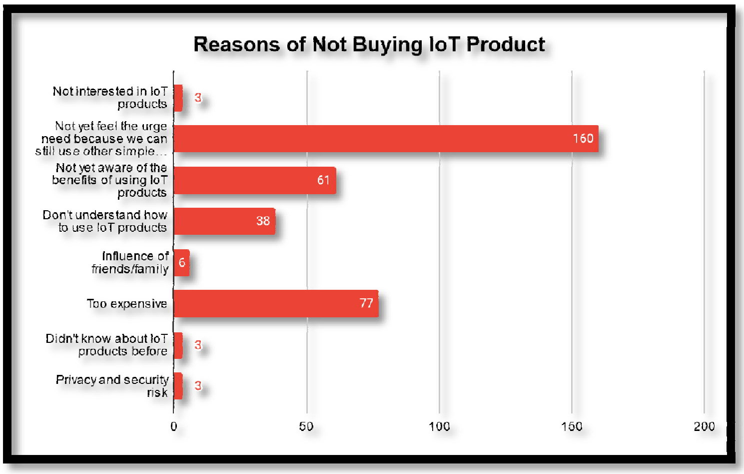

Figure 3: Reasons for Not Buying IoT Product
Source: Researchers Analysis

244 respondents were asked about the reasons for not buying IoT products. The majority of the respondents (160 respondents) said that they haven't felt the urge to buy IoT products because they still can use other simpler products that have the same function. 77 respondents said the price of IoT products are too expensive for their liking, 61 respondents don't know the benefits of using IoT products yet, 38 respondents don't know how to use IoT products, 6 of them were influenced by their friend and family to not buy the product, 3 respondents are not interested in IoT product, another 3 respondents didn't buy IoT product because they've never known that IoT product existed before, and 3 other respondents said they didn't buy IoT product because they're afraid of the privacy and security risks. By this, we know that people still tend to use another simple product with the same functionality as an IoT product and that's what makes them not buy IoT products yet.

The following question asked the possible purchase of IoT products from this type of respondent. The question of "If there's an IoT product whose price is quite high but can meet your needs, would you want to buy it?" the answer from 244 respondents is 135(55.3%) said yes and 109 (44.7%) said no. This indicates that there's a possibility to widen the market of IoT product from the people who haven't bought.

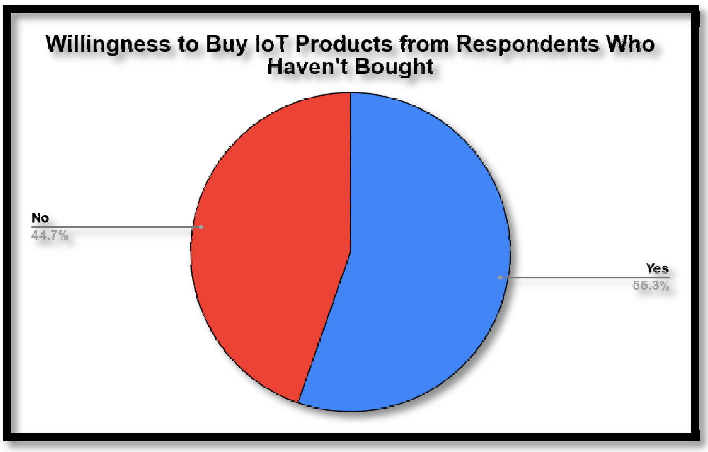

Figure 4: Willingness to Buy IoT Products from Respondents Who Haven't Bought
Source: Researchers Analysis

5.2. PLS-SEM Analysis

5.2.1. Model Fit

To test the model fit, Standardized Root Mean Square Residual (SRMR), CMIN/DF, and Normed Fit Index (NFI) were measured. Table 2 showed two different values from saturated and estimated models. The saturated model is defined as the model that evaluates the correlation between all the constructs, while the estimated model is defined as a model that is derived from the total effect scheme and calculated the model structure. Based on an article about model fit in smartpls.com, the estimated model said to be a reasonable choice to analyze. Thus, the estimated model will proceed to the analysis below.

