“The moderating impact of gender differences on the relationship between barriers and behavioral intentions to use mobile fintech services”

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THE MODERATING IMPACT OF GENDER DIFFERENCES ON THE RELATIONSHIP BETWEEN BARRIERS AND BEHAVIORAL INTENTIONS TO USE MOBILE FINTECH SERVICES

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Abstract

Drawing on an extended Innovation Resistance Theory, this study examines how various barriers – namely, usage, value, risk, tradition, image, information, and privacy – affect the behavioral intention to use mobile fintech services among bottom of the pyramid consumers. Moreover, it investigates the moderating role of gender difference on these relationships using Multi-Group Analysis. Primary data were collected through a self-administered online survey and gaining 200 responses from low-income users in urban city in Indonesia who already have smartphones but possess minimal experience or knowledge of mobile fintech services usage. Data analysis was conducted using Structural Equation Modeling-Partial Least Squares, with assistance from SmartPLS 4.0 software. The findings indicated that five barriers (usage, value, risk, tradition, and privacy) had a significant negative impact on the intention to use fintech services, while the other two (image and tradition) showed no significant effect. Additionally, it is revealed that gender did not affect the impact of usage and risk barriers, whereas differences were identified for the other barriers. These insights highlight the importance of addressing gender-specific needs in designing mobile fintech solutions for low-income consumers in emerging economies.

Keywords mobile fintech services, bottom of the pyramid, innovation resistance theory, gender difference, Multi-Group Analysis

JEL Classification M30, G40, M15, M39

INTRODUCTION

Mobile fintech services encompass financial technology solutions accessed through mobile devices like smartphones and tablets, including mobile payments, banking, wallets, and peer-to-peer platforms (Zou et al., 2023). For bottom of the pyramid consumers – those living below the USD 6.85 poverty line – these services are crucial not only for their well-being but also for broader market development (Prahalad, 2005; Arslan et al., 2022). Prahalad (2005) highlights that, despite their economic disadvantages and low literacy levels, this segment's collective purchasing power is estimated to surpass USD 5 trillion worldwide (Schoch et al., 2022). This underscores them as a significant high-growth market globally especially in developing countries. Indonesia, for instance, is recognized as one of the largest and most promising markets for financial services platforms (Ashoer et al., 2022). Statista predicts that the penetration rate of mobile fintech in Indonesia will exceed 69 percent soon, with ongoing growth in the digital payment user base. By 2027, e-commerce and mobile fintech

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services, such as mobile payments, banking, and money, are expected to grow by over 45 percent and 18 percent, respectively (Romero, 2024). This expansion opens numerous opportunities for vulnerable users to easily access and utilize financial services, thereby enhancing financial inclusion and economic empowerment (Arslan et al., 2022). As a result, these advancements not only empower individuals but also foster a more inclusive economy, allowing low-income consumers to participate actively in the financial landscape, improve their well-being, and contribute to the broader economic development of their communities.

Although fintech platforms offer numerous advantages, resistance among low-income consumers remains pervasive. Statista reports that half of Indonesia's in this population continues to avoid digital payment platforms, primarily due to a deep-rooted preference for cash transactions (Romero, 2024). A major obstacle is a lack of trust in mobile financial services or their providers, as evidenced in various contexts (Huang et al., 2021). Another significant issue is the gender divide, which serves as an added barrier to technology adoption (Ashoer et al., 2024). While these insights provide valuable context, a substantial gap remains in understanding how these barriers differ across various demographic groups within the segment.

1. LITERATURE REVIEW AND RESEARCH HYPOTHESES

The Innovation Resistance Theory (IRT) serves as a fundamental framework for comprehending consumer resistance to disruptive innovations (Ram & Sheth, 1989). Hew et al. (2019) describe innovation resistance as a reaction driven by logical reasoning and the evaluation of new innovations that could alter the current situation and challenge established beliefs. IRT provides an in-depth examination of consumer resistance by analyzing their reactions to new innovations through the lens of five key barriers: usage, value, image, tradition, and risk (Huang et al., 2021; Ram & Sheth, 1989). IRT is widely recognized as an effective framework for evaluating consumer resistance to innovations due to its comprehensive approach. It has frequently been applied in studies, either on single framework such as systematic literature review (Huang et al., 2021) and meta-analysis (Leong et al., 2021) or in combination with another framework like valence theory (Moorthy et al., 2017). The operational definitions of innovation barriers used in this study are shown in Table 1.

