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THE IMPACT OF PERCEIVED SURVEILLANCE ON CONTINUANCE USAGE INTENTION OF VOICE ASSISTANTS

Roja Abdussami, Candiwan
Faculty of Economics and Business, Telkom University, Bandung, Indonesia
E-mail: abdussamiroja@student.telkomuniversity.ac.id,
candiwan@telkomuniversity.ac.id

Abstract

Voice assistants (VAs) are devices that utilize AI, machine learning, and NLP to facilitate users to perform diverse tasks verbally. VAs also have a unique feature that allows them to be "always on" so that every sound generated in their background can be analyzed and start interacting with users when they recognize their wake-up command, for instance, "Hey Siri" or "Okay Google", which implies that VAs have to be listening to users at all time. This raises the issue of privacy in the form of perceived surveillance. This study aims to assess how perceived surveillance affects the continuance usage intention of VAs in Indonesia with the addition of personal information disclosure as a mediator. Surveillance effect model was utilized to measure perceived surveillance. The model was calculated using PLS-SEM based on online survey data (N=222) distributed over social media. It was revealed that perceived surveillance affects the continuance usage intention of VAs negatively and is partially mediated by personal information disclosure. The result also affirmed that trust, perceived risk, and prior negative experiences are predictors of perceived surveillance. Therefore, VA companies should be mindful of how their customers' continuance usage intention is affected by how much perceived surveillance they feel.

Keywords: *Continuance Usage Intention; Internet of Things; Perceived Surveillance; Privacy; Surveillance Effect; Voice Assistants.*

Introduction

Throughout the last few years, the popularity of voice assistants (VAs) has been on the rise (Moriuchi, 2019). Moreover, it is even predicted that by 2024, VAs will be available on more than 8.4 billion devices, which implies a 113% increase from 4.2 billion by the end of 2020 (Vailshery, 2021). As of 2019, Google Assistant, Apple's Siri, Amazon's Alexa, Microsoft's Cortana, and Samsung's Bixby are some of the most popular VAs that are commercially available (Pal et al., 2020).

Voice assistants are characterized as devices that employ a voice-based interface, utilizing AI, machine learning, and NLP to facilitate verbal interaction with their users to perform diverse tasks in a more convenient and enjoyable way, for instance, scheduling appointments, playing music, and placing grocery orders (Moriuchi, 2019);(Pal et al., 2020). Voice assistants' main advantage is their use of conversational interfaces, often

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perceived as more intuitive and straightforward than web and mobile interfaces that rely on keypad input (Vimalkumar et al., 2021);(Zhong & Yang, 2018).

Furthermore, it is also continuously developed as companies are constantly devising innovative strategies to capitalize on voice assistant services. For example, personalization, socialization, and self-engagement opportunities might be developed to enhance user experience and provide additional value-added services (Pal et al., 2020). Nevertheless, it is only natural that such innovation and convenience have a price to pay, specifically concerning the users' privacy and security. It is inevitable that voice assistants need users' personal information to function properly. For instance, location-based voice prompts won't work if the voice assistants cannot access the users' geolocation data (Pal et al., 2020).

Voice assistants have a unique feature that allows them to be "always on" so that every sound or voice generated in their background can be analyzed. Voice assistants rely on that feature to identify their wake-up commands, like "Hey Siri" or "Okay Google" and start interacting with users, which means that these devices have to be listening to users at all times (Pal et al., 2022);(Frick et al., 2021);(Aeschlimann et al., 2020);(Hoy, 2018). Additionally, random words may get misinterpreted as wake-up commands and trigger unauthorized commands Schönherr (2022), which happened back in 2018 as a family in Portland had their conversation recorded and sent to someone in their contact list.

