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Segmenting Women's Motivational Profiles in mHealth Adoption for Reproductive Health: A Cluster Analysis

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Abstract

While mHealth has the potential to improve access to reproductive health services, its adoption remains uneven in Indonesia. This study aimed to segment women of reproductive age based on motivational and contextual profiles related to mHealth use, rather than to identify causal determinants. A cross-sectional survey was conducted in 2025 among 350 Indonesian women aged 18–45 years. Guided by the Health Belief Model (HBM) and UTAUT2, k-means cluster analysis was used to identify user segments. Differences in motivational constructs were examined using t-tests, while contextual characteristics were assessed using chi-square tests. Two clusters emerged: highly motivated users ($n = 222$) and less motivated users ($n = 128$). The highly motivated group reported significantly higher self-efficacy ($M = 4.71$ vs. 3.66), perceived benefits (4.82 vs. 3.86), effort expectancy (4.78 vs. 3.86), and trust in technology ($\Delta = 0.96$; all $p < .001$). Moderate differences were observed for perceived susceptibility, while perceived barriers were not significant. Significant group differences were also found for income, perceived health literacy, prior use of reproductive health services, and intention to adopt mHealth ($p < .05$). These findings highlight distinct readiness-based user segments, supporting segmentation-driven digital health interventions.

Introduction

Inequity in the utilization and quality of reproductive health services remains a persistent concern in Indonesia and elsewhere in low and middle-income countries (Ross, 2015; Wulandari *et al.*, 2021). The expanding use of mobile and multimedia technologies, or mHealth, has been promoted as one approach to address these gaps while enhancing user experience and improving specific health outcomes (Aung, Mitchell & Braun, 2020; Maita *et al.*, 2024; Borges do Nascimento *et al.*, 2025). For the purpose of this study, mHealth is defined as targeted interventions, such as reminders for prenatal and antenatal care visits, and mass-marketed health services that include pregnancy and menstrual cycle trackers and telemedicine features embedded within health applications.

In Indonesia and other LMICs, mHealth initiatives have increasingly become integral to national digital health and reproductive health programs(Kristina & Mahyuni, 2024; Larasati, Antonio & Wuisan, 2024; Muniroh, Sulistyorini & Abihail, 2024). Regarding reproductive health, various services are offered through mHealth applications that help address barriers to access. These include virtual consultations that reduce geographic constraints, digital information about contraception, menstrual or fertility tracking, symptom checkers for reproductive health concerns, and reminders for medications or appointments supporting continuity of care and counseling (Onukwugha *et al.*, 2022; Kazakoff *et al.*, 2025). Together, these features position mHealth as a potentially

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transformative tool for improving reproductive health services (Kristina & Mahyuni, 2024). Despite the advantages, the application of mHealth in reproductive health remains very limited, especially among the underserved populations(Feroz *et al.*, 2021; Laar *et al.*, 2024). Though some studies have documented certain improvements in knowledge, attitudes, and health outcomes associated with the use of mHealth, according to (Aung *et al.*, 2020; Choudhury & Choudhury, 2022), such benefits are more often seen in people with a higher education level, better income, and access to digital literacy, as stated by (Udenigwe *et al.*, 2022; Jonayed & Rumi, 2024).

The adoption gap is usually attributed to sociodemographic factors such as income, geographic residence, age, and health or digital literacy (Feroz *et al.*, 2021; Laar *et al.*, 2024). However, the digital divide regarding psychosocial factors remains underexplored (Jonayed & Rumi, 2024), although evidence shows that psychosocial contexts shape belief systems, trust, confidence, and other determinants of behavioral outcomes (Kristina & Mahyuni, 2024). These motivational factors are closely related to structural barriers, given that behavioral and contextual influences work in a self-reinforcing way (Feroz *et al.*, 2021; Western *et al.*, 2025). For example, digital literacy is often associated with education and income, while perceived benefits may influence access to digital networks (Biga *et al.*, 2024). Understanding the interplay between psychosocial and demographic characteristics provides more detail on user segments and exposes potential disparities in readiness to adopt mHealth. Although still limited, a growing number of digital health studies have started to adopt clustering techniques such as k-means and latent class analysis to identify user typologies based on latent constructs, including motivational attributes (Swenson *et al.*, 2018; Grant *et al.*, 2020; Piette *et al.*, 2024; Wen & Tung, 2024). These methods classify users into groups sharing similar motivational profiles and behavioral patterns. For instance, (Ramírez-Correa *et al.*, 2020) segmented users in accordance with technological readiness, while (Wen & Tung, 2024) determined clusters in terms of users' valuation of various mHealth services.

