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NETWORK EXTERNALITY EFFECTS ON BEHAVIORAL INTENTION TO USE CONSUMER INTERNET OF THINGS AMONG URBAN CITIZENS IN INDONESIA

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Abstract:
One of the most popular technologies is the internet of things (IoT). It refers to the number of users and penetration in the industry (I-IoT) and consumer (C-IoT) sectors. The previous stud-ies indicated that the usage rate of the C-IoT is outperforming the I-IoT worldwide. However, the contrary indication occurred in Indonesia. Among developing countries, the spending level of IoT in Indonesia is significant, but the use level of the technology is less developed. This survey study purposed to predict what factors influence the behavior intention to use C-IoT. The researchers extended the unified theory of acceptance and use of technology (UTAUT) model by adopting the network externality aspects. Around 400 valid data were collected from urban communities in the six most populous provinces in the country. The scholars used the partial least squares structural equation modeling (PLS-SEM) method using SmartPLS 3.3 in the data analysis stage. The findings expressed that the number of users and social influence factors are not influential factors influencing behavior intention to use IoT. Besides that, the UTAUT model extension may also be one of the theoretical references for future similar studies. Practically, the findings may also be one of the considerations for the stakeholders of C-IoT implementation in Indonesia.

Key words: *IoT, consumer, intention to use, network externalities, Indonesia*

INTRODUCTION

IoT is one of the most widely used technologies worldwide [1, 2, 3, 4]. Besides the number of its users exceeding 30 billion devices worldwide [5, 6], the utilization in the industrial (I-IoT) and consumer (C-IoT) sectors is also its popularity indication [7, 8]. Previous studies [3, 4, 9] indicated that the sectors are the leading sectoral associations of this technology throughout 2018-2021. I-IoT refers to implementing this technology in industrial sectors, and C-IoT is about its consumer application [3, 10, 11]. Reports by Mordor Intelligence [3, 4] elucidated that the usage rate of the C-IoT sector tends to be larger, with 7.9 billion connected devices outperforming the I-IoT sector. In contrast, it is interesting that a different phenomenon has occurred in Indonesia. This developing country has the second-highest IoT spending among Southeast Asian nations [12], but Hootsuite's report [5] indicated that the use of the C-IoT sector is currently underdeveloped. The report showed that only around 15% use C-IoT devices. On the other hand, many facilitating factors support C-IoT devices use in this country [13]. The report [5] indicates that most urban consumers (±64%) have used the internet, especially in the urban area. Internet users are dominated (±55.7%) by young people (20-30 years old) who are high buying and selling interest. More than 60% of people use smart devices to support their daily activities.

The phenomenon above seems consistent with the previous studies [14, 15, 16, 17, 18]. Besides the IoT applications could also be complicated and, in some cases, challenging for the users [18, 19], the use of digital technology in a developing country may also relate to the digital divide issues [14, 15, 16, 17]. Lopez-Sintas, et al. [16]

pointed to the need to change the information technology research focus from household to individual aspects among the digital divide studies in developing nations. Referring to the significant role of C-IoT use for national development and the technology adoption phenomenon in Indonesia, one of the exciting issues is knowing the use of C-IoT issues in the country.

This study purposed to know factors influencing the behavioral intentions to use C-IoT among urban users in Indonesia. Understanding the factors may be one of the practical consideration points for stakeholders in terms of the technology used in this developing country. Theoretically, the extension of the behavior intention model to use C-IoT may be one of the theoretical references for similar studies in the context of using C-IoT among developing countries. In order to guide the research implementation, the researchers proposed two research questions:

RQ1: What network externality factors influence the use of C-IoT among urban users?

RQ2: What are the influential factors of C-IoT use among urban users?

Further, the second section describes the literature review that supported the study, including the model and its hypothesis developments. The third second explains the methodological issues of the study. The fourth section presents the data analysis results. The fifth section discusses the data analysis results by comparing the results with the theoretical base used in the study and explains the findings, limitations, and recommendations of the study, respectively. Lastly, this article is closed by the conclusion part in the sixth section.