This raises concern among the users, as their conversations may not only be recorded but also vulnerable to eavesdropping, thereby compromising their privacy (Hoy, 2018). This concern is commonly referred to as perceived surveillance (Farman et al., 2020);(Segijn & Van Ooijen, 2020). In addition, the users are apprehensive regarding the possibility of companies using their data for unintended marketing purposes or even the creation of user profiles (Keith et al., 2013). Moreover, as per a survey conducted by Microsoft Bing Ads, 41% of the respondents indicated a lack of trust towards digital assistants, expressing concerns about their privacy being compromised through passive listening, and approximately 52% of the respondents expressed concerns pertaining to the security of their personal information.

Privacy is a significant concern and major hindrance not exclusive to the growth of voice assistants but also for every other IoT services in general (McLean & Osei-Frimpong, 2019). According to prior studies, there are several issues and phenomena related to privacy that users of VAs experience, including but not limited to privacy cynicism, intrusion, and surveillance (Mols et al., 2022);(Hill, 2017). There are several models developed to measure privacy. For example, the technology acceptance model (TAM) Acikgoz (2022), UTAUT2 (2020), IUIPC, MUIPC, and surveillance effect model (Frick et al., 2021).

In the case of perceived surveillance of conversations (PSoC) in smart devices, the recent surveillance effect model developed by Frick et al. (2021) successfully provided a foundation for understanding the factors influencing perceived surveillance. According to the study, prior negative experiences, computer anxiety, and trust in smart devices were three predictors that affect PSoC in smart devices. Trust in smart devices was found to be negatively affecting PSoC. Meanwhile, prior negative experiences and computer anxiety were found to affect PSoC positively.

Voice assistants are deemed an emerging paradigm capable of bringing about rapid changes in users' behavior and perception in a relatively short time frame [8], which implies that it is essential to be explored thoroughly. In spite of that, it is unfortunate that research that delve into the issue of perceived surveillance in relation to voice assistant continuance usage intention are still scant.

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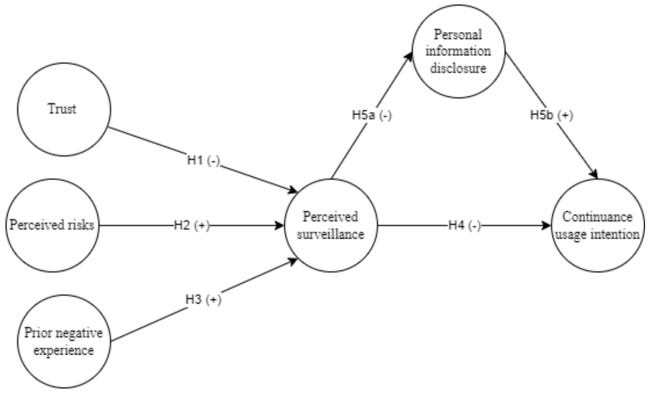

Figure 1 Research Model

Trust in correlation to the issue of privacy has always been a topic well discussed by existing research. Platforms that are perceived as less trustworthy may trigger reactance and privacy concerns among users (Bleier & Eisenbeiss, 2015). It is also discovered that when users have privacy concerns, trust that is based on structural assurance plays a more positive role in their continued usage intention (Zhu et al., 2023).

Trust is also a significant positive factor that affects the continuance usage intention of Go-Pay as a method of electronic payment (Putri, 2018). Meanwhile, users' trust can be attained by providing satisfaction and privacy (Girsang et al., 2020). Furthermore, measuring trust in relation to the usage of voice assistants has been proven to be important (Chung et al., 2017). Perceived surveillance would be the aspect of privacy that its relationship with trust would be assessed in this research in accordance with the surveillance effect theory, which revealed that trust is a significant factor not only during interactions between the users and the system but also in influencing the perception of being under surveillance (Frick et al., 2021). Therefore, this study proposed that H1: Trust in voice assistant platforms has a negative impact on perceived surveillance.

In using voice assistants, speech interaction may pose a risk to user privacy as it may reveal personal information that could be exploited by third parties Nguyen (2015), and potential risks associated with privacy and security can diminish individuals' propensity for the adoption of voice assistants. Perceived risk or risk belief refers to the extent that one believes there will be potential negative consequences or losses pertaining to the disclosure of personal information (Malhotra et al., 2004);(Dinev et al., 2006).