Much of the existing literature on behavioral segmentation is set in high-income or upper-middle-income countries in Europe and Latin America. Current research on mHealth is inclined to focus on either causal analyses or predictive models showing the determinants of adoption (Aung *et al.*, 2020; Mensah *et al.*, 2022). Beyond this, though informative, limited insights will be provided on different variations in motivation or readiness across different groups of users. Segmentation, alternatively, offers a different perspective by identifying patterns of motivation and access, aligned with guiding the development of more inclusive interventions, communication strategies, and digital health programs (Engl *et al.,* 2019).

This study identifies the disparity in the patterns of mHealth adoption among women by segmenting potential adopters based on motivational constructs from the Health Belief Model (Carpenter, 2010; Lufthiani *et al.*, 2022; Hakim & Sari, 2025) and UTAUT2 (Venkatesh & Bala, 2008; Nurhayati *et al.*, 2019; Chopdar, 2022; Min *et al.*, 2024; Su *et al.*, 2025) and examines associated sociodemographic profiles to understand the structural differences among groupsThese segments also clearly show psychosocial and sociodemographic differences in terms of diverse readiness and access to digital health services. Consequently, the findings will contribute to developing inclusive mHealth design and communication strategies that ensure equal access and improve user engagement in digital reproductive health. This study employed two behaviorally oriented models to inform the segmentation process: the Health Belief Model (HBM) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Such a combination has already been used in other works (Rahman *et al.*, 2022; van der Waal *et al.*, 2022; Paganin *et al.*, 2023; Min *et al.*, 2024) to indicate how the health-related beliefs and technology-related perceptions together define the motivational basis for the adoption.

HBM is composed of six constructs that describe individual decision-making for health behaviors (Carpenter, 2010; Lufthiani *et al.*, 2022). Core constructs include perceived benefits, self-efficacy, perceived barriers, and perceived health risk, which consistently have emerged as the strongest predictors of action (Carpenter, 2010; Jones *et al.*, 2015; Lufthiani *et al.*, 2022). UTAUT2 targets technology-related behavioral determinants, and its main predictors include performance expectancy and effort expectancy, figuring perceived usefulness and ease of use, respectively, while facilitating conditions are indicative of the availability of enabling resources (Venkatesh & Bala, 2008; Nurhayati *et al.,* 2019). Social influence characterizes the degree to which decisions are affected by family members, peers, or health professionals (Venkatesh & Bala, 2008). Price value is indicative of the assessment that gets made of costs relative to perceived benefits. Notwithstanding the fact that the prominence varies from one context to another, it is mostly perceived ease of use and performance expectancy that take the lead in most studies (Venkatesh & Bala, 2008).

These two were combined for perceived benefits of the HBM and performance expectancy of the UTAUT2 to minimize conceptual overlap, as done in (Batucan *et al.*, 2022; Chopdar, 2022). An additional construct of trust in technology was added to the model to address concerns regarding data security and privacy that have emerged as important determinants of technology adoption in recent studies, such as those by (Liu *et al.*, 2023; Salma *et al.*, 2024). The final motivational variables retained were from UTAUT2: effort expectancy, performance expectancy, facilitating conditions, trust in technology, price value, and social influence, as well as three factors from the HBM: perceived susceptibility, perceived barriers, and self-efficacy.

Methodology

This study employed a cross-sectional quantitative survey to identify user typologies of mHealth adoption. Data were collected in September 2025 from 350 Indonesian women aged 18–45 years using an online survey administered through a local survey platform. Participants were recruited using quota sampling based on age, gender, and residence. The segmentation analysis was conducted in two stages. First, motivational constructs derived from the Health Belief Model (HBM) and UTAUT2 were used as inputs for k-means cluster analysis to identify user segments. Clustering was performed using standardized mean scores, with the optimal number of clusters selected to ensure clear separation without overlap. Second, differences between clusters were examined using independent t-tests, while sociodemographic and contextual variables differences were assessed using chi-square tests (Yuan *et al.,* 2022).

