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THE FACTORS INFLUENCING THE ADOPTION OF MENTAL HEALTH APPLICATIONS

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ABSTRACT

Mental illnesses are a growing issue nowadays. According to the World Health Organization, the gap between the need for treatment for mental disorders and the accessibility of treatment is widening. One potential solution to making treatment more accessible is mental health apps. In recent years, mental health apps have been essential tools for providing healthcare services at an affordable cost. Despite the effectiveness and benefits of new technologies, the uptake of these apps remains a challenge, especially in Europe compared to the US. This study aims to investigate the factors that influence the adoption of mental health apps. To this end, a conceptual framework based on the UTAUT2 and the HBM was developed, which was tested using a quantitative study. For operationalization, 309 participants aged between 18 and 70 years old were collected through an online questionnaire. The results show that all of the tested factors impact behavioral intention. The determinants that stand out are performance expectancy, social influence, hedonic motivation, and cues to action, which significantly affect the behavioral choice to use a mental health application. The findings lead to implications for promoting and developing greater adoption of mental health apps.

KEYWORDS

Mental health applications; Mental health apps; Technology adoption; UTAUT2; HBM

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LIST OF ABBREVIATIONS AND ACRONYMS

TAM	Technology acceptance model
UTAUT	Unified theory of acceptance and use of technology
HBM	Health belief model
PE	Performance expectancy
EE	Effort expectancy
SI	Social Influence
HM	Hedonic motivation
PSE	Perceived severity
PSU	Perceived susceptibility
SE	Self-efficacy
CA	Cues to action
BI	Behavioral intention
mHealth	Mobile Health
SPSS	Statistical Package for the Social Science
WHO	World Health Organization
NIMH	National Institute of Mental Health

1. INTRODUCTION

Mental illnesses such as anxiety, depression, social anxiety, or substance abuse are a growing problem in our society. Already, between 35% and 50% of people with mental illness do not receive treatment because suitable treatment places are scarce (WHO, 2012).

This each trend is leading to a growing range of solutions. Internet-based therapy programs are clinically effective in treating various mental disorders. One advantage of online therapy is its time and cost-efficiency. The amount of time clinicians spend with each client is much less than in regular face-to-face treatment, which means more clients can be served than in a traditional therapy setting (Forona, MacWilliams & McArthur, 2016).

1.1. RESEARCH PROBLEM

Despite compelling evidence of mental health apps' effectiveness and market growth (Marshall et al., 2020), the adoption of these new technologies is still relatively low. Mental health apps are not a routine part of mental health care, nor has a mental health platform been widely adopted by consumers (Bovin et al., 2019).

Having this in mind, it is essential to understand the factors that influence user adoption of mental health applications and derive suggestions for further improvement. Several theories and models have been presented to explain technologies' adoption and long-term use (Gupta et al., 2008). Although there is much research in technology acceptance and adoption, previous research suggests that different technologies have diverse factors that influence user behavior, meaning that the determinants that influence user acceptance of mental health apps may not be consistent with other technologies (Gupta et al., 2008).

More recent, unified models may explain more of the variance in adoption and use. Still, most of this literature has traditionally focused on adopting technology in a substantially different context than mental health treatment in the workplace (Connolly et al., 2018).

1.2. CONTEXT OF THE STUDY

Today smartphones play a central role in our lives. According to Statista, the current number of smartphone users worldwide is 6.378 billion, which means that 80.69% of the world's population owns a smartphone. This figure is significantly higher than in 2016, when there were only 3.668 billion users, corresponding to 49.40% of the world's population (Statista, 2021).

Due to the proliferation of smartphones and the Internet, the market for mental health apps has grown continuously in recent years and will continue to do so (MarketsandMarkets, 2020). Mental health apps target various mental disorders and vary in design and functionality. According to the NIMH (2017), they can be classified into six categories based on their functionality: Self-management, cognition enhancement, skills training, social support, symptom tracking, and passive data collection. Mental health apps span all stages of clinical care provision, including immediate crisis intervention, prevention, diagnosis, primary treatment, supplement to in-person therapy, and post-treatment condition management. Research suggests that mental health apps can positively influence a wide range of health conditions (Marcollino et al., 2018).

In addition, mobile health devices and apps have the potential to save resources, reduce the cost of care, increase outreach, and improve health outcomes (Ventola, 2014). Mental health apps offer even more significant potential, particularly for mental health conditions where stigma and lack of independence are additional barriers to seeking treatment (Bovin et al., 2019). According to a report by UnivDatos, there are currently over 300,000 health apps in mobile app stores worldwide, with the mental health segment representing the most significant growth market. It is forecasted to grow at a

CAGR of 20.5% from 2021 to 2027, reaching USD 3.3 billion by 2027. The COVID-19 pandemic has given a sudden boost to the digital market. The US's top 20 mental health apps reached 4 million first-time downloads in April 2020. That is up 29% from 3.1 million in January (UnivDatos, 2021).

