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Adoption and Advocacy of Mental Health Apps Among Indonesia's Productive-Age Users: Influencing Factors and App Observations

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Abstract

Low- and Middle-Income Countries (LMICs), including Indonesia, are facing a significant shortage of mental healthcare facilities despite the growing need, leaving 20% of the population affected by related issues. In this context, Mobile health (mHealth) interventions offer potential solutions by overcoming barriers such as stigma and reluctance to obtain traditional services. Therefore, this research aims to evaluate the factors influencing the use and recommendation of mental health apps by analyzing data from online questionnaires distributed to 400 participants through a combination of purposive and random sampling. The analysis is conducted using Structural Equation Modeling with Partial Least Squares (SEM-PLS). Simultaneously, popular Indonesian mHealth apps providing mental health services are observed and categorized based on primary functionality to enhance comprehensiveness. The results show that intention to use these apps significantly impacts recommendations. Factors such as usefulness and social influence drive engagement, while affordability, symptom insights, and time constraints are cited as reasons for favoring apps over traditional services. Furthermore, Halodoc is recognized as the most effective app for meeting diverse user needs. Academic understanding of factors driving mental health app acceptance is also enhanced, and practical opportunities are provided for providers to customize app features to reach a wider audience, specifically underserved populations and areas.

Keywords: *Mobile Mental Health App, Intention To Use, Intention To Recommend, Perceived Stigma, Perceived Trust, Indonesian.*

Introduction

A wide range of mental health issues is reported to disrupt thoughts, feelings, behavior, physical health, relationships, education, and professions (World Health Organization, 2022a). Issues related to mental health remained a critical global health crisis due to widespread prevalence and significant impact on morbidity and expectancy of life. Almost one billion individuals worldwide had mental illnesses in 2019, showing the urgent need for transformations in healthcare practices (World Health Organization, 2022c). In addition, COVID-19 pandemic also increased the situation by disrupting or completely ceasing mental health services in 93% of nations. The demand for these services is quickly increasing due to the impact of the worldwide disaster (World Health Organization, 2020).

Beyond the demand, Indonesia is facing serious challenges in mental health services. Access gaps to mental health facilities are reported to be over 90% in Low and Middle-Income Countries (LMICs), reaching 95% in rural areas of Indonesia due to several challenges including the scarcity of professionals and services. Furthermore, perceived stigma associated with mental illness and the excessive expense of treatment prevent individuals from obtaining help (Putri et al., 2021). There is a disparity in the distribution of healthcare workers between urban and rural regions, with mental health service facilities predominantly located in urban areas. In this context, rural and urban areas show the prevalence of mental-emotional illnesses at 10 % and 9.8 %, respectively. The proportion of households with family members affected by schizophrenia in rural and urban areas is 7 % and 6.4 %, respectively (Ministry of Health of the Republic of Indonesia, 2018). The prevalence equates to approximately 20% of the population being at risk of mental health problems with one in every five Indonesians diagnosed.

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According to the National Institute of Health's Sample Registration System, five individuals commit suicide per day, or 1,800 each year, and 47.7% of victims are in the productive ages of 10 and 39 (Ministry of Health of the Republic of Indonesia, 2021). The numbers from the Indonesian Ministry of Health's Agency of Health Research and Development showed that approximately 450,000 families in Indonesia had at least a single individual diagnosed with schizophrenia. Meanwhile, over 4 billion families had at least one individual suffering from depression. (Inside Indonesia, 2020). A further review also discovered that mental health illnesses accounted for 13.4% of total burden, where the need for accessible services was more serious (Ministry of Health of the Republic of Indonesia, 2019). Regarding health facilities, Indonesia with a population of 273.5 million has only 49 mental hospitals with 11,340 beds. The general hospitals contain 370 psychiatric units with 3,820 beds, while 150 community residences have 2,000 beds with 609 outpatient facilities. In 2020, the country had a low density of professionals, with only 0.4 psychiatrists, 2.3 mental health nurses, and 0.2 psychologists per 100,000 individuals (World Health Organization, 2022b). Additionally, individuals with mental health issues often face stigma and discrimination from society and within healthcare settings. Another survey reported that only 9% of people obtain the help of a professional, such as a psychologist or psychiatrist when dealing with mental health condition (Databoks, 2023). Since Indonesians are among the most religious people in the world (The Jakarta Post, 2020), individuals with mental illnesses are prevalently stigmatized as having a lack of faith and are taken to spiritual leaders rather than consulting with professionals (Cipta & Saputra, 2022). Therefore, the issues remain unresolved and necessitate further attention, as delineated by the government in Law No. 17 of 2023 on Health. Section 11 pertaining to comprehensive mental healthcare provisions mandates the integration of services across all levels of healthcare system, ensuring equitable access to prevention, treatment, and rehabilitation for all individuals, without discrimination. Furthermore, the law shows the importance of promoting mental health awareness and combating stigma associated with the conditions (Undang-Undang Republik Indonesia, 2023).

Based on the description above, mobile health (mHealth) procedures incorporating the use of technology are proven to provide educational resources, assist clients in self-management of health problems and behaviors, and supply medical assistance to improve well-being. In comparison with conventional service methods, mobile interventions can be more cost-effective and may help consumers overcome demographic, socioeconomic, and geographic barriers to obtaining health services (Wei et al., 2020). Similarly, mental health apps dissolve barriers to face-to-face help-seeking, such as stigma or anxiety in discussing issues (Grist et al., 2017). Many eHealth initiatives in developing countries tend to focus on computer-based health information systems and the use of the Internet in enhancing health-related information and operational access. As wireless networks spread across the country and mobile devices become more economical, there is also increasing popularity for the potential of mHealth. Mobile technology allows eHealth systems to decentralize and reach out to remote areas (Hoque et al., 2020). The promise for increasing digital transformation in healthcare industry is enormous, specifically with the fourth place ranking Indonesia in the world with 170.4 million smartphone users, reflecting a domestic penetration rate of 61.7% (Databoks, 2021b). There were approximately 212.9 million internet users in January 2023, implying a usage rate of 77% of the total population at the beginning of the year. This showed an increase of 10 million users (+5.2%) between 2022 and 2023 (DataReportal, 2023). However, the occurrences do not guarantee the optimal adoption of mental health services because public awareness and use remain low. A survey reported that only 27% of the population could access mental healthcare services after considering different factors (Databoks, 2021a).

