INVESTIGATING STRATEGY FOR INDONESIA ISLAMIC FINTECH DEVELOPMENT

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Abstract: *This study aims to investigate Indonesia's Islamic Fintech and the strategy for future development. A theoretical model was collected from the Muslim society in Indonesia at various age levels, generations, education, duration of mobile device usage, and experience of transacting using digital platforms. In total 228 datasets were analyzed using partial least squares-structural equation modeling statistical software. We employ VOS Viewer, a bibliometric software, to enhance the depth of our analysis. The results showed that age, education, duration of mobile phone usage, and salary level significantly influence the use of new technology. Gender can indeed play a role in shaping attitudes toward new technology. The results indicate that Islamic fintech in Indonesia should innovate their platforms, integrate with another marketplace, and prioritize user-friendliness. The government of Indonesia is expected to build information technology infrastructure to support the ecosystem of Islamic financial technology advancement. This paper provides the empirical justification for a theoretical model of Indonesia's Islamic fintech development strategy.*

Keywords: Indonesia, Islamic, Fintech, Meta UTAUT, PLS-SEM**.**

1. INTRODUCTION

The field of financial technology is expected to bring about various advantages in different sectors and regions during the post-pandemic economic recovery phase, according to [1]. Nevertheless, when comparing Sharia-based financial technology platforms with their conventional counterparts, the former remains relatively small in scale and significance. A master's thesis concluded that Islamic religiosity has no significant impact on digital technology platforms within the Indonesian Muslim community, whereas it does have a considerable influence on the adoption of Islamic fintech in Saudi Arabia[2].

Feedback from a survey conducted among Islamic fintech consumers reveals that Islamic fintech in Indonesia is not integrated with popular marketplace applications like Lazada and Traveloka, as well as other daily support applications, limiting its reach and ability to fulfill consumer needs. Moreover, Islamic fintech in Indonesia is deemed less user-friendly due to incomplete features. In comparison to conventional fintech, which offers easier access, faster functionality, and simpler implementation, Islamic fintech lacks innovative features [3]. Additionally, the uneven information technology infrastructure in different regions contributes to the weaknesses of Islamic fintech in Indonesia. When studying the adoption of new technological advancements, several studies employ the Unified Theory of Acceptance and Use of Technology (UTAUT). In this research, the Meta UTAUT theory is utilized to distinguish between attitudes toward new technology and behavioral intentions to use it. People's attitudes towards new technology are not uniform and can differ from one individual to another. Several factors contribute to these variations, including personal values, beliefs, and past experiences with technology. Personal values play a significant role in shaping attitudes toward new technology. Individuals with a strong value for innovation and embracing change may generally exhibit more positive attitudes toward new technologies, while those who prioritize tradition and stability might be more skeptical or resistant to adopting new technology. Beliefs also influence attitudes toward technology. Pre-existing beliefs about the benefits or drawbacks of technology can shape how individuals perceive and approach new technological advancements. For example, someone who believes that technology enhances productivity and efficiency is more likely to have a positive attitude toward new technological tools. Past experiences with technology can significantly impact attitudes. Positive experiences with previous technologies can foster a favorable attitude towards new ones, while negative experiences might lead to skepticism or reluctance to adopt new technology. Overall, attitudes towards new technology are complex and influenced by a combination of personal factors, beliefs, past experiences, and the perceived benefits and ease of use associated with the technology. Some individuals view new technology positively, considering it a means to enhance their lives, increase productivity, or improve social connections. Others may hold a negative attitude, perceiving new technology as invasive, a threat to privacy, or a source of distraction from important tasks or relationships. This study adds the variables of gender, age, education level, experience in financial technology transactions, and Islamic religiosity to the UTAUT framework. Islamic FinTech literature has extensively covered various areas, including the intersection of technology and religion [4].

2. RESEARCH OBJECTIVE

The objective of this study is to investigate Indonesia's Islamic fintech and its strategy for future development. It examines the readiness of Indonesian Muslim society to adopt Islamic financial technology using the Meta UTAUT Theory. The data was collected from 228 respondents across different age groups, generations, education levels, durations of mobile device usage, and experiences in conducting transactions through digital platforms. Analyzing the strategic development of Islamic fintech is crucial due to its potential to enhance financial inclusivity, address financial crises, and contribute to the achievement of Sustainable Development Goals (SDGs) for a sustainable nation, as recognized by the

government [4]. Additionally, the Finance Outlook 2023 predicts challenges for the financial industry in the upcoming year, with emerging competitors such as fintech companies likely to face significant obstacles. The aim of this research is to identify the strategic development of Islamic fintech in Indonesia for the future. The remaining sections of this document are organized as follows: The second section is devoted to Indonesia's Islamic fintech ecosystem and the meta-UTAUT analysis. The third section focuses on the research framework and the development of hypotheses and examines the constructs of performance expectation, effort expectation, social influence, trust, and support conditions for behavioral attitudes and intentions when using new technologies. In addition, moderating variables such as gender, age, level of education, experience in financial technology transactions, and Islamic religiosity are considered. In the fourth section, the results of statistical modeling using partial least squares structural equation models are presented. Finally, the last section ends with a discussion and summary.