Moreover, in an online context, it is expected that users who are more aversive toward risk are less lenient regarding privacy leaks, and individuals who possess a higher degree of risk beliefs may exhibit greater concern compared to risk-tolerant users pertaining to the possibility of perceived surveillance. Thus, this study sought to affirm that H2: Perceived risk impacts perceived surveillance positively.

Prior negative experiences regarding personal information were discovered to be positively related to privacy concerns Škrinjarić (2018), and one's privacy concerns can increase by experiencing only one negative experience, regardless of any positive experiences they may have had beforehand. Users who have had negative experiences, such as privacy violations, are more inclined to experience perceived surveillance. The greater the number of negative experiences the users experienced, the more concerned they become regarding how they perceive risk and privacy (Okazaki et al., 2009). Therefore, this study derived that H3: Prior negative experience has a positive impact on perceived surveillance.

Prior studies revealed that privacy concerns negatively affect users' usage intention (Wahyudi et al., 2022);(Enaizan et al., 2022);(Jokisch et al., 2022). As mentioned previously, perceived surveillance would be the aspect of privacy that would be assessed in this research in accordance with the surveillance effect theory. Hence, to fulfill the main objective of this study, which was to measure how perceived surveillance affects the continuance usage intention of voice assistants, this study predicted that H4: Perceived surveillance is negatively associated with the continuance usage intention of voice assistants.

According to ISO/IEC 27002, personal information or personally identifiable information can be defined as any information that can be used to establish a link, either directly or indirectly, between the information and the natural person to whom such information relates (ISO, 2022). It is crucial to ascertain the presence of a relationship between personal information disclosure and continuance usage intention and how perceived surveillance affects personal information disclosure, as personal data continues to be collected even after the devices have been accepted by the user. Aside from that, Pal et al (2020) have revealed that personal information disclosure affects continuance usage intention positively.

Thus, this study predicted that H5a: Perceived surveillance is negatively associated with personal information disclosure and H5b: Personal information disclosure is positively related to continuance usage intention. Additionally, this study sought to ascertain that H5: Personal information disclosure mediates the linkage between perceived surveillance and continuance usage intention of voice assistants.

Therefore, this study aims to address that gap by using and adapting the surveillance effect model to assess perceived surveillance and how it affects the continuance usage intention of voice assistants, particularly in Indonesia. Unlike prior studies, this research tried to expand the theory by adding continuance usage intention as the consequence of perceived surveillance and personal information disclosure as its mediator.

Research Methods

This research used a quantitative approach. The data was collected by distributing an online questionnaire over social media, such as Instagram, Twitter, Facebook, WhatsApp, and Line, utilizing convenience and snowball sampling. Aside from demographic and screening questions, the questionnaire comprised 22 items. All items in this research were slightly modified to better fit the context of voice assistants and assessed via a 5-point Likert scale, which spanned from "strongly disagree" to "strongly agree". Furthermore, the questionnaire items were translated into Indonesian since the questions were originally in English. They went through a preliminary test involving 30 participants to ensure they would not cause ambiguity and multiple interpretations. Further details regarding the questionnaire are presented in Table 1.

