Understanding Digital Banking Adoption During Post-Coronavirus Pandemic: An Integration of Technology Readiness and Technology Acceptance Model

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***Abstract* – Digital banking can make banking transactions easier in daily life. However, the presence of technology does not seem to be welcomed. This is due to the unpreparedness of technology for digital banking technology. The target respondents are millennial generation users in Indonesia who use digital banking services during post-corona virus. The sample selection using random sampling with 422 respondents. The data analyses were performed using SEM-PLS. The results show that Optimism, Discomfort, and Insecurity affect the acceptance of digital banking based on perceived ease of use and usefulness. However, Innovativeness has no connection on perceived usefulness. This is because post-covid conditions, the most important thing is how digital banking can support survival. They also argue that digital banking can make it easier and useful for daily life, especially in payment features connected.**

***Keywords* – Behavioural Intention, Digital Banking, TAM, Technology Adoption, Technology Readiness.**

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1. Introduction

Since the COVID-19 pandemic in recent years, people's behavior has begun to change, including very high dependence on technology. Currently, people make transactions without going through physical contact. This situation is encouraged by the rapid global rise of technology, which enables traditional corporate organizations to transition into digital firms. This transformation has also changed the financial industry (online banking) [1]. The existence of technology allows organizations to move to be more effective and efficient. One of the technologies applied in banking is digital banking. Digital banking allows users to perform banking transactions without coming directly to the branch office. Banking activities such as opening accounts, bank transfers, e-commerce payments, electricity payments, and even opening other banking products such as credit cards can be done online. The survey shows that the growth of online shopping in Indonesia is greater than offline transactions. This is a result of social restrictions. Consumers are limited in their social movements to purchase goods and services for daily activities. This gives rise to digital literacy that is increasing rapidly. Now, both large and small businesses are upgrading by creating online channels. So, the payment method using mobile banking, for example, is a much-needed alternative. This convenience is certainly very helpful for the community, especially the millennial generation, synonymous with high mobility. From the banking side, of course, digital banking can reduce other costs that are quite large, such as reducing resources, renting a place, and operating branch office activities. In addition, the company can also increase sales, increase reach, and can get a wider range of new customers, especially the millennial generation [2].

A model devised by Davis called the technology acceptance model (TAM) is one of the models that are used to assess technology adoption [3]. TAM has evolved from initially measuring technology acceptance in organizations to measuring factors influencing technology adoption in non-organizational organizations. One of the most influencing factors for technology adoption is PU and PEOU [4]. Digital banking has advantages that make it easier for customers to make transactions easily without requiring much effort. The quality of digital banking makes users continuously use digital banking in their daily lives.

Most customers use mobile banking by 34% and online banking by 22.8% [5], but it turns out that there are still many customers who make transactions through bank tellers (21%) and ATMs (19.5%) [5]. This fact shows the potential to move away from digital banking technology. The high number of transactions through branch offices with large transactions shows that consumers are still hesitant when making transactions through digital banking services.

Digital banking is now necessary for users to carry out various banking transactions. The aforementioned is because banks themselves have good security. However, the Bank Indonesia report explained that during 2018 alone, there was still quite a lot of security going on, such as misuse of data by responsible parties. This causes personal data to be traded. Not to mention the skimming cases that caused the loss of customer money, so that this fact results in the reluctance to make transactions using digital banking services, some users still believe that ATM is still a safe transaction. It is different if the technology used is very vulnerable to security. Users also become worried that it makes them uncomfortable. This fact has led to a shift in intention caused by the lack of usefulness of the technology.

An additional component that influences Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) is technology readiness, which includes traits such as Optimism (OPTM), Innovativeness (INNV), Insecurity (INSC), and Discomfort (DSCM). Developed by Parasuraman (TR) to assess a person's technological preparation for new technology adoption, the Technology readiness model measures a person's technological readiness for new technology adoption [6]. There are two triggers: supporting factors (OPTM and INSC) and inhibiting factors (DSCM and INSC). These two factors can determine how ready users use the technology. OPTM shows that users are at the forefront of utilizing the features and facilities available in the technology. This follows the characteristics of the millennial generation connected to technology. The more optimistic the user, the more likely he is to perceive that the technology is easy and useful. So that someone who has high OPTM will easily master new technology, like the innovative characteristics of the millennial generation. They also always want technology to be at the forefront in supporting these supporting factors that make users feel that they have the convenience and benefits of adopting new technology.