LITERATURE REVIEW

IoT has connected around 30 billion devices worldwide at the end of the last decade [5, 6]. Studies of Social and Hootsuite [5] and Vailshery [6] estimated that the number will be around 50 billion devices by 2030. This phenomenon may indicate that IoT has become the most popular technology in the last decade [7, 8]. Besides industrial sectors [4, 9], the adoption by consumers has also been increasing since the emergence of coronavirus disease 2019 (COVID-19) [3, 10, 11]. The C-IoT sector is the sector that refers to individual use by consumers [3, 10]. IoT in these sectors tends to be more prominent around 7.9 billion connected devices outperforming the I-IoT sectors [3, 4, 5, 6, 9]. The growth of the C-IoT sector indirectly shows its high use level in society. C-IoT has dramatically changed people's lives [3, 10, 11]. Studies by Adil and Khan [11], Intelligence [3], and Khanna and Kaur [10] described that the application of this technology had ensured benefits, such as higher productivity, well-being, and satisfaction of its users. To achieve these benefits, people also pay for IoT. However, investing in IoT does not guarantee success and often leads to low returns [18, 19]. Given the consequences of IoT adoption among consumers, it is interesting to discuss. In brief, it is a good practice of innovation management in the consumer context [20, 21].

Researchers [22, 23, 24] have shown interest in the behavior of users of digital technologies nearly three decades ago, which is related to how they intend to use the technology after receiving it. Many theories and models have been introduced based on a psychological perspective on human acceptance behavior for understanding the acceptance and use of technology, e.g., the theory of reasoned action (TRA), theory of planned behavior (TPB), technology acceptance model (TAM), and UTAUT model. Expressly, Venkatesh, et al. [25] set out to develop a unified technology acceptance theory by integrating key constructs that predict intention and use behavior to provide a thorough understanding of technology acceptance. They demonstrated that the UTAUT model primarily describes the points of view of technology management and emphasizes the importance of cognitive responses to technology features for predicting user behavior. In short, the social computing theories and models provide general insights into the underpinnings of individual attitudes, making them applicable to various research contexts [22, 23, 24].

In this study, the researchers extended the UTAUT model [25, 26] by combining the model with two network externality factors [27, 28] (i.e., number of users [NU] and the number of peers [NP]) for examining the C-IoT use phenomenon (Fig. 1).

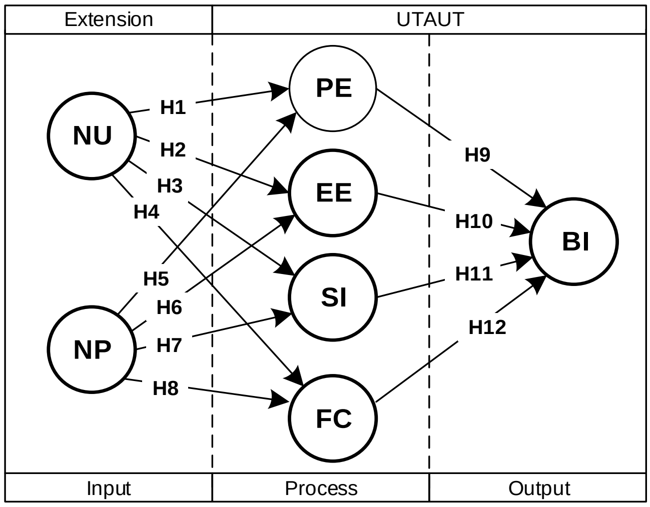

Fig. 1 Research model and its hypotheses

The authors proposed two justifications for extending the model. First, the scholars conceptualized using C-IoT as an input-process-output (IPO) procedure [29, 30]. They assumed NU and NP as two variables of the input dimension of the procedure and split the UTAUT model [25, 26] as the process and output dimensions. The process dimension includes the performance expectations [PE], effort expectations [EE], social influence [SI], and facility condition [FC] variables, and the output one contains the behavioral intention to use [BI]) variable. Second, the researchers assumed that two network externality factors [27, 28] were the external variables of the UTAUT model following the previous extension TAM studies [31, 32], considering the aim of understanding the effects of external factors on users' attitude, behavioral intention and actual use of technology.

In the context of C-IoT use, the quantity issues of using C-IoT may socially influence the acceptance and use by users. The scholars indicated that the number of users (NU1), growing use (NU2), and widespread use (NU3) are related to the NU variable of the C-IoT use [27, 28]. Similarly, they initiated the use by most peers (NP1), used by many peers (NP2), and future use by peers (NP3) are indicators of NP variables [27, 28]. Thus, the researchers proposed eight hypotheses:

H1: The number of users has a positive effect on performance expectations.

H2: The number of users has a positive effect on effort expectations.

H3: The number of users has a positive effect on social influence.

H4: The number of users has a positive effect on facility conditions.

H5: The number of peers has a positive effect on performance expectations.

H6: The number of peers has a positive effect on effort expectations.

H7: The number of peers has a positive effect on social influence.

H8: The number of peers has a positive effect on facility conditions.