This questionnaire contained 56 items in total, representing four domains of the HBM, namely, perceived risk, severity, barriers, and self-efficacy, and five domains of UTAUT2, namely, effort expectancy, performance expectancy, social influence, trust in technology, price value, and facilitating conditions. In the

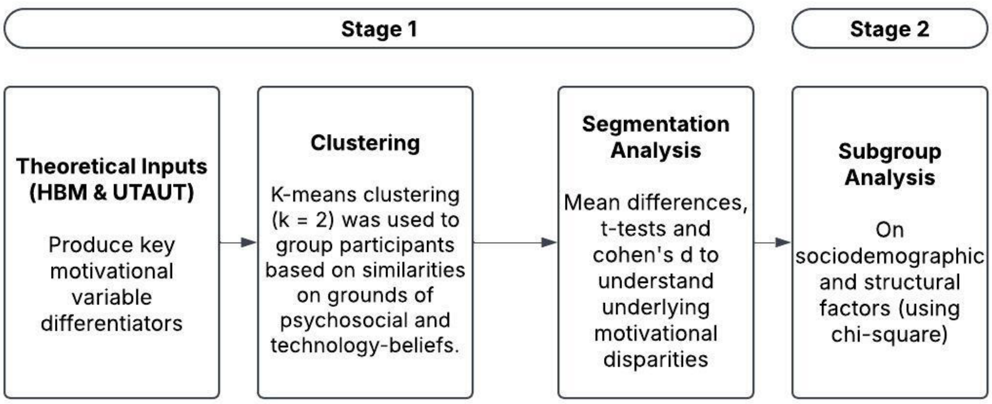


Figure 1. The Stages of Segmentation Analysis
Source: Processed by the author, 2025

HBM, perceived risk was assessed using four items; for example, “I am at risk of a reproductive health issue.” For perceived severity, three items were used; for example, “a reproductive health issue will affect my quality of life.” Four items measured perceived barriers; for example, “speaking about my reproductive health issue is difficult for me,” while four items assessed self-efficacy; for example, “I am confident in my ability to use mHealth for reproductive health.”

UTAUT2 constructs included effort expectancy (e.g., “Using mHealth would be easy for me”), performance expectancy (e.g., “Using mHealth would improve my access to reproductive health services”), facilitating conditions (e.g., “I have the necessary resources to use mHealth”), trust in technology (e.g., “I believe my personal data is secure when using mHealth”), social influence (e.g., “family members encourage me to use mHealth”), and price value (e.g., “The cost of using mHealth is reasonable for me”). All items were measured using a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Intention to use mHealth was included to assess readiness for future adoption. Important sociodemographic data were also gathered, including marital status, income, education, health insurance status, perceived health literacy, previously accessed services for reproductive health, and digital access. Intention to use mHealth was assessed to measure readiness to use future mHealth services.

All constructs showed adequate internal consistency measured by Cronbach’s Alpha (α) with a score above 0.7 (Taber, 2018), ranging from 0.78 to 0.90. In particular, reliability scores were acceptable for perceived susceptibility, $\alpha = 0.80$; perceived barriers, $\alpha = 0.78$; self-efficacy, $\alpha = 0.80$; performance expectancy, $\alpha = 0.87$; effort expectancy, $\alpha = 0.83$; facilitating conditions, $\alpha = 0.83$; trust in technology, $\alpha = 0.74$; social influence, $\alpha = 0.73$; and price value, $\alpha = 0.90$. Construct validity was assessed through confirmatory factor analysis. All the factor loadings scores were above the cut-off value (>0.7) (Taber, 2018), ranging from 0.613 to 0.988. Although one item loaded slightly above 0.60, it was still relatively close to the minimum recommended value and was retained, since it meaningfully reflected its construct. Analysis was conducted using R Studio (v1.2.2). The study was approved by the Research Ethics Committee of the Faculty of Medicine, Universitas Udayana, Indonesia (No: 2358/UN14.2.2.VII.14/LT/2025). All respondents were asked to provide informed consent before their participation and no personally identifiable information has been collected.

Result and Discussion

Across 350 women in the study, most 222 (63.4%) were aged 25–34, followed by 71 (20.3%) aged 18–24 and 57 (16.3%) aged 35–45 (M = 29, SD = 5.48). Most lived in urban areas (71.1%), with 20.6% in rural and 8.3% in semi-urban areas. The majority (89.4%) resided in Java, with the remaining 10.5% from Kalimantan, Sulawesi, Sumatra, and Bali. Average monthly household income was Rp 6,658,085 (SD = Rp 6,192,652), and income groups were divided into three hierarchial categories (lower, middle, and higher-income). Most respondents attained undergraduate degrees (58%), followed by high school or equivalent (38.6%). In terms of marital status, 71.7% were married with children, 22.9% were single, 4.9% married without children, and 0.6% divorced. Nearly all respondents (96.6%) had insurance coverage. All participants owned a smartphone (100%), and 87.4% used the internet daily. The majority (87.4%) had used reproductive health services in the past two years. Perceived health literacy was generally high, with 56.3% reporting high literacy and 31.4% consider themselves moderately health literate.