On the contrary, there are inhibiting factors, namely DSCM and INSC. Security is one of the most essential considerations in the adoption of new technologies [7]. The more secure the technology, the easier it will be for users to find it useful in their daily lives. Based on this explanation, the main objective of this study is to analyze the elements that influence the adoption of new technologies, especially on individual characteristics such as those in the technology readiness model, namely Optimism, Innovativeness, Insecurity, and Discomfort.

2. Literature Review

The implementation of new technology certainly requires technological readiness from its users. So, this technology readiness model is here to measure the level of technology readiness. The low readiness of technology will result in high risks such as security and PEOU. On the other hand, organizations with high technology readiness will make it easier for users to understand the technology. There are 4 constructs in the technology readiness model, namely Optimism (OPTM), Innovativeness (INNV), Insecurity (INS), and Discomfort (DSCM). TR is an important factor in determining user attitudes and behavior [8], [9]. Thus, each construct in the TR model becomes a determinant in one's technology adoption. The fact supported by Son and Han [1] findings shows that each construct in TR can affect PEOU and usefulness. One of the factors is OPTM. OPTM describes the expectation of positive events compared to bad events [9]. According to previous study, there is a positive association between OPTM and PEOU and usefulness of technology [11]. The role of a positive attitude towards technology will certainly lead to the perception that digital banking technology can be useful for work and daily life. When it comes to the application of technology, OPTM about the presence of technology can increase the adoption of technology use, especially in terms of convenience and usability [12]. So, the first and second hypotheses in this study are as described in the following:

H_1: OPTM has a positive effect on PU
H_2: OPTM has a positive effect on PEOU

Another factor that plays a role as a supporter in one's technological readiness is INNV (INNV). INNV is defined as the degree to which a person is at the forefront of understanding and desiring new technologies. Innovative users will be opened to accepting new things because for this type of user, technology can help them in their daily lives. Thus, innovative users will tend to accept technology and realize how useful it is before others in general [11]. INNV are proven to have a positive influence on the PEOU of health technology and digital payments [13]. The more interested someone is in technology, it indicates that the user is ready to use new technology so that it can increase user perceptions of ease and usefulness [14]. Other studies have also stated that INNV plays an important role in supporting PU [11]. So, the third and fourth hypotheses are as follows:

H_3: INNV has a positive effect on PU
H_4: INNV has a positive effect on PEOU

INSC and DSCM are inhibitors or barrier factors in the technology readiness model. The higher the factor, it will make someone view the technology negatively. Several previous researchers stated that security is one of the most important things to adopt a technology [15], [16]. The researchers discovered that INSC has a significant impact in negatively influencing PEOU of learning applications in their research on factors that influence student adoption of learning applications. This means that the lower a person's INSC, the easier it will be to use technology. This statement is supported by other researchers where INSC is proven to harm PU and PEOU [11], [17]. So, the research hypotheses in this journal are as follows:

H_5: INSC has a positive effect on PU
H_6: INSC has a positive effect on PEOU

Discomfort (DSCM) can affect users using simple technology [11]. This fact occurs because users are afraid to use new technology. Users are comfortable with existing conditions. In digital banking, customers are comfortable in making transactions using ATMs and through branch offices. The existence of digital banking services makes this type of user worried that the transaction would not reach the intended target. [18] agree that DSCM affects PEOU and usefulness negatively significantly. In the previous literature, the role of DSCM has a significant negative effect on PU and PEOU [11], [17]. So based on this explanation, the seventh and eighth hypotheses are as follows:

H_7: DSCM has a positive effect on PU
H_8: DSCM has a positive effect on PEOU

Bank financial institutions have to provide a sense of security and comfort for customers, especially regarding privacy, security, information quality, and Ease of Use. This model can measure the extent of perceived technology acceptance. The person who first developed the TAM model said that technology adoption requires a rhythmic integration of constructs such as Perceived Usefulness (PU) and perceived Ease of Use (PEOU) [3]. These factors allow a person to receive the benefits of using the technology. The increase in the Ease of use of the user shows that the process of receiving the benefits is increasing. This shows that convenience cannot stand alone without the benefits of technology. The previous literature stated that the implementation of the TAM model had been carried out in various organizations [19]. However, over time, technology adoption using TAM is also used to measure the adoption of mobile payment usage [14], [20]. Other researchers also support this fact where TAM is used to measure technology adoption in non-organizational settings. The context of technology adoption in this study is about digital banking channels, especially for millennial users. When it comes to technology adoption, PU and PEOU are two of the most important elements to consider. The two constructs are the most widely used. Previous researchers found that the factors that can strengthen the Intention to use are the factors PU and PEOU [14], [21], [22].

