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MOBILE MENTAL HEALTH UPTAKE AMONG EMERGING ADULTS: INTEGRATING HEALTH COMMUNICATION AND TECHNOLOGY ACCEPTANCE PERSPECTIVES

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ABSTRACT
This study identifies key factors influencing the use of mobile applications for mental well-being (m-Mental Health) among emerging adults. Integrating health communication and technology acceptance frameworks, it develops a new model to understand m-Health technology adoption, examining how privacy, safety concerns, and the app's commercial status affect user decisions. A mixed-methods design using a survey and experimental manipulation was employed to test the new model among adults aged 18-29. Conducting a PLS-SEM analysis of 229 observations, the study confirmed the model's solid predictive ability and supported the positive impact of social influence, self-efficacy, and health technology efficacy on attitudes toward m-Mental Health and usage intentions. However, stronger privacy and safety concerns negatively affected these attitudes, with the app's (non-)commercial status showing no significant impact.

KEYWORDS
mobile health applications • mental health • emerging adults • technology adoption • health communication

INTRODUCTION

Rising depressive symptoms and suicide rates among young people present significant public health challenges (Twenge, 2006; WHO, 2013), particularly as mental health disorders frequently begin between ages 18 and 25 (Public Health England, 2014; Stroud et al., 2013). Defined as emerging adulthood, this period of life involves significant independence and exploration (Arnett, 2000), expanded to ages 18-29 to account for varying socioeconomic and ethnic backgrounds (Arnett et al., 2011).

Although numerous recent studies point to a link between the use of new technologies and psychological problems (e.g., Coyne et al., 2018; Twenge et al., 2018; van Velthoven et al., 2018), the very same platforms can also serve as facilitators of positive health behaviour change (Mohr et al., 2013), reducing stigma and addressing barriers to accessing traditional prevention such as long waiting times for in-person consultations with professionals (Stiles-Shields et al., 2016; Watts & Andrews, 2014). Online mental health interventions and support platforms may be preferred to offline sources of help by young people for their anonymity (Wong et al., 2021) and rapid availability (Rickwood et al., 2016) and have the potential to successfully reduce problems such as depression or anxiety (Ahmedani et al., 2016; Mahoney et al., 2021), particularly in the early, less severe phases. Specifically, m-Mental Health apps (i.e., mobile apps developed to help tackle or prevent psychological problems; Apolinário-Hagen, 2017) based on proven methodologies such as mindfulness (Tan et al., 2022) are among the approaches most commonly highlighted for their potential to cost-effectively improve psychological wellness (Kumar et al., 2013; Price et al., 2014) with wide-reach prevention and treatment solutions (Sort, 2017). The past decade brought a boom in m-Mental Health apps for smartphones (Powell, 2016), with many commercial companies saturating the market with their own solutions for psychological well-being (Tucker & Goodings, 2015). The recent COVID-19 pandemic further boosted the potential of and need for accessible m-Mental Health as many emerging adults experienced significantly heightened levels of depression and anxiety while having limited access to face-to-face support (Wirkner & Brakemeier, 2024).

Despite the ongoing influx of novel m-Mental Health services and their undeniable potential (Harrison et al., 2011), young people's uptake of and engagement with mobile-based self-help interventions for mental health could be improved (Bear et al., 2024; Fleming et al., 2018) to widen their impact. Research into why individuals do or do not use specific health technologies often follows one of these two avenues: health communication, which examines attitudes, social norms, and self-efficacy (Fishbein & Ajzen, 1975); and studies building on the foundation of the Technology Acceptance Model

(TAM), which considers perceived usefulness and ease of use (Davis, 1986). Previous research employing the TAM and other related models pointed to efficacy beliefs (Holtz et al., 2023) or privacy concerns (Becker, 2016) as important determinants of the m-Mental Health use of young people, while health communication-oriented studies suggested the levels of convenience (Kornfield et al., 2023), personalization and technology (Koulouri et al., 2022) might be key drivers of the uptake of such apps among emerging adults. However, a comprehensive overview of young adults' decision-making factors regarding m-Mental Health adoption is lacking.

To fill this gap, the present study aims to test a comprehensive new model of m-Mental Health uptake determinants within the population of emerging adults. The model, which serves as the study's framework, is grounded in both digital health communication and technology acceptance research. The study integrates these approaches to form and test a model that also introduces a novel variable, Confidence in Health Technology, addressing privacy concerns within the sensitive context of mental health. While m-Mental Health apps offer continuous access and innovative features at lower costs than traditional care, their effectiveness is often questioned due to lack of supporting evidence (Hilty et al., 2017; Derks et al., 2017). A significant number of these apps lack empirical backing (Donker et al., 2013), and privacy concerns further complicate their adoption, as potential users might fear data misuse (Patel et al., 2018). This research therefore seeks to clarify the role of efficacy and privacy concerns in the adoption of digital mental health solutions which remains unclear despite previous research attempts (e.g., Apolinário-Hagen et al., 2016). More specifically, the present study aims to uncover whether the (non-)commercial nature of a m-Mental Health tool may inspire different levels of trust, which could subsequently interplay with the determinants of the tool's uptake among emerging adults.