Indonesia Islamic Fintech Ecosystem

Islamic FinTech is the use of technology in the financial sector in accordance with Sharia rules. Their implementation can lead to innovative business models, applications, processes, or products that can have a significant impact on financial markets, institutions, and the provision of financial services. This particular form of FinTech is intended to serve Islam-compliant institutions or countries [4]. As [5] points out, the history of FinTech dates back to 1866 and can be divided into three distinct stages of development. In the first phase, which lasted from 1866 to 1967, transatlantic cables and telegraphs were used as a means of financial communication. In the second phase, which took place between 1967 and 2008, online banking and ATMs emerged as financial institutions began to integrate information technology into their offerings. The third phase, which began in 2008, marked the emergence of high-tech tools used by new entrants with unique characteristics, and resulted in a new competitive landscape for financial institutions.FinTech encompasses several business models identified by [6]. These models include credit, capital markets, insurance services, wealth management, payments, and crowdfunding. [7] further develop the FinTech field by describing seven different activities within it. These activities cover various aspects such as payment methods (online and mobile payment models), deposits and loans (crowdfunding, peer-to-peer lending, microcredit, and consumer lending models), and investment management activities (robo-advising, social trading, and automated systems).). Advisory models), distributed ledger technology business (digital currency and blockchain models), banking infrastructure business (UI and open banking models), analytics, and insurance business.

Meta UTAUT Theory

The UTAUT model is commonly used to explain how people embrace and accept technology in different situations. It shows that intention and use of technology are influenced by four main factors: their belief that using technology will improve their job performance, their perception of how easy it is to use technology, and the impact of technology. These factors can be influenced by individual and contextual factors such as gender, age, education, and experience. The meta UTAUT further extends the model by integrating UTAUT factors with attitude to understand behavioral dispositions.

3. PREVIOUS RESEARCH

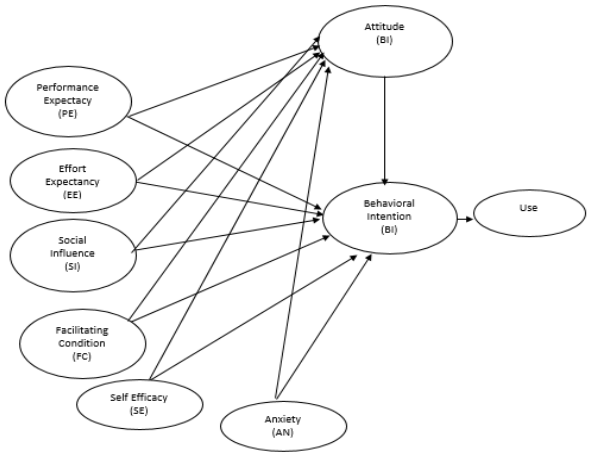
Research conducted in Brazil and Malaysia found that performance expectations play a crucial role in the intention to adopt fintech. However, a study in Indonesia showed that expectation of performance has a greater impact on actual use of technology than intent to use it. In Saudi Arabia, research suggests that Islamic religiosity moderates the relationship between behavioral intention and FinTech use. Meanwhile, research results that Islamic religiosity does not affect Indonesia's Islamic fintech usage. This implies that the Indonesian Muslim community, which primarily uses general financial technology, is becoming more selective in using technology for halal transactions as the understanding of Islam increases. Studies have shown that factors such as the expectation of performance, an expectation of effort, and trust influence the intention to use fintech. Trust and security are particularly important to the Indonesian Muslim community. When using fintech, they value trust, performance expectations, and favorable terms rather than being solely swayed by societal influence through advertising. In summary, the UTAUT model explains factors influencing technology adoption, including the role of Islamic religiosity in the Indonesian context. Trust, performance expectations, and framework conditions are critical to fintech adoption, and vendors need to focus on enhancing trust and security to improve customer experiences.