This research aims to deliver a comprehensive analysis of factors affecting intention to use and recommend mental health mobile apps in Indonesia. A robust, empirically validated, and comprehensive framework is provided using the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These frameworks are selected due to widespread use and effectiveness in understanding the acceptance of technology. UTAUT can be seen as an expansion and broadening of TAM, which takes a straightforward method, emphasizing individual perceptions of usefulness and ease of use. In contrast, UTAUT offers a broader perspective by considering social and facilitating factors. This combination is particularly advantageous, allowing for the identification of a comprehensive set of factors influencing adoption of mental health apps, integrating individual perceptions and external influences. The scope is expanded by incorporating additional elements such as perceived trust and stigma for the unique mental health landscape. Therefore, this research aimed to be more comprehensive in recognizing the crucial role of trust and the pervasive impact of stigma in mental healthcare, particularly in cultures with prevalent skepticism. Observations were conducted to identify existing mental health apps and evaluate the capability of the

features in delivering the required services. These insights offer valuable recommendations for mental healthcare providers to develop improved and intuitive mobile apps tailored to individual needs. The initiative harnesses the potential of mobile technology to enhance accessibility to mental health services, with the overarching aim of improving the overall well-being of Indonesians.

Methods

The research instrument incorporates two methods, namely distributing online questionnaires to respondents with specific sets of criteria and simultaneously conducting observations on widely used mobile apps to provide mental health services in Indonesia.

Apps observation

A review of popular mHealth apps providing mental health services was conducted to show the assistance rendered by the features to users in accessing support. The aim is to offer insights that help users make informed decisions about mental well-being, providing a clear overview of the features and services.

App search was conducted using the terms "mental health apps in Indonesia" on Google in May 2023. A set of criteria was followed in selecting mobile apps for inclusion in observation stage (Rickard et al., 2022).

1) Mobile mental health apps accessible in the Indonesia region.
2) Mobile mental health apps available to be downloaded through mobile device using App Store (iOS) and the Google Play Store (Android).
3) Mobile mental health apps designed as standalone without requiring additional devices such as remote mood detectors or other wearables.

Meanwhile, the exclusion criterion includes the following.

1) App is not specifically made for mobile devices at all (web-based service).
2) App is designed solely for academic institutions, health professionals, or specific health facilities.

Questionnaire Design

The questionnaire contained 29 questions divided into three different sections as reported below.

1) Screening consists of only a single question to filter individuals experiencing mental health issues and have used mobile apps to provide services in Indonesia.
2) Respondent background and demographics, consisting of questions about details (sex, age, social economy status, occupation, and educational level) and mental health apps usage, such as what apps were used, reasons for use, and average daily smartphone usage.
3) The final 24 questions covered 8 research variables and were structured around each construct with an Agreement Likert scale (Amadu et al., 2018) ranging from 1 (strongly disagree) to 5 (strongly agree).

Questionnaire Analysis

Data are measured and statistically analyzed using the Structural Equation Modeling - Partial Least Square (SEM PLS) method through the SmartPLS app v4.0.9.3 (SmartPLS, 2023). The method is advantageous to handle intricate models with multiple constructs and interrelations efficiently. This is also characterized by flexibility with non-normally distributed data and effectiveness in providing valid results without the need for large sample sizes typically required by other statistical methods. SEM PLS focuses on enhancing the explained variance of dependent variables and is robust against missing data. Additionally, the method includes comprehensive features for assessing the reliability and validity of the constructs within the model (Hair et al., 2016; Ringle et al., 2015).

The analysis is divided into three steps, first, the measurement model (outer model) assesses the indicators of reliability and validity to ensure accurate reflection of latent variables. Second, the structural model examines the relationships between latent variables, analyzing the strength and significance of the connections. Third, hypothesis testing is performed to confirm the proposed relationships between variables using statistical tests through bootstrapping.

Research Target Population

Based on data from the Directorate General of Population and Civil Registration (Dukcapil) of the Ministry of Home Affairs, the population of Indonesia reached 275.36 million in June 2022 with 190.83 million (69.3%) in a productive age of 15-64 years (Kusnandar, 2022). A survey stated that 52% had mental health problems but only 54% used telemedicine apps to access services for reasons of accessibility, flexibility, affordability, privacy, solutions, and trends (Populix, 2022). Based on this information, the target population was 53.585.064, as reported in Table 1.

Table 1. Research Population

Research population (n)		
x = Total Indonesian population of productive age (15-64 years)	y = Number of Indonesians who reported that they have a mental health issue	N = Number of people using telemedicine apps to access mental health services
x = 190.830.000	y = 52% of x	N = 54% of Y
	y = 52 % x 190.830.000	n = 54 x 99.231.600
	y = 99.231.600	**N = 53.585.064**

Respondents Selection

A purposive homogenous sampling method was used to balance the data with the research objectives, aimed at an in-depth understanding of a particular group sharing common characteristics (Campbell et al., 2020). In this context, the population of Indonesians aged between 18 and 55 years old, which counts as productive age groups and have prior experience using available mental health apps, are included as respondents.

A paid survey agency, Poplite by Populix, was used for respondent selection. The agency ensured that respondents fulfilled the required criteria and provided appropriate responses using the predetermined pool. This made the data collection swiftly executed in two days between May 22 and 23, 2023.