In terms of the process and output dimensions of the C-IoT use [29, 30], the researchers adopted (1) the perceived usefulness (PE1), extrinsic motivation (PE2), job-fit (PE3), relative advantage (PE4), and outcome expectations (PE5) as indicators of PE variable; (2) the complexity (EE1), perceived ease of use (EE2), and ease of use (EE3) as indicators of EE variable; (3) the mass media influence (SI1), subjective norm (SI2), social factors (SI3), and image (SI4) as indicators of SI variable; (4) the perceived behavioral control (FC1), facilitating conditions (FC2), and compatibility (FC3) as indicators of FC; and (5) the intention to use (BI1), planning to use (BI2), prediction to use (BI3) as indicators of BI variable [25, 26]. The scholars hypothesized that:

H9: Performance expectations have a positive effect on behavioral intention to use.

H10: Effort expectations have a positive effect on behavioral intention to use.

H11: Social influence has a positive effect on behavioral intention to use.

H12: Facility conditions have a positive effect on behavioral intention to use.

METHODOLOGY

This survey study was conducted within eight sequential stages (Fig. 2). The population was the urban citizens across six provinces in the most densely populated island in Indonesia, Java Island [33]. The researchers randomly selected the sampled people based on their IoT experience [21, 34, 35, 36]. They collected around 400 valid data via an online survey using social media applications. The questionnaires consisted of 10 individual profile questions and 24 five-Likert scale assessment questions [37].

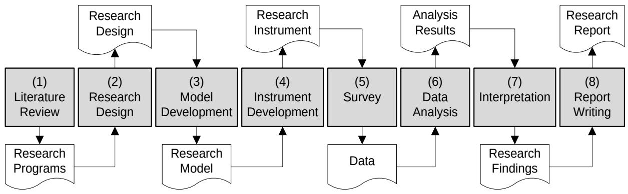

Fig. 2 The research procedure

The collected data were processed using MS. Excell 2013 and IBM SPSS Statistics 25. Meanwhile, the data was analyzed using the PLS-SEM method with SmartPLS 3.3 [38, 39, 40]. The authors tested the outer model using indicator reliability, internal consistency reliability, convergent validity, and discriminant validity assessments. Further, they assessed the inner model employing the path coefficient (*β*), coefficient of determination (R^2), hypothesis (*t*-test), effect size (f^2), predictive relevance (Q^2), and relative impact (q^2) assessments. In the interpretation stage, the researchers focused on the hypothetical assessment results and compared the results with the theoretical bases used in the model development for answering the research questions.

RESULTS

First, women dominated respondents of the study (±53%), people who are 20-25 years old (±68%), and undergraduate students (±55%). Most people revealed that they know about ICT (±74%) and IoT (±71%). Besides, most of the people expressed that they have skills in ICT (±57%) and IoT (±47%), and they have also experienced using IoT (±60%). Moreover, the highest number of respondents was from the Province of West Java (±40%), and the lowest was from the Special Region of Yogyakarta (±3%).

Second, the measurement model assessments demonstrated that the overall outer loading values of the indicators are above their threshold (0.6), and the composite reliability (CR) and average variance extracted (AVE) values of each variable are higher than the threshold of 0.7 and 0.5 respectively (Table 1).

Further, the cross-loading values of each AVE square root fulfill Fornell-Larcker's criteria [38, 39, 40] (Table 2). These external model evaluations indicated there is no indicator rejection.

Third, there are the six results of the structural model assessments. (1) *β* was assessed using a threshold value of 0.1 or more as a significant path. Table 3 shows that two of the 12 paths (i.e., H3 and H11) were insignificant. (2) R^2 was assessed with threshold criteria of around 0.25, 0.5, and 0.75 as weak, moderate, and substantial, respectively. Table 3 presents two weak paths (i.e., H3 and H7) and ten moderate ones. (3) *t*-test was examined using the bootstrapping method with the acceptance threshold of 5% (two-tailed, t-values = 1.96). Table 3 and Fig. 3 show two hypothesis rejections, i.e., H3 and H11.