PU shows the level of comfort and security in using digital banking channels to support daily productivity [4]. This function is inherent in technology. If the technology used does not provide benefits for its use, it is not a priority for users to use the technology. The easier technology is to use, the tendency to use the technology increases [4], [23], and likewise, with the features that users can use for digital banking. The more features that help users in their daily lives, digital banking will increase. Previous research has shown that the intention factor greatly impacts technology adoption [24], [25]. After users use technology and feel convenience and benefits, the tendency to adopt technology continuously gets bigger. Previous researchers have stated that Intention to use is the biggest factor in influencing technology adoption [4], [7], [26], [27]. So, the hypotheses are as follows:

H_9: PEOU has Positive Effect on Intention to use Digital Banking
H_{10}: PU has Positive Effect on Intention to use Digital Banking
H_{11}: Intention to use Digital Banking has Positive Effect on Digital Banking Adoption

Based on the explanation above, each of these constructs has a relationship with other constructs to form a hypothesis. Then the hypotheses are collected into one to become a research model. Figure 1 below shows the relationship between the hypotheses that became this research model.

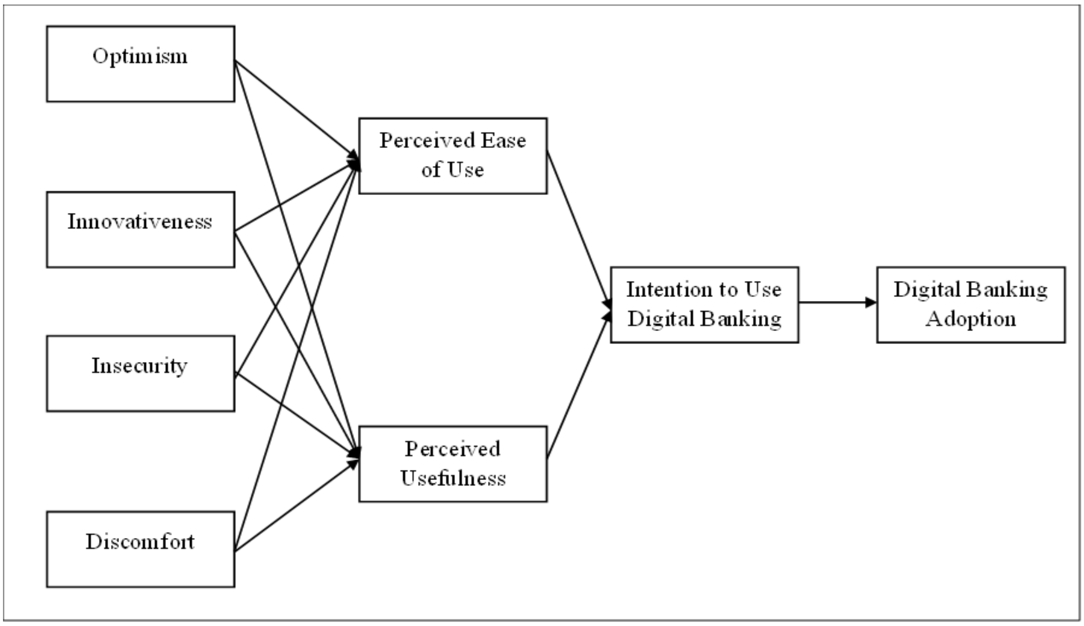

Figure 1. Research Model

3. Methodology

Data Collection

This section explains how the data is obtained and utilized to answer the hypotheses that have been proposed. The population in this study are users of digital banking services in Indonesia with the millennial generation category. Respondents who can fill in this questionnaire use digital banking channels such as mobile banking, internet banking, or other digital services. Then those who can fill out the questionnaire are the millennial generation digital payment users born in 1980-1995. The sampling method used is convenience sampling. The reason for choosing this method is the large population. Hence, the authors chose to take samples based on the dissemination results through social media such as Instagram, Facebook, What's App, and other social media. Questionnaires have been compiled, then distributed to produce a total sample of 422 respondents. There are several stages in the questionnaire. First, respondents fill in their education level, gender, income, etc. Of course, filling out the database does not contain personal information such as full name or address. In the second stage, respondents were asked to fill out 5 Likert scales with a choice of strongly agree (5) and strongly disagree (1).