Sample Size Determination

The sample size was calculated using Slovin's formula (Slovin, 1960) to ensure a statistically significant representation of the target population. This method was selected to determine the optimal number of respondents needed to minimize the margin of error. Subsequently, random sampling (Creswell, 2014) was used to select respondents, providing each member of the population with an equal chance of being included in the sample. This enhances the reliability and validity of the results to accurately reflect the characteristics of the sample population. The sample size of respondents was calculated using Slovin's formula when the population is finite and a specific margin of error is desired.

$$n = N / (1 + N * e^2) \quad (1)$$

Where:

n: sample size

N: total population size; we use N = 53.585.064 as calculated above

e: margin of error (expressed as a decimal); we use a margin of error as 5% (commonly used in many social science surveys for a balance between accuracy and feasibility)

The calculated sample size is approximately 400 respondents using Slovin's formula with a margin of error of 5% for a population size of 53,585,064.

Variable Measurement

This research incorporated both formative and reflective variables. The indicators of formative variables collectively shape the overall construct. In contrast, reflective variables are characterized by the construct influencing the indicators. The adopted variables were taken directly from previous

research without changes, while the adapted variables were modified to be consistent with the context of mental health apps.

Table 2. Research Variable Measurement

Variable	Indicators	Descriptions	Type of Variable	Sources
Perceived Usefulness (PU)	Speed (PU1)	I believe a mental health mobile app enables me to obtain mental health information faster.	Formative/ Adopted	(Amanda & Layman, 2022)
	Initial treatment (PU2)	I believe a mental health mobile app can help me throughout the initial assessment and treatment phase.		(Amanda & Layman, 2022)
	Mental health awareness (PU3)	I believe mental health mobile apps encourage me to be more mindful of my mental health.		(Amanda & Layman, 2022)
	Accuracy (PU4)	I believe a mental health mobile app can provide accurate information about mental healthcare in the same way as physical professionals do.		(Amanda & Layman, 2022)
Perceived Ease of Use (PEOU)	Useful feature (PEOU1)	I do not find it difficult to use the features of the mental health mobile app.	Formative/ Adopted	(Akhmad & Didik, 2021; Alsyouf et al., 2023)
	Convenience use (PEOU2)	I do not find it difficult to use the mental health mobile app (user interface is easy to understand).		(Akhmad & Didik, 2021; Alsyouf et al., 2023)
Perceived Trust (PT)	Security (PT1)	I believe that mental health mobile apps are safe and trustworthy for accessing mental health services online.	Formative/ Adapted	(AlHadid et al., 2022; Alsyouf et al., 2023)
	Privacy (PT2)	I believe that my privacy and personal information are protected while using the mental health mobile app.		(Alsyouf et al., 2023)
	Reliability (PT3)	I believe that mental health mobile apps' recommendations and information are credible and valuable.		(Amanda & Layman, 2022)
	Professional expertise (PT4)	I believe that the professionals (psychiatrists/psychologists) available and provided by mental health mobile apps are suitably qualified to treat mental health issues.		(Amanda & Layman, 2022)
Perceived Stigma (PS)	Stigma (PS1)	I am worried about being judged or stigmatized by others if I use a mental health mobile app.	Formative/ Adapted	(Borghouts et al., 2021; Zieger et al., 2016)

Variable	**Indicators**	**Descriptions**	**Type of Variable**	**Sources**
	Reputational impact (PS2)	I am worried that using a mental health mobile app will damage my reputation.		(Zieger et al., 2016)
	Social impact (PS3)	I am worried that people will treat me differently if they know that I am using a mental health mobile app.		(Boge et al., 2018; Zieger et al., 2016)
Facilitating Conditions (FC)	Required resources (FC1)	I believe I have the resources needed to use a mental health mobile app, such as internet connectivity, a smartphone, particularly so on.	Formative/ Adopted	(**Yu et al., 2021; Duarte & Pinho, 2019**)(Mensah et al., 2020)
	Required knowledge (FC2)	I believe I am capable of knowing how to use a mental health mobile app.		(**Yu et al., 2021; Duarte & Pinho, 2019**)(Mensah et al., 2020)
	Social support (FC3)	When I have problems using a mental health mobile app, I can seek assistance from people around me.		(**Yu et al., 2021; Duarte & Pinho, 2019**)(Mensah et al., 2020)
Social Influence (SI)	People who influence (SI1)	People who influence my behavior think that I should use a mental health mobile app.	Formative/ Adopted	(**Yu et al., 2021; Duarte & Pinho, 2019**)(Mensah et al., 2020)
	Respected people (SI2)	People I respect think that I should use a mental health mobile app.		(**Yu et al., 2021; Duarte & Pinho, 2019**)(Mensah et al., 2020)
	Important people (SI3)	People who are important to me think I should use a mental health mobile app.		(**Yu et al., 2021; Duarte & Pinho, 2019**)(Mensah et al., 2020)
Intention to Use Mental Health Apps (ITU)	Intention to regular use (ITU1)	I intend to continue using the mental health mobile app regularly.	Reflective/ Adapted	(AlHadid et al., 2022; Mensah et al., 2022)
	Intention to continue use (ITU2)	I intend to continue using the mental health mobile app in the future.		(AlHadid et al., 2022; Mensah et al., 2020, 2022)
Intention to Recommend Adoption of Mental Health Apps (ITR)	Intention to overall Recommend (ITR1)	I would recommend the mental health mobile app to others.	Reflective/ Adapted	**(Mohammed et al., 2022**) (AlHadid et al., 2022; Boge et al., 2018; Mensah et al., 2022)

Variable	Indicators	Descriptions	Type of Variable	Sources
	Intention to recommend usefulness (ITR2)	I am willing to tell others about the good aspects of the mental health mobile app.		(Mensah et al., 2022)
	Intention to recommend a good experience (ITR3)	I am willing to tell others about my good experience using a mental health mobile app.		(Mensah et al., 2020) **(Mohammed et al., 2022)**;

Based on occupation, educational level, and residence, 41.75%, 50.5%, and 19.25% of respondents work full-time, have a bachelor's degree, and live in West Java, respectively. Based on daily average usage, 44.75% use smartphones more than 8 hours a day.