Table 1
Results of the measurement model assessments

Indicators	Outer Loading	Cross Loading							CR	AVE
		BI	EE	FC	NP	NU	PE	SI		
BI1	.852	.852	.560	.653	.516	.460	.579	.444		
BI2	.840	.840	.568	.596	.461	.462	.515	.367	.896	.741
BI3	.890	.890	.648	.674	.565	.595	.655	.403		
EE1	.840	.550	.840	.570	.393	.382	.519	.442		
EE2	.840	.556	.840	.561	.437	.494	.566	.425	.878	.707
EE3	.841	.626	.841	.604	.501	.496	.644	.447		
FC1	.782	.529	.477	.782	.432	.380	.421	.429		
FC2	.838	.587	.503	.838	.425	.457	.458	.374	.863	.678
FC3	.848	.702	.688	.848	.613	.606	.744	.454		
NP1	.810	.439	.393	.450	.810	.478	.433	.399		
NP2	.892	.534	.474	.529	.892	.573	.539	.425	.897	.745
NP3	.885	.569	.500	.583	.885	.689	.628	.331		
NU1	.913	.523	.487	.540	.627	.913	.651	.334		
NU2	.924	.566	.521	.586	.658	.924	.710	.318	.940	.838
NU3	.910	.533	.497	.516	.580	.910	.685	.317		
PE1	.854	.546	.553	.599	.563	.656	.854	.347		
PE2	.872	.583	.617	.618	.576	.671	.872	.409		
PE3	.861	.619	.611	.567	.488	.632	.861	.318	.935	.741
PE4	.859	.591	.603	.554	.526	.629	.859	.442		
PE5	.859	.592	.584	.589	.539	.620	.859	.444		
SI1	.720	.365	.371	.408	.409	.344	.347	.720		
SI2	.801	.312	.365	.331	.290	.233	.299	.801	.843	.574
SI3	.826	.379	.457	.435	.367	.290	.431	.826		
SI4	.673	.360	.378	.353	.244	.172	.279	.673		

Table 2
The square roots of the AVEs

	BI	EE	FC	NP	NU	PE	SI
BI	.861						
EE	.689	.841					
FC	.746	.689	.823				
NP	.600	.531	.608	.863			
NU	.591	.548	.599	.679	.916		
PE	.681	.690	.680	.625	.745	.861	
SI	.471	.522	.511	.443	.353	.455	.758

Table 3
Results of the β, t, and R² assessments

Hypotheses	*β*	*t*	R^2	Analysis Results		
				β	*t*	R^2
H1	.595	13.416	.581	Significant	Accepted	Moderate
H2	.348	5.774	.347	Significant	Accepted	Moderate
H3	.096	1.735	.201	Insignificant	Rejected	Weak
H4	.345	6.434	.433	Significant	Accepted	Moderate
H5	.221	4.329	.581	Significant	Accepted	Moderate
H6	.295	4.725	.347	Significant	Accepted	Moderate
H7	.377	5.562	.201	Significant	Accepted	Weak
H8	.373	6.446	.433	Significant	Accepted	Moderate
H9	.157	2.397	.648	Significant	Accepted	Moderate
H10	.225	3.811	.648	Significant	Accepted	Moderate
H11	.024	.555	.648	Insignificant	Rejected	Moderate
H12	.380	6.463	.648	Significant	Accepted	Moderate

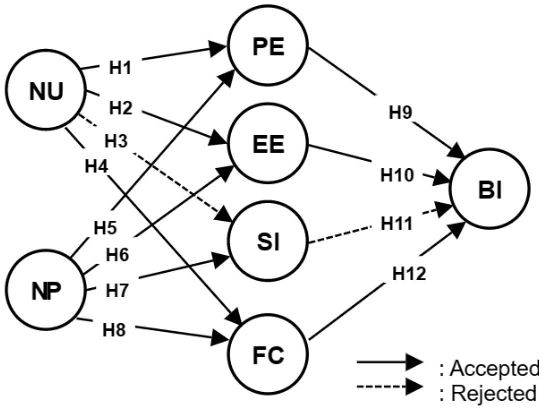

Fig. 3 Result of the hypothetical evaluation

(4) Q^2 was assessed with a threshold above zero to justify each path's predictive relevance, and the results showed that all paths are predictive relevant (Table 4). (5) f^2 was tested using threshold values of 0.02 (small), 0.15 (medium), and 0.35 (large). Table 4 presents seven small influence paths (i.e., H3, H5, H6, H7, H9, H10, and H11), three medium influence paths (i.e., H2, H4, and H12), and a large influence path (i.e., H1). (6) q^2 was assessed similarly with the threshold of f^2 assessment.