Table 1 Research instrument

Constructs	Items	Code
Personal information disclosure (Xu et al., 2011)	I am likely to disclose my personal information	PID 1
	I am willing to disclose my personal information	PID 2
	I am likely to disclose my personal information when using voice assistants	PID 3
Prior negative experiences (Okazaki et al., 2009)	I have seen my personal information misused by online companies without my authorization	PNE 1
	I feel dissatisfied with my earlier choice to send my personal information to online advertisers	PNE 2
	My experience in responding to online advertising is very unsatisfactory	PNE 3
	In the past, my decision to send my personal information to online advertisers has not been a wise one	PNE 4
Perceived risks (Dinev et al., 2006);(Xu et al., 2011)	Disclosing my personal information to the VA devices will be risky	PR 1
	The chances of loss by disclosing my personal information to the VA devices will be high	PR 2
	Providing personal information to the VA devices can cause many unexpected problems	PR 3
Perceived surveillance (Frick et al., 2021)	I am concerned that VAs record conversations to provide personalized advertising on websites and social media	PS 1
	I think there are companies that analyzed audio files recorded by VAs to provide personalized advertising online	PS 2
	My VA listens to me and forwards the data to companies to provide personalized advertising on websites and social media.	PS 3
	I worry that my VA is recording conversations when I talk to my friends.	PS 4
	I am concerned that my VA is capturing information even though I am not actively using it.	PS 5
Trust (Malhotra et al., 2004);(Dinev et al., 2006)	I believe that the VAs can always be trusted	T1
	VA platforms are competent and effective in handling all my daily interactions with it	T2
	I believe that the services provided by the VAs are done in a reliable way such that business transactions can be conducted	T3
	VA service providers handle personal information in a competent manner	T4

Continuance usage intention (Chen & Lin, 2015);(Davis, 1989)	I intend to keep using VAs in near future	C 1
	I intend to recommend my friends to use VAs on a daily basis	C 2
	I would like to continue using my VA device rather than discontinuing its use	C 3

In this study, the rule of thumb was adhered to, which recommends a sample size of equal number or greater than ten times the number of constructs (J. F. Hair et al., 2011). The questionnaire was filled out from January 30 until April 20, 2023, targeting Indonesian citizens who use voice assistants. Initially, 270 participants completed the survey. Nonetheless, after excluding participants who did not meet the research criteria or whose responses showed anomalies, the final dataset used in the analysis comprised 222 participants, of whom 94 were males (42.34%), and 128 were females (57.66%).

The participants mainly consisted of 133 generation z (59.91%), followed by 63 generation y (28.38%), and 26 generation x (11.71%). Meanwhile, the participants' academic background consisted of 128 bachelor graduates (57.66%), 72 high school graduates (32.43%), 14 master graduates (6.31%), 6 level 3 diploma graduates (2.70%), and 2 level 4 diploma graduates (0.90%). Furthermore, the collected data revealed that there are 183 Google Assistant users (82.43%), followed by 73 Apple Siri users (32.88%), 40 Samsung Bixby users (18.02%), 32 Microsoft Cortana users (14.41%), and 15 Amazon Alexa users (6.76%). Additionally, Table 2 depicts the details regarding the respondents' geographical data.

Table 2 Geographical data

Island	Province	N	%
Java (50.90%)	Banten	14	6.31%
	West Java	50	22.52%
	Jakarta	14	6.31%
	Central Java	11	4.95%
	Yogyakarta	3	1.35%
	East Java	21	9.46%
Sumatra (14.41%)	North Sumatra	11	4.95%
	Lampung	4	1.80%
	Riau	2	0.90%
	South Sumatra	12	5.41%
	West Sumatra	2	0.90%
	Jambi	1	0.45%
Bangka Belitung (0.90%)	Bangka Belitung	2	0.90%
Kalimantan (11.26%)	South Kalimantan	4	1.80%
	East Kalimantan	13	5.86%
	West Kalimantan	8	3.60%
Sulawesi (11.26%)	Gorontalo	2	0.90%
	North Sulawesi	5	2.25%
	South Sulawesi	6	2.70%
	Central Sulawesi	5	2.25%
	West Sulawesi	2	0.90%
	Southeast Sulawesi	5	2.25%
Papua (11.26%)	Papua	4	1.80%
	West Papua	2	0.90%
	Central Papua	9	4.05%

	South Papua	2	0.90%
	Highland Papua	6	2.70%
	Southwest Papua	2	0.90%
Total		222	100%

The research model was assessed through PLS-SEM using SmartPLS (v. 3.0). This approach was chosen due to its high capability to provide strong estimates for the final research estimation (J. F. Hair et al., 2011). Furthermore, it is suitable for developing and evaluating untested models or conducting exploratory model building and is also capable of accommodating small sample sizes, non-normalized data, or complex models with numerous interconnected elements and relationships (Guhr et al., 2020).