Table 3. Respondent Demographics

Measure	Item	Freq.	Percentage
Gender	Male	177	44.25%
	Female	233	55.75%
Age	18-24 years	162	40.5%
	25-30 years	126	31.5%
	31-35 years	61	15.25%
	36-40 years	26	6.5%
	41-45 years	13	3.25%
	46-50 years	7	1.75%
	51-55 years	5	1.25%
Social Economy Level	Upper 1	77	19.25%
	Upper 2	95	23.75%
	Middle 1	96	24%
	Middle 2	65	16.25%
	Lower 1	53	13.25%
	Lower 2	14	3.5%
Occupation	Working full-time	167	41.75%
	Not working (Student)	96	24%
	Working part-time (freelance)	62	15.5%
	Business owner	30	7.5%
	Not working (looking for a job)	28	7%
	Not working (housewife/ disabled/retired)	17	4.25%
Educational Level	Did not attend school	1	0.25%
	Elementary school	1	0.25%
	Junior high school	5	1.25%
	Senior high school	147	36.75%
	Diploma	29	7.25%
	Bachelor	202	50.5%
	Master	9	2.25%
	Doctorate	6	1.5%
Residence	West Java	106	19.25%
	DKI Jakarta	77	16.75%
	East Java	67	11%
	Central Java	44	5.25%
	Banten	21	3.75%

	North Sumatra	15	3.5%
	DI Yogyakarta	14	2.25%
	South Sumatera	9	1.75%
	South Kalimantan	7	1.25%
	Bali	5	1.25%
	East Kalimantan	5	1%
	West Sumatera	4	0.75%
	South Sulawesi	3	0.75%
	Aceh	3	0.75%
	North Sulawesi	3	0.75%
	East Nusa Tenggara	3	0.75%
	Riau	3	0.5%
	Riau Islands	2	0.5%
	Lampung	2	0.5%
	West Kalimantan	2	0.25%
	Bengkulu	1	0.25%
	Central Kalimantan	1	0.25%
	West Sulawesi	1	0.25%
	Bangka Belitung Island	1	0.25%
	West Papua	1	0.25%
Average Daily Smartphone Usage	Almost every time (more than 8 hours)	179	44.75%
	Many times a day (4 to 8 hours)	130	32.5%
	Multiple times a day (every 2 to 4 hours)	71	17.75%
	Not frequently (less than 2 hours)	20	5%

Mhealth App Usage

Respondents are given the option to pick more than one app to determine the Mobile Mental Health app used. Therefore, 359 respondents preferred to use the Halodoc app when seeking mental health services. Only 44 individuals (11%) used the Bicarakan.id app as presented in Table 4.

Table 4. Mobile Mental Health App Used

Mental Health Apps Used	Freq.	Percentage
Halodoc	359	90%
Alodokter	251	63%
GoodDoctor	74	19%
PsikologiMu	78	20%
YesDok	67	17%
Bicarakan.id	44	11%
Riliv	62	16%
SehatQ	87	22%
MyDoctors	64	16%
KlikDokter	136	34%

Respondents can optionally pick more than one reason for using apps. Therefore, affordable price (65%), the ability to obtain an initial examination of the symptoms of mental health issues experienced (57%), and a limited time to access services physically (54%) are the top three reasons for using mobile mental health apps.

Table 5. Reasons to use a Mobile Mental Health App

Reasons to Use Mental Health Apps	Freq.	Percentage
More affordable	261	65%
I don't have time to access physical services	214	54%
I am worried about other people's assumptions and stigma	162	41%
I have limited access to adequate physical services	111	28%
I want to get an initial idea of what I am experiencing	230	57%
I can choose how to communicate with professionals flexibly (chat, phone call, video call)	211	53%
I want to access services in a practical way	210	53%

Measurement/Outer Model Validation

The measurement model describes the relationship between latent variables and indicators, consisting of a validity test, Loading Factor (LF) and Average Variance Extracted (AVE), with a reliability test of Cronbach's Alpha and Composite Reliability (CR) (Alfa et al., 2017).

Reliability and Convergent Validity

In this research, the LF is considered valid when the values are> 0.708 for confirmatory factor analysis. Therefore, the construct accounts for more than 50% of the variance, ensuring sufficient item reliability (Hair et al., 2019). There was no need to drop any of the indicators since the threshold was exceeded. This also confirms that the convergent validity for LF meets the criteria.

For AVE, only indicators with a value > 0.50 are considered valid since the construct explains 50% of the variance (Fornell & Larcker, 1981). The construct has a result > 0.50, and the convergent validity requirement for AVE can also be met.

As part of the reliability test, Cronbach's Alpha or CR value should be greater than 0.70 (J. Hartono & Abdillah, 2009). In this research, every construct has proven the reliability, as shown by Cronbach's Alpha and CR values, all exceeding the 0.7 threshold.