	Saturated Model	Estimated Model
SRMR	0.059	0.073
CMIN/DF	1845.338/703=2.625	1880.209/703=2.675
NFI	0.748	0.743

Table 2: Model Fit
Source: Researchers Analysis

According to Cangur and Ercan (2015), Standardized Root Mean Square Residual or SRMR value designated the acceptable fit if the score is less than 0.1. The result of the model fit from the SmartPLS analysis showed a value of 0.073 for the SRMR estimated model score. This indicated that the model is a good fit because the score is less than 0.1.

Another method to assess the goodness of fit is to divide the chi-square (CMIN) value with the degrees of freedom (DF). Degrees of freedom can be obtained by the formula p(p+1)/2 where p is the number of parameters (Raykov&Marcoulides, 2006). In this research, there are 37 parameters used, thus the DF score is 703. The value of 3 or lower indicates the acceptable CMIN/DF score of acceptable fit values (Civelek, 2018). The CMIN/DF score in the estimated model is 2.675 which means that the model can be considered as a good fit.

According to Byrne (2013), the Normed Fit Index or NFI has to have a score above 0.9 to be considered as acceptable. This value represents the incremental fit because it measures the fitness of the model on a comparative basis to the baseline or null model. Based on table 2, the NFI score is 0.743 which is rather insufficient and can indicate an unfitness of the model. However, since the majority of the indicators measured has sufficient results, we can conclude that the overall model is a good fit.

5.2.2. Reliability

Reliability is defined by Malhotra (2010) as the extent to which the scale will show a consistent result when it is being repeated. The indicator reliability evaluation in SmartPLS can be measured from the outer loadings score and the minimum value to be accepted is 0.7, while the composite reliability score needs to be 0.7 or higher to measure the internal consistency reliability (Wong, 2013). The outer loadings results showed some indicators that have a value of less than 0.7 which are DIS1, DIS3, INS1, and INS4. The four indicators appeared as unreliable therefore it has to be removed because it didn't meet the criteria. After removing these indicators, the analysis was then continued.

Internal consistency reliability is applied to determine whether all of the indicators that measure the construct is consistent with the value scores (Hair et al, 2014). Wiryanto (2018) stated that composite reliability is an alternative method that can handle inappropriate assumptions that Cronbach's alpha made to measure internal consistency reliability. The value has to be more than 0.7 to be acceptable (Wong, 2013). The composite reliability scores of all the variables in Table 3 are larger than 0.7, which means that the internal consistency reliability is at a high level. Thus, we can conclude that all the variables are reliable.

Construct		Outer Loadings	Composite Reliability	AVE	VIF
Attitude	ATT1	0.878	0.933	0.776	2.619
	ATT2	0.892			2.815
	ATT3	0.89			2.771
	ATT4	0.864			2.354
Discomfort	DIS1	0.469	0.835	0.718	
	DIS2	0.888			1.25
	DIS3	0.489			
	DIS4	0.773			1.25
Innovativeness	INN1	0.803	0.853	0.592	1.535
	INN2	0.757			1.436
	INN3	0.749			1.553
	INN4	0.767			1.636
Insecurity	INS1	0.488	0.758	0.612	
	INS2	0.707			1.056
	INS3	0.841			1.056
	INS4	0.278			
Intention to Use	ITU1	0.873	0.909	0.77	2.044
	ITU2	0.869			2.07
	ITU3	0.89			2.125
Optimism	OPT1	0.821	0.889	0.668	1.734
	OPT2	0.847			2.047
	OPT3	0.841			1.939
	OPT4	0.756			1.61
Perceived Ease of Use	PEOU1	0.871	0.913	0.726	2.562
	PEOU2	0.913			3.26
	PEOU3	0.878			2.483
	PEOU4	0.736			1.583
Perceived Usefulness	PU1	0.909	0.939	0.793	3.612
	PU2	0.907			3.542
	PU3	0.876			2.558
	PU4	0.868			2.429
Subjective Norm	SN1	0.711	0.828	0.617	1.341
	SN2	0.817			1.622
	SN3	0.824			1.334
Willingness to Pay	WTP1	0.846	0.898	0.746	1.729
	WTP2	0.818			2.441
	WTP3	0.923			3.33

Table 3: Outer Loadings, Composite Reliability, AVE, and VIF score
Source: Researchers Analysis

5.2.3. Validity

Validity defined by Malhotra (2010) as the extent to which the difference of scale scores that are observed can reflect the actual difference between the object and the characteristics that are being measured. The validity test is to measure whether the respondents' answers are appropriate or not. According to Fornell and Larcker (1981), to pass convergent validity the AVE score must be 0.5 or higher to be accepted. The AVE score in table 3 showed an overall validity from all the constructs.