After bridging the languages of technology acceptance research and health communication scholars, the study turns to the young population currently under an increasing danger of mental health issues, in striving to answer the following research question:

- *What are the determinants of the use of m-Mental Health among emerging adults?*
- *And to what extent do they differ for commercial and non-commercial applications?*

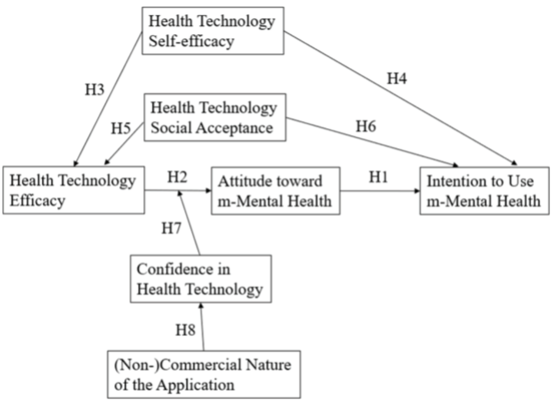
1. THEORETICAL BACKGROUND

To offer a synthesis of health communication and technology acceptance perspectives to explain the uptake of m-Mental Health, the present study extracts parts of several theories which are relevant to the field of mental health promotion, the mobile app technology, and the target group of emerging adults, and merges them into a new contextualized model. It employs a user-oriented approach to studying the selection and use of a particular medium, focusing on user characteristics and expectations rather than the features of a technology (Flanagin & Metzger, 2001).

This theoretical framework is structured around the model's main variables. While the Intention to Use m-Mental Health, Attitude toward m-Mental Health, Health Technology Efficacy, Health Technology Self-efficacy, and Health Technology Social Acceptance variables are defined by aligning the theoretical perspectives and glossaries of technology acceptance studies and health communication, Confidence in Health Technology and its accompanying (Non-)Commercial Nature of the Application variable are newly conceptualized based on recent empirical and industry insights specifically relevant for the context of m-Mental Health.

The relationships between the variables expected to influence emerging adults' intentions to use m-Mental Health apps, depicted in Figure 1, are proposed in the subsequent sub-chapters through a process of identifying overlaps and relevant complementary decision-making elements in prominent technology acceptance and health communication theories, while also considering relevant empirical learnings about e-Health, m-Health, and the uptake of other new technologies. Rather than following a perhaps more common sequential logic, the structure of this theoretical chapter (and consequently also its hypotheses) moves from the presumably core variables (intention to use, attitudes, efficacy) to variables of anticipated secondary importance (self-efficacy, social acceptance) before it introduces the new concepts (trust in the technology, influence of (non-)commercial origin).

Figure 1: Conceptual model. Source: Author



As Figure 1 illustrates, the proposed model hypothesizes that the intention to use mobile apps for mental health is directly associated with one's attitudes toward them, as well as with perceived social acceptance of and self-efficacy related to such apps. These two concepts are also anticipated to predict one's beliefs regarding m-Mental Health solutions' efficacy, or helpfulness, which is hypothesized to directly correspond with attitudes. This relationship is expected to be moderated by one's (privacy and safety-related) trust in mobile mental health apps, a concept hypothesized to be predicted by the commercial or non-commercial origin of an app.

For ease of reading, Table 1 below provides a glossary of the abbreviations for theories and concepts that will be used in the remainder of the present section.

Table 1: Glossary of abbreviations. Source: Author

TPB	Theory of Planned Behaviour
TAM	Technology Acceptance Model
HTE	Health Technology Efficacy
HTSE	Health Technology Self-Efficacy
HTSA	Health Technology Social Acceptance
CHT	Confidence in Health Technology

1.1. Attitude toward and intention to use m-Mental Health

Studies commonly assess the intention to adopt e-Health tools (e.g., Razmak et al., 2018) rather than actual usage (e.g., Or et al., 2008). While behavioural intention plays the role of the central dependent variable in both the Theory of Planned Behaviour (TPB; Fishbein & Ajzen, 1975) and the Technology Acceptance Model (TAM; Davis, 1986), the construct of attitude derives solely from the latter where it stands for an evaluative affect about a behavior (Fishbein & Ajzen, 1975) and is mostly determined by beliefs about the behavior's outcomes (Doğanyiğit, 2018). TPB suggests that alongside positive subjective norms and higher self-efficacy, a more favourable attitude boosts behavioural intentions (Fishbein & Cappella, 2006); hence the study's first hypothesis (H1):

- *H1: More favourable attitudes toward m-Mental Health positively predict the intention to use m-Mental Health apps.*

1.2. Health Technology Efficacy

Health Technology Efficacy (HTE) represents the perceived ability of a technology to treat or prevent health issues, specifically to improve mental health within the context of this study. HTE combines two concepts from health communication theory - behavioral beliefs and outcome evaluations, reflecting the perceived likelihood that using the technology will achieve health goals, which influences the persuasiveness of health messages (Fishbein and Cappella, 2006; Cismaru et al., 2009). It also encompasses technology acceptance aspects like perceived usefulness and performance expectancy (Luo & Remus, 2014; Razmak et al., 2018; Venkatesh et al., 2003).

Addressing theoretical inconsistencies in how perceived usefulness affects technology use (Davis, 1986; Venkatesh & Bala, 2008), this study employs the Combined Technology Acceptance Model and Theory of Planned Behaviour (C-TAM-TPB; Venkatesh et al., 2003) to examine how health technology efficacy predicts attitudes towards m-Mental Health; hence the second hypothesis (H2):

- *H2: Health Technology Efficacy positively predicts more favourable attitudes toward m-Mental Health.*

1.3. Health Technology Self-Efficacy

Health Technology Self-Efficacy (HTSE) reflects an individual's perceived ability to use specific health technologies effectively, theoretically aligning with Fishbein & Capella's (2006) understanding of self-efficacy as perceived barriers to a target behavior, as well as with Bandura's (1986) concept of self-efficacy tailored to domain-specific actions. Within the context of this study, HTSE encapsulates both one's perceived ability to use technologies to improve their health (Ramzak et al., 2018) and perceived ability to use mobile apps (i.e., mobile self-efficacy; Doğanyiğit, 2018), specifically in mental health.