4. METHODOLOGY AND DATA ANALYSIS

A. Dataset

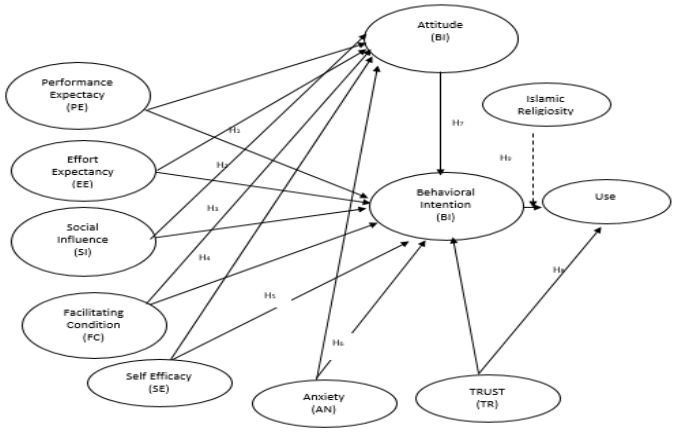
This section discusses the role played by moderator variables such as gender, age, education, and experience in the use of digital money transactions in financial technology.

Research framework



Meta UTAUT Model Adopted from Ventakesh et al., (2012)

B. Hypothesis Development



Research Model Meta UTAUT modification

The first construct that, according to the theoretical framework, influences behavioral intention is performance expectancy. In the proposed UTAUT concept, there are four factors that influence behavioral intention and technology use: the expectation of performance, expectation of effort, enabling conditions, and social influence. The developed extension of UTAUT incorporates additional constructs such as hedonic motivation, low cost, and habit to provide a more comprehensive explanation of the relationship between the constructs and behavioral intention. Subsequently, Meta UTAUT was developed to integrate UTAUT factors with attitude, thus gaining a better understanding of behavioral dispositions.

Performance expectancy

Performance expectancy is a person's belief in the effectiveness of new technology in improving their performance. It includes multiple indicators including perceived usefulness, extrinsic motivation, job aptitude, relative advantage, and outcome expectations as suggested by [9]. Regarding fintech, research has shown that higher levels of fintech services are associated with greater fintech adoption. Performance expectancy plays an important role in influencing behavioral intention to use such technology, as studies by [10, 11, 12].

H_1: Performance Expectancy (PE) positively influences attitudes toward the use of financial technology in Indonesian Muslim society

H_2: Performance Expectancy (PE) has a positive effect on Behavioral Intention to the use of financial technology in Indonesian Muslim society

Effort Expectancy (EE)

Expected effort refers to the degree of ease associated with using the technology as defined by [13]. It includes key indicators such as perceived ease of use, complexity, and ease of use, among others [13]. Studies focusing on fintech adoption have consistently shown that expectation of effort (EE) is a highly influential factor in determining fintech adoption. The research by [14, 15, 16, 17] have provided evidence demonstrating the significant impact of expected efforts on fintech adoption.

H_3: Effort Expectancy (EE) positively influences attitudes toward the use of financial technology in Indonesian Muslim communities

H_4: Effort Expectancy (EE) has a positive effect on Behavioral Intention to the use of financial technology in Indonesian Muslim communities

Social Influence (SI)

Social influence is the level at which individuals perceive that their environment recommends the use of technology, as suggested by [8]. Social influence plays a crucial role in influencing people's behavior when adopting technology. Key indicators include subjective norms, social factors, and image. These include factors such as the perceived expectations of significant others, social norms, and the influence of peer groups. Social factors, another indicator of social influence, include the impact of social interactions and relationships on an individual's decision to adopt technology. These factors can include social networks, social interactions, social support, and the social influence of influential individuals or groups. Image refers to an individual's perception of how the use of a particular technology affects their social standing or reputation. Consider how the adoption of a particular technology affects a person's desired self-image or social identity. In general, social influence plays a crucial role in shaping individuals' attitudes and behavioral intentions toward technology adoption. Perceived social recommendations, subjective norms, social factors, and the influence of the image combine to influence an individual's decision to adopt and use technology.

H_5: Social Influence (SI) positively influences attitudes toward the use of financial technology in Indonesian Muslim communities

H_6: Social Influence (SI) has a positive effect on Behavioral Intention to the use of financial technology in Indonesian Muslim communities

Facilitating Condition (FC)

Facilities are traditionally considered structural factors. Past research has indicated that Facilitating Conditions can have a positive impact on behavioral intention, as demonstrated by [8].

H_7: Facilitating Condition (FC) positively influences attitudes towards the use of financial technology in Indonesian Muslim communities

H_8: Facilitating Condition (FC) has a positive effect on Behavioral Intention to the use of financial technology in Indonesian Muslim society

Self-efficacy

Self-efficacy refers to a person's belief in their own ability to use a technology effectively to perform specific tasks, as defined by [13]. Fintech introductory research has repeatedly shown that self-efficacy influences behavioral intention to use fintech. Studies by [18, 19, 15, 20] have provided evidence of the significant impact of self-efficacy on people's intention to adopt and use FinTech.