The optimum number of clusters (k) was determined using the Elbow method and average silhouette coefficient, where k = 2 or a two-cluster group was identified as the optimum solution. Greater or lower than k=2, the model loses its explanatory power, as seen in Figure 2a. The average silhouette coefficient reflects how well each individual data point fits within its assigned cluster. In this study, the value was 0.36, which falls below the ideal >0.50 threshold. Scores above 0.50 are considered strong, while values in the 0.25–0.40 range remain acceptable (Dalmaijer *et al.*, 2022). However, values below the typical range is common in behavioral research, as variables are

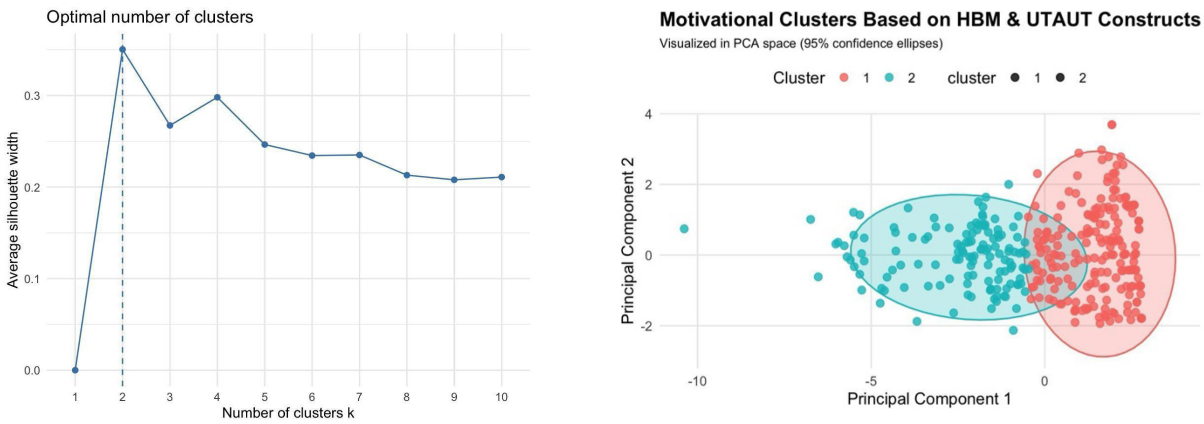


Figure 2. Result of Optimum Cluster Centroid and Cluster Separation Illustration using Scatterplot
Source: primary data, processed by the author, 2025

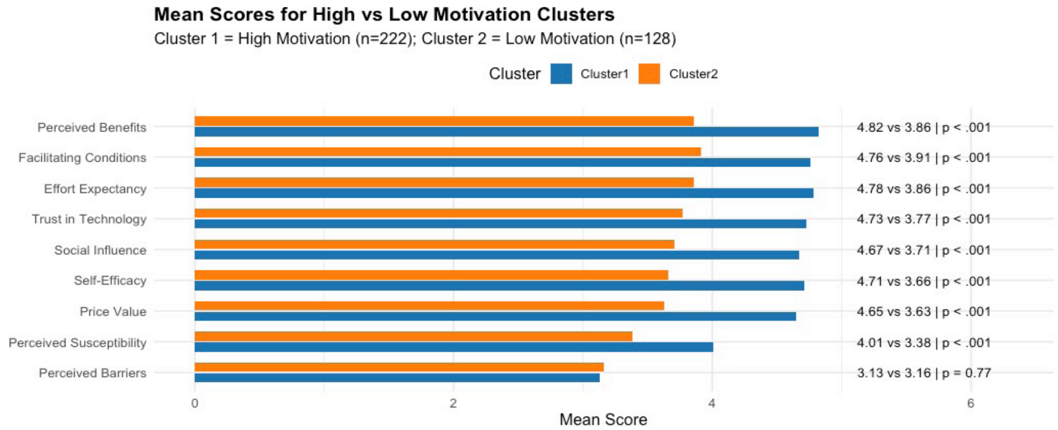
latent and single datapoints are more diverse, resulting in less distinct clusters (Dalmaijer *et al.*, 2022). The model explained 32.3% of the total variance, indicating a moderate level of cluster separation. Values between 0.30 and 0.50 are considered moderate, and those above 0.50 are high (Hair *et al.*, 2019). As shown in Figure 2b, the cluster scatterplot displays minimal overlap between groups, supporting this interpretation.

