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Behavioral Intention and Adoption of Digital Bank Mobile Application Among Housewives Using Mixed Method Approach

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ABSTRACT

This mixed-method research using PLS-SEM and fsQCA analysis aims to identify the factors that influence the behavioral intention of Indonesian housewives to adopt digital banking applications, particularly by examining the UTAUT2 model's variables. For this study, data was collected using a quantitative approach. The study involved 120 Indonesian housewives who were digital bank users and were asked to complete a questionnaire. The study found that facilitating conditions, price values, and habits are significant factors that affect the behavioral intention of housewives to use digital banks. Furthermore, the study suggests that paying attention to the factors of effort expectancy, social influence, facilitating conditions, and habits simultaneously is the most effective approach to generating behavioral intention factors in digital bank adoption. The findings have important implications for digital bank companies, the government, financial institutions, and fintech startups. Future research should strive to obtain a more even distribution of respondents from different regions in Indonesia to reduce bias and obtain results that truly represent the conditions of housewives in Indonesia as a whole.

Keywords: Behavioral Intention; Digital Bank**;** fsQCA; Mixed-method; PLS-SEM; UTAUT2

INTRODUCTION

Emerging technologies can disrupt long-standing industries, leading to systemic changes in markets and behaviors (Skog et al., 2018). Digital innovation can alter both how companies operate and how people behave, creating new habits and transforming market demands (Gujrati & Uygun, 2020; Metallo et al., 2021). To address the challenges of shifting market needs, digital transformation is the answer. Digital transformation can bring companies to the fore in terms of the scalability of production processes and service provision (Nepelski, 2019). Therefore, companies need to carry out digital transformation to remain competitive and relevant in the industries. Increasingly, companies recognize this importance, as the speed, reach, and impact of digital transformation have accelerated significantly in recent times (Matzler et al., 2018).

Digital transformation is not limited to the Information and Communication Technology (ICT) sector rather, it is taking place across multiple industries. One clear indicator is the growing trend toward digitization among companies that primarily produce non-digital goods. As a result, the greatest potential for digitalization does not come from the ICT sector alone but comes from its application to the economy as a whole (Nepelski, 2019). The economy is crucial for meeting basic necessities, with the financial sector playing a significant role in economic cycles and driving the pace and quality of change. Given the high demand for financial services, there is growing interest in digital innovation from both established and new companies. As a result, the financial sector is a pioneer in leveraging cutting-edge technologies and digital services for consumers (Litvishko et al., 2020).

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Digitalization in the financial sector offers opportunities for various financial sector companies, such as banking companies, to grow by placing consumers at the center of development (Bachaev & Karpova, 2018). Banking companies have undergone significant transformation due to digitalization, from serving customers exclusively in person to offering online banking services, culminating in the emergence of digital banks that offer all services online (Faccia et al., 2020). Digital banks are present in various countries around the world, and Indonesia is no exception. The market potential in Indonesia is very high considering the fact released by Bank Indonesia that there are 91.3 million Indonesians who are still not served by financial services (Bank Indonesia, 2019). Digital banks can be a solution because they can reach people from various regions, including areas that do not yet have KCP (Sub-Branch Offices) from conventional banks that already exist in Indonesia. With this market potential, several digital banks have been established and developed in Indonesia. As of 2021, 5 digital banks have obtained OJK (Indonesian Financial Services Authority) permits and 7 other digital banks that are in the process of registering to obtain permits as digital banks from OJK (Linggadjaya et al., 2022).

Digital banking companies aiming to penetrate the market should consider consumer demographics, particularly occupation and age, which can affect the adoption rate of their services (Soemodipoero, 2019). Housewives, farmers, and retirees are skeptical of technology-based financial services, which may negatively impact digital bank adoption (Das & Das, 2020). Therefore, this research was conducted by targeting one of the groups with this skeptical view, namely the group of housewives. The group of housewives is a potential target market considering the role of housewives in managing family finances.

This study aims to explore the factors that impact the behavioral intention of Indonesian housewives in using digital bank applications. Using the UTAUT2 research model and a mixed-method approach that incorporates PLS-SEM and fsQCA data analysis techniques, this study seeks to identify the behavioral intention factors that can increase the interest of housewives in Indonesia to use digital bank services. The use of mixed-method analysis will allow for a comprehensive understanding of how individual conditions as well as their combinations can influence behavioral intention. By increasing their interest in these services, it is hoped that more unbanked individuals in Indonesia will gain access to financial services.