In making the questionnaire, the researcher also adopted from previous researchers. The technology readiness model consists of 3 question items by each construct: OPTM, INNV, and DSCM [28]. Meanwhile, the INSC construct consists of 4 question items [28]. Then in the technology acceptance model, the PU construct consists of six question items for PU and five question items for PEOU [3], [27]. Then on the construct of Intention to use digital banking [29] consists of 6 question items. Finally, the digital banking adoption item consists of 5 question items [30].

The following Table 1 summarizes the demographic profile of the respondents to this study. Most respondents in this study were 68% female and 36%, male. Meanwhile, in terms of education, most undergraduates and graduates are 48% and 28%, respectively. Then another characteristic is that most respondents have a monthly income of 59% IDR below 5 million. Meanwhile, in terms of frequency of use, the majority use digital banking services several times a month, 42%. Then those who use it several times a month are 23% and those who use it twice a week are 23%. Detailed information on each respondent's demographics is reported in Table 1 below.

Table 1.Respondent Characteristic

	Category	Frequency	Percentage
Gender	Man	153	36%
	Woman	289	68%
Education	High School	53	13%
	Undergraduate	204	48%
	Graduate	120	28%
	Postgraduate	65	15%
Revenue (IDR/month)	Below 5 million	247	59%
	5 – 10 million	152	36%
	11 – 20 million	43	10%
	More than 20 million	0	0%
Frequency to use	A few times a week	23	5%
	Once a week	98	23%
	Twice a week	96	23%
	A few times a month	178	42%
	Once a month	47	11%

Data Collection

After compiling the research instrument, the next step is to distribute the questionnaire form online through social media. After obtaining the number of samples, the data was analyzed using SEM PLS using the help of smart pls 3.0. The researcher chose to use the SEM-PLS model because the PLS model can be used to test the model that has been constructed by the researcher, initiating with an analysis of the inner and outer models, as well as the suitability of the model, and then evaluating the outcome based on the hypotheses that have been constructed [31]. PLS is very effective for analyzing data during the early stages of developing a theory. In other words, PLS is used to test the development of a particular model.

4. Result

The first stage in determining the hypothesis in SEM PLS is to do the validity and reliability, then measure the structural model. The last step is to test the hypothesis.

Measurement Model

There are 3 stages in the measurement model, and the first is to analyze internal consistency. Second, evaluate the validity of the construct. Furthermore, the final step is to determine discriminant validity. The internal consistency value is obtained by assessing Cronbach alpha (CA) and Composite Reliability (CR) values, as shown in Table 2. The recommended value to meet good reliability is above 0.7 [31].

Table 2.Validity and Reliability

Construct	Outer Loading	CA	CR	AVE
OPTM (OPTM)		0,842	0,904	0,759
OPTM1	0,883			
OPTM2	0,856			
OPTM3	0,875			
INNV (INNV)		0,801	0,883	0,716
INNV1	0,852			
INNV2	0,810			
INNV3	0,875			
INSC (INSC)		0,820	0,881	0,650
INSC1	0,813			
INSC2	0,865			
INSC3	0,733			
INSC4	0,808			
DSCM (DSCM)		0,766	0,865	0,681
DSCM1	0,800			
DSCM2	0,859			
DSCM3	0,817			
PEOU (PEOU)		0,927	0,945	0,775
PEOU1	0,858			
PEOU2	0,917			
PEOU3	0,902			
PEOU4	0,881			
PEOU5	0,844			
Perceived Usefulness (PU)		0,960	0,968	0,832
PU1	0,894			
PU2	0,908			
PU3	0,914			
PU4	0,924			
PU5	0,930			
PU6	0,904			
Intention to Use Digital Banking (INTDB)		0,922	0,939	0,721
INTDB1	0,857			
INTDB2	0,797			
INTDB3	0,844			
INTDB4	0,869			
INTDB5	0,882			
INTDB6	0,841			
Digital Banking Adoption (DBA)		0,944	0,957	0,816
DBA1	0,879			
DBA2	0,908			
DBA3	0,924			
DBA4	0,902			
DBA5	0,903			

The largest CR and AVE values are in the PU construct (CR = 0.968, AVE = 0.832), while the smallest value of CR and AVE lies in construct INSC (CR=0.881, AVE=0.65). Thus, all constructs in this research have exceeded the recommended value (0.7). It can be concluded that all constructs in this research have good internal consistency.