Although previous m-Health research has shown that perceived ease of use can boost perceived usefulness and indirectly enhance behavioral intentions through perceived usefulness (Hung & Yen, 2012), Holden and Karsh's (2010) review of more than 20 technology acceptance-driven e-Health studies suggests that its direct influence may limited. To inspect HTSE's relationships with both HTE and intention to use m-Mental Health, this study tests two separate hypotheses:

- *H3: Health Technology Self-Efficacy positively predicts one's perceived Health Technology Efficacy.*
- *H4: Higher Health Technology Self-Efficacy positively predicts one's intention to use m-Mental Health.*

1.4. Health Technology Social Acceptance

Health communication theory regards social norms as one of the determinants of health-related behavioural intentions, whereby social norms represent the observed behaviours and presumed normative opinions of one's important others (Fishbein & Ajzen, 1975; Fishbein & Cappella, 2006). Technology acceptance scholars use the term subjective norms to describe a person's beliefs about whether or not their important others want them to use the technology of interest (Venkatesh & Davis, 2000). The width of the Health Technology Social Acceptance (HTSA) concept this study proposes rests more on the health communication approach; it combines both descriptive (i.e., observed behaviours) and injunctive norms (i.e., assumed opinions; Prentice, 2008) to capture the normative influence, as well as the sociological factor of an increased awareness of m-Mental Health apps as proposed by Razmak et al. (2018).

Prior research in web-based e-Health (Ryan et al., 2017), m-Health (Doğanyiğit, 2018), and technology acceptance studies (Venkatesh et al., 2003) provides empirical grounds to assume that the degree to which one believes other people use and approve of using a mobile app for mental health could positively predict behavioural intentions, and perhaps even outweigh any negative beliefs regarding the efficacy or ease of use of m-Mental Health. However, similarly to HTSE, technology acceptance studies have also found strong links between social influence and perceived efficacy (Buccoliero & Bellio, 2014; Venkatesh & Bala, 2008); hence there are two hypotheses reflecting the role of social influence:

- *H5: Health Technology Social Acceptance positively predicts one's perceived Health Technology Efficacy.*
- *H6: Health Technology Social Acceptance positively predicts one's intention to use m-Mental Health.*

1.5. Confidence in Health Technology

Van Schaik et al. (2004) emphasize that balanced models assessing both benefits and risks enhance the predictive power in technology acceptance studies. When risks such as data privacy concerns are evident, trust in technology decreases, potentially hindering e-Health adoption (Sillence & Briggs, 2015; Beldad et al., 2010). Empirical evidence shows that credibility and accuracy concerns significantly influence trust in online health resources (Montagni et al., 2016; Lee & Cho, 2016; Musiat et al., 2014; Stiles-Shields et al., 2017). This study introduces Confidence in Health Technology (CHT) to encapsulate such worries.

Evidence suggests that many m-Mental Health apps lack empirical support, raising concerns about their effectiveness and safety (Donker et al., 2013; Hale et al., 2015; Hilty et al., 2017; Lal & Adair, 2013). In this highly sensitive context (Anderson & Agarwal, 2011), numerous studies have shown that data privacy and security concerns can reduce users' confidence in an app, thus decreasing the app's uptake (e.g., Gulliver et al., 2015; Young, 2005; van Velthoven et al., 2018). Together with the worries about treatment accuracy, the degree to which a person believes their highly confidential mental health input will be safely encrypted and secured (Kumar et al., 2013) and not disclosed to any third parties without their explicit consent constitutes a general sense of trust in m-Mental Health. Since the potential ineffectiveness or even harmfulness of a mental health app is directly linked to perceived efficacy, and privacy concerns were found to be closely linked to perceived usefulness by Chung et al. (2010), this study hypothesizes a moderating role for CHT:

- *H7: Confidence in Health Technology positively moderates the relationship between Health Technology Efficacy and attitude toward m-Mental Health.*

1.6. (Non-)commercial nature of an app

Users often have to rely on heuristic cues such as provider credibility to assess an app's trustworthiness (Briggs et al., 2002; Petty & Cacioppo, 1986). As noted by Pornpitakpan (2004), messages from more credible sources typically have a larger impact on the attitude and behaviour of the receiver. Building on Gulliver et al.'s (2010) suggestion that young people are strongly influenced by the credibility of mental health service providers, this study aims to uncover if a similar effect exists for commercial and non-commercial m-Mental Health apps.