LITERATURE REVIEW

Digital Bank

At first, the bank only served consumers who came to the bank branch directly. With the presence of online banking services, people can gradually enjoy many bank services without having to go to the bank. Digitalization continues to drive the transformation of banking companies until they reach the final stage of evolution, becoming digital banks. Digital banking is a breakthrough in which all banking services can be fully carried out online. Starting from creating an account to creating savings and various types of payment transactions, everything can be done online (Faccia et al., 2020). A digital bank can be defined as a bank entity that conducts its business primarily through electronic channels and may only have a limited physical office or service point (Linggadjaya et al., 2022).

Housewives

Housewives were chosen as the research target due to the limited number of previous studies on technology adoption among this group. Meanwhile, they are among the groups that are skeptical of technology-based financial services, which may harm digital bank adoption (Das & Das, 2020). The study population comprises all housewives in Indonesia who use digital bank applications. The research population comprises 37,450,697 women over the age of 15 who are primarily responsible for managing their households in Indonesia, as reported by the Ministry of Women's Empowerment and Child Protection (Kementerian Pemberdayaan Perempuan dan Perlindungan Anak, 2020).

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UTAUT2

Researchers have commonly used several models, such as TAM (Technology Acceptance Model), Diffusion of Innovations Theory, and UTAUT (Unified Theory of Acceptance and Use of Technology), to explain mobile application adoption. UTAUT2 is an extended version of UTAUT, which includes three new dimensions: hedonic motivation, price value, and habit, in addition to the original four dimensions. In total, there are seven dimensions being tested as conditions that influence Behavioral Intention: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Condition (FC), Hedonic Motivation (HM), Price Value (PV), and Habit (HT) (Duarte & Pinho, 2019).

PLS-SEM

PLS-SEM is an alternative to SEM which is generally based on covariance and aims to test causality in theory. If covariance-based SEM focuses on how closely the research model represents the covariance matrix in the observed data sample, meanwhile, PLS-SEM focuses on explaining variance in the dependent variable. PLS-SEM uses a causal-predictive approach so it is used to test or develop theories for the sake of making predictions (Jr. et al., 2021). Previous UTAUT2 studies that use the PLS-SEM method include Marpaung et al. (2021), Anggraeni et al. (2021), and Kwateng et al. (2019).

FsQCA

Qualitative Comparative Analysis (QCA) itself is a combination of a case-based qualitative approach and a variable-oriented quantitative approach with the characteristic of generalizing large numbers of cases. There are several types of QCA and two of them that were popularly used by previous researchers were csQCA and fsQCA. Crisp-set QCA was the first variation of QCA to rely on a Boolean data structure with binary (0 or 1) input. Fuzzy-set QCA is present as an alternative to the limitations of csQCA. FsQCA incorporates fuzzy set theory and fuzzy logic principles to allow for values between 0 and 1. (Pappas & Woodside, 2021). Previous UTAUT2 studies that use the fsQCA approach include Yang et al. (2023) and Mezei et al. (2022).

Mixed-method

PLS-SEM and fsQCA are widely recognized and established methods for data analysis among researchers. Each method is proven to be effective in testing hypotheses and propositions. PLS-SEM is useful in examining whether a condition influences the outcome, while fsQCA is used to analyze condition or the set of conditions that are necessary or sufficient for an outcome. This research is a mixed-method study that employs both data analysis methods with the aim of integrating the findings. Previous UTAUT2 studies using mixed-method PLS-SEM and fsQCA include Duarte & Pinho (2019) and Reyes-Mercado (2018).

METHOD

A quantitative approach was used to collect data for this study. Research is being held out with a target sample size of 120 respondents based on previous research conducted by Duarte & Pinho (2019). Additionally, the fsQCA analysis technique can be used for various sample sizes. FsQCA can be utilized to process small (<50 cases) to very large (thousands of cases) samples (Pappas & Woodside, 2021). Stratified-disproportionate-random sampling will be used, based on the frequency of digital bank usage.