Table 6. Construct Validity and Reliability Result

Construct	Indicator	LF	AVE	Cronbach's Alpha	CR
FC	FC1	0.820	0.652	0.730	0.848
	FC2	0.861			
	FC3	0.736			
ITR	TR1	0.897	0.799	0.874	0.922
	ITR2	0.904			
	ITR3	0.880			
ITU	ITU1	0.940	0.886	0.871	0.939
	ITU2	0.942			
PEOU	PEOU1	0.930	0.864	0.842	0.927
	PEOU2	0.929			
PS	PS	0.927	0.901	0.946	0.965
	PS2	0.961			
	PS3	0.959			
PT	PT1	0.856	0.728	0.875	0.915
	PT2	0.864			
	PT3	0.846			
	PT4	0.847			
PU	PU1	0.887	0.725	0.874	0.913
	PU2	0.863			

	PU3	0.838			
	PU4	0.817			
SI	SI1	0.835	0.781	0.860	0.914
	SI2	0.911			
	SI3	0.903			

Discriminant Validity

According to Hair et al., 2019), Heterotrait-Monotrait Ratio (HTMT) is defined as the average value of item correlations between constructs compared to the mean of the average. The Fornell-Larcker criterion (Fornell & Larcker, 1981) showed that the shared variance of each construct was smaller than the corresponding AVE. Cross-loadings were used to assess discriminant validity, and the results showed that all data satisfied the necessary criteria. Specifically, the variables showed high loadings (>0.6) on the corresponding factors and low loadings on other factors, confirming the discriminant validity, as reported in Tables 7 and 8.

Table 7. HTMT Ratio and Fornell-Larcker Criterion Test Results

HTMT	FC	ITR	ITU	PEOU	PS	PT	PU	SI
FC								
ITR	0.825							
ITU	0.785	0.888						
PEOU	0.808	0.756	0.722					
PS	0.149	0.089	0.181	0.132				
PT	0.856	0.848	0.791	0.822	0.113			
PU	0.836	0.798	0.802	0.838	0.091	0.891		
SI	0.681	0.671	0.732	0.55	0.47	0.662	0.601	
Fornell-Larcker criterion	FC	ITR	ITU	PEOU	PS	PT	PU	SI
FC	0.807							
ITR	0.661	0.894						
ITU	0.627	0.777	0.941					
PEOU	0.636	0.65	0.618	0.929				
PS	0.104	0.082	0.17	0.116	0.949			
PT	0.685	0.743	0.691	0.707	0.103	0.853		
PU	0.668	0.698	0.702	0.719	0.076	0.779	0.852	
SI	0.542	0.587	0.637	0.471	0.42	0.578	0.528	0.884

Table 7 shows that each item or indicator correlates more strongly with the intended measure than with any others. Therefore, the conditions for discriminant validity based on cross-loading are fulfilled.

Table 8. Cross-Loading Test Results

Cross Loading	FC	ITR	ITU	PEOU	PS	PT	PU	SI
FC1	0.82	0.517	0.478	0.495	-0.016	0.550	0.543	0.316
FC2	0.861	0.591	0.552	0.573	0.052	0.585	0.578	0.434
FC3	0.736	0.487	0.484	0.464	0.219	0.521	0.492	0.561
ITR1	0.596	0.897	0.740	0.612	0.100	0.678	0.626	0.542
ITR2	0.604	0.904	0.690	0.577	0.064	0.673	0.629	0.530
ITR3	0.572	0.880	0.646	0.551	0.053	0.64	0.616	0.499
ITU1	0.599	0.717	0.940	0.584	0.153	0.637	0.649	0.604
ITU2	0.582	0.745	0.942	0.580	0.165	0.663	0.672	0.594
PEOU1	0.596	0.606	0.575	0.930	0.089	0.649	0.678	0.435
PEOU2	0.585	0.603	0.574	0.929	0.126	0.664	0.659	0.441
PS1	0.118	0.077	0.114	0.122	0.927	0.090	0.084	0.373

PS2	0.092	0.078	0.182	0.099	0.961	0.089	0.074	0.426
PS3	0.095	0.080	0.171	0.114	0.959	0.113	0.064	0.391
PT1	0.604	0.673	0.604	0.607	0.033	0.856	0.702	0.459
PT2	0.567	0.626	0.589	0.630	0.130	0.864	0.634	0.497
PT3	0.559	0.609	0.574	0.555	0.121	0.846	0.665	0.524
PT4	0.607	0.626	0.590	0.618	0.070	0.847	0.657	0.495
PU1	0.565	0.621	0.595	0.657	0.051	0.684	0.887	0.447
PU2	0.548	0.613	0.613	0.625	0.025	0.659	0.863	0.444
PU3	0.596	0.570	0.544	0.586	-0.003	0.657	0.838	0.337
PU4	0.567	0.572	0.630	0.579	0.175	0.654	0.817	0.553
SI1	0.420	0.434	0.488	0.354	0.447	0.419	0.411	0.835
SI2	0.534	0.551	0.595	0.471	0.322	0.563	0.515	0.911
SI3	0.475	0.559	0.596	0.416	0.362	0.538	0.468	0.903

Structural/Inner Model Validation

In structural model analysis, R Square and Q Square are used. The R Square results show that PU, PEOU, PT, PS, FC, and SI collectively influence ITU by 60.3%, showing a strong impact. ITU also strongly affects the ITR variable by 62.2%. According to (Chin, 1998), the R square values of 0.67, 0.33, and 0.19 fell into the strong, moderate, and weak category, respectively. Q Square evaluates the predictive accuracy of the model by assessing the prediction of the dependent variable using the data adopted in the development. The Q2 values >0, 0.25, and 0.50 signify low, moderate, and high accuracy, respectively. Intention to Use Mental Health Apps (ITU) and ITR the Use of Mental Health Apps (ITR) have been accurately reconstructed, as evidenced by Q2 > 0. This implies that the model holds predictive significance.

Table 9. Coefficient of determination test results: R square and Q square

Variable	R Square	R Square Adjusted	Q Square
Intention to Recommend the Use of Mental Health App (ITR)	0.603	0.602	0.581
Intention to Use Mental Health Apps (ITU)	0.622	0.616	0.600

F Square value measures the impact of variables at the structural level. According to (Hair, 2021), an F Square value of 0.02, 0.15, and 0.35 falls into the low, moderate, and high category, respectively.