Two clusters were identified: the high-motivation cluster (Cluster 1, n = 222) and

Table 1. Mean Scores of All Variable Differentiators and p-values

Variables	Mean Score Cluster 1: High Motivation (n=222)	Mean Score Cluster 2: Low Motivation (n=128)	Mean difference (95% CI)	t-value (df)	p-value	Cohen's d (95% CI)
Perceived Benefits	4.82 (z=0.58)	3.86 (z=-0.98)	0.96 [0.84,1.06]	17.152 (160.55)	0.000**	2.26 [1.98, 2.53]
Facilitating Conditions	4.76 (z=0.55)	3.91 (z=-0.92)	0.85 [0.74, 0.94]	16.892 (195.55)	0.000**	2.07 [1.8, 2.33]
Effort Expectancy	4.78 (z=0.58)	3.86 (z=-0.98)	0.92 [0.79, 0.99]	17.711 (178.5)	0.000**	2.24 [1.96, 2.51]
Trust in Technology	4.73 (z=0.59)	3.77 (z=-0.94)	0.96 [0.85, 1.05]	18.587 (194.45)	0.000**	2.28 [2.00, 2.55]
Social Influence	4.67 (z=0.56)	3.71 (z=-0.89)	0.96 [0.85, 1.06]	17.442 (210.26)	0.000**	2.08 [1.81, 2.35]
Self-Efficacy	4.71 (z=.55)	3.66 (z=-0.92)	1.05 [0.933, 1.15]	18.352 (207.81)	0.000**	2.2 [1.93, 2.47]
Price Value	4.65 (z=0.57)	3.63 (z=-0.91)	1.02 [0.911, 1.13]	18.14 (223.96)	0.000**	2.12 [1.81, 2.35]
Perceived Susceptibility	4.01 (z=0.25)	3.38 (z=-0.43)	0.63 [0.45, 0.8]	6.99 (298.56)	0.000**	0.74 [0.52, 0.96]
Perceived Barriers	3.13 (z=0.006)	3.16 (z=-0.01)	-0.03 [-0.24, 0.18]	-0.28 (347.99)	0.77	-0.02 [-0.24, 0.19]

Note: = β Beta Coefficient; df= Degree of Freedom; CI= Confidence Interval
Source: Primary data, processed by the author, 2025



Note: p= p-value

Figure 3. Illustrative Comparison of Mean Scores Of All Variable Differentiators and p-values

Source: Primary data & processed by the author, 2025

the low-motivation cluster (Cluster 2, n = 128). Independent samples t-tests showed that almost all motivation and technology-related constructs were significantly different across the clusters. Across all domains, perceived barriers showed the fewest differences across clusters, M = 3.13 versus 3.16, Δ= –0.03, p= .77, suggesting that obstacles were not a distinguishing factor. The contribution of perceived susceptibility was also modest, with a smaller but significant difference between clusters, M = 4.01 versus 3.38, Δ = 0.63, 95% CI 0.45–0.80, p < .001, d = 0.74. Larger mean differences were observed in facilitating conditions, M = 4.76 versus 3.91, Δ = 0.85, 95% CI 0.74–0.94, p <.001, d = 2.07, and effort expectancy, M = 4.78 versus 3.86, Δ = 0.92, 95% CI 0.79–0.99, p <.001, d = 2.24, supporting their role as significant contributors to cluster separation.

Perceived benefits emerged among the strongest differentiators (M = 4.82 vs. 3.86, Δ = 0.96, 95% CI 0.84–1.06, p < .001, d = 2.26), alongside trust in technology (M = 4.73 vs. 3.77, Δ = 0.96, p < .001, d = 2.28) and social influence (M = 4.67 vs. 3.71, Δ = 0.96, p < .001, d = 2.08), each displaying large, comparable differences. An even larger difference was observed in price value (M = 4.65 vs. 3.63, Δ = 1.02, p < .001, d = 2.12). The greatest separation between clusters emerged for self-efficacy, where Cluster 1 scored notably higher (M = 4.71 vs. 3.66, Δ = 1.05, 95% CI 0.93–1.15, p < .001, d = 2.20). Cluster 1 reported consistently strong positive beliefs, with the highest scores in perceived benefits (M = 4.82), followed by effort expectancy (M = 4.78), facilitating conditions (M = 4.76), and trust in technology (M = 4.73). This reflects a segment that values mHealth, feels confident using it, and perceives adequate support for digital technology usage. In Cluster 2, the relatively highest domains were facilitating conditions (M = 3.91), perceived benefits (M = 3.86), effort expectancy (M = 3.86), and trust in technology (M = 3.77), indicating some awareness of usefulness and support, but not far lower than cluster 1. Overall, these patterns indicate that motivational and technology-related beliefs distinguish the two user segments. It illustrates that the high-motivation cluster is more benefit-oriented and has higher trust in digital tools for reproductive health.