Discriminant validity is another method to test validity through cross-loadings (Hair et al., 2015). To be acceptable, the square root of the AVE coefficient in each variable has to be greater than the correlation of the other latent variable (Wong, 2013). Table 4 shows the results of the cross-loadings for each indicator (written in bold) which can be seen below:

	ATT	DIS	INN	INS	ITU	OPT	PEOU	PU	SN	WTP
ATT	0.881									
DIS	0.148	0.847								
INN	0.391	0.142	0.769							
INS	0.052	0.318	-0.082	0.782						
ITU	0.712	0.131	0.322	0.069	0.877					
OPT	0.532	0.13	0.454	-0.053	0.452	0.817				
PEOU	0.609	0.051	0.433	0.1	0.525	0.481	0.852			
PU	0.657	0.168	0.354	0.088	0.554	0.668	0.56	0.89		
SN	0.542	0.203	0.298	0.065	0.491	0.35	0.373	0.394	0.786	
WTP	0.313	0.019	0.243	0.008	0.48	0.129	0.225	0.203	0.217	0.864

Table 4: Cross-Loadings Score
Source: Researchers Analysis

5.2.4. Collinearity Test

Collinearity test is applied by calculating the Variance Inflation Factor (VIF) scores (Wong, 2013). To avoid collinearity problems, the VIF value has to have a value of 5 or lower to be acceptable. The VIF score on table 3 is less than 5 which means that all of the indicators have passed the criteria. Therefore, we can conclude that there is no multicollinearity between the variables.

5.2.5 Structural Path Significance

Partial Least Square is completed to assess the causal effect from the conceptual framework that is used in this research. Through bootstrapping and blindfolding test in SmartPLS application, the researcher wants to evaluate the relationship between TRI factors (optimism, innovativeness, discomfort, and insecurity), TAM factors (perceived usefulness, perceived ease of use, attitude, intention to use), subjective norms, and the consumer's willingness to pay. The model was built by these 10 variables connected to 15 paths. The measurement model using reflective constructs is shown by the diagram below:

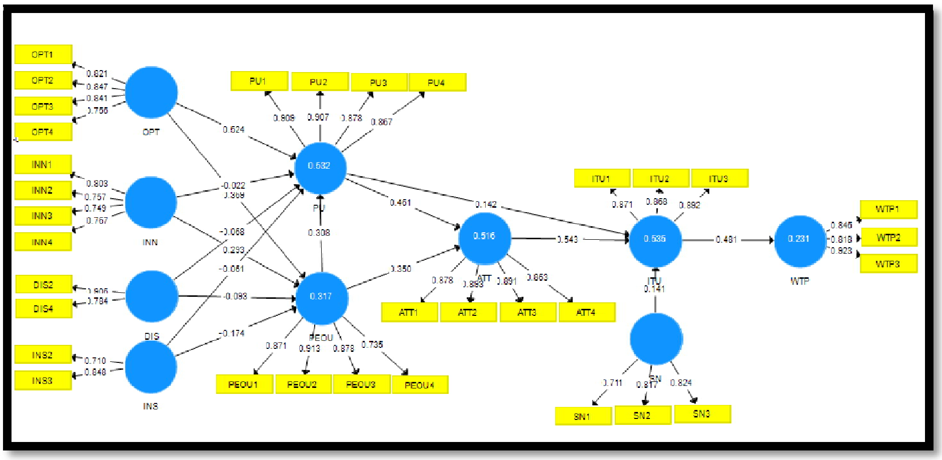

Figure 5: Structural Path Significance
Source: Researchers Analysis

The coefficient of determination (R^2) is intended to measure the model's predictive accuracy (Wong, 2013). The R^2 varies between 0 and 1 depending on the level of the predictive accuracy from the dependent variable (Hair et al., 2014). The R^2 of perceived ease of use is 0.317 which means that the TRI factors can explain 31.7% of the variance in the perceived ease of use of IoT products. The R^2 value for perceived usefulness is 0.532 which indicates that the TRI factors and perceived ease of use can explain 53.2% variance in perceived usefulness. Attitude has R^2 of 0.516 which explains that 51.6% of the variance of attitude can be explained by the perceived usefulness and perceived ease of use. Intention to use has R^2 of 0.535 which indicates that 53.5% of the variance of intention to use can be explained by attitude, perceived usefulness, and subjective norm. The last one is the R^2 of willingness to pay which is 0.231. That means the intention to use can explain 23.1% variance in willingness to pay.