In PLS-SEM analysis, outer model evaluation was conducted to primarily evaluate the validity and reliability of the construct measures. Meanwhile, inner model evaluation was conducted to measure direct significance effects between latent variables, which were used as a basis for assessing the hypotheses. 300 iterations of the path weighting scheme were used in the PLS algorithm utilizing 10−7 as the stop criterion. Additionally, bootstrapping was executed by utilizing the two-tailed BCa confidence interval method (Henseler et al., 2016).

Results and Discussion

A. Measurement model evaluation

To evaluate the validity and reliability of indicators, several tests must be conducted. To evaluate the validity of indicators, convergent validity from loading factors and AVE accompanied by discriminant validity, which can be assessed using several methods, such as cross-loading or Fornell-Larcker Criterion (R. Hair & JJ, 2019). Furthermore, the composite reliability (CR) must also be tested to ensure the reliability and internal consistency of the research instrument, which would be further supplemented by Cronbach’s alpha (CA) and Rho_A (RA) (Yang & Lee, 2019). Table 3 shows the data for the loading factors, VIF, CR, AVE, CA, and RA.

Table 3 Outer model evaluation

Indicator	Loading	VIF	CR	AVE	CA	RA
PID 1	0.924	2.979	0.943	0.846	0.909	0.913
PID 2	0.913	3.006				
PID 3	0.921	3.071				
PNE 1	0.704	1.558	0.907	0.710	0.862	0.880
PNE 2	0.903	2.993				
PNE 3	0.864	2.425				
PNE 4	0.885	2.614				
PR 1	0.824	1.823	0.907	0.764	0.845	0.852
PR 2	0.922	2.846				
PR 3	0.874	2.185				
PS 1	0.874	2.099	0.930	0.815	0.887	0.890
PS 4	0.911	3.009				
PS 5	0.924	3.088				
T1	0.880	2.172	0.898	0.689	0.851	0.881
T2	0.834	1.957				
T3	0.746	1.665				
T4	0.854	2.144				
C1	0.887	2.367	0.924	0.801	0.876	0.880

C2	0.894	2.221
C3	0.905	2.690

The indicators used in the research would be considered good if their loading value, CA, RA, and CR > 0.7 and AVE > 0.5 (R. Hair & JJ, 2019). According to the data in Table 3, all indicators fulfill the minimum criteria for loading value except for PS 2 and PS 3, which according to Hair et al. (2019), should be deleted. Meanwhile, CA, CR, and RA were all above 0.7, which ensured the research instrument's reliability and internal consistency. Furthermore, it is also clear that the convergent validity size is satisfactory, as the AVE values were all above 0.5. Additionally, it is indicated that collinearity isn't an issue in the measurement model as the outer VIF values shown in Table 3 are all lower than 5, while most of them are lower than 3.

Lastly, the Fornell-Larcker criterion, shown in Table 4, was used to examine discriminant validity, ensuring that a construct is entirely different from the others (Wahyudi et al., 2022). To ensure good discriminant validity in this approach, the square root of each construct's AVE should be greater than the correlations between that construct and the others in the model (Wahyudi et al., 2022). Upon reviewing the data presented in Table 4, it can be inferred that the research instruments exhibit adequate discriminant validity in accordance with the previously mentioned criterion.

Table 4 Fornell-Larcker criterion

	C	PID	PNE	PR	PS	T
C	0.895					
PID	0.473	0.920				
PNE	-0.448	-0.541	0.843			
PR	-0.386	-0.406	0.651	0.874		
PS	-0.527	-0.298	0.684	0.666	0.903	
T	0.778	0.450	-0.499	-0.477	-0.556	0.830

Structural model evaluation

Before the direct effects between variables were examined, several other tests should be conducted to ensure the quality of the research model. The first was the R2 test which measured the model's explanatory power. Although higher values would signify the presence of a more substantial effect, it is still important to interpret these values in accordance with the context of the conducted study, as valuable insights related to the research model can still be provided by lower values of explanatory power. This would be supplemented by Stone-Geisser Q2 to measure predictive relevance, which was divided into three effect sizes, including small (Q2>0), medium (Q2>0.25), and large (Q2>0.5) [48]. Table 5 shows the data for R2 And Q2.