The next step is to evaluate construct validity by analysing several criteria, namely outer loading and AVE. Outer loading shows how big the impact of variance between constructs and indicators is. The outer loading value for the largest construct is PU, especially for the PU5 indicator. Meanwhile, the smallest outer loading value is in the INSC construct, especially the INSC3 indicator. All outer loading in this research has a value of more than 0.7. All the constructs and indicators in this research have good construct validity. Then, another way to determine the validity of a construct is to evaluate the AVE value. If the AVE value exceeds 0.5, it can have a good validity construct. Based on Table 2, the largest AVE value is in the PU construct (0.832). Meanwhile, the smallest AVE in the INSC construct (0.65). All constructs in Table 2 above have an AVE above 0.5. Thus, all constructs in this research have good validity. The next step is to analyze discriminant validity. Discriminant validity is used to see the extent of the differences between the constructs and other constructs. There are three ways to see discriminant validity: cross-loading and fornel-larcker criteria.

Table 3. Cross Loading

	DBA	DSCM	INNV	INSC	INTDB	OPTM	PEUE	PU
DBA1	0,879	0,562	0,633	0,684	0,714	0,673	0,753	0,754
DBA2	0,908	0,603	0,649	0,698	0,778	0,707	0,812	0,820
DBA3	0,924	0,607	0,656	0,718	0,783	0,715	0,814	0,799
DBA4	0,902	0,608	0,666	0,697	0,742	0,649	0,796	0,778
DBA5	0,903	0,596	0,623	0,693	0,752	0,654	0,799	0,773
DSCM1	0,583	0,800	0,570	0,558	0,575	0,572	0,601	0,559
DSCM2	0,549	0,859	0,594	0,671	0,547	0,538	0,599	0,558
DSCM3	0,495	0,817	0,586	0,631	0,508	0,444	0,568	0,480
INNV1	0,609	0,532	0,852	0,602	0,580	0,652	0,633	0,578
INNV2	0,574	0,585	0,810	0,583	0,552	0,548	0,591	0,530
INNV3	0,629	0,675	0,875	0,652	0,624	0,623	0,647	0,606
INSC1	0,605	0,631	0,563	0,813	0,576	0,595	0,669	0,559
INSC2	0,731	0,638	0,660	0,865	0,696	0,694	0,747	0,725
INSC3	0,541	0,504	0,505	0,733	0,545	0,513	0,557	0,528
INSC4	0,595	0,641	0,596	0,808	0,563	0,566	0,671	0,548
INTDB1	0,731	0,588	0,601	0,635	0,857	0,667	0,726	0,805
INTDB2	0,652	0,516	0,542	0,572	0,797	0,523	0,640	0,653
INTDB3	0,666	0,537	0,602	0,595	0,844	0,587	0,660	0,714
INTDB4	0,753	0,586	0,612	0,632	0,869	0,643	0,728	0,784
INTDB5	0,711	0,566	0,576	0,673	0,882	0,643	0,702	0,757
INTDB6	0,732	0,563	0,591	0,668	0,841	0,613	0,729	0,742
OPTM1	0,628	0,523	0,611	0,647	0,630	0,883	0,644	0,644
OPTM2	0,661	0,580	0,624	0,616	0,626	0,856	0,634	0,652
OPTM3	0,678	0,546	0,646	0,670	0,636	0,875	0,671	0,696
PEOU1	0,720	0,588	0,642	0,717	0,688	0,644	0,858	0,660
PEOU2	0,814	0,630	0,657	0,744	0,765	0,659	0,917	0,783
PEOU3	0,781	0,663	0,694	0,768	0,724	0,714	0,902	0,714
PEOU4	0,819	0,637	0,641	0,704	0,770	0,675	0,881	0,788
PEOU5	0,736	0,629	0,612	0,696	0,672	0,588	0,844	0,689
PU1	0,804	0,574	0,656	0,672	0,821	0,722	0,759	0,894
PU2	0,780	0,567	0,600	0,659	0,783	0,695	0,732	0,908
PU3	0,787	0,597	0,590	0,663	0,783	0,679	0,746	0,914
PU4	0,806	0,603	0,618	0,698	0,804	0,710	0,754	0,924
PU5	0,811	0,587	0,608	0,686	0,822	0,699	0,768	0,930
PU6	0,768	0,615	0,630	0,665	0,785	0,668	0,765	0,904