The study uses an online platform, Google Form, for distributing and collecting data to increase accessibility for respondents across Indonesia. A total of 120 Indonesian housewives who use digital banks participated and filled out a questionnaire. Respondent validation is conducted to ensure that respondents meet the target sample criteria, including housewives who have used digital bank applications. The questionnaire begins with respondent background (age, latest education, frequency of digital bank usage,

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name of used digital bank application) and uses Likert scale questions with points 1-5 (strongly disagree to strongly agree) based on indicators of the variables.

The research model applied in this study is the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). The UTAUT2 model in this study uses constructs in accordance with previous research conducted by Duarte & Pinho (2019). The independent variables in the research model include Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Condition (FC), Hedonic Motivation (HM), Price Value (PV), and Habit (HT). These independent variables were then tested for their effect on the Behavioral Intention (BI) variable. The model is depicted in Figure 1.

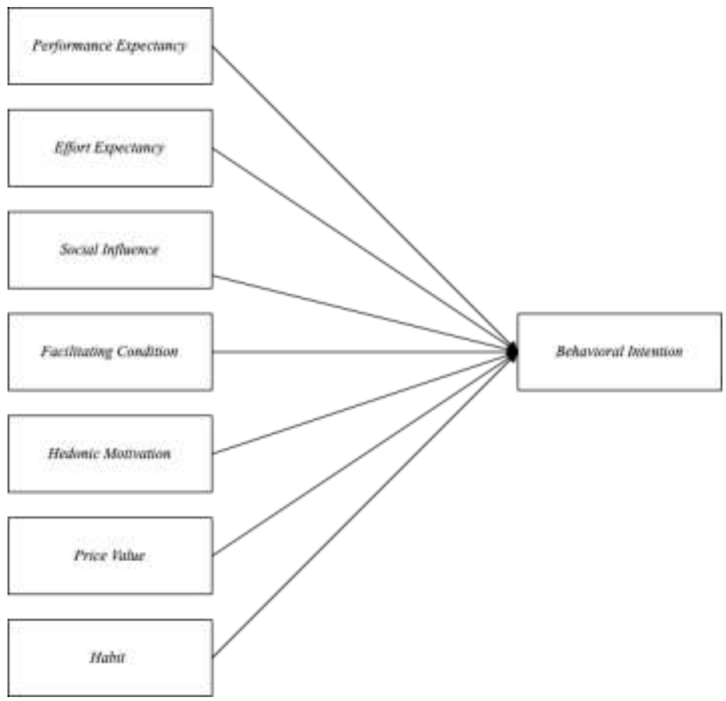

Figure 1. UTAUT2 as Research Model

Based on the research model, the following are the hypotheses that need to be tested in this study.

H_0^1: Performance Expectancy (PE) has no influence on Behavioral Intention (BI).
H_A^1: Performance Expectancy (PE) has an influence on Behavioral Intention (BI).
H_0^2: Effort Expectancy (EE) has no influence on Behavioral Intention (BI).
H_A^2: Effort Expectancy (EE) has an influence on Behavioral Intention (BI).
H_0^3: Social Influence (SI) has no influence on Behavioral Intention (BI).
H_A^3: Social Influence (SI) has an influence on Behavioral Intention (BI).
H_0^4: Facilitating Condition (FC) has no influence on Behavioral Intention (BI).
H_A^4: Facilitating Condition (FC) has an influence on Behavioral Intention (BI).
H_0^5: Hedonic Motivation (HM) has no influence on Behavioral Intention (BI).
H_A^5: Hedonic Motivation (HM) has an influence on Behavioral Intention (BI).
H_0^6: Price Value (PV) has no influence on Behavioral Intention (BI).
H_A^6: Price Value (PV) has an influence on Behavioral Intention (BI).
H_0^7: Habit (HT) has no influence on Behavioral Intention (BI).
H_A^7: Habit (HT) has an influence on Behavioral Intention (BI).

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In addition to the seven pairs of null hypotheses and alternative hypotheses, there are 2 propositions offered.

Proposition 1: The seven dimensions of UTAUT2 are not necessary conditions by themselves to influence Behavioral Intention (BI).

Proposition 2: The seven dimensions of UTAUT2 are not sufficient by themselves to influence Behavioral Intention (BI).

Data analysis involves two methods: PLS-SEM and fsQCA. PLS-SEM analysis consists of two steps: testing the measurement model (outer model) for validity and reliability and testing the structural model (inner model) to test the hypotheses. fsQCA analysis also involves two steps: data calibration and standard analysis to analyze the truth table. Software packages used for data analysis include SmartPLS 3.2.9 for PLS-SEM analysis and fs/QCA 4.0 for fsQCA analysis.