Table 10. F Square Test Results

Relationship between Variables	F Square	Interpretation
FC -> ITU	0.015	Low
ITU -> ITR	1.521	High
PEOU -> ITU	0.010	Low
PS -> ITU	0.001	Low
PT -> ITU	0.020	Low
PU -> ITU	0.065	Low
SI -> ITU	0.118	Moderate

Variance Inflation Factor (VIF) shows that a VIF < 5 for any variable relationship suggests the absence of multicollinearity (Hair et al., 2019). According to Table 11, all VIF values are under 5, confirming the absence of multicollinearity.

Table 11. VIF Test Results

Relationship between Variables	VIF
FC -> ITU	2.258
ITU -> ITR	1
PEOU -> ITU	2.446
PS -> ITU	1.277
PT -> ITU	3.298
PU -> ITU	3.146
SI -> ITU	2.021

Hypothesis Testing Validation

A total of three of the seven hypotheses examined are valid, while the remaining are unproven.

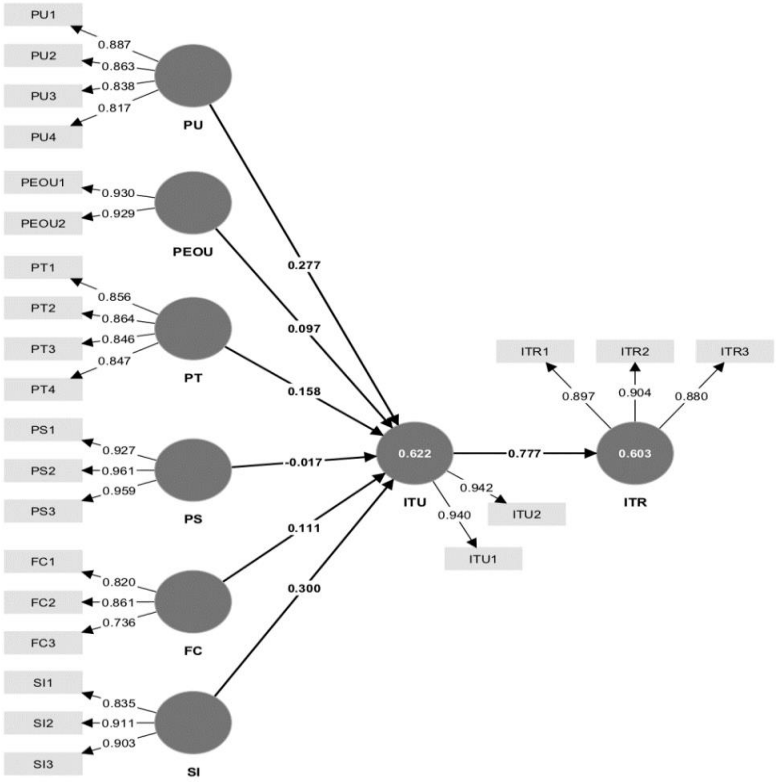

Figure 4. Hypothesis Testing Result

The significance level of the hypothesis was verified using bootstrapping, with 5000 subsamples and a two-tailed test. A significance level of 0.05 signifies a 5% divergence from the normal distribution, with a 95% confidence level. Meanwhile, bias-corrected and accelerated (BCa) were selected to correct bias and asymmetry in the distribution of estimated parameters, allowing for more exact judgments about the statistical significance of the parameters.

Table 12. Hypothesis Test Results

Hypothesis	Path	T statistics (> 1.96)	Original sample (O)	Sample mean (M)	*p* values (< 0.05)	Results
H1	Perceived Usefulness (PU) → Intention to Use Mental	3.532	0.277	0.283	0.000	Accepted

	Health Apps (ITU)					
H2	Perceived Ease of Use (PEOU) → Intention to Use Mental Health Apps (ITU)	1.677	0.097	0.103	0.094	Rejected
H3	Perceived Trust (PT) → Intention to Use Mental Health Apps (ITU)	1.901	0.158	0.148	0.057	Rejected
H4	Perceived Stigma (PS) → Intention to Use Mental Health Apps (ITU)	0.620	0.017	-0.015	0.535	Rejected
H5	Facilitating Conditions (FC) → Intention to Use Mental Health Apps (ITU)	1.792	0.111	0.111	0.073	Rejected
H6	Social Influence (SI) → Intention to Use Mental Health Apps (ITU)	5.744	0.300	0.300	0.000	Accepted
H7	Intention to Use Mental Health Apps (ITU) → Intention to Recommend the Use of Mental Health App (ITR)	30.485	0.777	0.777	0.000	Accepted

The first hypothesis (H1) confirms that perceived usefulness (PU) influences individual intention to use mental health apps (ITU). This is in line with TAM theory, where perceived usefulness (PU) is equivalent to performance expectation (UTAUT), as reported by (Alsyouf et al., 2023; Salsabila & Sari, 2022)(Kurniawan et al., 2022; Nurul, 2023; Lie et al., 2021). However, (Akhmad & Didik, 2021; Septiani et al., 2017) presented contrasting results, where perceived usefulness (PU) does not impact intention to use mental health apps (ITU). In this context, the result shows the importance of individuals perceiving mental health apps as beneficial to influence the likelihood of usage. Considering the unique challenges and cultural considerations, mental health app providers play an important role in tailoring features for a wider audience, ensuring accessibility, and community engagement. Regular assessments, such as user feedback surveys and usability testing, ensure apps remain relevant and effective in addressing diverse mental health needs.

The second hypothesis (H2) shows that perceived ease of use (PEOU) does not impact individual intention to use mental health apps (ITU). This contradicts TAM theory, where perceived ease of use (PEOU) and perceived usefulness (PU) drive system adoption. In TAM, perceived usefulness (PU) is equivalent to Effort Expectancy in performance expectation (UTAUT). Even though Hsu et al. (2017) and Yuan et al. (2015) supported the results, Akhmad & Didik, 2021) and Lie et al. (2021) suggested otherwise. The result reports that perceived ease or difficulty of using mental health apps does not affect intention to use. In Indonesia, where mental health issues such as anxiety and depression are prevalent, providers should prioritize educating individuals on the effectiveness. Emphasizing efficacy, community support, and cultural relevance can enhance adoption rates even though user-friendly design remains important.

