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MORALITY BEFORE KNOWLEDGE

Behavioral intention among gen z: An analysis of digital banking adaptation factors in Jabodetabek

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ABSTRACT

Background: Many traditional banking arrangements have changed as a result of the financial sector's new technological revolution. One method the company seeks to provide consumers with more value is by delivering digital transformations that are especially designed to match their needs and preferences and that use mobile devices such as cell phones to access banking services. This study aims to examine the effect of performance expectancy and effort expectancy to behavioral intention of adopting digital banking. **Method**: This study collects data from 243 respondents aged 17 to 27 who live in Jabodetabek area, had experienced to do offline transaction, and have at least one digital bank account. Partial Least Squares Structural Equation Modeling (PLS-SEM) was then used to process the data collected. **Findings**: The findings of this study shows that shows that effort expectancy has a positive effect on behavioral intention on using digital banking. Meanwhile, performance expectations do not have a significant positive effect on behavioral intention. **Conclusion**: The results of the research may be used to develop a strategic plan and put recommendations into practice to better understand user intentions to use digital banks.

KEYWORDS*: performance expectancy, effort expectancy, facilitating conditions, behavioral intention, digital banking adoption

1. Introduction

The latest, dynamic technology ecosystem requires the digitalization of all economic sectors, as stated by Deng, Huang, and Cheng (2019). In order to enhance a function by making major structural changes, Vial (2019) defines digital transformation as an activity that integrates data, communication, information technology, and connective technologies. There are countless examples of how technology can make or shatter people's lives and organizations; one such example is the banking industry (Sardana & Singhania, 2018).

According to Act of the Republic of Indonesia Number 8 of 1998, "Bank is a corporate entity mobilizing funds from the public in the forms of Deposits and channeling them to the public in the forms of Credit and/or other forms in order to improve the living standards of the common people". Based on the latest Indonesia Banking Statistics published by Otoritas Jasa Keuangan on November 2022, Indonesia has 107 commercial banks and 1442 rural banks. Due to the numerous banks already in existence, there is even greater competitiveness amongst them. One of the ways the business tries to provide users better value is by offering digital transformation that are specifically created to meet their requirements and preferences that utilize mobile devices like personal digital assistants or cell phones in order to access banking services (Zhou et al., 2010).

Kegiatan Usaha Perbankan (Bank Industries Operation)			
Indikator / *Indicator*	2019	2020	2022 Nov
Jumlah Bank / *Total Banks*			
Bank Umum / *Commercial Banks*	110	109	107
Bank Perkreditan Rakyat / *Rural Banks*	1,542	1,506	1,442
Jumlah Kantor / *Total Bank Offices*			
Bank Umum / *Commercial Banks*	31,127	30,733	25,344
Bank Perkreditan Rakyat / *Rural Banks*	5,964	5,913	6,046

Figure 1 Total number of banks in Indonesia for 2019 - 2022
(Otoritas Jasa Keuangan, 2022)

Due to digitization, radical innovation, and rising technology, traditional business conceptions and methods are altering. Banks should change their business strategies in order to better engage with consumers, manage front and back-office operations, remain relevant, and be ready for the future. (Cziesla, 2014). Digital disruption is being adopted by consumers more frequently, and new types of solutions are developing in this sector.

The term "digital bank" refers to the provision of banking services and transactions via digital platforms. It enables users to do all financial transactions utilizing internet-connected smart gadgets. Unlike conventional banking, which primarily relies on physical branches and in-person interactions, users may instead access and manage their accounts digitally from anywhere.

In recent years, Indonesia has seen substantial progress in the development of digital banking. The first digital bank to open was Jenius by BTPN in 2016, followed by Digibank by DBS Bank in 2017. In 2020, a state-owned bank, one of Bank Rakyat Indonesia's subsidiaries, would transition into Bank Raya. Not to mention that Bank Central Asia, Indonesia's largest bank, will launch BLU by BCA in 2021.

The remarkable development of digital banking in Indonesia driven by factors such as rising internet penetration, demographic behavior, and government initiatives. Indonesia, more specifically Jabodetabek, the largest urban area, characterized by its population density and economic significance has the highest internet penetration rate. With Jakarta itself having a 72% active internet users (BPS, 2021). The behavior and preferences of bank users is also changing. Looking at the Indonesia's population now dominated by Gen Z, representing 27.94% of the total population, they have grown up in a technologically driven era, and the internet is an important component of their everyday life, giving them a tech-savvy disposition. Because of their familiarity with technology, they have developed preferences and behaviors that have led them to adopt digital banking (Donovan, 2020).