Usage barriers arise when users perceive a technology as too complex or difficult to use. For low-income consumers with limited digital literacy, such barriers diminish their willingness to adopt these services, as they often feel unsure about their ability to navigate and utilize the technology effectively. For example, when mobile fintech are introduced to financially vulnerable populations in Pakistan and China, these innovations may trigger cognitive dissonance about its benefits (Ali et al., 2022; Migliore et al., 2022). They may also doubt the tangible benefits of mobile fintech services when the perceived value does not outweigh the effort or cost involved, which discourages adoption in several context (Laukkanen & Kiviniemi, 2010; Yu & Chantatub, 2016; Huang et al., 2021; Nel & Boshoff, 2022; Baklouti & Boukamcha, 2024).

Concerns about unexpected risks can significantly deter poor people from trusting an innovation. This barrier is especially pronounced in contexts with limited consumer protection or awareness, which undermines their confidence in using mobile fintech platforms (Mani & Chouk, 2018). For instance, Leong et al. (2020) found that value risk negatively influences mobile wallet adoption within consumers in Malaysia. Similarly, Kumar et al. (2022) identified this factor as a key driver of resistance to home service apps in India.

Cultural norms and preferences for traditional financial practices, like cash transactions and face-to-face services, can hinder mobile fintech adoption. These familiar practices often feel more reliable. Additionally, negative perceptions of mobile fintech, such as associating it with exclusivity or distrust, further discourage adoption. Some prior research from different technology have report-

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ed that consumers' cultural preferences and perceived irrelevance of technology to their needs can significantly impact adoption (Kaur et al., 2020; Nel & Boshoff, 2021; Chen et al., 2022; Kumar & Chawla, 2023; Kautish et al., 2023), especially in lower-income contexts (Saxena et al., 2022; Van Klyton et al., 2021).

The next overlooked barrier is the information barrier (Huang et al., 2021), which refers to obstacles arising from a lack of relevant information, insufficient knowledge sharing, or difficulties in accessing necessary data. Previous studies have shown that information barriers can significantly hinder the adoption of mobile fintech services, such as mobile wallets or mobile banking (Laukkanen, 2016; Laukkanen & Kiviniemi, 2010; Leong et al., 2020; Talwar et al., 2023; Onay et al., 2023). For financially disadvantaged consumers, limited access to information sources, such as the internet or digital literacy programs, further exacerbates this barrier (Joshi, 2024). The last barrier is privacy, defined as concerns over data misuse, identity theft, or unauthorized access to personal financial information discourage users from adopting mobile fintech. This barrier is particularly critical for users as well, who may have heightened sensitivity to privacy risks (Hew et al., 2019; Reinhardt et al., 2019; Huang et al., 2021; Kwangsawad & Jattamart, 2022).

Another problematic condition in fintech adoption is gender differences, as it is generally reported that women often face limited access to technology, lower digital literacy, and societal norms that restrict their participation in financial and technological activities (Ashoer et al., 2024; Kim et al., 2018). For example, women may perceive fintech services as more complex (usage barrier) or be more concerned about risks (risk barrier) due to less exposure to technology and financial services (Ashoer et al., 2024).

Despite previous research has applied the IRT framework to examine resistance to various technological adoptions, key barriers such as information and data privacy have often been overlooked. Additionally, the critical role of gender differences remains understudied, particularly within low-income segments (Srivastava, 2022). These gaps highlight the need for further exploration. To address these theoretical gaps, this study extends the IRT framework by incorporating information and data privacy barriers and integrating the moderating role of gender into the model.