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	R^2	Q^2
Attitude	0.516	0.397
Intention to Use	0.535	0.405
Perceived Ease of Use	0.317	0.222
Perceived Usefulness	0.532	0.414
Willingness to Pay	0.231	0.162

Table 5: R^2 and Q^2 score
Source: Researchers Analysis

Meanwhile, Q^2 or cross-validated redundancy is intended to measure the predictive relevance for the inner model (Wong, 2013). By using blindfolding tests in SmartPLS, the Q^2 score can be seen from table 5. Q^2 value above 0 indicates a predictive relevance in a model. Because the Q^2 value from all the factors is above 0, we can conclude that the model has predictive relevance.

5.2.6. Hypothesis Testing

According to Wong (2013), bootstrapping tests in SmartPLS can develop the score of T-Value that can be used to test the significance of the inner and outer model. This test can be used in hypothesis testing to find out the level of significance from each variable that is being tested. T-Value must be greater than 1.96 at 5% significant level so the path coefficient can be considered as significant. Table 6 showed a summary of hypothesis testing in this research.

Hypothesis	Structural Path	Path Coefficient	T Values	P Values	Result
H1a	Optimism -> Perceived Usefulness	0.524	12.076	0	Accepted
H1b	Optimism -> Perceived Ease of Use	0.369	7.589	0	Accepted
H2a	Innovativeness -> Perceived Usefulness	-0.022	0.414	0.679	Rejected
H2b	Innovativeness -> Perceived Ease of Use	0.293	5.689	0	Accepted
H3a	Discomfort -> Perceived Usefulness	-0.068	1.519	0.129	Rejected
H3b	Discomfort -> Perceived Ease of Use	-0.093	1.345	0.179	Rejected
H4a	Insecurity -> Perceived Usefulness	-0.061	1.36	0.174	Rejected
H4b	Insecurity -> Perceived Ease of Use	-0.174	2.693	0.007	Accepted
H5a	Perceived Ease of Use -> Perceived Usefulness	0.308	5.494	0	Accepted
H5b	Perceived Ease of Use -> Attitude	0.35	6.815	0	Accepted
H6a	Perceived Usefulness -> Attitude	0.461	9.442	0	Accepted
H6b	Perceived Usefulness -> Intention to Use	0.142	2.663	0.008	Accepted
H7	Attitude -> Intention to Use	0.543	8.653	0	Accepted
H8	Subjective Norm -> Intention to Use	0.141	2.488	0.013	Accepted
H9	Intention to Use -> Willingness to Pay	0.481	12.426	0	Accepted

Table 6: Hypothesis Testing
Source: Researchers Analysis

From 15 hypotheses that were developed in this research, four of them are rejected. H2a, H3a, H3b, and H4a appears to be insignificant because the T-Value is below 1.96 at the significant level of 5%. Innovativeness appears to give a negative impact on PU and showed as insignificant. The discomfort didn't give a negative significant correlation for both PU and PEOU, and Insecurity didn't have a significant correlation to PU although the path correlation appears as negative. Other than that, the rest of the hypotheses are accepted because they have T-Value above 1.96 at a significant level of 5%. The highest significant score can be seen from H9 where the T-Value of intention to use to WTP is 12.426.

5.2.7. Total Effect and Total Indirect Effect

Bootstrapping test in SmartPLS can give the total effect and total indirect effect from independent variables to dependent variables to measure the size of influence both directly and indirectly. A specific indirect effect is also used to measure the mediating effect (Wong, 2013). Table 7 showed the total direct and indirect effects from one variable to another.