Across the two clusters, significant group differences were observed for income, marital status, perceived health literacy, prior use of reproductive health services, and intention to use mHealth, with Cluster 1 consistently reporting higher levels across these variables. No significant differences for the remaining variables were established. The two clusters were similar in terms of residence, which was divided into urban (71.17% vs. 71.09%), rural (20.72% vs. 20.31%), and semi-urban (8.11% vs. 8.59%). Age groups did not differ significantly between clusters, with the following distributions: 18–26 years (20.72% vs. 19.53%), 27–35 (63.06% vs. 64.06%), and 36–45 (16.21% vs. 16.40%). Insurance ownership was also quite similar between the clusters (96.39% vs. 97.65%), and education level, which is concentrated between undergraduate completion (57.65% vs. 58.59%)

Table 2 Sociodemographic Subgroup Analysis Using Chi-Square Test

		Cluster 1 (highly motivated)	**Cluster 2 (low-motivation)**	χ^2 **(df)**	**p-value**
Province	Java (West, East, Central Java, DI Yogyakarta, Greater Jakarta Area)	199 (89.64%)	114 (89.06%)	0.351(1)	0.55
	Non-Java (Kalimantan, Sumatera, Sulawesi, Bali)	23 (10.36%)	14 (10.93%)		
Urban & Rural	Rural	46 (20.72%)	26 (20.31%)	0.00 (2)	0.998
	Semi-Urban	18 (8.11%)	11 (8.59%)		
	Urban	158 (71.17%)	91 (71.09%)		
Age Group	18-26	46 (20.72%)	25 (19.53%)	0.501 (2)	0.77
	27-35	140 (63.06%)	82 (64.06%)		
	36-45	36 (16.21%)	21 (16.4%)		
Income Group	Lower	19 (8.55%)	18 (14.06%)	7.613* (2)	0.022
	Middle	73 (32.88%)	54 (42.18%)		
	Upper	130 (58.55%)	56 (43.75%)		
Marital Status	Married with Children	174 (78.37%)	77 (60.15%)	17.723** (3)	0.000
	Married with no Children	11 (4.95%)	6 (4.68%)		
	Single	37 (16.67%)	43 (33.59%)		
	Divorced	0 (0%)	2 (1.56%)		
Insurance Ownership	No	8 (3.6%)	3 (2.34%)	0.116 (1)	0.739
	Yes	214 (96.39%)	125 (97.65%)		
Own a smartphone	Yes	222 (100%)	128 (100%)	23.547** (1)	0.000
	No	0 (0%)	0 (0%)		
Education	High School & Equivalent	85 (38.29%)	50 (39.06%)	0.97 (3)	0.806
	Postgraduate	8 (3.60%)	1 (0.78%)		
	Middle School / Elementary	1 (0.45%)	2 (1.56%)		
	Undergraduate	128 (57.65%)	75 (58.59%)		

Perceived health literacy	Low (6-8)	0 (0%)	4 (3.12%)	57.102** (2)	0.000
	Mid (9-11)	7 (3.15%)	38 (29.68%)		
	High (12-15)	212 (96.84%)	86 (67.18%)		
Have used reproductive health service in the past 2 years	No	16 (7.21%)	27 (21.09%)	16.068** (1)	0.000
	Yes	206 (92.79%)	101 (78.91%)		
Internet usage behavior	All day	192 (86.48%)	114 (89.06%)	0.55 (2)	0.71
	Hardly/when needed	2 (0.91%)	1 (0.78%)		
	Several times a week	28 (12.61%)	13 (10.15%)		
Have used any digital application over the past 3 months	Yes	222 (100%)	128 (100%)	25.246** (1)	0.000
	No	0 (0%)	0 (0%)		

Note: χ^2 = chi-square; df=Degrees of Freedom
Source: Primary data & processed by the author, 2025

and high school (38.29% vs. 39.06%). Internet use habit was highly similar, where frequent users comprised 86.48% and 89.06% across clusters. Finally, both clusters showed 100% smartphone ownership and recent digital app use (a ceiling effect), and therefore, the statistically significant results suggest no meaningful distinction.