When being unable to map trust-forming factors such as information quality, usability, or popularity of a particular app (Hale et al., 2015), users have no other choice but to look for heuristic indicators of quality, security, and privacy (Sillence & Briggs, 2015), including organization logos or accreditation endorsements by governmental entities (Batterham et al., 2015). Although there is no guarantee that m-Mental Health apps adhere to evidence-based standards (Luxton et al., 2011), non-commercial apps often align with rigorous data privacy and security norms, such as the European Commission's (2016) Voluntary Code of Conduct. In contrast, commercial apps may lack comprehensive quality and safety frameworks (Mental Health Commission of Canada, 2014). Thus, this study hypothesizes that non-commercial apps are trusted more:

- *H8: Confidence in Health Technology is greater for non-commercial m-Mental Health apps compared to commercial ones.*

1.7. The present study

To summarize, the theoretical framework was established primarily via a merger of concepts and terminology from key theories in technology acceptance and health communication studies but also supported by insights from relevant empirical e-Health and m-Health research. The intention to use mobile apps for mental health is presumably positively predicted by how much one believes in their ability to use an m-Mental Health solution, how socially accepted they think it is, and how positive their attitudes toward it are. The attitudes are hypothesized to be more positive if one finds the m-Mental Health solution helpful, which is expected to be more likely if they also find it socially accepted and if they believe they themselves can use it well. The extent to which stronger efficacy beliefs predict more positive attitudes is anticipated to be higher with greater confidence in an app for mental health, which is hypothesized to decrease if the app in question is commercial, compared to a non-profit application.

The primary objective of this study is to test this comprehensive model in the context of mobile applications for mental health and with emerging adults, a population segment that could potentially greatly benefit from improved adoption rates of effective m-Mental Health solutions. Another key target contribution of the study lies in the investigation of the impact of privacy and safety-related trust and the extent to which such trust among young adults is or is not determined by (non-)commercial origins of mobile apps in the highly sensitive area of mental health.

To complete these research objectives, a survey study with an experimental vignette element was conducted. Based on previous empirical research, the study anticipated potential confounding effects of age (e.g., Chung et al., 2010; Hung & Yen, 2012), sex (e.g., Cho et al., 2014; Venkatesh et al., 2003), education (e.g., Cho et al., 2014), health technology awareness (e.g., Apolinário-Hagen 2017), e-Health literacy (e.g., Apolinário-Hagen 2017; Khazaal et al., 2008), and previous health technology use (e.g., Apolinário-Hagen 2017; Venkatesh et al., 2003). Additionally, following the example of Fonseca et al. (2016), the current state of mental well-being – one's ability to cope with common stress, be productive and contribute to their community (World Health Organization, 2014) – was also included as a control variable.

2. METHODS

The forthcoming sections depict the survey research approach of the present study, explaining the operationalization of the main variables, sampling, experimental vignette technique, and other important characteristics of the research method.

Cross-sectional survey design was chosen for its suitability for measuring beliefs, attitudes, and intentions of a large number of people (Bryman, 2012). Moreover, the confidential nature of an individually administered, Web-based, self-completion questionnaire should encourage the openness of respondents even for questions regarding highly sensitive topics such as one's mental health (Fowler, 2014).

2.1. Participants

Due to the lack of a sampling frame, convenience sampling was adopted to recruit participants aged 18-29 using social media posts and private messages. A charitable incentive was employed to counter the growing survey fatigue (Fowler, 2014).

The data collection was conducted between April 28 and May 9, 2019. After deleting 11 responses by ineligible participants (2 did not own a smartphone, 9 had participated in the development of an m-Mental Health app) and 2 responses by people aged higher than 29, the final sample, N = 229, was 52% female, with age distribution quite diversely between 19 and 29 (minimum 19, median 23, maximum 29, SD = 1.82). The respondents lived predominantly in Czechia and the Netherlands and reported diverse educational backgrounds and employment statuses, although the majority were university-educated (61.1%). In total, 27 different countries of residence were reported. Nationality was not monitored. All the respondents completed the survey in English.

Table 2: Demographics of the sample. Source: Author

Characteristic	(N = 229); M (SD) or %
Sex	
Male	48
Female	52
Age	23.40 (1.82)
Country of Residence	
Czech Republic	57
Netherlands	21.5
Other (25 different countries)	21.5
Education	
High school	38.9
University degree	61.1
Professional status	
Unemployed or full-time student	33.6
(Self-)employed part-time	03.9
(Self-)employed part-time and student	41.9
(Self-)employed full-time	20.5

2.2. Procedure

The independent variable encapsulating the (non-)commercial nature of m-Mental Health was included in the survey via an experimental manipulation. Experimental vignettes are used in survey research to elicit respondents' opinions or sentiments about a certain situation (Atzmüller & Steiner, 2010) and to study the target population's decision-making (Evans et al., 2015). After reading short general definitions of m-Mental Health apps and mental well-being, the respondents were randomly assigned to read one of two vignettes – descriptions of either a non-commercial (condition A, N = 115) or commercial (condition B, N = 114) fictional m-Mental Health app (see Figure 2) – and keep it in mind while answering the following set of questions about their opinions and beliefs regarding m-Mental Health apps. The controlled random assignment with the goal of even distribution was conducted automatically by the *Qualtrics* survey software.

Figure 2: Randomly assigned survey vignettes. Source: Author

Example A – non-commercial app

Mindiooo is a **non-commercial smartphone app** developed by a team of university researchers. The app is freely available via App Store and Google Play. Mindiooo is intended to **increase your overall mental wellness** and **help you manage your daily stress** or any negative thoughts **without any contact with a therapist**. Based on the results of an intake psychological questionnaire, Mindiooo provides a user with relevant mental health information and training tailored to their needs. Moreover, the app enables users to keep track of their moods and thoughts, as well as to improve their stress-coping through a series of guided exercises.