Structural Path	Total Effect			Total Indirect Effect		
	Path Coefficient	T Value	P Values	Path Coefficient	T Value	P Values
ATT -> ITU	0.543	8.653	0			
ATT -> WTP	0.261	7.642	0	0.26	7.202	0
DIS -> ATT	-0.015	0.411	0.681	-0.014	0.425	0.671
DIS -> ITU	-0.002	0.1	0.921	-0.002	0.095	0.924
DIS -> PEOU	-0.093	1.345	0.179			
DIS -> PU	-0.039	0.885	0.377	-0.029	1.262	0.207
DIS -> WTP	-0.001	0.1	0.921	-0.001	0.096	0.924
INN -> ATT	0.134	3.696	0	0.134	3.926	0
INN -> ITU	0.082	3.004	0.003	0.083	3.173	0.002
INN -> PEOU	0.293	5.689	0			
INN -> PU	0.068	1.384	0.167	0.09	3.878	0
INN -> WTP	0.04	2.933	0.004	0.04	3.112	0.002
INS -> ATT	-0.114	3.022	0.003	0.114	3.188	0.002
INS -> ITU	-0.078	2.903	0.004	0.078	2.971	0.003
INS -> PEOU	-0.174	2.693	0.007			
INS -> PU	-0.115	2.404	0.017	0.053	2.48	0.013
INS -> WTP	-0.037	2.771	0.006	0.037	2.923	0.004
ITU -> WTP	0.481	12.426	0			
OPT -> ATT	0.424	13.045	0	0.423	12.894	0
OPT -> ITU	0.32	9.264	0	0.32	9.3	0
OPT -> PEOU	0.369	7.589	0			
OPT -> PU	0.638	16.337	0	0.114	4.199	0
OPT -> WTP	0.154	7.451	0	0.154	7.482	0
PEOU -> ATT	0.492	10.606	0	0.142	4.782	0
PEOU -> ITU	0.311	7.402	0	0.311	7.213	0
PEOU -> PU	0.308	5.494	0			
PEOU -> WTP	0.149	6.479	0	0.149	6.12	0
PU -> ATT	0.461	9.442	0			
PU -> ITU	0.392	7.986	0	0.25	6.349	0
PU -> WTP	0.188	6.859	0	0.188	6.837	0
SN -> ITU	0.141	2.488	0.013			
SN -> WTP	0.068	2.447	0.015	0.067	2.48	0.013

Table 7: Total Effect Size
Source: Researchers Analysis

Discomfort gave insignificant influence to attitude, intention to use, PU, PEOU, and WTP. Innovativeness also gave an insignificant influence on PU. Other than that, all of the correlations between the variables are positive and the highest total direct effect score is from optimism to perceived usefulness. From Table 7 score, we can see the most influencing factor from TRI to TAM. In this case, optimism gave the most influence to PU with a score of 16.337 and to PEOU with a score of 7.589. Optimism also gave the highest indirect influence on attitude with a score of 12.894.

	Path Coefficient	T Value	P Values
DIS -> PEOU -> ATT -> ITU -> WTP	-0.009	1.296	0.196
INN -> PEOU -> ATT -> ITU -> WTP	0.027	3.369	0.001
INS -> PEOU -> ATT -> ITU -> WTP	-0.016	2.322	0.021
OPT -> PEOU -> ATT -> ITU -> WTP	0.034	4.017	0
DIS -> PU -> ATT -> ITU -> WTP	-0.008	1.39	0.165
INN -> PU -> ATT -> ITU -> WTP	-0.003	0.417	0.677
INS -> PU -> ATT -> ITU -> WTP	-0.007	1.325	0.186
OPT -> PU -> ATT -> ITU -> WTP	0.063	5.806	0
DIS -> PEOU -> PU -> ATT -> ITU -> WTP	-0.003	1.3	0.194
INN -> PEOU -> PU -> ATT -> ITU -> WTP	0.011	3.316	0.001
INS -> PEOU -> PU -> ATT -> ITU -> WTP	-0.006	2.292	0.022
OPT -> PEOU -> PU -> ATT -> ITU -> WTP	0.014	3.813	0
DIS -> PEOU -> PU -> ITU -> WTP	-0.002	1.114	0.266
INN -> PEOU -> PU -> ITU -> WTP	0.006	1.969	0.049
INS -> PEOU -> PU -> ITU -> WTP	-0.004	1.699	0.09
OPT -> PEOU -> PU -> ITU -> WTP	0.008	2.004	0.046
DIS -> PU -> ITU -> WTP	-0.005	1.21	0.227
INN -> PU -> ITU -> WTP	-0.001	0.374	0.708
INS -> PU -> ITU -> WTP	-0.004	1.232	0.219
OPT -> PU -> ITU -> WTP	0.036	2.503	0.013
PEOU -> ATT -> ITU -> WTP	0.091	4.792	0
PU -> ATT -> ITU -> WTP	0.12	6.343	0
PEOU -> PU -> ATT -> ITU -> WTP	0.037	4.405	0
PEOU -> PU -> ITU -> WTP	0.021	2.146	0.032
PU -> ITU -> WTP	0.068	2.561	0.011
ATT -> ITU -> WTP	0.261	7.642	0
SN -> ITU -> WTP	0.068	2.447	0.015