H_9: Self Efficacy positively influences attitudes toward the use of financial technology in Indonesian Muslim society

H_{10}: Self Efficacy has a positive effect on Behavioral Intention to the use of financial technology in Indonesian Muslim society

H_{11}: Computer anxiety positively affects attitudes toward the use of financial technology in Indonesian Muslim society

H_{12}: Computer anxiety has a positive effect on Behavioral Intention to the use of financial technology in Indonesian Muslim society

Behavioral Intention

Intent and utility are two interrelated variables associated with the concept of behavior as highlighted by [21]. Intent refers to a person's willingness or inclination to engage in a particular behavior, while usage represents a person's actual behavior according to multiple evaluations of the technology, as [21] point out. These variables are often examined together to understand the connection between individuals' intentions to use technology and their actual usage behavior.

H_{13}: Behavioral Intention has a significant effect on the usage of financial technology in Indonesian Muslim communities

Islamic Religiosity

The role of religiosity in customers' decision to use Islamic banking services has been a topic of discussion among scholars and practitioners, as highlighted by [4]. Islamic religiosity can be considered as either an intrinsic or extrinsic factor that may influence individuals' behavior. Previous studies have suggested that Islamic religiosity can impact materialistic behavior, particularly in terms of recognizing social status, as indicated by [22, 23]. However, research on the influence of religiosity on the adoption of information technology is limited. It has been found that religiosity can affect attitudes, as discussed by [24]. In GCC (Gulf Cooperation Council) countries, Islamic religiosity holds significant importance, and religious adherence strongly influences various aspects of life, as highlighted by Usman et al. In the context of FinTech services, adherence to Shariah principles has become crucial to ensure customer satisfaction. Therefore, enhancing the quality and performance of Islamic banking services, especially in mobile banking, is important to maintain customer loyalty and satisfaction based on these insights, it is suspected that Islamic religiosity may moderate the relationship between behavioral intention and the usage of financial technology.

H_{14}: Islamic religiosity positively moderates the relationship between Behavioral Intention and Usage of the use of financial technology in Indonesian Muslim communities

Data collection technique

In this study, the data collection process involved conducting a survey among the participants. The survey consisted of questions about the variables studied, and participants were asked to indicate their responses using a 5-point Likert scale. The survey was distributed through an online platform, specifically Google Forms, which allowed participants to fill out the questionnaire conveniently over the Internet. The questionnaire was divided into two parts. The first part focused on gathering demographic information about the participants, including their gender, age, educational level, and their use of digital platforms. These demographic questions were designed to provide basic information about the participants that could potentially influence their attitudes and perceptions about technology. The second part of the questionnaire was used to measure the UTAUT metamodel, a theoretical framework for understanding behavioral dispositions towards technology. In this section, the Likert scale was used, in which participants were presented with statements about the constructs of the meta UTAUT model and asked to indicate how strongly they agreed or disagreed with each statement using the 5-point Likert scale. The Likert scale is a commonly used method of measuring perceptions and attitudes in research. It allows participants to express their opinion and attitude towards certain statements or constructions by choosing the most appropriate answer option on a scale from “strongly agree” to “strongly disagree”.This scale provides a structured and standardized approach to quantifying participants' responses and allows for data analysis in a meaningful and statistically valid way, as recognized by [25]. Overall, the survey methodology employed in this study involved collecting data through a questionnaire administered online using Google Forms. The Likert scale was utilized to measure participants' perceptions and attitudes, with the survey divided into two parts, including demographic questions and statements related to the meta UTAUT Model.

Data screening Process and Diagnostic Test

A normality test assesses whether the data conforms to a normal distribution, which resembles a bell-shaped curve. Conversely, a non-significant p-value implies that the data can be assumed to conform to a normal distribution. Testing for normality is critical because many statistical analyzes and models rely on the assumption of normality to provide accurate results and interpretations. Skewness and kurtosis are commonly used as measures of normality and provide information about the shape and distribution of the data. The z-statisticfor the skewness value is calculated:

$$\text{z skewness} = ,\frac{\text{skewness}}{\sqrt{\frac{6}{N}}}$$

where N is the sample size. The Z value can also be calculated using the kurtosis value with the formula:

$$\text{z kurtosis} = \frac{\text{kurtosis}}{\sqrt{\frac{24}{N}}}$$

Discriminant Validity

Discriminant validity is a type of validity that ensures that a construct differs from other constructs that are theoretically unrelated [26]. Cross-loading is a statistical technique for assessing discriminant validity by examining how much an indicator of one construct weighs on another construct. If an indicator shows a greater load on a construct other than the intended construct, this indicates poor discriminant validity. On the other hand, if an indicator has a heavier burden on its own predicted construct than on other constructs, this indicates good discriminant validity. Therefore, in order to ensure good discriminant validity, it is important that the transverse loads of each indicator are higher in its own predicted construction than in other constructions [27].