Example B – commercial app

Mindiooo is **a commercial smartphone app** developed by O-care, a tech company designing digital healthcare products. You can download the app via App Store or Google Play and use all the main features for free, with optional paid-for add-ons. Mindiooo is intended to **increase your overall mental wellness** and **help you manage your daily stress** or any negative thoughts **without any contact with a therapist**. Based on the results of an intake psychological questionnaire, Mindiooo provides users with relevant mental health information and training tailored to their needs. Moreover, the app enables users to keep track of their moods and thoughts, as well as to improve their stress-coping through a series of guided exercises.

Following the vignette element, the scales for main variables were presented in random order, except for the instruments measuring attitude and intention which were placed at the end of this block, with items randomized within each scale. After completing the main section, participants provided control variable data and demographics before being debriefed and voting for a charity to receive a donation from the study's author.

In line with research ethics standards, the respondents first briefly informed about the study and its approval by the Ethics Review Board of the University of Amsterdam and reassured of the study's confidentiality. Informed consent was collected while highlighting the unlimited opt-out possibility.

The survey was piloted on a small convenience sample (N = 11) of emerging adults to refine clarity before broader distribution.

2.3. Main variables

(Non-)commercial nature of an app
Participants were instructed to keep their commercial or non-commercial app example in mind while answering the ensuing questions. Manipulation of the app characteristics was based on a review of both commercial and non-commercial m-Mental Health apps by Anthes (2016). The app and company names were fabricated.

Scale validation
All the main latent variables were measured with multiple items using a 7-point Likert scale (*1 = Completely disagree, 7 = Completely agree*) and answered by all respondents, *N = 229*. All survey questions were mandatory, preventing item-level non-response. After recoding negatively worded items, the reliability of all latent variables was tested, and their validity inspected using exploratory factor analyses with a principal-axis factoring extraction.

Health Technology Efficacy
To measure this newly conceptualized variable that encapsulates the perceived ability of a specific technology to help people improve their health, a four-item indicator was developed, with each item referring to one specific potential outcome of using m-Mental Health: effective management of mental well-being, prevention of mental health issues, convenient access to help regarding mental health, and guidance in self-improving mental health. Respondents were asked to indicate to what extent they agree or disagree with statements such as ***"m-Mental Health apps could help me effectively manage my mental well-being"***, which were based on the original perceived usefulness operationalization (Davis, 1989) and inspired by similar items contextualized in mental health (Apolinário-Hagen et al., 2018). A mean scale computed to measure this composite latent variable reported good reliability, Cronbach's alpha = .82. On average, the sample scored slightly higher on Health Technology Efficacy scale than the mid-score (M = 4.68, SD = 1.11).

Health Technology Self-Efficacy
Three items largely derived from the study by Rahman et al. (2016) and inspired by the perceived ease of use measures of Razmak et al. (2018) were used to capture one's beliefs about their ability to effectively use m-Mental Health apps. Specifically, the respondents indicated the extent to which m-Mental Health apps are (or would be) ***"easy to use"*** for them,

if they felt ***"comfortable using them"***, or if they felt ***"worried about pushing the wrong button and putting their mental health at risk"***. The instrument was found to have low reliability in this sample, Cronbach's alpha = .55. The mean scale (M = 5.18, SD = 1.10) seemed to be in line with the presumption that mobile app self-efficacy would be rather high in a young population (Cho et al., 2014).

Health Technology Social Acceptance

Following Fishbein and Ajzen (2010), as well as Razmak et al. (2018), this variable comprised injunctive ***("Most people who are important to me (would) approve of me using of an m-Mental Health app.")***, as well as descriptive norms (***"Many people similar to me use an m-Mental Health app."***) surrounding the use of health technologies. While the injunctive norm scores were nearly one point above the mid-point (M = 4.99, SD = 1.41), the sample reported a relatively low observability of the use of m-Mental Health among people similar to them (M = 2.82, SD = 1.44). The two items in this scale were weakly but significantly correlated, r = .19, p = .003. The mean scale averaged slightly lower than the mid-point (M = 3.10, SD = 1.10).

Confidence in Health Technology

This variable considered potential disadvantages of using m-Mental Health apps and focused on safety and privacy concerns. Its two privacy-related items were adapted from the MUIPC (Mobile User's Information Privacy Concerns) scale (Xu et al., 2012) and covered two factor sub-scales with the highest reliability in the study by Bol et al. (2018), namely perceived intrusion (***"As a result of me using an m-Mental Health app, others might know more about me than I am comfortable with."***) and unauthorized secondary use of personal data. The other two items followed the attitude-measuring scale of Rahman et al. (2016) and covered safety concerns through negative outcome beliefs about mobile apps providing incorrect and potentially harmful mental health advice, and about m-Mental Health use potentially creating negative mental health impact. All four items were negatively worded, meaning higher scores indicated greater concern about health technology. To ensure that higher scores represented greater Confidence (i.e. lower concern) in Health Technology, all items were reverse-coded prior to analysis. The Cronbach's alpha of .64 indicated rather low reliability of the mean scale. Respondents reported on average a slightly higher Confidence in Health Technology than the mid-score, M = 4.29, SD = 1.16.

Attitude toward m-Mental Health

Respondents' attitude toward m-Mental Health was measured using a three-item scale. Two rather general items were adapted from Schnall et al. (2018) into statements about m-Mental Health apps potentially improving people's lives and encouraging people, by virtue of their anonymity, to use them openly and honestly for mental health prevention or treatment. The third item, more reflective of the specifics of m-Mental Health, was added from Apolinário-Hagen et al. (2018): "I think m-Mental Health apps are a positive addition to the variety of mental health self-help tools available." The mean scale reported slightly low yet still acceptable reliability, Cronbach's alpha = .72. On average, the sample reported a rather positive attitude compared to the mid score, M = 5.42, SD = .98.