Income groups, on the other hand, were significantly different (χ^2 = 7.613 p < .05), although the effects were borderline. The highly motivated group had a lower number of low-income individuals (8.55%) than in the low-motivation group (14.06%). Marital status was also significantly different across clusters (χ^2 = 17.723, p < .001), where 78.37% of the highly motivated members are married with children, whereas 33.59% of the low motivation group are unmarried. Perceived health literacy was also much higher among individuals in cluster 1 (χ^2 = 57.102, p < .001), where 96.84% report greater health literacy compared to 67.18% in the low motivation group. Previous utilization of reproductive health services was also more common in cluster 1 members (92.79%) compared to cluster 2 (78.91%), with statistically significant differences (χ^2 = 16.068, p < .001). To further understand if the differences in motivation and contextual variables correspond with intention to adopt as a key behavioral mechanism, a chi-square post-hoc analysis is conducted. mHealth use intentions were significantly greater among the highly motivated group (χ^2 = 143.9, p < .001), 77.02% had the highest intention to adopt mHealth in reproductive health services, compared to just 11.71% in cluster 2. This pattern suggests that stronger motivation goes hand in hand with higher readiness to use mHealth services.

The results altogether reveal two distinct profiles based on motivational factors guided by HBM and UTAUT2. Based on the average silhouette coefficient and the model's variance, the formed clusters demonstrated moderate but valid separation, indicating that interpretations are meaningful and reliable. The high-motivated group showed higher perceived benefits, trust in technology, price value, social influence, effort expectancy, self-efficacy, and facilitating conditions, while the low-motivation group scored lower across these domains consistently. Sociodemographic disparities (education, income, digital literacy) often align with patterns of cluster membership. These differences

Table 3. Intention To Adopt Across Clusters (A Post-Hoc Analysis)

Variables	Category	Cluster 1 (high motivation group)	Cluster 2 (low-motivation group)	t-value (df)	p-value
Intention to Use	Very Unlikely	0 (0%)	6 (4.68%)	143.9 (3)**	0.000
	Unlikely	4 (1.80%)	31 (24.21%)		
	Likely	47 (21.17%)	76 (59.37%)		
	Very Likely	171 (77.02%)	15 (11.71%)		

Note: df=Degrees of Freedom
Source: Primary data & processed by the author, 2025

also corresponded to the significantly higher intention to adopt mHealth among members in the high-motivation group. Findings suggest that women who are highly motivated, have positive beliefs towards mHealth, are confident, and are sociodemographically advantaged are more likely to adopt mHealth.

Perceived susceptibility across clusters showed little variation, consistent with evidence indicating its limited role in mHealth adoption (Ahadzadeh *et al.*, 2023). Perceived barriers were the least contributing to the segmentation. These barriers reflect challenges related to social stigma, access, and digital skills within the context of reproductive health, in which service utilization is usually influenced by gender norms (Feroz *et al.*, 2021). The low barrier scores observed across clusters are supported by studies indicating that perceived benefits are prioritized by adopters more than perceived obstacles. This is also depicted by (Khatun *et al.*, 2015; Addotey-Delove *et al.*, 2020; Hoque *et al.*, 2020; Octavius & Antonio, 2021). In addition, the differential impact of perceived barriers explains why the perceived benefits, enhanced support in health management, and improved decision-making emerged as strong differentiators. This pattern reinforces evidence that while perceived benefits are one of the consistent predictors of mHealth adoption, perceived barriers have often proven less important (Addotey-Delove, Scott & Mars, 2020; Sujarwoto & Maharani, 2023).

The level of trust in technology that comprises perceptions of privacy, data security, and technical support was evidently higher in the high-motivation group. On the whole, trust is seen to reduce perceived risk and facilitate digital adoption, especially in users who already recognize a platform's usefulness (Alam *et al.*, 2020; Octavius & Antonio, 2021; Rahman *et al.*, 2022; Liu *et al.*, 2023). There is also an interrelationship between trust and perceived benefits in that those who recognize technological advantages tend to report higher trust (Rahman *et al.*, 2022; Liu *et al.*, 2023). Effort expectancy was also a strong contributor to segmentation, with highly motivated users finding mHealth platforms easy to use in addition to being beneficial. This supports evidence pointing out effort expectancy as a key determinant of technology adoption (Alam; van der Wal; Hoque). Prior experience and familiarity with similar technologies also contribute to the formation of ease-of-use perceptions (Venkatesh; Alam). In the high-motivation cluster, self-efficacy was considerably higher. This finding supports evidence in mHealth that describes self-efficacy as one of the major determinants of adoption, which, in turn, is influenced by perceived support, resources, and ease of use (Zhao *et al.*, 2018; Liu *et al.*, 2022). These results reflect the enabling role of self-efficacy in translating beliefs into behavioral intention.