Composite Reliability

Reliability is the degree of consistency or stability of a variable in measuring what it is designed to measure [26]. Internal consistency is a specific aspect of reliability that assesses the extent to which items or indicators within a construct measure the same underlying concept [27]. Cronbach's alpha is a commonly used measure of internal

consistency. A recommended minimum value of 0.7 indicates acceptable reliability of [27]. Provides anstimate of the reliability of a scale or questionnaire by measuring the degree to which items within a construct are related or consistent. A higher Cronbach alpha score indicates greater internal consistency, suggesting that the scale items are reliably measuring the construct.The composite reliability formula is as follows:

$$c = \frac{(\sum_{i=1}^{n} Li)^2}{(\sum_{i=1}^{n} Li)^2 + (\sum_{i=1}^{n} var(ei)^2}$$

Inner Model

Hypothesis testing involves analyzing the statistical significance of path coefficients or structural relationships in the internal model. By comparing the estimated path coefficients with their corresponding critical values, researchers can determine whether or not the hypothesized relationships are compatible. This helps validate the theoretical framework proposed byand draw conclusions about the relationships between variables. In general, the assessment of the goodness of fit and the testing of hypotheses in the internal model are essential to evaluate the adequacy of the model and to determine the importance of the relationships between the variables under study.

Coefficient of Determinant (R-Square)

R2 values can be interpreted as follows: an R2 value of 0.67 or more is considered high, indicating a strong relationship between exogenous and endogenous variables; an R2 value between 0.33 and 0.66 is considered moderate, indicating a moderate association; and an R2 value of 0.19 or less is considered weak, indicating a relatively weak relationship [28]. To improve the accuracy of the model in this study, a modified fitted coefficient of determination was used.The modified fitted coefficient of determination is a fitted version of R2 that accounts for the number of exogenous variables and the degrees of freedom in the model. It provides a more robust measure of the model's explanatory power by accounting for the complexity of the model. By using the modified fitted coefficient of determination, the researchers aim to obtain a more accurate assessment of the model's performance and the extent to which exogenous variables explain the variation in endogenous latent variables. This fitted measure helps account for the potential impact complexity of the model and provides a more reliable indication of the model's explanatory power.

Predictive Relevance (Q-Square)

In addition to the coefficient of determination (R2), the Stone-Geisser Q2 value is another criterion for assessing the accuracy of predictions in a structural model. Q2 measures the predictive relevance of the model, particularly for certain endogenous latent variables.To assess the magnitude of the R2 value in terms of predictive accuracy, researchers calculate the Q2 value. For a given endogenous latent variable, Q2 must be greater than 0 to indicate that the Partial Least Squares (PLS) model path contains relevant predictions. A positive Q2 value indicates that the model is able to make accurate predictions for the specified endogenous latent variable.The Q2 value provides a further assessment of the model's predictive power and its ability to generate meaningful predictions. By examining Q2, researchers can determine whether the model is effectively capturing the relevant relationships and making accurate predictions for the specified endogenous variables. [29] contributed to the understanding and application of PLS-SEM (Partial Least Squares Structural Equation Modeling) and their work includes considerations of the Q2 value as a measure of predictive relevance in PLS models.

Convergent Validity

Convergent validity is a measure of how well multiple indicators within a construct are related to each other and represent the same underlying construct. It demonstrates the unidimensionality of the construct, indicating that the indicators are measuring the same concept or trait. One commonly used measure of convergent validity is the average variance extracted (AVE), as proposed by [30]. The AVE represents the average amount of variance captured by the indicators in relation to the construct they are intended to measure. A higher AVE indicates a stronger convergent validity, suggesting that the indicators are collectively capturing a substantial portion of the construct's variance. To assess convergent validity using the AVE, researchers calculate the average of the squared factor loadings for each indicator and compare it to the average variance shared between the indicators. If the AVE value exceeds a threshold (usually 0.5 or 0.7), it indicates satisfactory convergent validity, implying that the indicators are adequately representing the construct. [27] discuss the importance of convergent validity in evaluating the measurement model in structural equation modeling (SEM). They highlight the use of the AVE as a standard measure to assess convergent validity, providing researchers with a practical guideline for evaluating the unidimensionality and reliability of their measurement scales.