The third hypothesis (H3) reports that perceived trust (PT) does not impact intention to use a mental health app (ITU). This is a novel discovery considering previous research showing the significance of consumer trust in health-related information, which enhances positive attitudes toward using mHealth apps or websites. Recent research emphasized factors such as trustworthiness, dependability, competency, and integrity in shaping customer trust in health platforms (Lie et al., 2021)(Gong et al., 2019; Hamdan et al., 2021; Kabakuş & Küçükoğlu, 2022). In this landscape, the discovery may have several underlying reasons, such as cultural stigma and the reliance on traditional support systems. Disparities in technology literacy and access, with limited awareness and education regarding the effectiveness of mental health apps, may also play a role in diminishing the influence of perceived trust. Meanwhile, personal experiences and recommendations may have a stronger influence on decision-making. These contextual factors show the uniqueness of the research and provide insights into the intricate dynamics shaping the adoption of mental health apps.

The fourth hypothesis (H4) shows that intention to use a mental health app (ITU) is not influenced by perceived stigma (PS). This result is unexpected since the majority of relevant research contradicts (Corrigan & Watson, 2002; Mitchell et al., 2022), where mental health stigma significantly decreases the use of apps. Stigma is recognized as a barrier to obtaining services and undermines the effectiveness of mental healthcare systems. Constant efforts to raise awareness and destigmatize mental health issues are gaining momentum, improving a more accepting attitude toward seeking help, particularly since the current phenomenon of social media plays a significant role in promoting awareness and conversations about overall well-being. Additionally, demographic disparities, socioeconomic status, and urban-rural distinctions contribute to varied perceptions of stigma and access to mental health services across different segments of the population.

According to hypothesis (H5), facilitating condition (FC) to use mental health apps does not affect intention to use (ITU). This result is supported by relevant research, such as (Preeti et al., 2018) where strong beliefs in the benefits of technology persist in intention to use telemedicine without technical infrastructure support. However, other research shows that facilitating conditions have an effect on intention to use (ITU) and the variable identifies factors influencing individual behavioral intention to adopt specific technologies (Andreia et al., 2019; Zhu et al., 2023)(Yu et al., 2021). These results are related to the disparity between perceived facilitative conditions and the actual usability or effectiveness of mental health apps. Individual preferences and attitudes towards technology may vary widely, with some users expressing skepticism or disinterest in adopting digital solutions. Despite the presence of facilitative conditions, such as accessibility and functionality, users may not perceive factors as influential in the decision to use apps.

The sixth hypothesis (H6) suggests that intention to use mental health apps (ITU) is impacted by social influence (SI), as supported by (Yu et al., 2021)(Hsu et al., 2017). However, contrary research (Afshan & Sharif, 2016; Arenas-Gaitán et al., 2015) reported that SI did not affect ITU. In Indonesia, where connections and relationships hold significant importance, social influence from family, friends, or community members plays a crucial role in shaping attitudes and behaviors toward obtaining mental health support. Furthermore, the proliferation of social media and online communities has created new opportunities for influence. Online platforms also provide spaces for individuals to share experiences with mental health apps, offer recommendations, and provide support to others. In regions with limited access to traditional mental health services, social networks may be considered for guidance on alternative forms of support.

The seventh hypothesis (H7) states that intention to use mental health apps (ITU) affects the inclination to recommend to others (ITR), as stated by AlHadid et al. (2022), Mensah et al. (2020; Oliveira et al. (2016). Conversely, (Mensah et al., 2022) proposed an opposing conclusion. In Indonesia, where interpersonal relationships are highly valued, word-of-mouth recommendations have an

enormous effect. Due to the cultural importance of connection to others, recommendations from friends, family, or peers are valuable. Additionally, the widespread effect of online and offline social media platforms contributes to disseminating recommendations for mental health apps. Positive experiences shared can have a knock-on effect, improving trust and perceived usefulness of potential users, and increasing the likelihood of using and recommending the app.

As part of observation, only the MyDoctors app does not offer Mental Health Promotion and Psychoeducation functionalities. Implementation of the functionality varies across different apps but typically includes content in various formats, such as articles, videos, or dedicated podcasts, and is accompanied by a search bar or specific tags for easy navigation. This content serves as a comprehensive resource, providing information on symptoms, medications, therapies, and addressing topics relevant to everyday life, such as coping with burnout during the pandemic or preventing toxic productivity. Some apps ensure the validity of articles by referencing scientific sources and including doctors as reviewers. Users also engage with the content by liking or commenting, facilitating interaction with others, and receiving responses from doctors to their queries. Only 4 out of 10 apps offer Monitoring and Tracking capabilities, namely Bicarakan.id, Riliv, Halodoc, and MyDoctors. These apps offer a variety of kinds of functionality. For instance, journaling can help with self-awareness, emotional management, goal planning, and personal growth. Breathing exercises are also beneficial for managing a variety of symptoms, including anxiety, panic attacks, and insomnia. Mood tracking capabilities enable users to keep track of regular emotional states and identify patterns of significant mood fluctuations. Furthermore, meditation supervised by qualified medical professionals is available as an addition to therapy and other treatment options. Some apps provide reminder abilities for daily medicine intake or future appointments, while others contain emergency contacts to help users in difficult situations, such as suicide attempts or any mental health emergencies.

Based on the description above, all apps offer Intervention and Treatment functionalities, with consultations primarily conducted online through chat, voice, or video calls. Some provide offline services when users prefer nearby options. Certain apps exclusively feature Psychologists, and some offering telemedicine services include Psychiatrists as options. In the Halodoc app, users initially discuss symptoms with a general practitioner before being directed to a Psychologist or Psychiatrist. Within these functionalities, detailed profiles of therapists are accessed, containing information such as name, registration number, degree, educational background, expertise, rates, practice hours, as well as ratings and reviews from other users. Psychiatrists are medical doctors specializing in mental health to prescribe medication, while Psychologists offer non-drug therapy. Payment options across most apps include e-wallets, bank transfers, and credit cards for convenience.