Table 8: Specific Indirect Effect
Source: Researchers Analysis

A specific indirect effect is performed to analyze the mediating effect of the model. In this case, we want to know whether TRI factors can have an indirect effect on WTP where TAM factors act as the mediator. Discomfort showed an insignificant effect on every path to the WTP. This means that discomfort was not a factor that could influence WTP. Insecurity shows an insignificant indirect effect on WTP if the path is through PU because the correlation between insecurity to PU alone is not significant. Innovativeness also has an insignificant indirect effect on WTP if the path is through PU. Meanwhile, optimism seems to have a positive indirect effect on WTP through PU and PEOU. The highest effect from TRI factors itself came from the path OPT → PU → ATT → ITU → WTP with a specific indirect score of 5.806. It can indicate that from all of TRI factors, optimism can give the greatest influence to WTP through PU, attitude, and intention to use as the mediator.Out of all the TAM factors that are used in this study, attitude gave the highest indirect effect (7.642) to WTP with variable intention to use as the mediator.The subjective norm, which is the external variable, also appears to have an indirect effect on WTP through intention to use.

5.3. Contingent Valuation Method

In this part, we analyze the contingent valuation method from the respondents' answers of willingness to pay. Alfikriet al. (2019) use CVM to measure the WTP of halal-certified beef through the mean results. In this research, respondents were asked to state their willingness to pay for one of the examples of IoT products, which is a smart garden. With 5 scale answer ranging from 1 (I'm not willing to pay for this product); 2 (I will pay below Rp 375.000); 3 (I will pay between Rp 375.000 to Rp 749.000); 4 (I will pay between Rp 750.000 to Rp 1.124.000); and 5 (I will pay between Rp 1.125.000 to Rp 1.1500.000). After analyzing the answer with excel, both the median and mode of this question are on scale 3 which has a willingness to pay from Rp 375.000 to Rp 749.000. The mean from the willingness to pay itself is on the price of Rp 497.250, which then rounded up to Rp 500.000. This means that the consumer is preferred to pay about Rp 500.000 for IoT smart garden.

6. Discussion

This research is intended to find the relationship between the readiness and acceptance of IoT products to the willingness to pay in the Indonesian market. Hypothesis 1a and 1b are accepted, which means that optimism has a positive significant correlation to PU and PEOU. This result is aligned with the findings from Jin (2013), Oh et al. (2014), and Chiu and Kim (2019). It means that people's positive view of technology can influence their belief that IoT product will enhance their performance and will give them less effort in working. Meanwhile, hypotheses 2a and 2b have a contradictive result. Innovativeness gives an insignificant correlation to PU yet giving PEOU positive significant results. This could explain that although the level of tech literacy from the people can influence their belief that IoT products will give them less effort, it didn't influence their belief that IoT could enhance their work performance. Innovativeness also appears to get low scores since not everyone in Indonesia tends to be a tech pioneer.

Hypothesis 3a and 3b are rejected because discomfort has insignificant correlation to PU and PEOU. This means that the lack of control from using technology didn't impact people's perceived usefulness and perceived ease of use from IoT products. Hypothesis 4a is rejected because insecurity gave no impact on perceived usefulness. Meanwhile, hypothesis 4b is accepted. The possible explanation from this is while the distrust of technology can impact people's believe that IoT will give them less effort in working, it didn't impact them for thinking that IoT could enhance their work performance. The results from H3a, H3b, and H4a are not aligned with the findings from Jin (2013), Oh et al. (2014), and Chiu and Kim (2019) but H4b is.