Consequently, this research aims to investigate the impact of various barriers – usage, value, risk, tradition, image, information, and privacy – on behavioral intention, and the moderating role of gender differences among those relationship. Based on these considerations, the following research model (Figure 1) and hypotheses are proposed:

H1: Usage barrier will negatively influence behavioral intention.

H2: Value barrier will negatively influence behavioral intention.

H3: Risk barrier will negatively influence behavioral intention.

Table 1. Operational definitions of innovation barriers

No	Constructs	Operational definition	Source
1	Usage barrier	A conflict between new technological innovations and existing consumer habits, lifestyles, or practices	Ram and Sheth (1989)
2	Value barrier	The lack of incentive for customers to switch to an innovation when it does not offer an advantage compared to existing product alternatives	Huang et al. (2021), Ram and Sheth (1989)
3	Risk barrier	Uncertainty and the potential for unexpected side effects inherent in innovations	Hew et al. (2019), Ram and Sheth (1989)
4	Tradition barrier	Obstacles posed by any innovation if that innovation brings changes in a user's existing culture and behavior	Hew et al. (2019), Ram and Sheth (1989)
5	Image barrier	The negative perceptions user develops towards innovations due to their perceived complexity or unfamiliarity	Huang et al. (2021), Ram and Sheth (1989)
6	Information barrier	Challenges that arise due to a lack of relevant information, insufficient knowledge sharing, or difficulties in accessing necessary data	Laukkanen and Kiviniemi (2010)
7	Privacy barrier	The concerns that consumers have regarding the protection of their personal or sensitive information when adopting new technologies or innovations	Hew et al. (2019)

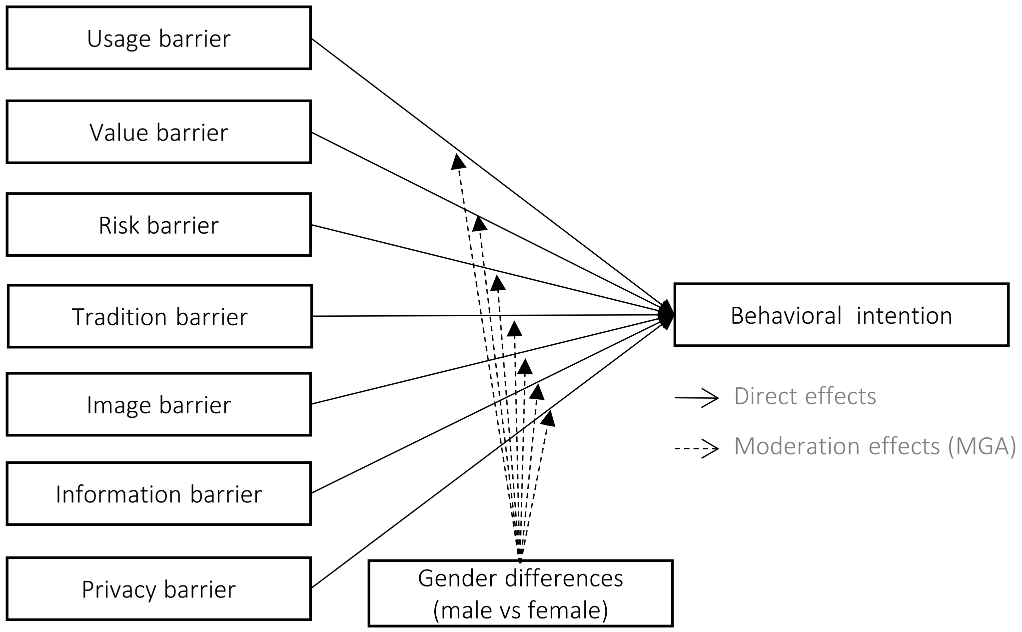

Figure 1. Research model

H4: Tradition barrier will negatively influence behavioral intention.

H5: Image barrier will negatively influence behavioral intention.

H6: Information barrier will positively influence behavioral intention.

H7: Privacy barrier will negatively influence behavioral intention.

H8a-g: The relationship between barriers (usage, risk, value, tradition, image, information, and privacy) and the intention to adopt mobile fintech services is moderated by gender.