In terms of Assessment and Prevention features, only four apps include the functionality, namely Psikologimu, SehatQ, Halodoc, and MyDoctors. These features primarily provide simple personality, aptitude, interest, or job interest tests. However, some apps have developed quick assessment tests for self-screening purposes to determine the current mental state. In this context, users are required to pay for a specific test, with the results being sent to emails, while others offer the service free of charge for initial assessments. The majority of individuals use mental health apps due to affordability and the ability to provide initial insight into symptoms, as well as time constraints for face-to-face meetings with professionals. Halodoc is the most popular app among users, offering Mental Health Promotions, Psychoeducation, Monitoring, Tracking, Intervention, Treatment, Assessment, and Prevention. This telemedicine app offers an exclusive mental health service on the homepage, emphasizing the significance of awareness and physical health. The unique feature improves the experience by assisting new users in deciding on a psychiatrist or a psychologist according to health concerns. The simple and intuitive designs facilitate the discovery of mental health services. Halodoc offers a complete service package with various features consolidated into one app. These include articles to raise awareness, early detection tests for issues, help in finding counseling experts, prescriptions, medication purchases, booking physical appointments, medication reminders, and consultations. Enhancing current mental health mobile apps through AI integration includes personalized intervention and support.

The academic significance of this research lies in the innovative method of combining established frameworks such as TAM and UTAUT with newer factors, including stigma and trust, offering a more nuanced understanding of user acceptance of mental health apps. Additionally, incorporating observation into the research methodology adds practical depth by providing real-world insights into the delivery of services through mobile technology. Since mental health services continue to rapidly expand, this research contributes to the ongoing discourse on integrating mobile technology into healthcare

systems. Valuable insights are also offered to optimize the platforms and explore innovative technological solutions for intervention and support.

This research confirms that mental health issues are no longer confined to a specific gender since men and women have nearly equal experience. The information holds significance for service providers to consider marketing strategies to cater more towards women or adopt inclusive methods to attract men as potential users. Moreover, the largest proportion of respondents belongs to the productive age group, emphasizing the importance of considering the demographic in mental health initiatives. Addressing socioeconomic disparities, this research shows the need to ensure universal access to mental health apps, regardless of financial status. Providers might support policies to support social inclusion, such as integrating local government health insurance (BPJS) with apps or offering discounts for students. Mental health services are also provided at reduced rates for low-income individuals at risk of these issues. The result suggests that stressors from various job roles in the workforce or at home can contribute to challenges. Therefore, providers should not overlook specific occupations when offering support. Regulators also need to develop policies to enhance access to mental health services, specifically in remote areas. Leveraging the Internet can play an important role in extending mental health support to underserved regions, ensuring equitable access to resources.

Considering the extensive use of smartphones, regulators should adopt mental health services to ensure robust telecommunications support and implement privacy measures to protect users. As part of current enhancements, Artificial Intelligence inclusion is a great addition. By leveraging AI, apps can analyze behavioral patterns, interactions, and preferences to tailor interventions uniquely suited to needs. This includes dynamically adjusting the content, timing, and format of mindfulness exercises, therapy modules, or mood-tracking features based on real-time feedback and historical data. Furthermore, regulators can leverage the influence of social media on app adoption by promoting awareness of benefits through trusted influencers or public figures. These results can also be used to develop policies for promoting the use and recommendation of mental health apps. Additionally, policymakers are expected to develop incentives or certification programs for providers meeting certain standards of quality, effectiveness, and user safety. Providers who achieve certification or receive positive feedback are publicly recognized through official announcements or inclusion in government-sponsored mental health initiatives. Furthermore, partnerships between mental health app providers and community organizations, such as schools, workplaces, or healthcare facilities, facilitate the use of certified apps within the community and provide resources for users. A grassroots method is suggested for technology adoption through the promotion of community partnerships, crucial for building trust in digital healthcare solutions.

The result is consistent with several broader trends in digital health, specifically the increasing use of mHealth technologies to provide accessible, scalable, and user-friendly healthcare solutions. Globally, digital health platforms have become integral to healthcare delivery, particularly for services where the stigma of traditional therapy often limits access. The focus of this research on Indonesian mental health apps resonates with the wider movement towards democratizing healthcare through mobile platforms, as seen in many countries where mHealth is breaking down barriers related to geographic access, socioeconomic disparities, and social stigma. The insights are highly relevant to healthcare technology trends, emphasizing the need for personalization, inclusivity, and policy support to optimize mental health apps and other mHealth technologies for widespread use.

Conclusion

In conclusion, this research offered a comprehensive examination of mental health mobile apps to understand factors influencing adoption and recommendation intentions. A total of three out of the seven hypotheses examined were supported through testing, while the remaining four were unproven. The results showed that intention to use mental health apps was primarily influenced by perceived usefulness and social influence, rather than perceived ease, trust, stigma, or facilitating conditions. Perceived stigma did not significantly impact intention to use mental health apps, reporting the evolution of attitude towards mental health and the growing influence of social media in destigmatizing discussions surrounding well-being. Available mental health apps were observed to understand intention to use, and the results showed that affordability was a significant reason. A large proportion of participants found apps beneficial in recognizing symptoms at an early stage. Meanwhile, others appreciated the convenience of accessing mental health assistance remotely, specifically when faced with time constraints. Halodoc was reported as the most used app among respondents, offering mental health promotions, psychoeducation, monitoring, tracking, intervention, treatment, assessment, and prevention.

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Author Contribution Statement

The Author Contributions Statement should be uploaded in the Uploading Supplementary File section when submitting the manuscript.

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