The cross-loading indicator shows the relationship between constructs. The way to see if an indicator meets the criteria for good discriminant validity is to see if the value of all loadings exceeds the cross-loading value. In Table 3 above, the 3 indicators (OPTM1 – OPTM3) on the OPTM construct (OPTM) are greater in value than the OPTM1 – OPTM3 construct for the other constructs (DBA, DSCM, INNV, INSC, INTDB, PEUE, PU). Likewise, the indicator in each related construct has a value exceeding the specified construct. Thus, that discriminant validity has been established. The next step is to evaluate the value of the Fornell-Larcker Criteria as shown in Table 4 below:

Table 4. Fornell-Larcker Criterion

	DBA	DSCM	INNV	INSC	INTDB	OPTM	PEUE	PU
DBA	**0,903**							
DSCM	0,659	**0,825**						
INNV	0,715	0,706	**0,846**					
INSC	0,773	0,751	0,725	**0,806**				
INTDB	0,835	0,660	0,692	0,742	**0,849**			
OPTM	0,753	0,630	0,720	0,740	0,724	**0,871**		
PEOU	0,880	0,715	0,738	0,825	0,823	0,746	**0,881**	
PU	0,869	0,647	0,676	0,739	0,877	0,763	0,827	**0,912**

The Fornell-Larcker Criterion compares the latent variable with the value of the square root of the AVE construct. The value of the square roots in each AVE construct must be greater than the other constructs. Table 4 above shows the value of the square roots of the AVE construct on the sloping side and the correlation between the constructs below it. The digital banking adoption (DBA) construct has a value of 0.903, greater than the other constructs. Likewise, the constructs of OPTM (0.871), DSCM (0.825), INNV (0.846), INSC (0.806), Intention to use Digital Banking (0.849), PEOU (0.881), and PU (0.912), all of which have higher values. Thus, it can be concluded that all constructs have a valid measure.

Structural Model

The next step is to perform a structural model analysis. At this stage, an analysis of the effect size, R square, and predictive relevance is carried out. The first step is to evaluate the R square. The R Square test was conducted to determine how the correlation between endogenous constructs and all exogenous constructs had correlations. The value of R square is divided into 3 types, namely substantial (0.75), moderate (0.5), and weak (0.25) [31]. Based on Table 5 below, the largest R square value is in the Intention to use Digital Banking (0.8) or is in the substantial criteria. So that the related constructs, namely PU and PEOU, have a collective impact. At the same time, the smallest value is in PU (0.66) or on moderate criteria. So, if we conclude, the constructs related to PU, namely OPTM, INNV, INSC, and DSCM, have a moderate or 66% relationship. Meanwhile, the PEOU construct has an r-square value of 0.744 or a moderate criterion. Thus, the constructs related to PU, namely OPTM, INNV, INSC, and DSCM, have an effect together with a moderate relationship level or 74.4%

Table 5. R Square

	R Square	R Square Adjusted	Criteria
DBA	0,697	0,697	Moderate
INTDB	0,800	0,799	Substantial
PEOU	0,744	0,742	Moderate
PU	0,660	0,657	Moderate

After analyzing the value of the R square, the next step is to test the effect size (f2). Effect size is done to evaluate whether each construct substantially impacts the endogenous construct. There are three categories to distinguish the effect size between each endogenous construct, namely small (0.02), medium (0.15), and large effect (0.35) [31]. Based on Table 6 below, the largest effect size value is in the construct of Intention to use digital banking on digital banking adoption (2,304) or categorized as a large effect. In contrast, the smallest effect size is in the INNV construct on PU (0.01) or is categorized as a small effect. Table 6 below shows the construct with large and small relationships. There are two categories of large effects: the construction of the relationship between Intention to use digital banking and digital banking adoption (2.34) and the construct of the relationship between PU and Intention to use digital banking (0.61). Then three relationship constructs have a medium effect size, namely, INSC and PEOU (0.246), OPTM and PU (0.198), and PEOU and Intention to use digital banking (0.152). While the remaining six construct relationships have a small effect size.