Table 5 R2 and Q2 test result

Indicator	R^2	R^2 Adjusted	Q^2
C	0.387	0.381	0.304
PID	0.089	0.085	0.074
PS	0.587	0.581	0.468

Based on the data provided in Table 5, it can be inferred that the research model accounts for approximately 58.7% of the variance in perceived surveillance, 8.9% of personal information disclosure's variance, and 38.7% of the variance of continuance usage intention. Furthermore, the Stone-Geisser Q2 measure shown in Table 5 depicts a medium predictive relevance of the model for perceived surveillance and continuance usage intention as its value is higher than 0.25, but a small predictive relevance for personal information disclosure as it is below 0.25. Additionally, collinearity among constructs shouldn't be an issue, as the inner VIF values presented in Table 6 are all lower than 3.

Table 6 Inner VIF

	C	PID	PNE	PR	PS	T
C						
PID	1.098					
PNE					1.886	
PR					1.834	
PS	1.098	1				
T					1.406	

Subsequently, path coefficients were measured through bootstrapping using 5000 subsamples and a 0.5 significance value. The direct effect test results are presented in Table 7, wherein the T and P values associated with each path can be used to determine the path coefficients' significance (Wahyudi et al., 2022).

Table 7 Specific direct effect test result

	Original Sample (O)	T Statistics	P Value
PID → C	0.346	7.139	0.000
PNE → PS	0.363	5.211	0.000
PR → PS	0.325	4.554	0.000
PS → C	-0.423	7.836	0.000
PS → PID	-0.298	4.525	0.000
T → PS	-0.220	3.866	0.000

According to the data shown in Table 7, it can be inferred that trust (-0.220) in voice assistant platforms has a significant negative effect on perceived surveillance as its path coefficient is negative, thus confirming H1 as true. Aside from that, perceived risk (0.325) and prior negative experiences (0.363) have a significant positive effect on perceived surveillance, affirming H2 and H3, respectively, as true.

It can also be observed that perceived surveillance (-0.423) has a significant negative effect on the continuance usage intention of voice assistants, hence confirming H4 as true. Furthermore, it can be inferred that perceived surveillance (-0.298) has a significant negative impact on personal information disclosure, which affirms that H5a is true. Meanwhile, personal information disclosure (0.346) is positively and significantly associated with continuance usage intention, thus corroborating the validity of H5b.

Mediation analysis

Finally, mediation analysis was conducted to assess the mediating role of personal information disclosure (PID) in the relationship between perceived surveillance (PS) and continuance usage intention (C). The results shown in Table 8 revealed that the total effect of PS on C was significant. When PID was included as the mediating variable, the impact of PS on C maintained its significance. In addition, the indirect effect of PS on C through PID was found significant. These findings suggest that the linkage between PS and C is indeed partially mediated by PID, therefore providing support for H5.

Table 8 Mediation analysis

Total Effect	Coefficient	-0.527
	T Statistics	10.495
	P Value	0.000
Direct Effect	Coefficient	-0.423
	T Statistics	7.836
	P Value	0.000
Indirect Effect	Coefficient	-0.103
	T Statistics	3.877
	P Value	0.000

Albeit the growing attention and adoption of voice assistants and their projected growth, academic research on perceived surveillance and its impact on continuance usage intention is scant, especially in Indonesia. As stated by Pal et al. [8] and Yang and Lee [49], voice assistants' adoption is still in the early stage and can be deemed as an emerging paradigm with the potential to bring about rapid changes in users' behavior and perception in a relatively short time frame. Therefore, understanding the drivers behind the usage habits of VAs is especially important, which is what this study addressed. The theoretical model explained 63.7% of the perceived surveillance's variance and 38.7% of the variance of continuance usage intention. Furthermore, research results show that all of the hypotheses proposed in this study were corroborated.