In order to succeed, banks, according to Podder (2015), must comprehend why users decide to use digital banking. However, only a few empirical studies have been done on the adoption of or intention to use digital banking (Vally & Shankar, 2020). In response to the researcher's findings, there were only 26 journals with the keyword "digital banking adoption" in Proquest over the last ten years. Using the application of a unified theory of acceptance and use of technology model, it is observed that several countries, including Indonesia, have minimal access to information in this context (Kiliari & Koesrindartoto, 2019).

This model's implementation is expected to increase this research's implications and predictability as past literature related also showed inconsistency in the relationship between variables. When the model was used to explore the adoption of digital banking, it confirmed the role of performance expectancy. This driver is used to drive research into the

variables that may influence behavioral intent to adopt and utilize digital banking in order that the bank can determine what needs to be changed and the customer's acceptance of digital banking services may be maximized. The factors from users in Jabodetabek will be further investigated in this study using the UTAUT model framework with new variables that are habit, hedonic motivation, perceived value (Vally & Shankar, 2020).

1.1 Unified theory of acceptance and use of technology

Venkatesh established the Unified Theory of Acceptance and Use of Technology (UTAUT) in 2003 by examining and synthesizing previous theories and models of technology usage. UTAUT has provided as a baseline model for the investigation of a wide range of technologies in both corporate and non-organizational contexts. The critics and proponents of models such as the technology acceptance model (TAM) have underlined the need to broaden the scope of theoretical methods in the context of technology adoption (Venkatesh, 2007). Here, the UTAUT2 identifies crucial new consturcts that is incorporated into UTAUT, adapting it to a consumer use context.
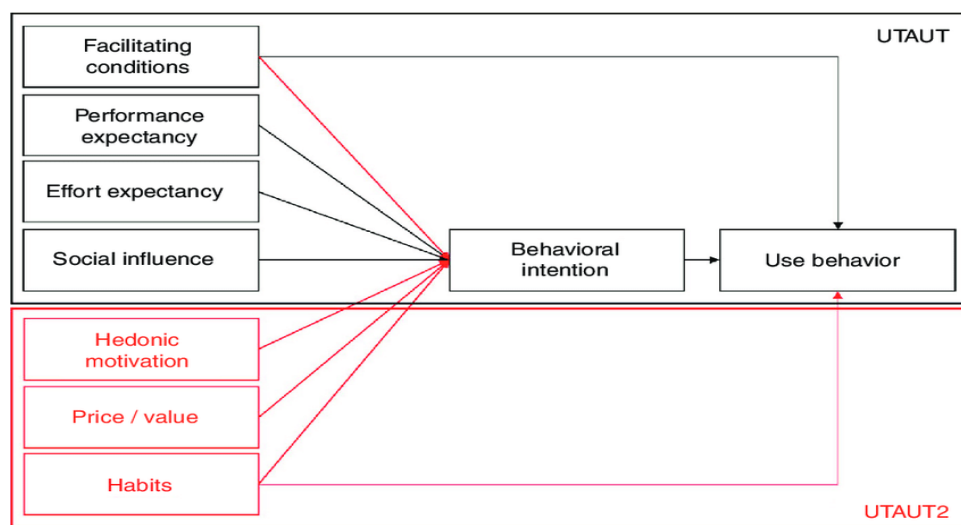

Figure 2. UTAUT vs UTAUT2 Model
(Bianchi & Figueiredo, 2017)

1.2 Performance expectancy

Performance expectation pertains to the extent to which an individual foresees that utilizing technology will contribute to the enhancement of their job performance. This anticipation is shaped by various factors encompassing the five integral components of the models: perceived usefulness, job-fit, extrinsic motivation, relative advantage, and outcome expectations.