The AVE value is calculated using the following formula;

$$AVE = \frac{\sum_{i=1}^{n} Li^2}{n}$$

Assess Coefficient of Determination (R2 and adjusted R2)

These measures allow for a more comprehensive assessment of model fit, considering various aspects of model performance and considering observed and expected data patterns. [31] acknowledge the limitations of R2 and emphasize the importance of using multiple measures to assess the goodness of fit of structural models.They advocate a holistic approach to model assessment that considers various fit indices and statistical tests to ensure a comprehensive assessment of model performance. Therefore, adj R2 (R2adj) was used in this study to avoid bias to the chosen model for many constructs. The formula for calculating R2adj is as follows:

$$R2adj = 1 - (1 - R2). \frac{n-1}{n-k-1}$$

Assess the Effect Size f2

By examining the effect size, researchers can determine the relative importance of individual exogenous constructs in explaining the variance in the endogenous construct. It aids in identifying influential variables and understanding their impact on the model. The formula is as follows:

$$f2 = \frac{R^2 included - R^2 excluded}{1 - R^2 included}$$

As you mentioned, there are general guidelines for interpreting the effect size value (f2). A small effect size (f2=

0.02) indicates minimal influence of the exogenous construct on the endogenous construct.A medium effect size (f2 = 0.15) indicates a moderate effect, while a substantial effect size (f2 = 0.35) represents a significant effect of the exogenous construct over the endogenous construct. By examining effect size, researchers can assess the practical or essential importance of including or excluding certain exogenous constructs from the model. It helps assess the relevance and contribution of each variable to explain the variability in the endogenous construct.

Analysis of Moderating Variable

If the interaction term is statistically significant, it means that the moderator variable has a significant impact on the relationship between the two variables. The meaning of the moderating effect is important as it helps to understand the conditions under which the relationship between the two variables is stronger or weaker. It provides information about the boundary conditions and the contexts in which the relationship is true or varies. By identifying and studying moderator variables, researchers can gain a deeper understanding of the complexities of the relationships between the variables and the conditions under which they operate.

5. RESULTS AND FINDINGS

Table 1. Respondents Profile

Profile of Respondents	Frequency	Percentage (%)
Gender		
Male	157	68.86
female	71	31.14
age		
Less than 20	6	2.63
20 – 29	35	15.35
30 – 39	45	19.74
40 – 49	100	43.86
Above 50	42	18.42
Generation Type		
1946 - 1964 (Baby Boomers)	11	4.82
1965 - 1980 (Generation X)	99	43.42
1981 – 1996 (Generation Y/Millennial)	91	39.91
1997 – 2012 (Generation Z)	27	11.84
Education Level		
Professor	0	0.00
Doctoral Degree	4	20.61
Master's Degree	47	21.60
Bachelor Degree	139	60.96
high school	38	16.67
Cell Phone Usage		
never	2	0.88
Less	6	2.63
sometimes	41	17.98
often	53	23.25
very often	126	55.26
E-Money Transactions		
never	7	3.07
Less	17	7.46
sometimes	41	17.98
often	63	27.63
very often	100	43.86

Path Coefficient	β	Mean	σ	t stat	p Values
Age -> Use Technology	-0.190	-0.188	0.094	2.024	0.043
Attitude -> Behavioral Intention	0.123	0.123	0.089	1.378	0.169
BI*Age -> Use Technology	0.116	0.099	0.117	0.994	0.321
BI*Education -> Use Technology	-0.053	-0.053	0.063	0.840	0.402
BI*Gender -> Use Technology	-0.050	-0.045	0.059	0.838	0.402
BI*Generation -> Use Technology	0.105	0.093	0.104	1.016	0.310
BI*IR -> Use Technology	-0.127	-0.125	0.074	1.720	0.086
BI*Phone Duration -> Use Technology	0.144	0.144	0.074	1.948	0.052
BI*Salary -> Use Technology	-0.024	-0.022	0.069	0.348	0.728

BI*Trust -> Use Technology	-0.042	-0.037	0.070	0.594	0.553
Behavioral Intention -> Use Technology	0.139	0.144	0.061	2.268	0.024
Education -> Use Technology	0.104	0.103	0.053	1.967	0.050
Effort Expectancy -> Attitude	0.233	0.218	0.075	3.104	0.002
Effort Expectancy -> Behavioral Intention	0.085	0.085	0.094	0.903	0.367
Facilitating Condition -> Attitude	0.121	0.136	0.087	1.379	0.168
Facilitating Condition -> Behavioral Intention	0.186	0.182	0.115	1.617	0.107
Gender -> Use Technology	0.134	0.131	0.051	2.648	0.008
Generation -> Use Technology	-0.111	-0.104	0.085	1.309	0.191
Islamic Religiosity -> Use Technology	0.110	0.103	0.072	1.526	0.128
Performance Expectancy -> Attitude	0.444	0.445	0.076	5.866	0.000
Performance Expectancy -> Behavioral Intention	0.172	0.175	0.089	1.930	0.054
Phone Duration -> Use Technology	0.480	0.480	0.057	8.470	0.000
Salary -> Use Technology	0.143	0.146	0.058	2.479	0.013
Social Influence -> Attitude	0.128	0.125	0.063	2.044	0.042
Social Influence -> Behavioral Intention	-0.027	-0.024	0.073	0.369	0.712
Trust -> Use Technology	0.067	0.067	0.065	1.045	0.296

Robustness Check

In this study we conduct robustness check using quadratic effect and Unobserved Heterogeneity Test.