Table 4
Results of the f², Q², and q² assessments

Hypotheses	f^2	Q^2	q^2	Analysis Results		
				f^2	Q^2	q^2
H1	.456	.428	.244	Large	Predictive relevance	Large
H2	.100	.239	.059	Medium	Predictive relevance	Small
H3	.006	.109	.002	Small	Predictive relevance	Small
H4	.113	.279	.054	Medium	Predictive relevance	Small
H5	.063	.428	.034	Small	Predictive relevance	Small
H6	.072	.239	.040	Small	Predictive relevance	Small
H7	.096	.109	.047	Small	Predictive relevance	Small
H8	.132	.279	.063	Medium	Predictive relevance	Small
H9	.022	.468	.005	Small	Predictive relevance	Small
H10	.059	.468	.024	Small	Predictive relevance	Small
H11	.001	.468	.000	Small	Predictive relevance	Small
H12	.163	.468	.078	Medium	Predictive relevance	Small

Table 4 shows only one large influence path (H1); the rest were the small influence paths.

DISCUSSION

There are three discussion points of the study, i.e., the representation of data used in this study, the statistical property of the proposed model, and the answers to two research questions proposed in this study.

First, the descriptive analysis results indicated the demographic data used in this study [33] – for example, the population distribution rate of the original city. The highest number of respondents was from the Province of West Java (±40%), and the lowest was from the Special Region of Yogyakarta (±3%). It is consistent with the national report of Indonesia Statistics [33]. In short, the data used in the study represented the study's population, confirming the validity of the data used [36, 41].

Second, the psychometric property of the outer model without any indicator rejections may indicate the excellent quality of the research model used in this study. The statistical property is mandatory for further inner model assessments in the PLS-SEM method [38, 39, 40]. In brief, besides the validity of the outer model supported for the next inferential analysis stage, the indicators and each measurement item proposed in the model development may also be one of the references for further similar studies.

Third, there are replies to the two research questions of the research. They refer to two highlighted points of the inferential analysis results, mainly related to the hypothetical interpretation of the results (Figure 3).

RQ1: What network externality factors influence the use of C-IoT among urban users?

The hypothesis evaluation results showed that both network externality variables (i.e., NU and NP) influence BI mediated by the PE, EE, and FC variables (Fig. 3). The influential relationships proved the assumption used in the UTAUT model extension in the context of IPO causal logic [29, 30] and external factors of C-IoT use [31, 32]. Fig. 3 presents the relationship between NU and SI (H3) as the only rejected hypothesis among eight hypotheses that predicted connecting the network externality variables to the UTAUT model variables. The researchers argue that the rejection was due to similarities between NU and SI factors or biased perceptions among respondents towards these two factors. Thus, this may be one of the consideration points for subsequent studies. In sum, it is clear that the network externality factors influenced the use of C-IoT among consumers in Indonesia.

RQ2: What are the influential factors of C-IoT use among urban users?

Besides the hypothesis evaluation results (Table 3, Table 4, and Fig. 3) demonstrating rejection of the relationship path between NU and SI, the results also rejected the relationship path between SI and BI (H11). It is inconsistent with the previous studies [21, 42, 43, 44], which used similar assumptions in the model development. All in all, the inferential analysis results of this study presented that NU, NP, PE, EE, and FC are the five significant factors influencing BI in the context of C-IoT among urban users in Indonesia.

Moreover, knowing the factors may be one of the practical consideration points for stakeholders in terms of the use of consumer IoT in developing countries like Indonesia. Theoretically, the model extension may be one of the theoretical references for similar studies in the context of the use of IoT among developing countries.

CONCLUSION

Nowadays, the use of IoT is widespread worldwide, including among developing countries like Indonesia, the fourth most populous country in the world. The amount of IoT spending in this country is high in the Southeast Asia region, but the use of the C-IoT sector currently needs to be developed. This study aimed to estimate what factors influence the behavioral intentions to use C-IoT based on the urban people's perspectives. The researchers developed the research model based on the adoption, combination, and adaptation of the UTAUT and two network externality variables. Besides the psychometric property of the outer model, this survey study presented that the number of users and social influence are not influential factors on the behavioral intentions to use C-IoT. In contrast, the study revealed that the number of peers, performance expectation, and effort expectation are the essential factors related to the behavioral intentions to use the technology.

In the context of the technology acceptance and use model, the findings contribute theoretically to the model extension. In addition, they are also one of the practical consideration points for the stakeholders of C-IoT acceptance and use in developing countries like Indonesia. For instance, while people may have believed that factors of the number of users and social influence look like factors affecting the behavioral intentions to use C-IoT, the study has proved that both elements are not influential. Of course, the findings of this survey study cannot be generalized to other research phenomena, and it is because each phenomenon has its specific characteristics. Moreover, it is also related to the use of the data and methodological aspects used specifically in the study. Therefore, this study recommended that similar future studies consider the two issues mentioned earlier.

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