2. METHODOLOGY

This study employed a quantitative method with an explanatory approach to systematically analyze the causality impact between constructs. The research focused on the experiences of potential low-income consumers with mobile fintech technologies in developing economies. Due to the uncountable and unspecified population in Indonesia, a non-probability sampling method was chosen, specifically purposive sampling (Cooper & Schindler, 2014). This technique was selected because it enables the identification of participants based on specific criteria, ensuring that the sample accurately represents the target group. The criteria included low-income users residing in urban areas of Indonesia who had little to no prior experience or familiarity with mobile fintech services, such as mobile payments, mobile money, or mobile banking.

Primary data were collected through a self-administered online survey (Fielding et al., 2017). This method was selected for its automation and accuracy; tools like Google Forms facilitate automatic data collection and recording, which reduces human error and enhances efficiency. This approach has been commonly used in previous research. To minimize response bias, several trained undergraduate students were assigned to personally administer the online questionnaire to potential respondents. The survey link was distributed via WhatsApp groups from April to June 2024. Initially, 254 responses were received. After a technical review and filtering to ensure relevance and accuracy, 200 participants were deemed to meet the study's criteria, resulting in a final sample size and a good response rate of approximately 78.7% (Fan & Yan, 2010). This high response rate indicates a significant level of participation in the on-

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line survey and underscores the representativeness of the data for analysis.

Most of the low-income participants in this study were men (63.3%), aged between 28 and 43 years (75.7%), belonging to Generation Y (millennials). Their educational backgrounds ranged from junior high to high school (45.7%). Their income typically fell between 1 million to 3 million rupiah (82.2%), classifying them within the lower-middle income bracket in Indonesia. Participants were also employed in service sectors such as app-based drivers (32.5%), cleaners (15.6%), kitchen hands (15.9%), housemaids (12.4%), and unemployment (23.6%). In terms of mobile payment services, most had a moderate level of knowledge and experience. This suggests that while they are familiar with and have used mobile payment services at least once, their understanding and proficiency are neither very basic nor highly advanced.

The measurement items section covered constructs such as usage barriers, value barriers, risk barriers, tradition barriers, image barriers, information barriers, data privacy barrier, and behavioral intentions. It comprised a total of 28 questionnaire items primarily adopted from various previous studies (Hew et al., 2019; Laukkanen, 2016; Leong et al., 2020). A five-point Likert scale, ranging from "strongly disagree" to "strongly agree," was utilized to assess all the measurement items. In terms of data analysis, this study opted for a variance-based Partial Least Squares Structural Equation Modeling (PLS-SEM) technique due to several reasons:

a) the aim of the research was theory development;

b) the sample size was relatively small; and

c) variance-based PLS-SEM imposes modest assumptions on data distribution (Hair et al., 2019).

The data analysis was conducted using SmartPLS software and was reported in two stages: the measurement model and the structural model (Hair et al., 2019).

3. RESULTS AND DISCUSSION

3.1. Measurement model assessment

This study follows the guidelines and steps for measurement model reports provided by expert (Hair et al., 2019). The process begins with assessing convergent validity by examining loading factors. The results show that all items have loading factors above the threshold of 0.7, confirming convergent validity (Table 1). Next, discriminant valid-

Table 2. Assessment of the outer model

Variables and their reflective measurements		Loadings	CA	CR	AVE
Usage barrier					
UB1	I think MFS difficult to use	0.894	0.883	0.892	0.667
UB2	I find using MFS is inconvenient	0.892			
UB3	In my view, using MFS is too time-consuming	0.909			
UB4	I find MFS transaction process is confusing	0.857			
Value barrier					
VB1	Using MFS can incur high costs	0.793	0.852	0.857	0.598
VB2	Using MFS do not seem to have any benefits	0.773			
VB3	I have limited control over the specifics of my transactions or payments when MFS	0.738			
Risk barrier					
RB1	I worry that I might spend more money if I use MFS	0.740	0.869	0.884	0.629
RB2	I worry that using MFS might lead to accidentally sending money to the wrong person	0.707			
RB3	I am worried that I might enter my billing information incorrectly when using MFS	0.739			
RB4	I am concerned that someone could hack into my account and misuse it	0.741			
Tradition barrier					
TB1	I prefer visiting physical stores rather using MFS platform	0.742	0.822	0.856	0.570
TB2	I prefer face-to-face customer service interactions rather than virtual ones (such as MFS)	0.735			
TB3	I find it hard to transition to MFS	0.738			