Some authors recognized the correlation between these five concepts as they developed in the research as the root construct for this variable, including:

a. Usefulness: The degree to which a person believes that utilizing a particular technique will increase their capacity to complete their task (Davis et al. 1989).
b. Extrinsic motivation: The idea that users are going to take part in a certain action because they believe it will help them achieve desired outcomes that are separate from the action itself (Davis et al. 1992).
c. Job-fit: How a system's capacities improve a person's ability to accomplish their job (Thompson et al. 1991).
d. Relative advantage: the extent to which utilizing an innovation is thought to be superior than utilizing its predecessor (Moore & Benbasat, 1991).

e. Outcome expectations: In situations in which these two dimensions strain on a single element, outcome expectations correlate to the effects of the behavior. (Compeau & Higgins, 1995).

1.3 Effort expectancy

The degree of comfort associated with system utilization is referred to as effort expectation. The concepts of perceived ease of use, complexity, and ease of use are all encompassed by three elements from the current models. The definitions of the constructs and the measurement scales are quite similar. In earlier studies, the commonalities between these notions were discovered and the correlation between these three concepts are being the root construct for this variable, including:

a. Perceived ease of use: The extent to which someone thinks utilizing a system will be effortless. (Davis et al. 1989)
b. Ease of use: The extent to which utilizing an invention is thought to be challenging (Moore & Benbasat, 1991).
c. Complexity: The extent to which a system is regarded as being relatively challenging to comprehend and operate (Thompson et al. 1991).

1.4 Behavioral intention

The Technology Acceptance Model (TAM), a theory of information systems that explains how people come to accept and use technology, which is derived from the Theory of Reasoned Action (TRA), which defines behavior change depending on the result of behavioral intents, suggests that the speed of adopting new technologies is influenced by behavioral intention. Simultaneously, beliefs, specifically perceived usefulness and perceived ease of use, play a role in shaping behavioral intention. Initially, the variable method was introduced in the TAM framework, but it was subsequently discarded as it failed to mediate the relationship between beliefs and behavioral intention (Venkatesh & Davis, 2000).

The TAM model describes the purpose of behavior. The behavioral intention remains a personal interest even if behavior and behavioral intention are two distinct concepts. A desire to engage in an action is referred to as interest. Whereas conduct refers to actual, carried out actions or activities. So, it may be inferred that conduct will occur if someone is interested in doing so (Delone & McLean, 2003). According to the reasoning above, someone's desire to use the digital banking system may act as a motivator for them to engage in certain behaviors.

2. Methods

This study incorporated findings from a study by Vally and Shankar (2020), which modified the unified theory of acceptance and use of technology UTAUT2 model by dropping 2 constructs namely social influence and use behavior. By removing social influence from the research, behavior analysis can offer greater insights into the individual components under investigation and how they affect behavior. In spite of the fact that social influence was important, Alalwan et al. (2017) discovered that individual factors, such as performance expectations and effort expectations, had a greater impact on users' behavior. Behavior analysis can emphasize context-specific elements through eliminating social influence, offering more precise and targeted insights.

According to prior study, "Use Behavior" is mostly the result of behavioral intention. It might cause statistical multicollinearity and inflate model fit indices if it is included as a distinct variable. Because of this overlap, "Use Behavior" might not significantly contribute any additional distinctive variation to these categories. We can prevent possible redundancy and raise the model's validity by removing this variable (Hilal & Varella, 2022).

3. Resul and discussion

3.1 Wording test

After asking 10 potential respondents a series of questions to see if they fully comprehended the things stated in the questionnaire. The majority of the suggestions made by the respondents were to the questionnaire's word choice and sentence structure. The questionnaire was modified by the researcher after taking into account all of the feedback received and taking into account the proper and correct usage of Bahasa Indonesian language and grammar according to the Kamus Besar Bahasa Indonesia, a more accurate translation from English to Bahasa Indonesia, and the use of more prevalent or general words.

3.2 Pre-test analysis

The pre-test for this study was conducted after the questionnaire's final version was already developed. The researcher has conducted a pre-test to 30 respondents by providing screening questions that fulfilled the previous pre-selected criteria and answered the questionnaire completely. After collecting the pre-test data, the researcher will conduct validity and reliability tests on the data from the respondents.