Intention to use m-Mental Health

In line with Fishbein and Ajzen (2010), behavioural intention was measured with one item reflecting recommendations to close ties (*"How likely is it that you would recommend one of your friends or family members to use an m-Mental Health app?"*), M = 4.11, SD = 1.86, and the other focused the respondents' own use, M = 4.26, SD = 1.80. Each item was accompanied by an example situation of encountering mental health difficulties (*"… going through mentally and emotionally challenging times or start feeling symptoms of some psychological problems…"*) adapted from Fonseca et al. (2016). On average, the sample reported behavioural intentions slightly higher than the mid-score (M = 4.19, SD = 1.69). The two items of this instrument were strongly correlated, $r = .70$, $p < .001$.

2.4. Control variables

e-Health literacy was measured with three items on a 5-point Likert scale adapted from Razmak et al. (2018) who originally derived them from the eHEALS instrument, developed and validated by Norman and Skinner (2006). The statements were about knowing *"how to find helpful health resources on the Internet"* and correctly interpret and use this information. The mean scale (M = 3.42, SD = .86) reported fairly good reliability, Cronbach's alpha = .78, and showed that the sample had a slightly higher e-Health literacy than the mid-score.

Table 3 summarizes the distribution of the awareness and use of m-Mental Health apps alongside the relevant survey items and possible answers, showing that most respondents did not know any specific m-Mental Health apps and an overwhelming majority had no experience with using them.

Table 3: Use and awareness of m-Mental Health apps. Source: Author

Characteristic	(N = 229); n %
Awareness ("Do you know any m-Mental Health apps?")	
Yes	54 (23.6)
No	147 (64.2)
Not sure	28 (12.2)
Use ("Have you ever used any kind of...?", "During the past 6 months, how frequently...during a regular week?")	
Never	
Yes, but not in the past 6 months	191 (83.4)
Once per week	14 (6.1)
Multiple times per week	10 (4.4)
Once each day	1 (0.4)
Don't know	1 (0.4)

The respondents' current mental well-being was measured with the seven-item Short Warwick-Edinburgh Mental Well-being Scale (Stewart-Brown et al., 2011), asking respondents to indicate how often (in the past two weeks) they felt positive about the future and their ability to deal with problems, think clearly, and make up their own mind, and how often they felt useful, relaxed, and close to other people on a 5-point Likert scale (1 = None of the time, 5 = All of the time). In line with the official guide to using this instrument (NHS Health Scotland et al., 2006), a sum scale was computed with fairly good reliability, Cronbach's alpha = .79. On average, in comparison with scores published in the instrument's guide, the sample reported a rather low level of mental well-being, M = 24.21, SD = 4.24.

Age, biological Sex, and the highest level of education were collected at the end of the survey together with the rest of the demographics.

2.5. Statistical analysis

Structural equation modeling (SEM), specifically the variance-based partial least squares technique (PLS-SEM), was employed for its suitability for complex models with latent constructs, smaller sample sizes, and non-normal data (Hair et al., 2014; Lowry & Gaskin, 2014). Contrary to a regression approach, PLS-SEM runs equations simultaneously and interdependently to provide a more accurate picture of complex models such as the one proposed in this study.

Data preparation and exploratory analyses were conducted using SPSS 26 by IBM, and the model was tested with *SmartPLS 3*. Initially, each control variable was tested separately to identify significant confounders. The final model addressing the study's hypotheses only incorporated control variables with significant effects.

3. RESULTS

PLS-SEM was employed after testing several regression assumptions. Multivariate normality, lack of multicollinearity (VIF 1.17-2.06), absence of autocorrelation (Durbin-Watson 2.00), homoscedasticity, and linear relationships were verified. Harman's single factor test indicated no significant common method bias, with a single factor explaining 31.28% of the variance (Podsakoff et al., 2003).

The social acceptance and behavioural intention constructs were labelled as formative in ***SmartPLS 3*** due to their composite nature. Therefore, regular PLS algorithm and bootstrapping were chosen for the analyses over the Consistent algorithm, which is intended for fully reflective models.

Formative constructs for social acceptance and behavioral intention necessitated using the regular PLS algorithm over the Consistent algorithm. Several control variables showed significant effects on the model outcomes, particularly e-Health literacy and frequency of m-Mental Health usage being positively linked to attitudes and intentions respectively, while previous usage and knowledge were negatively linked to Confidence in Health Technology.

Model fit was assessed via the PLS algorithm and bootstrapping, with an SRMR of .065 indicating good fit. The model accounted for 46.3% of variance in intention to use m-Mental Health ($R^2 = .46$, $p < .001$), 56.1% in attitude toward m-Mental Health ($R^2 = .56$, $p < .001$), and 33% in Health Technology Efficacy ($R^2 = .33$, $p < .001$), but only 6.4% in Confidence in Health Technology ($R^2 = .06$, $p = .071$).