Table 2 (cont.). Assessment of the outer model

	Variables and their reflective measurements	Loadings	CA	CR	AVE
	Image barrier				
IB1	I think MFS providers have a poor image	0.764	0.871	0.879	0.613
IB2	I think new technology such as MFS is too difficult to use	0.791			
IB3	I think using MFS is not easy	0.787			
	Information barrier (R)				
IFB1	I think there is plenty of information in MFS platform	0.794	0.868	0.849	0.591
IFB2	I believe the providers of MFS have given me sufficient guidance and instructions	0.886			
IFB3	I believe the providers of mobile fintech services will offer adequate advice or guidance when I need it	0.791			
	Privacy barrier				
PB1	I am concerned that the data I provide to MFS might be misused	0.877	0.861	0.885	0.631
PB2	I am worried that someone could find personal information about me online	0.869			
PB3	I am anxious about what might happen to my personal information if I share it with an MFS	0.821			
	Behavioral intention				
BI1	I plan to use MFS regularly	0.769	0.833	0.849	0.605
BI2	I intend to use MFS for making payments	0.802			
BI3	I believe using mobile fintech services is better for me	0.814			

Note: R = reverse items; MFS: mobile fintech services.

Table 3*.* Discriminant validity assessment using Heterotrait-monotrait ratio (HTMT)

	UB	VB	RB	TB	IB	IFB	PB	BI
UB	–	–	–	–	–	–	–	–
VB	0.818	–	–	–	–	–	–	–
RB	0.523	0.706	–	–	–	–	–	–
TB	0.247	0.593	0.742	–	–	–	–	–
IB	0.431	0.665	0.641	0.822	–	–	–	–
IFB	0.416	0.446	0.529	0.733	0.684	–	–	–
PB	0.363	0.340	0.372	0.821	0.553	0.571	–	–
BI	0.621	0.773	0.526	0.695	0.524	0.602	0.793	–

ity was assessed using the Heterotrait-Monotrait Ratio (HTMT) criteria. Table 2 shows that the HTMT ratios are within the acceptable threshold of HTMT.90. This indicates that discriminant validity has been confirmed. Lastly, discriminant reliability is tested using three key criteria: AVE, Cronbach's alpha (CA), and composite reliability (CR). For a construct to be validated, the AVE should exceed 0.5, CA should be greater than 0.6, and CR should be above 0.7 (Hair et al., 2019). As shown in Table 1, all AVE, CA, and CR values for the latent constructs exceed these thresholds, confirming that the constructs meet the minimum standards for discriminant reliability.

3.2. Structural model assessment

Evaluating the variance inflation factor (VIF) is crucial for identifying potential issues with collinearity and common method bias (CMB) in the structural model. The VIF value should preferably be around 3.3 or lower; values exceeding 5 may indicate collinearity issues within the indicators of the constructs (Kock, 2017). Table 4 present that all VIF scores for the constructs are below 3.3, indicating that the study does not encounter concerns related to collinearity. Moreover, the study assessed the predictive capability of the internal latent variable by analyzing the R^2 coefficients. The R^2 value for behavioral intention (BI) is 0.593 (59.3%), demonstrating that the model exhibits strong predictive power (Hair et al., 2019).