3.3 Measurement model analysis main test

3.3.1   Internal consistency evaluation

Table 1. internal consistency evaluation

	Cronbach's Alpha	Composite Reliability
Behavioural Intention	0.703	0.834
Effort Expectancy	0.770	0.853
Performance expectancy	0.855	0.907

Source: output processed by researcher

The results of internal consistency testing of all respondent data used show that all variables in this study meet Cronbach's alpha value ≥ 0.6 and the composite reliability value ≥ 0.7. Therefore, it can be said that all research variables are reliable so that researchers can proceed to the next stage.

3.3.2   Convergent validity

In this section, researchers test the validity of the measurement model by testing convergent validity and discriminant validity. The convergent validity test is carried out by looking at the cross loadings and Average Variance Extracted (AVE) with a value of is> 0.5 Then the researcher will also look at the outer loading value which must meet the criteria ≥ 0.7

Table 2. Convergent validity

	Average Variance Extracted (AVE)
Behavioural Intention	0.627
Effort Expectancy	0.591
Performance expectancy	0.765

Source: output processed by researcher

From the validity test results, it is known that the outer loadings value on the variable indicators is already above 0.70. All items in the questionnaire have met the required

Validity test value. The item really measures what you want to measure in this study. So it can be concluded that all statement items in the research questionnaire instrument are declared to meet the valid value and can be used in the next data processing stage.

3.3.3 Discriminant validity

Discriminant Validity of the Outer Model measurement with reflexive indicators is assessed based on the Cross Loadings of measurements with constructs. If the correlation of the construct with the measurement items is greater than that of the other constructs, then it indicates that the latent constructs predict the measures in their block better than the measures in the other block. In the cross loadings table above, it can show that the correlation results between each indicator and its construct are greater than the correlation results of indicators with other constructs, the indicators of each latent variable are better than the indicators of other variables so that all constructs in the model meet the criteria of discriminant validity.

Table 3 Fornell-larcker testing

	Behavioural Intention	Effort Expectancy	Performance expectancy
Behavioural Intention	0.792		
Effort Expectancy	0.709	0.769	
Performance expectancy	0.052	0.009	0.874

Source: output processed by researcher

In the Fornell-Larcker Criterion table, you can see the test results for Fornell-Larcker for all respondent data. From this table, all data has met the requirements so that the measurement can be proven valid.

3.4 Inner model analysis

3.4.1 Collinearity test

In the regression model, VIF is utilized to identify issues with multicollinearity amongst the independent variables (Hair et al., 2017). If the number is more than 5, the study's independent variables are multicollinear. Based on the results of the collinearity test in the outer VIF values table above, it can be seen that all values are <5, so based on the guidelines of Hair et al, (2017) it can be said that all items do not experience multicollinearity problems and can be continued to the next stage of research.

3.4.2 Coefficient of determination

In order to forecast the link between constructs, the significant value, and the R-Square (R^2) of the research model, Ghozali (2021) claims that testing the inner model or structural model is carried out. The significance of the structural route parameter coefficients and the R-Square (R^2) for the dependent construct T test are used to assess the structural model. Starting with the R-Square (R^2) for each dependent latent variable, the structural model with PLS is evaluated. *The R-Square table above shows that the R-Square (R^2) value of the Behavioural Intention variable is 0.713 or 71.3%.*

3.4.3 Predictive of relevance test

At this stage, researchers conduct a predictive relevance test which aims to assess the predictive relevance of constructs from the structural model (Hair et al, 2010). Hair et al. (2010) explains that Q^2 is used to test how well the model is developed and how well the dependent variable is predicted using cross validation. A model said to have a predictive

relevance of more than 0 means that the model has a good prediction level (Meiriyana 2021; Hair et al, 2010).

Table 4. Predictive of relevance test

	Q^2_predict
Behavioural Intention	0.692

Source: output processed by researcher

A Q-Square value above zero means that it is proven that the model has good predictive relevance. In the sense that the relative impact of the structural model on the measurement of the dependent variable.

3.4.4 Goodness of fit test

To determine the level of goodness of fit, researchers look at the root-mean square error (SRMR) value. A model is declared an acceptable fit if the value of SRMR is <0.08 (Malhotra, 2016). Based on the value of the goodness of fit test, the value of the SRMR obtained is 0.075. This value is of course <0.08 so it can be said that the model in this study is fit and acceptable and can be continued for further analysis.