The research results affirmed that trust is negatively related to perceived surveillance. It is consistent with previous studies associated with the role of trust and further cemented that trust is an essential factor in relation to the usage of voice assistants (Chung et al., 2017). The more users put their trust in VA platforms, the less likely they will feel that they are under surveillance. Thus, it can be understood that trusting VA and its capabilities could lead users to believe that the platform has good intentions and is using their data for helpful purposes, making them less likely to feel surveilled.

Meanwhile, it is revealed that perceived risk has a significant and positive impact on perceived surveillance. This implies that users who feel more risk regarding the use of VAs will make them more vulnerable to feeling that they are under surveillance. It adheres to what is known from prior studies, as potential risks associated with privacy and security can diminish individuals' propensity to adopt VAs. Aside from that, it also conforms with prior studies regarding perceived risk in other contexts, such as in intelligent connected vehicles, which according to Walter et al. (2020), privacy risk is considered one of the most significant perceived risks associated with data services in connected vehicles and negatively affects users' attitude.

Meanwhile, in contrast to the results of this study, Frick et al. (2021) found that perceived risk is not a significant factor in influencing users' perceived surveillance. However, it doesn't necessarily mean that either is incorrect, as that difference might be caused by other factors, such as the cultural and demographical conditions of Indonesia, which entails the need for further research.

Moreover, it is found that previous negative experience is positively related to perceived surveillance, which aligns with prior studies (Škrinjarić et al., 2018). It indicates that users who have had more negative experiences before will also be more prone to feel that they are under surveillance (Okazaki et al., 2009). This ought to be happening because users who have had negative experiences, such as privacy violations, are more inclined to experience perceived surveillance.

Furthermore, the fourth hypothesis managed to predict that perceived surveillance affects the continuance usage intention of VAs negatively, meaning that the more users feel that they are under surveillance, the more diminished their intent to continue using VAs will be. This further corroborates prior studies, which denote that privacy concerns negatively affect users' usage intention (Enaizan et al., 2022);(Jokisch et al., 2022).

Last but not least, personal information disclosure is found to be an important factor in the linkage between perceived surveillance and continuance usage intention, as it partially mediates that relationship. It indicates that the more users feel they are under surveillance, the less likely they will be willing to share their personal information, which will diminish their intent to continue using VAs. This supported the findings of previous studies related to how personal information disclosure affects continuance usage intention [4].

Conclusion

This study aims to assess how perceived surveillance, measured using the surveillance effect theory, affects the continuance usage intention of voice assistants in Indonesia. The research model used in this study is based only on the surveillance effect model, which only covers the issue of perceived surveillance in the context of privacy in VAs. Be that as it may, this study yielded satisfactory results and gave new and valuable insight into the growing literature related to privacy.

Overall, the findings suggest that perceived surveillance affects the continuance usage intention of VAs negatively and is also partially mediated by personal information disclosure. It is also affirmed that trust, perceived risk, and prior negative experiences are significant predictors of perceived surveillance. This implies that VA companies should be mindful of how their customers' continuance usage intention is affected by how much perceived surveillance they feel. However, since it is only natural that VAs need users' data to perform and improve, VA companies can help alleviate the negative effect of perceived surveillance by making users more willing to share their personal information. Aside from supporting organizations in optimizing their customer relations, the findings in this study also contribute as a foundation for future studies. For future research directions, it is recommended to examine additional predictors of perceived surveillance and further explore its relationship with continuance usage intention, such as involving privacy cynicism or combining perspectives from other models, such as privacy calculus and other models. Aside from that, it is also encouraged to further affirm how perceived risk affects perceived surveillance by involving other variables that might influence how one would perceive and react to risk, such as aspects of culture and demography.

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