The structural model assess the causal relationships among the constructs within the model. The significance values (t-statistics and p-values) and standard coefficient paths were derived using a non–parametric approach through subsample multiplication (bootstrapping) with 5000 iterations (Henseler et al., 2016). The results of the

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Table 4. The results of structural model analysis

Hypotheses and Relationships		β	Std. error	t-value	Confidence interval bias		Decision	VIF	f^2
					LB	UB			
H1	UB → BI	–0.335	0.068	–4.926**	0.156	0.322	Supported	1.229	0.379
H2	VB → BI	–0.311	0.063	–4.937**	0.273	0.463	Supported	1.407	0.202
H3	RB → BI	–0.340	0.076	–4.473**	0.191	0.574	Supported	1.143	0.350
H4	TD → BI	–0.276	0.089	–3.102*	0.086	0.358	Supported	1.381	0.169
H5	IB → BI	–0.179	0.112	1.598	0.034	0.467	Not supported	2.165	0.021
H6	IFB → BI	0.144	0.082	1.756	0.022	0.345	Not supported	1.944	0.057
H7	PB → BI	–0.216	0.094	2.287*	0.117	0.366	Supported	1.372	0.084

Note: two-tailed significance, * = p < 0.05; ** = p < 0.001. UB: usage barrier; VB: value barrier; RB: risk barrier; TD: tradition barrier; IB: image barrier; IFB: information barrier; PC: privacy barrier.

structural model are displayed in Table 2. It is evident that usage (β = –0.335, p < 0.001), value (β = –0.311, p < 0.001), risk (β = –0.340, p < 0.001), traditional (β = 0.276, p < 0.05), and privacy (β = –0.205, p < 0.05) have a positive and significant impact on behavioral intention to use mobile fintech. Conversely, it is found that image (β = –0.179, p > 0.05) and information (β = 0.144, p > 0.05) barriers were not significant in influencing behavioral intention. Hence, five hypotheses (*H1, H2, H3, H4, H7*) were accepted, and two (*H4, H5*) were rejected.

Notwithstanding the significance of the relationships, it is also suitable to report the effect size (f^2) of the paths to rank predictors by their explanatory importance (Hair et al., 2019). The recommended cut-off values for f^2 are 0.02 for small, 0.15 for medium, and 0.35 for large effect sizes (Cohen, 1988). The results reveal that usage (f0.38 = ²) and risk (f0.35 = ²) have large effects on the behavioral intention to use mobile fintech. Value (f0.20 = ²) and tradition (f0.16 = ²) exhibit medium effects, while privacy (f0.08 = ²), information (f= ² 0.05), and image (f0.02 = ²) have small effects. In summary, while all these factors contribute to the behavioral intention to use mobile fintech services, focusing on usage and risk will likely yield the most significant improvements in adoption rates in low-income segment.

3.3. Multi-Group Analysis

Figure 3 displays the results of the Multi-Group Analysis (MGA) conducted using PLS-SEM (Cheah et al., 2020). The sample was divided into two groups based on gender (male and female) to compare the relationships between innovation barriers and the behavioral intention to use mobile fintech. The MGA results revealed that gender significantly influences the relationship between certain innovation barriers – specifically usage and risk – and the behavioral intention to use mobile fintech among subsistence consumers in Indonesia. However, no significant gender differences were observed for the value, tradition, image, information, or data privacy barriers. These findings suggest that gender-specific strategies may be necessary to address concerns related to usage and risk, while a more generalized approach may be effective for other barriers.

Table 5. Multi-Group Analysis test results

Relationship	β		Idiffl	p-value	Decision
	Male	Female			
UB → BI	0.288	0.194	0.275	0.007	Supported
VB → BI	0.019	0.083	0.146	0.068	Not supported
RB → BI	0.307	0.325	0.394	0.001	Supported
TD → BI	0.026	0.101	0.058	0.409	Not supported
IB → BI	0.116	0.123	0.107	0.083	Not supported
IFB → BI	0.004	0.012	0.158	0.525	Not supported
PB → BI	0.253	0.267	0.239	0.012	Supported

Note: two-tailed significance at p < 0.05; UB: usage barrier; VB: value barrier; RB: risk barrier; TD: tradition barrier; IB: image barrier; IFB: information barrier; PC: privacy barrier.