3.4.5 Significance of path coefficients test

In the next stage, the significance level of the variables will be tested by bootstrapping and a significance level of 0.05. The type used is one-tail because it is intended to test a directed hypothesis. The hypothesis can be said to be significant if the value of the T-value ≥ 1.645. Then, it is necessary to see the value of the P-Value where the value of the P-Value must have a value <0.05.

Table 5. Significance of path coefficients test

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Effort Expectancy -> Behavioural Intention	0.402	0.403	0.070	5.710	0.000
Performance expectancy -> Behavioural Intention	0.086	0.078	0.065	1.328	0.092

Source: output processed by researcher

3.5 Hypothesis testing

Based on the results of patch coefficient testing at the previous stage, the researcher will explain the relationship between variables that occurs in this study. Then, the researcher will compare the results found with the results from the journals referred to by the researcher to conduct this research.

Table 6. Hypothesis testing

Hypothesis	Hypothesis Statement	Result	Reference Journal Result
H1	Performance expectancy has a positive influence on behavioral intention	Hypothesis testing not supported by data	Hypothesis testing supported by data
H2	Effort expectancy has a positive influence on behavioral intention	Hypothesis testing supported by data	Hypothesis testing supported by data

Source: output processed by researcher

H1: Performance expectancy has a positive influence on behavioral intention.

The results of the hypothesis testing for the first proposed hypothesis are not supported by the data, as can be seen in table 4.21. It appears that the results of the hypothesis testing for the first proposed hypothesis do not support the hypothesis. The p-value of 0.092 is greater than the significance level of 0.05, indicating that the effect of performance expectancy on behavioral intention is not statistically significant. Additionally, the t-statistics value of 1.328 is lower than the critical value of 1.645, further suggesting that the effect is not significant.

However, this outcome differs from a prior study conducted by Vally and Shankar in 2020. In their study, they found supporting evidence for the hypothesis that behavioral intention is positively influenced by performance expectancy. However, compared to the earlier reference research by Vally and Shankar (2020), the outcome for this research is different, the data does not provide sufficient evidence to conclude that performance expectancy has a significant positive effect on behavioral intention.

H2: Effort expectancy has a positive influence on behavioral intention.

The suggested hypothesis is supported by the data, according to the hypothesis testing presented in table 4.21. It appears that the results of the hypothesis testing for the second proposed hypothesis support the hypothesis. The p-value of 0.000 is less than the significance level of 0.05, indicating that the effect of effort expectancy on behavioral intention is statistically significant. Additionally, the t-statistics value of 5.710 is higher than the critical value of 1.645, further suggesting that the effect is significant.

This outcome shares the same result from a prior study conducted by Vally and Shankar in 2020. In their study, they found supporting evidence for the hypothesis that behavioral intention is positively influenced by effort expectancy. Compared to the earlier reference research by Vally and Shankar (2020), the outcome for this research is similar, the data provides sufficient evidence to conclude that effort expectancy has a significant positive effect on behavioral intention.

4. Conclusion

This study builds upon the research conducted by Vally and Shankar (2020) and extends the existing Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework proposed by Venkatesh et al. (2012). The objective is to investigate the impact of various factors, namely effort expectancy and performance expectancyon the behavioral intention of individuals. Specifically, the research focuses on understanding the perspective of Generation Z regarding the usage of digital banks in the Jabodetabek region.

To achieve the research objectives, a questionnaire-based survey was conducted to collect data from a sample of 243 respondents. These individuals were selected based on their affiliation with Generation Z and their residency in the Jabodetabek area, allowing for a targeted examination of digital bank usage factors within this specific demographic. The data collection process involved the distribution of questionnaires, subsequent respondent selection, testing, and data processing.

Upon thorough analysis and interpretation of the collected data, the research findings can be summarized as follows:

First, performance expectancy does not have a significant positive influence on behavioral intention. This statement suggests that the perceived performance or usefulness of a product or service does not positively impact an individual's intention to engage in a particular behavior. Second, effort expectancy has a positive influence on behavioral intention. This statement indicates that the perceived ease of use or the level of effort required to engage in a behavior positively affects behavioral intention. This aligns with UTAUT, which suggests that users are more likely to adopt a technology or engage in a behavior if they perceive it to be easy to use or require minimal effort.

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All authors contributed to the research.

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The authors declare no conflict of interest.

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