Quadratic Effect

The robustness test conducted in this study aims to examine the potential non-linear relationship between the exogenous and endogenous constructs. Non-linearity refers to a relationship that cannot be adequately represented by a straight line and may involve curved or U-shaped patterns. To test for non-linearity, the study incorporates a quadratic effect in the polynomial model. The quadratic effect allows for the examination of whether the relationship between the constructs is best described by a linear or non-linear function. By including the quadratic term, the study investigates whether there is a significant curvilinear (non-linear) relationship between the constructs. By conducting this robustness test, the study ensures that the assumed linear relationship between the constructs holds and that the model adequately captures the observed data. This test strengthens the validity of the findings and provides confidence in the interpretation of the linear relationships between the variables studied.

Unobserved Heterogeneity Tests

In reality, individual behavior and preferences can vary within a sample. Neglecting this heterogeneity can lead to biased or inaccurate analysis results. To address the issue of heterogeneity in PLS-SEM, researchers can conduct an Unobserved Heterogeneity (UH) test. This test aims to detect potential differences in the relationships between constructs across subgroups within the sample. It helps identify if there are distinct segments or groups of respondents with different patterns of behavior or relationships. The UH test is typically conducted by employing techniques such as Finite Mixture Partial Least Squares (FIMIX-PLS) or Latent Class Analysis (LCA). These methods allow for the identification of unobserved subgroups within the sample based on their response patterns or latent characteristics. By considering and accounting for heterogeneity in the data, researchers can obtain more accurate and reliable results in PLS-SEM analyses. It helps to uncover variations in behavior and relationships that may exist within the sample, leading to a better understanding of the underlying phenomena and more precise conclusions.

Tabel 3. Unobserved Heterogeneity Tests

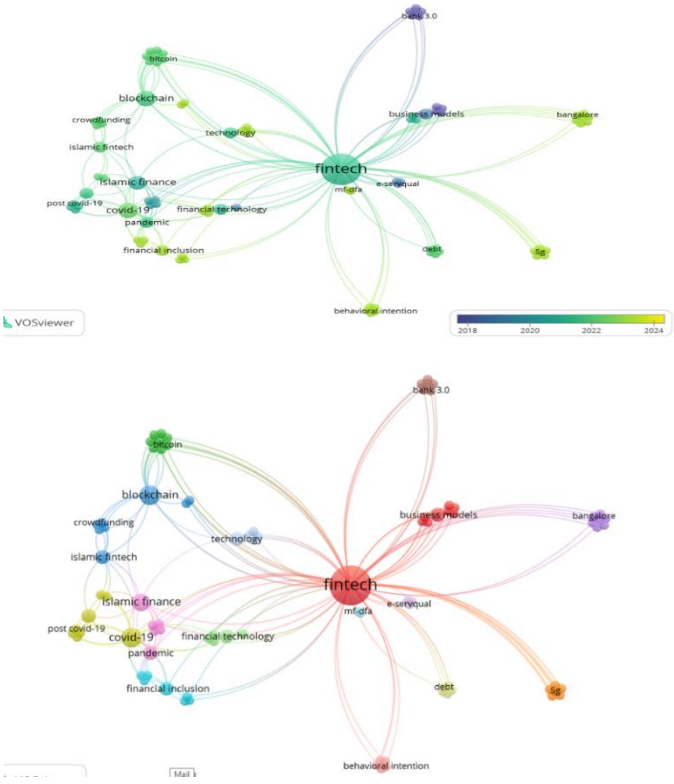
	Segment 1	Segment 2	Segment 3
AIC (Akaike's Information Criterion)	1529.715	1046.622	**1013.275**
AIC3 (Modified AIC with Factor 3)	1570.715	**1129.622**	1138.275
AIC4 (Modified AIC with Factor 4)	1611.715	**1212.622**	1263.275
BIC (Bayesian Information Criteria)	1670.318	**1331.258**	1441.943
CAIC (Consistent IC	1711.318	**1414.258**	1566.943
HQ (Hannan Quinn Criterian)	1586.444	**1161.464**	1186.230
MDL5 (Minimum Description Length with Factor 5)	2560.731	3133.800	4156.616
LnL (Loglikelihood)	-723.857	-449.311	-381.638
EN (Entropy Statistics (Normed))	n/a	0.999	0.971
NFI (Non-Fuzzy Index)	n/a	0.999	0.974
NEC (Normalized Entropy Criterion)	n/a	0.313	6.722