RESULT

Respondents' Characteristics

Respondents' characteristics refer to the demographics and other relevant information about the participants in a research study, including age, education, frequency of digital bank usage, and name of used digital bank application. The aim of providing respondents' characteristics is to offer context and to demonstrate the generalizability of the research findings. This study collected questionnaire data from 120 housewife respondents who live in Indonesia and have used digital banks. Table 1 shows the complete list of respondents' characteristics.

Table 1
Respondents' Characteristics

Respondents' Characteristics	Frequency	Percentage
Age		
17-25 years old	34	28,3%
26-35 years old	61	50,8%
36-45 years old	18	15%
>45 years old	7	5,8%
Latest Education		
High School (SMA/SMK/MA)	41	43,2%
Associate Degree (D2/D3)	20	16.7%
Bachelor's Degree (S1/D4)	56	46,7%
Master's Degree (S2)	2	1,7%
Doctoral Degree (S3)	1	0,8%
Frequency of Digital Bank Usage		
Every day (once or more than once)	27	22,5%
Every week (once or more than once)	52	43,3%
Every month (once or more than once)	39	32,5%
Ever used (but not regularly)	2	1,7%

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Name of Used Digital Bank Application		
Seabank	55	45,83%
BCA Digital (Blu)	45	37,50%
Jago	44	36,67%
Jenius by BTPN	20	16,67%
Hana (LINE Bank)	19	15,83%
PermataME	9	7,50%
Allo by Mega	8	6,67%
TMRW by UOB	5	4,17%
Nyala by OCBC	3	2,50%
Neocommerce	3	2,50%

Descriptive Statistics

A descriptive statistic is used to present a summary of the data which aims to provide an overview of the research object without giving any conclusion (Putri et al., 2021). Table 2 shows research's descriptive statistics.

Table 2
Descriptive Statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation
BI	120	2,00	5,00	4,4194	0,43105
PE	120	1,67	5,00	4,3917	0,47074
EE	120	1,33	5,00	4,4500	0,47466
SI	120	1,50	5,00	4,3062	0,49521
FC	120	1,67	5,00	4,4556	0,43629
HM	120	1,67	5,00	4,3806	0,50265
PV	120	2,00	5,00	4,4333	0,39511
HT	120	1,67	5,00	4,4028	0,46722

PLS-SEM Analysis

Analysis of the research data is followed by testing the measurement model or outer model. The measurement model test is carried out by carrying out validity and reliability tests. The indicator used to test the validity is the Average Variance Extracted (AVE) value while the reliability test indicator uses Composite Reliability. Table 3 below shows the results of the validity and reliability tests of variables and question items along with their respective factor loadings.

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Table 3
Measurement Model Testing

Variable	Coding	Indicator	FL
Performance Expectancy (CR = 0,789, AVE = 0,558)	PE1	Using digital bank applications enhances my opportunity to accomplish important tasks.	0,639
	PE2	Using digital bank applications improves my productivity in daily activities.	0,843
	PE3	Using digital bank applications facilitate my work processes.	0,745
Effort Expectancy (CR = 0,813, AVE = 0,592)	EE1	Learning how to use digital bank applications is easy for me.	0,764
	EE2	I find digital bank applications user-friendly.	0,763
	EE3	I quickly become proficient at using digital bank applications.	0,781
Social Influence (CR = 0,817, AVE = 0,528)	SI1	People who influence my behavior suggest that I should use digital bank applications.	0,735
	SI2	People whose opinions I value recommend using digital bank applications.	0,709
	SI3	Important people in my life encourage me to use digital bank applications.	0,715
	SI4	Trusted individuals support the use of digital bank applications.	0,748
Facilitating Conditions (CR = 0,794, AVE = 0,562)	FC1	I possess the necessary knowledge to use digital bank applications.	0,764
	FC2	I feel confident using digital bank applications.	0,759
	FC3	I encounter no issues when using digital bank applications.	0,725
Hedonic Motivation (CR = 0,821, AVE = 0,605)	HM1	Digital bank applications are fun.	0,819
	HM2	I find the use of digital bank applications to be enjoyable.	0,789
	HM3	Using digital bank applications is entertaining.	0,722
Price Value (CR = 0,748, AVE = 0,500)	PV1	Digital bank applications provide good value for the money.	0,745
	PV2	Digital bank applications offer a suitable amount	0,694