Table 4: PLS-SEM path analysis results summary. Source: Author

Path[1]	β	p	t	R^2 (p)	Adjusted R^2 (p)
ATT → BI	.42	.000***	6.17	0.46 (.000)	0.46 (.000)
HTSA → BI	.10	.133	1.50		
HTSE → BI	.26	.000***	4.27		
USE_1pW → BI	.11	.000***	3.50		
HTE → ATT	.56	.000***	10.30	0.56 (.000)	0.56 (.000)
EHL → ATT	.11	.034*	2.13		
Moderation	-.12	.008**	2.68		

1 *ATT:* Attitude toward m-Mental Health; *BI:* Intention to Use m-Mental Health; *HTSA:* Health Technology Social Acceptance; *HTSE:* Health Technology Self-Efficacy; *HTE:* Health Technology Efficacy; *EHL:* e-Health Literacy; *CHT:* Confidence in Health Technology; *(Non-)Com:* (Non-)Commercial Nature of an App; *USE_1pW:* used an m-Mental Health app once per week in the past six months; *USE_Never:* never used an m-Mental Health app; *USE_NotIn6m:* did not use an m-Mental Health app in the past six months; *AWA_Yes:* knows some specific m-Mental Health apps

HTSA → HTE	.25	.000***	3.87	0.33 (.000)	0.33 (.000)
HTSE → HTE	.43	.000***	6.81		
(Non-)Com → CHT	.02	.812	0.24	0.06 (.071)	0.05 (.245)
USE_Never → CHT	-.24	.001**	3.24		
USE_NotIn6m → CHT	-.16	.037*	02.9		
AWA_Yes → CHT	-.17	.020*	2.34		

**p < .05, **p < .01, ***p < .001*

The summary of hypotheses testing is provided in Table 5. The relationship between attitude toward m-Mental Health and intention to use such apps was found to be highly significant, $\beta = .42$, $t = 6.17$, $p < .001$, thus confirming H1. Similarly, the significant strong association between Health Technology Efficacy and attitude toward mobile mental health provided support for H2, $\beta = .56$, $t = 10.30$, $p < .001$.

Furthermore, confirming H3 and H4 respectively, Health Technology Self-Efficacy had a significant positive relationship with Health Technology Efficacy, $\beta = .43$, $t = 6.81$, $p < .001$, as well as with the behavioural intention to use m-Mental Health, $\beta = .26$, $t = 4.27$, $p < .001$. Similarly, Health Technology Social Acceptance had a significant positive relationship with Health Technology Efficacy, confirming H5. On the other hand, Health Technology Social Acceptance was not significantly related to the intention to use m-Mental Health, $\beta = .10$, $t = 1.50$, $p = .133$; therefore, H6 was not supported.

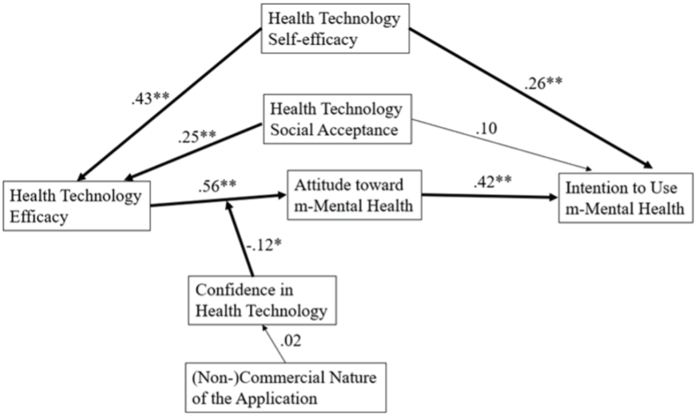
Table 5: Summary of hypotheses testing. Source: Author

Hypothesis	**Relationship tested**[2]	**β**	**p**	**Results**
H1	ATT → BI	.42	.000	Supported
H2	HTE → ATT	.56	.000	Supported
H3	HTSE → HTE	.43	.000	Supported
H4	HTSE → BI	.26	.000	Supported
H5	HTSA → HTE	.25	.000	Supported
H6	HTSA → BI	.10	.133	Not supported
H7	Moderation	-.12	.008	Not supported
H8	(Non-)Com → CHT	.02	.812	Not supported

2 *ATT:* Attitude toward m-Mental Health; *BI:* Intention to Use m-Mental Health; *HTSA:* Health Technology Social Acceptance; *HTSE:* Health Technology Self-Efficacy; *HTE:* Health Technology Efficacy; *EHL:* e-Health Literacy; *CHT:* Confidence in Health Technology; *(Non-)Com:* (Non-)Commercial Nature of an App; *USE_1pW:* used an m-Mental Health app once per week in the past six months; *USE_Never:* never used an m-Mental Health app; *USE_NotIn6m:* did not use an m-Mental Health app in the past six months; *AWA_Yes:* knows some specific m-Mental Health apps

Figure 3 offers a visual depiction of the main results by showing path coefficients along with their level of significance.

Figure 3: Conceptual model with main results. Source: Author



$^{*}p < .01$, $^{**}p < .001$

The moderating relationship between Confidence in Health Technology and Health Technology Efficacy in predicting the attitude toward m-Mental Health was found to be significant, β = -.12, ***t*** = 2.68, ***p*** = .008. However, contrary to H7's predicted positive direction, the negative beta-value revealed that increased Confidence in Health Technology in fact reduced Health Technology Efficacy's predictive power on attitudes towards m-Mental Health.

Finally, the effect of the (Non-)Commercial Nature of an App was insignificant, β = .02, ***t*** = 0.24, ***p*** = .812, hence no support was found for H8.