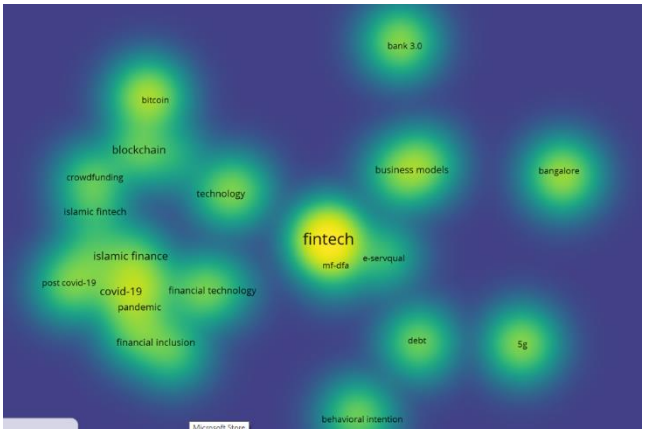
Relative segment size is a measure used in FIMIX-PLS analysis to assess the relationship between variables within each segment. It is similar to R-squared in traditional regression analysis and provides an indication of the amount

of variance explained by the model within each segment. As part of this study, relative segment size was calculated to understand the relationship between variables in the identified segments. AIC is a measure of the model's goodness of fit, with lower values indicating a better fit.Based on the results, it was found that there were three segments and the minimum AIC value was observed in segment 3.The relative size of the segment can be interpreted as the fraction of the variance in the dependent variable that is explained by the independent variables within each segment. A larger relative segment size indicates a stronger relationship between the variables in that segment. This is a useful measure for understanding the strength of relationships and the overall fit of the model within each segment. By calculating the relative size of the segment, researchers can gain insight into the effectiveness of themodel in explaining the variation in the dependent variable within each segment.This information can help assess model performance and assess the importance of relationships between variables in different segments.

6. CONCLUSSION AND RECOMMENDATION

The path coefficient results show that age significantly influences the use of new technology (p-value 0.043 and β = -0.190), meaning that older individuals use new technology less frequently. Behavioral intention moderated by Islamic religiosity also significantly influences the use of new technology (p-value = 0.086, β = -0.127), indicating that individuals who are more religious use new technology less due to their consideration of shariah rules. Additionally, behavioral intention moderated by phone duration significantly influences the use of new technology (p-value = 0.052, β = 0.144), meaning that individuals with longer mobile device usage prefer to use mobile payment applications instead of conducting transactions at a bank branches. Furthermore, behavioral intention significantly influences the use of new technology (p-value = 0.024, β = 0.139), indicating that intention is followed by the use of new technology. Education also significantly influences the use of new technology (p-value = 0.050, β = 0.104), with higher education resulting in a greater willingness to use new technology. Effort expectancy influences attitude (p-value 0.002, β = 0.233), with greater ease of use leading to a more positive attitude towards new technology. Gender significantly influences the use of new technology (p-value 0.008, β = 0.134), as different attitudes towards new technology adoption are observed in different genders. Performance expectancy significantly influences attitude towards new technology (p-value 0.000, β = 0.444), and it also significantly influences behavioral intention (p-value 0.054, β = 0.172). Phone duration significantly influences the use of new technology (p-value 0.000, β = 0.480). These findings align with the SMEs Ministry's program to develop supporting facilities for financial inclusion. As phone duration is related to internet connectivity, developing the internet infrastructure in rural areas is necessary to support the ecosystem of financial technology. The findings of the study indicate that salary has a significant influence on the use of new technology for financial transactions, with higher salaries leading to greater adoption of mobile payment methods. This suggests that individuals with higher incomes are more inclined to utilize mobile payment services for their financial needs. Furthermore, social influence was found to significantly impact individuals' attitudes toward new technology. This implies that the recommendations and opinions of others in their social circles have a notable effect on shaping individuals' perceptions and attitudes towards adopting new technologies. However, the study reveals that trust does not have a significant influence on the use of new technology in Indonesia. The primary drivers for technology adoption in this context are ease of use and the need for financial support, rather than placing trust in the platform itself. Similarly, the study suggests that Islamic religiosity does not significantly impact the use of new technology, as individuals in Indonesia do not differentiate between Islamic and conventional financial technology platforms, perceiving them as similar. Additionally, the study highlights the development of Islamic fintech using bibliometric techniques. Islamic fintech is found to be associated with concepts such as blockchain, crowdfunding, behavioral intention, and financial inclusion. Integrating fintech into Islamic finance has the potential to offer advantages to small and medium-sized enterprises, as well as the unbanked population, by providing them with access to financial services and promoting financial inclusion. These findings contribute to the understanding of factors influencing the adoption of new technology and shed light on the current state of Islamic fintech development and its potential implications for various sectors in Indonesia.





Density of Network

7. ACKNOWLEDGEMENT

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