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Variable	Coding	Indicator	FL
		corresponding to the money I pay.	
	PV3	In my opinion, using digital bank applications is an economical choice.	0,677
Habit (CR = 0,781, AVE = 0,544)	HT1	Using digital bank applications has become a habit for me.	0,798
	HT2	I have developed a dependence on using digital bank applications.	0,664
	HT3	The use of digital bank applications comes naturally to me.	0,744
Behavioural Intention (CR = 0,808, AVE = 0,585, R-sq = 0,671, R-s a = 0,651)	BI1	I am committed to integrating digital bank applications into my daily life.	0,817
	BI2	I believe using digital bank applications would be beneficial.	0,749
	BI3	I have a positive perception of using digital bank applications.	0,726

Note: CR = Composite Reliability, AVE = Average Variance Extracted, FL = Factor Loadings, R-sq = R-square, R-s a = R-square adjusted.

The research instrument's reliability was tested using the Composite Reliability (CR) and all constructs had CR values above 0.7, indicating high reliability. Convergent validity was tested using the Average Variance Extracted (AVE) and all constructs exceeded the threshold of 0.5. Discriminant validity was confirmed using the Fornell-Larcker criteria. This study uses a factor loading threshold of 0.6 or higher so that all indicators in the table are used in data collection and analysis (Susanto et al., 2020). The Behavioral Intention (BI) variable had R-square and adjusted R-square values over 0.65, indicating that the independent variables can explain Behavioral Intention (Marpaung et al., 2021). Overall, the research instrument is both valid and reliable.

The structural model or inner model is tested after passing the measurement model test. The PLS-path analysis is used for this test, and the results including Standard Deviation, T Statistics, and P Values are presented in Table 4 for hypothesis testing purposes.

Table 4
Structural Model Testing

Relationships	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Performance Expectancy → Behavioral Intention	0.071	1,423	0,155
Effort Expectancy → Behavioral Intention	0.082	0,367	0,714
Social Influence → Behavioral Intention	0.075	1,158	0,247

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Facilitating Conditions → Behavioral Intention	0.096	2,280	0,023*
Hedonic Motivation → Behavioral Intention	0.101	0,794	0,427
Price Value → Behavioral Intention	0.083	7,304	0,000*
Habit → Behavioral Intention	0.073	2,016	0,044*

Note: * = P Values < 0,05

T Statistics and P Values in the table were obtained through a bootstrapping process on the sample using the SmartPLS software. The seven pairs of research hypotheses were then tested through the P and T Statistics values of each path. The threshold value of P below 0.05 and T Statistics greater than 1.96 is the basis for making a decision on the null hypothesis or alternative hypothesis to be accepted.

The results of the structural model testing using PLS-SEM showed that only three alternative hypotheses were accepted, indicating that there are only three independent variables that have an impact on behavioral intention. These variables are facilitating conditions, price values, and habits. Table 5 below is modified from Table 4 with additional the decision result and comparison with the previous study.

Table 5
Hypothesis Testing Result

Relationships	T Statistics (|O/STDEV|)	P Values	Alternative Hypothesis	Previous Studies with Matching Result
PE → BI	1,423	0,155	Rejected	(Anggraeni et al., 2021; Kwateng et al., 2019)
EE → BI	0,367	0,714	Rejected	(Anggraeni et al., 2021; Duarte & Pinho, 2019; Kwateng et al., 2019)
SI → BI	1,158	0,247	Rejected	(Duarte & Pinho, 2019; Kwateng et al., 2019; Nguyen et al., 2020)
FC → BI	2,280	0,023*	Accepted	(Gharaibeh et al., 2018)
HM → BI	0,794	0,427	Rejected	(Gharaibeh et al., 2018; Kwateng et al., 2019)
PV → BI	7,304	0,000*	Accepted	(Kwateng et al., 2019)
HT → BI	2,016	0,044*	Accepted	(Anggraeni et al., 2021; Duarte & Pinho, 2019; Kwateng et al., 2019; Nguyen et al., 2020)