H5 until H9 is accepted and gave positive significant results. All of the TAM factors hypotheses result from H5 to H7 are aligned with the findings from Chung and Han (2015) and Karahoca et al. (2017).Subjective norm gave a positive indirect effect on WTP, which explains that social environments like family, friends, and media could influence people's willingness to pay for IoT products. The result from H8 is aligned with the findings from Hussein (2018) and Lau et al. (2019).

H9 is accepted and the result is aligned with the findings from Wang et al. (2013) and Anwar et al. (2015). Intention to use proven as the most influencing factor to WTP, it means that people's willingness to pay for IoT products came from their intention to use IoT. People's acceptance of IoT products is proven to be the influencer of their willingness to pay. Meanwhile, their readiness towards new technology can indirectly affect their willingness to pay for IoT products. In this case, the readiness factor is from their optimist view to technology.

7. Conclusions and Recommendations

7.1. Conclusions

Based on the data analysis results, the Indonesian market has optimism towards new technology that they thought new technology will contribute to a better quality of life. They also feel insecure about the use of technology that might invade their privacy. The market's innovativeness appears low because not all of the people have high technology literacy. Their acceptance of IoT products appears to be positive. From their perceived usefulness, perceived ease of use, attitude, and intention to use IoT products. This explains that the market has positive believes that IoT products can give them better work performance and less effort. They also behave positively towards IoT and have an interest in using the product. Subjective norm appeared as the influence of people's intention to use IoT too and have an indirect effect on the willingness to pay for IoT products.

Overall, the willingness to pay for IoT is mostly influenced by their consumer's intention to use because it is directly correlated. Other than that, the optimism toward technology has the greatest indirect influence on IoT WTP with perceived usefulness, attitude, and intention to use as the mediating variables.

7.2. Recommendations

Indonesian IoT companies have to understand the market's behavior toward IoT products. The market is pretty optimistic about new technology, but not all of them have the same level of innovativeness. They also tend to have some distrust about privacy and security matters. People that haven't bought IoT products in Indonesia tend to use simpler products with the same function. That is why not all of the market feels the need to use IoT products. Overall, non-buyers gave positive feedbacks saying they would like to buy the IoT product as long as their needs are fulfilled. It is a great opportunity for the IoT market in Indonesia. In this case, IoT companies and marketers have to educate the market more about the different features and functions that IoT brings that could make the consumer understand the benefit from using IoT so that they can boost their sales as well as widen their market. To build more trust, companies should protect their user's privacy as well as keeping a good communication with them. The budget allocations also should be centered on marketing to spread product awareness first. Giving promotions and advertisements through social media and websites, using a marketplace like *Bukalapak, Shopee*, and *Tokopedia* to sell the IoT products, as well as collaborating with local communities could be implemented. For example, in Indonesia, the community of housewives can be a channel to market household-related IoT products like smart garden and smart home because if one person uses the product, the others are most likely to follow.

People also prefer to pay around Rp 500.000 for a compact product like the smart garden, and their willingness to pay is mostly based on their fulfillment from the product. That's why IoT companies and marketers have to deliver the exact value that matches the market's needs. The willingness to pay is going to be different in each type of product. By understanding the market needs and giving an appropriate pricing strategy that suits the market, IoT companies and marketers can maximize their company's growth.

8. Limitations and Future Research

Despite all of the findings obtained from this research, there are still some limitations happening. This study didn't do a comprehensive research about the market's behavior in a more diverse region of Indonesia. The researchers recommend more in-depth study in each region so that we could know the different patterns of people's willingness to pay and the acceptance towards IoT products from each region.

This research is also limited in finding the consumer's willingness to pay from TRI and TAM factors, which only explained the market's readiness and acceptance for IoT products. For future research, the researcher suggests finding other factors that could significantly influence the consumer's willingness to pay. Because the market tends to buy IoT products from the functions and the benefit that the product offered, It is appropriate to find out more about the correlation between the value offered and the consumer's willingness to pay for IoT products.

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