Table 6. Effect Size f^2

	DBA	INTDB	PEUE	PU
DSCM			0,021	0,012
INNV			0,042	0,010
INSC (INSC)			0,246	0,070
INTDB	2,304			
OPTM			0,066	0,198
PEOU		0,152		
PU		0,610		

The next step is to evaluate predictive relevance (Q^2). Predictive relevance value serves to assess the prediction of a model. If the predictive relevance value is above 0, it is considered to meet the predictive relevance model. Based on Table 7 below, the largest predictive value is in the construct of Intention to use digital banking and PEOU, each of which is 0.533. at the same time, other constructs have a value greater than 0, namely digital banking adoption (0.53) and PU (0.507). Thus, it can be concluded that all constructs in this research have good predictive relevance.

Table 7. Predictive Relevance Q^2

	SSO	SSE	Q² (=1-SSE/SSO)
DBA	2.110,000	992,447	0,530
DSCM	1.266,000	1.266,000	
INNV	1.266,000	1.266,000	
INSC	1.688,000	1.688,000	
INTD	2.532,000	1.181,395	0,533
OPTM	1.266,000	1.266,000	
PEOU	2.110,000	985,954	0,533
PU	2.532,000	1.249,275	0,507

Hypothesis Testing

The last step is to evaluate the hypothesis by comparing the t statistic and the table. In addition, evaluation can also be done by comparing the p-value with the specified error rate (5%). The statistical results of the smart pls output are as follows Table 8 below:

Table 8. Hypothesis testing

		Original Sample	T Statistics	p-values	Decision
H_1	OPTM -> PEUE	0,210	4,002	0,000	Accepted
H_2	OPTM -> PU	0,420	7,312	0,000	Accepted
H_3	INNV -> PEUE	0,173	3,293	0,001	Accepted
H_4	INNV -> PU	0,099	1,571	0,117	Rejected
H_5	INSC -> PEUE	0,455	8,221	0,000	Accepted
H_6	INSC ->PU	0,279	4,163	0,000	Accepted
H_7	DSCM) -> PEUE	0,119	2,487	0,013	Accepted
H_8	DSCM -> PU	0,103	2,116	0,035	Accepted
H_9	PEUE -> INTDB	0,310	6,071	0,000	Accepted
H_{10}	PU -> INTDB	0,621	11,832	0,000	Accepted
H_{11}	INTDB -> DBA	0,835	35,372	0,000	Accepted

Table 8 above explains the relationship between the magnitude of the influence between constructs and the conclusion of the hypothesis. The 4 constructs in the technology readiness model have a significant relationship to PEOU, namely OPTM (0.210 or 21%), INNV (0.173 or 17.3%), INSC (0.455 or 45.5%), and DSCM (0.119 or 11.9%). The biggest relationship is in the INSC construct (45.5%). Meanwhile, the smallest relationship is on the DSCM construct (11.9%). Then on the impact of the 4 constructs on the technology readiness model on PU, the largest construct relationship to PU is the OPTM construct (43%) while the smallest construct is on DSCM (10.3%). the 11 hypotheses proposed in this research, there are 10 accepted hypotheses and 1 rejected hypothesis (H4). These results were obtained based on comparing the p-value and the error rate (5%). In the OPTM construct of PEOU, the p-value of 0.000 is smaller than the error rate. Thus, hypothesis 1 is accepted. Likewise, the DSCM construct (p-value = 0.035 <, 5%) and INSC (p-value = 0.000 <, 5%) on PU has a significant impact. This step is also carried out on other hypotheses whose decisions are rejected. For example, INNV on PU has a p-value of 0.117, greater than the error rate. Thus, it can be concluded that the construct does not have a significant effect.

5. Discussion

The construct of Intention to use digital banking is proven to be the variable that has the most influence on digital banking adoption compared to other construct relationships. This shows that in the acceptance model, user intentions are very important to pay attention to, especially from the PEOU and PU factors. The TAM model in this study shows a strengthening if it is integrated with the technology readiness model. This is evidenced by the role of the constructs of OPTM and INNV, which have become quite large in influencing the ease and usefulness of digital banking channels. The previous frame of reference [14] mentioned that PU could increase interest in using digital banking because of its function, increasing work productivity.