Note: * = P Values < 0,05

FsQCA Analysis

The fsQCA technique analyzes samples with a data range of 0 to 1. Therefore, collected data from respondents on a 5-point Likert scale must first undergo the data calibration process. The calibration process involves two stages, where the author first calculates the average value per construct based on respondents' responses to each indicator and their respective factor loading weight. In the second stage, data calibration is conducted using quartiles derived from the calculated average construct values. These quartiles help to determine the full membership and full non-membership groups for each observation. The intersection value (0.5) is then established using the median or 2nd quartile (Huang et al., 2022). This process ensures that the data is appropriately calibrated for fsQCA analysis. The descriptive statistics of the calibrated research data are shown in Table 6.

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Table 6
Descriptive Statistics of Calibrated Data

Variable	N	Minimum	Maximum	Mean	Std. Deviation
BI	120	0,00	1,00	0,5620	0,38789
PE	120	0,00	1,00	0,5515	0,39208
EE	120	0,00	1,00	0,5050	0,44046
SI	120	0,00	0,99	0,4876	0,39048
FC	120	0,00	1,00	0,5246	0,44495
HM	120	0,00	1,00	0,5191	0,42295
PV	120	0,00	1,00	0,4699	0,43088
HT	120	0,00	1,00	0,5317	0,43069

The author performs a truth table analysis on the calibrated data matrix to test the two propositions proposed in this study, which are whether the seven independent variables of UTAUT2 are necessary or sufficient conditions to influence the adoption of digital bank applications' Behavioral Intention (BI). Table 7 presents the list of independent variables or conditions tested, along with their consistency and coverage for each Behavioral Intention (BI) and its negation (~BI).

Table 7
Necessary Conditions Analysis

Behavioural Intention (BI)			**Negation of Behavioural Intention (~BI)**		
Conditions	Consistency	Coverage	Conditions	Consistency	Coverage
PE	0,714	0,728	PE	0,484	0,385
~PE	0,396	0,497	~PE	0,657	0,642
EE	0,638	0,710	EE	0,464	0,403
~ EE	0,463	0,526	~ EE	0,666	0,589
SI	0,636	0,733	SI	0,443	0,398
~SI	0,478	0,524	~SI	0,702	0,600
FC	0,672	0,720	FC	0,407	0,340
~FC	0,384	0,454	~FC	0,664	0,612
HM	0,626	0,677	HM	0,494	0,417
~HM	0,462	0,539	~HM	0,618	0,563
PV	0,705	0,843	PV	0,266	0,248
~PV	0,371	0,393	~PV	0,832	0,687
HT	0,685	0,725	HT	0,439	0,361
~HT	0,396	0,475	~HT	0,666	0,622

A necessary condition has a consistency value of 0.9 or higher. All variables had a maximum consistency value of 0.832, supporting the proposed proposition 1. This suggests that no variable is a necessary condition on its own for behavioral intention to adopt digital bank applications (Duarte & Pinho, 2019). Furthermore, a standard fsQCA analysis is carried out to determine what solutions can lead to behavioral intention. Table 8 below contains a list of 6 intermediate solutions that can generate behavioral intention.

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Table 8
Configurations Lead to Behavioral Intention (BI)

Configurations	**Solutions**					
	1	**2**	**3**	**4**	**5**	**6**
Performance Expectancy (PE)	●		●		●	●
Effort Expectancy (EE)				●		
Social Influence (SI)			●	●		○
Facilitating Conditions (FC)		●	●	●	●	●
Hedonic Motivation (HM)	○	○			●	●
Price Value (PV)	●	●				●
Habit (HT)	●	●	●	●	●	
Consistency	0,903	0,897	0,879	0,900	0,881	0,902
Raw Coverage	0,187	0,144	0,353	0,313	0,337	0,125
Unique Coverage	0,061	0,014	0,013	0,025	0,222	0,335
Overall Solution Consistency	0,886					
Overall Solution Coverage	0,563					

Note: black dot (●) indicates that the variable appears in the solution configuration, meanwhile, white dot (○) indicates that the negation of the variable appears in the solution configuration and empty means that the variable is absent in the solution configuration.