DISCUSSION

This study explores the drivers of m-Mental Health uptake among emerging adults. It strives to contribute to both academic and practical developments in this promising area of mental health treatment and prevention by generating a comprehensive quantitative insight into the factors related to emerging adults' intentions to use or not use m-Mental Health tools. To complete this objective, the study bridges theoretical models and concepts from technology acceptance and health communication studies, creates a new complex model grounded in the context of mental health and mobile health applications, and tests the model with a population which could largely benefit from more widespread adoption of m-Mental Health – young adults. Another important objective of the study was to investigate the potential moderating role of privacy and safety concerns about m-Mental Health, which were hypothesized to be higher for commercial applications.

The proposed model accounted for significant variance in usage intentions and the significant paths were in line with both theory and previous studies. The findings suggest that when emerging adults are to decide whether or not to use an app to prevent or improve their mental well-being, several factors come into play: Perceived efficacy of the app, positively linked with one's self-efficacy (H3) and social influence (H5), predicts behavioural intention through the attitude toward m-Mental Health (H2 & H1), while health technology self-efficacy is also directly related to the intention to use such an app (H4). In other words, a young adult's beliefs about the helpfulness of an m-Mental Health app positively predict the young adult's intention to use the app through their attitude toward it. These helpfulness beliefs are more positive if the young adult perceives the app as commonly used by others and if they think they could easily use it for their mental health benefit, which is a decision-making factor that is also directly linked to intentions to use the app.

Moreover, a significant moderation by the newly developed Confidence in Health Technology variable was found, but its direction was the opposite than hypothesized: Higher trust in m-Mental Health predicted a weaker relationship between the respondents' beliefs about the efficacy of m-Mental Health and their attitudes toward such tools. The unexpected direction of the moderation suggests need for more thorough theoretical exploration in order to accurately place this novel variable in such a complex model. With stigma- and privacy-related fears being identified as major obstacles to young people's help-seeking regarding their mental health in prior research (Kim et al., 2022; Mitchell et al., 2017), the role of emerging adults' trust in m-Mental Health apps in their uptake of such tools ought to be investigated further.

Interestingly, the study failed to deliver supportive evidence for the assumed effect of the (non-)commercial nature of an m-Mental Health app on the privacy and safety concerns it arouses in emerging adults. Given the predominantly cross-sectional nature of the data, this was the only causal relationship tested in the model. By not supporting it, this study disconfirmed the assumption that young people would be less confident in the app if they were confronted with signs of its profit-driven origin. However, the lack of a pre-test and attention check made it impossible to fully verify the effectiveness of the manipulation - a failed manipulation can be deemed a quite likely explanation of the lack of significant results in this part of the model.

One possible cause of an unsuccessful manipulation could be the design which relied on the respondents actively thinking about the randomly assigned vignette with a specific example app throughout the survey while answering questions about m-Mental Health apps in general. Another viable explanation could be that the negatively worded survey items did not accurately capture the positively worded concept of Confidence in Health Technology, i.e. that the lack of concerns about m-Mental Health might not necessarily imply the presence of trust in m-Mental Health.

A major limitation was the participants' general unfamiliarity with specific m-Mental Health apps, which makes the findings bound to apps designed to increase overall mental wellness through daily stress self-management (based on the app descriptions provided in the survey). Another important limitation is the rather low reliability of many of the scales, which could have impacted the results. The most likely reason behind the low reliability is inadequate scale length, caused by the combination of a complex model, accompanied by several control variables, and the study's ambition to obtain a relatively high number of online respondents from a population which could be easily deterred by a very extensive survey. The short scale length might have also caused low internal consistency, as many of the variables were newly created as a merger of overlapping yet still distinctive concepts. While efforts were made to ensure content validity through careful, theory-informed item selection, the ad hoc nature of scale development may have contributed to lower internal reliability. It is desirable for future research to develop and validate more robust multi-item scales with higher reliability that would enable a more confident interpretation of the findings.

Identifying key uptake drivers offers practical value for m-Mental Health practitioners aiming to improve app engagement among young adults. Despite limited app awareness, participants exhibited readiness to use m-Mental Health solutions. Identifying the most influential uptake factors may help both commercial and non-commercial practitioners translate the past decade's boom in m-Mental Health (Powell, 2016) into actual usage growth. However, because this study analyzed data collected in 2019 and the m-Mental Health industry has substantially transformed since then (Ding et al., 2023), the findings of this study should be read and applied with caution.

Future studies should focus on in-depth qualitative, as well as follow-up quantitative investigations into privacy and safety concerns, potentially redefining how these factors are modeled in health technology research and practice. It would also be interesting to assess the role of privacy concerns in the uptake of other highly confidential e-Health areas such as women's health apps.

CONCLUSION

Despite being often listed among the main contributors to the deteriorative mental well-being of emerging adults nowadays, smartphones offer vast potential in the field of preventing or treating mental health issues. The study advanced m-Mental Health research and practice by delivering a comprehensive exploration of uptake determinants and introducing a novel variable, Confidence in Health Technology. A PLS-SEM analysis of 229 online survey responses by adults aged 19-28 reported solid predictive power of the newly developed model, grounded in both technology acceptance and health communication theories. The findings can inform the efforts of m-Mental Health providers to utilize the potential of the generally positive attitudes of emerging adults toward apps for mental well-being. Future research should provide in-depth exploration of the role of privacy and security concerns to shed more light on the various roles they might play in m-Mental Health uptake and other highly sensitive areas of e-Health.

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