The main advantage of digital banking services is their ease and function in replacing the role of branch offices. Digital banking can carry out almost all functions in the banking business, such as opening accounts, credit cards, deposits, transfers, charging mobile payments, water and electricity payment functions, and even supports payments without going through an ATM card. This is following the characteristics of the millennial generation, which require technology that is integrated quickly and precisely. This convenience makes the millennial generation increasingly adopt the use of digital banking. This fact is reinforced by previous researchers who revealed that PU and PEOU had a significant positive effect on technology adoption [14], [20], [22], [10]. Then after users are interested in using digital banking services, it will indirectly affect the intensity of their use. As seen in several studies where Intention to use has a significant effect on behavior use [7], [25], [27]. This finding also illustrates that the biggest factor influencing digital banking adoption is Intention to use. The Intention to use is influenced by the PEOU and usefulness. This fact is reinforced by the findings of other researchers [14], [25], where the biggest factor in adopting technology is the Intention to use. The results of this research also illustrate where the function of digital banking is the biggest factor for the millennial generation in using digital banking continuously. According to the millennial generation in this study, among the favourite features is that digital banking services can be connected to companies, mobile payments, and e-commerce. So, they can quickly make transactions quickly and easily. Another significant finding from this research is that INSC plays a key role in increasing users' PEOU.

Another important finding is that one of the models in technology readiness, namely OPTM, has a significant impact on PU. The existence of new technology is responded with joy because it can provide convenience and the function of new tools to increase productivity. This finding is supported by previous researchers that there is a positive relationship between OPTM and PEOU and usefulness. Different from Shim et al. [8], the INNV construct does not have a significant impact on PU. However, it has a significant negative effect on the PEOU. Meanwhile, the INSC construct is proven to have a large enough influence in influencing PU. This is because there has been quite a lot of misuse of data by irresponsible parties. This causes a snowball effect on other users of digital banking services. Whereas in the previous literature, it was stated that security is one of the most important things in adopting new technology [15], [16]. The lower a person's INSC and DSCM, he will have the convenience and feel the technology is useful. This statement is supported by other researchers where INSC and DSCM have been shown to have a significant negative effect on PU and PEOU [11], [17]. In short, the better the positive side (OPTM and INNV) in one's technology readiness behavior, the greater the tendency to adopt the technology. Conversely, suppose the barrier factor (INSC and DSCM) is greater than the supporting factor. In that case, it will result in low technology readiness so that users tend only to want to use old technology or simple technology that is familiar to them, such as ATMs or through branch offices.

6. Conclusion and Implementation

This research integrates TAM and TR, especially in the acceptance model in the context of Millenial Generation users during the Post-Coronavirus Pandemic Age. Of the eleven hypotheses proposed, there are 10 supporting and 1 rejected hypothesis. This research provides factual findings were applying the technology acceptance model to millennial generation users during the post-coronavirus pandemic age can strengthen the model, where the Intention to use digital banking factor is the biggest construct in digital banking adoption. This research has also found that it is possible to integrate the Technology readiness model and the technology acceptance model. Although there is a construct of INNV on PU, it does not significantly affect it. In this context, users from the millennial generation consider that the benefits of technology are prioritized during a pandemic like this. So that in the technology readiness model, only the constructs of OPTM, DSCM, and INSC have a significant contribution to the TAM model.

This research contributes to the technology acceptance model (TAM), especially on the technology readiness factor, which includes OPTM, INNV, DSCM, and INSC. The results of this study illustrate that technological readiness, especially the INNV factor, plays an important role in growing the ease and usability of digital banking channels. So, the banking sector has to strive for its digital banking channel to suit the millennial generation's needs, such as the speed of technology development under current and future conditions. The millennial generation also likes connections between data, making it easier to do banking transactions. This also pays attention to the government to provide a safe banking environment through appropriate regulations to foster a security climate in the banking world. This finding is also important for the researcher's perspective as part of the main contribution that the measurement scale in this research has been tested validly and reliably. So that the questionnaire can be adapted for further researchers, especially in the study of digital banking. Second, the results of this research prove that the TAM theory is strongly relied on in measuring technology adoption, especially in banking technology. Then added with the factors that influence the TAM model, namely the Technology Readiness model, which has been proven to strengthen the TAM model. Although in the results of this research, one construct is not significant, namely INNV to PU. So, previous researchers can adopt the results of this research by reviewing the previous literature more fully. This research is also an input for business actors who use digital banking to integrate payment systems using digital payments that are integrated with digital banking services. This is because the millennial generation is very connected to the internet, so they also want integration of payment models that can be easily accessed and used.

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