Table 8 shows that no individual condition can independently lead to behavioral intention, supporting proposition 2. Along with listing the six intermediate solutions, the table also displays the overall solution consistency and coverage values. The consistency value is 0.886, exceeding the threshold of 0.80, and the coverage value is 0.563, surpassing the threshold of 0.45, indicating the appropriateness of the approach used. Solution 4 is deemed the best solution due to its high consistency and coverage values when compared to solutions 1 and 6, which have high consistency but low coverage values.

DISCUSSIONS

By comparing the results of PLS-SEM analysis and fsQCA analysis, it becomes evident that the two variables, FC (Facilitating Conditions) and HT (Habit), are central to the study's findings. PLS-SEM analysis identified three factors, including facilitating conditions, price values, and habits, that have an impact on the Behavioral Intention variable. On the other hand, fsQCA analysis suggests that a configuration of effort expectancy, social influence, facilitating conditions, and habits is the best solution for Behavioral Intention. Although other factors did not have a direct effect on the BI variable, they still played a role in creating a sufficient solution configuration for the emergence of Behavioral Intention.

For instance, the EE (Effort Expectancy) and SI (Social Influence) variables, along with the FC and HT variables, contributed to producing Behavioral Intention to adopt digital banks. Moreover, the PE (Performance Expectancy) variable was part of solution 1 and solution 6 in the fsQCA analysis, which was not chosen as the best solution but is worth considering due to their high solution consistency. Furthermore, each condition variable contributed to at least one solution configuration among the six solutions presented

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in the fsQCA analysis, indicating that each variable works together with other variables in generating behavioral intention, particularly the FC and HT variables, which dominated the study's results.

Understanding these factors can help digital bank companies, particularly Indonesian digital banks, to grow Indonesia's digital economy by promoting campaigns that increase the exposure and knowledge of housewives, creating a habit of using digital banking applications. The government can also play a crucial role in creating facilitating conditions by providing adequate technology, including internet access, to accelerate the adoption of digital banking applications by housewives.

In addition to digital bank companies and the government, financial institutions and fintech startups can also benefit from the findings of this research. By understanding the factors that influence the behavioral intention of housewives to adopt digital bank applications, they can design products and services that cater to the needs and preferences of their target customers. This can lead to the development of more user-friendly and accessible digital banking applications, which in turn can increase adoption rates among housewives and contribute to the growth of Indonesia's digital economy.

This study has utilized a mixed-method analysis approach comprising PLS-SEM and fsQCA. This combination of data analysis techniques is beneficial in complementing the findings and enhancing research insights. The author recommends the use of mixed data analysis techniques in future studies to produce richer and more insightful research.

It is important to note that the limitation of this study is the dominance of respondents from Java and Sumatra. Therefore, future research should strive to obtain a more even distribution of respondents from different regions in Indonesia to reduce bias and obtain results that truly represent the conditions of housewives in Indonesia as a whole.

Furthermore, this research can also serve as a basis for future studies on digital banking adoption in Indonesia, especially among other demographic groups such as men and the elderly. By expanding the scope of the research, a more comprehensive understanding of the factors that influence digital banking adoption in Indonesia can be obtained. This can lead to more targeted policies and interventions aimed at promoting the adoption of digital banking applications, and ultimately, contribute to the development of a more inclusive and digitalized financial system in Indonesia.

CONCLUSION

This study aimed to determine the factors that influence the adoption of digital bank applications by Indonesian housewives, with the goal of increasing their interest in using these services. To achieve this objective, a mixed-method analysis approach of PLS-SEM and fsQCA was employed to investigate the factors that contribute to the behavioral intention of Indonesian housewives to adopt digital banking applications. The findings suggest that facilitating conditions and habit variables play a central role in the emergence of behavioral intention. While PLS-SEM analysis identified three factors, fsQCA analysis suggests that a configuration of effort expectancy, social influence, facilitating conditions, and habits is the best solution for behavioral intention. Understanding these factors can help digital bank companies, the government, financial institutions, and fintech startups to design products and services that cater to the needs and preferences of their target customers, contributing to the growth of Indonesia's digital economy. However, the study's limitation is the dominance of respondents from Java and Sumatra, and future research should strive to obtain a more even distribution of respondents from different regions in Indonesia. This research can also serve as a basis for future studies on digital banking adoption in Indonesia, expanding the scope of the research for a more comprehensive understanding of the factors that influence digital banking adoption. The author recommends the use of mixed data analysis techniques in future studies to produce richer and more insightful research.

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