The differences in facilitating conditions further reveal that access to devices and technical support created the segmentation. Therefore, mHealth adoption is influenced by factors aside from psychological and trust-related factors: it depends on environmental support. This contributes to the digital divide in reproductive health uptake, as healthcare (Venkatesh & Bala, 2008; Alam *et al.*, 2020) documents. Such integration of HBM and UTAUT2 is consistent with prior studies, in which several constructs interrelate to form an adoption motive. Paganin et al., Rahman mentioned it in their works. Our results confirm previous studies by demonstrating that HBM and UTAUT explain digital health disparities, as personal skills, health beliefs, and technological access interactively drive reproductive health mHealth uptake. Subgroup analysis revealed that socio-economic and demographic factors are some of the reasons for disparities across clusters. Income, health literacy, marital status, and use of reproductive health services in the past were all statistically different, thus reflecting a structural disparity in mHealth readiness. Structural and motivational differences are in line with evidence on psychosocial factors affecting broader social inequalities (Feroz *et al.*, 2021; Jonayed & Rumi, 2024). In general, the group with high motivation had higher socio-economic status, more stable families, better health literacy, more experience with reproductive health services, and better digital access.

Differences in motivation then manifested as differences in intention to adopt, which is a key behavioral mechanism. Intention is an established predictor of (Alam *et al.*, 2020; Mensah *et al.*, 2022; Azam *et al.*, 2023). Significantly higher intention exhibited by the cluster with high motivation supports evidence that motivational and sociodemographic factors together shape behavioral readiness of subjects (Khatun et al., 2015; Kwee *et al.*, 2022). The findings are in tune with results from other studies based on clustering-based segmentation approaches (Ramírez-Correa *et al.*, 2020; Wen & Tung, 2024). In all these studies, self-efficacy, perceived barrier, and perceived usefulness are common distinguishing variables. Studies also report sociodemographic differences across segments (Liu *et al.*, 2023). Wen & Tung, 2024 identify access to digital technology, literacy, privacy concern, perceived benefit, and effort expectancy as distinguishing variables, whereas Ramírez-Correa *et al.* (2020) cite self-efficacy, familiarity, perceived benefit, and ease of use as the main contributors behind variation across segments.

The present study had several limitations. The exploratory design of this study limits causal inference and generalization, which may reduce the ability to associate findings in the broader population in various contexts. Overall, however, these findings build a rich foundation for psychosocial and contextual disparities in mHealth adoption among Indonesian women and those living in resource-limited settings. Future research can validate these findings using larger, more representative samples of the population and employ a determinant or predictive design for more robustness. These findings are important to inform interventions aimed at ensuring equitable digital reproductive health access. Interventions for highly motivated users at baseline may focus on sustaining engagement. For lower-motivation users, interventions are needed to improve digital literacy, enhance perceived benefits, and build self-confidence. Segmenting communication and services by motivational and structural differences may serve to narrow the digital divide. The value of segmentation in identifying opportunities for adoption and better informing targeted digital health strategies was further demonstrated in this study. Programs aimed to improve digital equity should therefore also target and tailor strategies for those in the lower socioeconomic standings based on income, health literacy, and initiate access to reproductive health services, as motivation align with structural inequalities. This includes integrating digital literacy support, improving service features and ease of use, and outreach initiatives. Integrating this approach within the wider national digital health strategies could help reduce the psychosocial and structural gaps in reproductive health access, as identified in this study.

Conclusion

This study used cluster analysis to identify two clear motivational profiles of potential users of reproductive mHealth; it showed how key motivations such as self-efficacy, perceived benefits, effort expectancy, and facilitating conditions differentiated them. Women within the highly motivated cluster had higher levels of confidence, access to enabling support, and were adept at perceiving the benefits of mHealth. Differences in structure were also described in terms of income, marital status, health literacy, and previous access to reproductive health services, which further differentiated the clusters and showed how motivation aligns with broader social and digital inequalities. The findings support policy priorities in strengthening reproductive health through informing equitable digital health strategies to ensure benefits are evenly distributed across all population groups. Future studies can build from this by analyzing changes in motivation, among other demographic categories, influencing behavior (adoption) and, therefore, how various patterns of adoption contribute to broader health outcomes.

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