4. DISCUSSION

The findings indicate that usage, value, risk, tradition, and privacy barriers have a significant negative impact on the behavioral intention to use mobile fintech services among bottom of the pyramid consumers in Indonesia. In other words, the more barriers' users perceive, the less inclined they are to use this technology, and vice versa. These findings corroborate prior studies (Hew et al., 2019; Joachim et al., 2018; Kaur et al., 2020). This is reasonable because low-income users often lack the knowledge and understanding of how certain features or functionalities can be beneficial for their financial activities. Additionally, they may face many technical difficulties when processing payments correctly and promptly, leading to reluctance in transitioning. For value barriers, it seems that poor consumers are concerned about additional costs associated with using this technology, such as transaction or admin fees. From the perspective of financially disadvantaged consumers, these costs may be too burdensome to handle. Moreover, it was proven that they perceive traditional concerns as critical. Cultural preferences for paying in cash may still be favored because they have not yet fully understood the benefits of fintech in for the financial well-being, or because this habit is deeply rooted in the participants' community in Indonesia, hindering innovation. The next barrier relates to privacy protection on fintech platforms. It seems that low-economic status users resist mobile fintech because they fear that their sensitive and personal financial information could be compromised when registering their accounts on these platforms. In some cases, when signing up for fintech services like GoPay or OVO, they must input all their private data (name, address, national ID number, phone number, etc.) via apps. Given their limited familiarity with digital technology protection, they may hesitate to adopt fintech as they doubt that their data can be adequately protected by the company.

The results conversely shown that image and information barriers do not significantly influence the intention of low-income consumers in Indonesia to adopt mobile fintech services. This contradicts previous studies (Laukkanen, 2016; Laukkanen & Kiviniemi, 2010; Leong et al., 2020). It seems that this segment may have difficulty understanding the information provided in fintech apps, such as features, benefits, and usage, even when it is clearly presented. For example, they might find payment instructions too complex or challenging to process. Regarding image, the respondents are more likely to prioritize practical considerations like cost and convenience over concerns related to image when deciding whether to adopt mobile fintech services.

CONCLUSION

This study aims to explore how various barriers from the IRT framework – namely, usage, value, risk, tradition, image, information, and data privacy – affect the behavioral intentions to use mobile fintech services. It further extended the framework by assessing the moderating effect of gender difference through MGA. The findings revealed that usage, value, risk, tradition, and data privacy barriers significantly influenced the intention to use fintech services, whereas image and information barriers had no significant impact. Additionally, the results indicated no gender differences in the influence of usage and risk barriers, while differences for other barriers were observed. These findings provide theoretical and practical implications.

The results theoretically contribute to the body of knowledge by enhancing the applicability of the IRT model to subsistence market consumers, providing a deeper insight into the resistance factors affecting the adoption of mobile financial technologies. Additionally, the use of MGA based on gender offers a nuanced understanding of how resistance factors may vary between male and female consumers, thereby contributing to the refinement of gender-specific strategies in the literature. Practically, this study suggests an insight to relevant stakeholders for better encourage the use of mobile fintech in subsistence segment. For instance, fintech providers should address key barriers – such as usage, value, risk, tradition, and data privacy – through simplified app designs, educational campaigns, and assuring data secu-

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rity. Additionally, a tailored gender-specific strategies are essential, given the varying resistance factors between male and female users. Collaborations with local communities and NGOs can help build trust and cultural acceptance, while policymakers can support adoption through financial literacy programs, incentives, and stronger data privacy regulations. These efforts will enhance financial inclusion and empower them to engage in fintech services.

This study highlights several limitations that may inspire future research avenues. First, it relies solely on IRT model to predict bottom of the pyramid consumers' intentions towards mobile fintech services. Future research could integrate other theories, such as self-determination theory, or social exchange theory, to enrich the literature on resistance to innovation. Additionally, this study focuses specifically on the low-income consumer segment in Indonesia, which may limit its generalizability. Future research should consider including other populations from different developing regions or countries to broaden or compare the findings. Lastly, although this study employed gender-based multi-group analysis, there is potential to explore other groups – such as cultural, geographic, and generational cohorts – to gain a deeper understanding of mobile fintech resistance within the unique demographic.

AUTHOR CONTRIBUTIONS

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