Despite the positive outlook, there are differences in market growth. While North America dominates the mental health market, the share of Europe, Asia Pacific, and Latin America remain comparatively lower (MarketsandMarkets, 2020).

1.3. RESEARCH PURPOSE AND OBJECTIVES

The goal of this study is to analyze and understand the factors that influence the adoption of mental health apps. A better understanding of people's perspectives on mental health apps is needed to support the development of targeted implementation strategies and platform changes that ultimately promote adoption. This study aims to understand the extent to which performance expectancy, effort expectancy, social influence, perceived susceptibility, severity, action incentives, self-efficacy, hedonic motivation, and consumer intention influence user behavior.

1.4. RESEARCH SIGNIFICANCE

The increase in mental health problems, the impact of social media and COVID-19, along with a low capacity of therapy places, pushes to find alternatives for traditional help. Mental health apps offer the solution to this.

Growing advertising and increasing preference for mobile apps drive the health app market. Increasing smartphone penetration is underpinning the growth (Grand View Research, 2021). Nevertheless, it is essential to identify other factors that influence the adoption of mental health apps. The findings lead to implications for promoting and developing greater adoption of mental health apps. The success of these apps depends on understanding people's concerns and identifying the factors that promote or inhibit their use.

1.5. Research question

In this case, this study aims to determine the acceptance of mental health applications among the population. To achieve this goal, this study targets to answer the following research question: Which factors influence the adoption of mental health applications?

It aims to identify and analyze the selected determinants in the conceptual framework: Performance expectancy, effort expectancy, social influence, perceived susceptibility, perceived severity, action incentives, self-efficacy, and hedonic motivation. In addition, the parameters will be analyzed in terms of participants' age, gender, and country of origin to identify demographic differences. Finally, the relationship between these factors and intention to use will be explored, i.e., whether there are negative, positive, or no ties and whether some elements have a more significant influence on consumer behavior than others.

1.6. Outline of the report

This work consists of six chapters. Each of them addresses a critical research topic.

Chapter 1 introduces the major themes of this research, focusing on the key factors that influence the adoption of mental health applications. A short introduction to the research field and a question statement were provided. The purpose and objectives of the research were explained in detail. In addition, the context of the study was presented in this chapter, followed by an explanation of the significance of the study. Finally, the thesis structure is outlined, and a brief description of each chapter is given.

Chapter 2 reviews and examines the existing literature and studies on mental health applications, highlights the research problem and identifies the significant factors that influence the adoption of mental health applications. This chapter presents mental disorders, mental health applications, and the theoretical frameworks used in this research area. A brief historical overview of mental health applications is provided, and the main advantages and disadvantages are examined. The primary models and theories developed and used to assess and describe individuals' acceptance and adoption of new technologies or products are introduced.

Chapter 3 addresses the research methodology. It identifies the research questions and explains the overall research design process and the justification of the research methods chosen. It begins by stating the research objectives and introducing the conceptual framework and the hypothesis developed. The respondents and the procedure by which the data were collected are described. This is followed by a presentation of the measures and materials and a description of the data collection process.

Chapter 4 presents the most important results of the study. It analyzes and discusses the quantitative results in light of the original conceptual model proposed in Chapter 3 about adopting mental health apps. The quantitative research was conducted through a questionnaire-based survey to explore the factors that influence the adoption of mental health apps. The chapter provides descriptive statistics of the data collected, discusses the implications of the survey results, and summarizes the main findings of the analysis. Finally, the proposed hypotheses are tested, and the conceptual model is revised based on the survey results.

Chapter 5 is the discussion part of the thesis. It contains the interpretation and explanation and will explain the implications of the results and make predictions and suggestions for future research.

Chapter 6 summarizes the empirical results with the literature and revises the proposed conceptual model based on the factors that have the most significant influence on the use of mental health apps. In addition, factors that emerged in this research and were not included in the original conceptual model are considered. Finally, this chapter summarizes the study’s findings, draws conclusions, highlights implications for research and practice, identifies limitations, and provides recommendations for future research.

2. LITERATURE REVIEW

2.1. OVERVIEW

This chapter reviews the relevant literature on the introduction of mental health applications. It begins with an introduction to mental disorders, a detailed discussion of mental health applications, and a presentation of various theories of technology acceptance and the Health Belief Model. Based on this, research gaps are identified, and hypotheses are developed.

2.2. MENTAL HEALTH DISORDERS

2.2.1. DEFINITION

According to the DSM-IV mental disorder is “a clinically significant behavioral or psychological syndrome or pattern that occurs in an individual. Associated with present distress (…) or with a significantly increased risk of suffering death, pain, disability, or an important loss of freedom (…)” (Stein et al., 2021). It encompasses our emotional, psychological, and social well-being and influences how we think, feel and act. However, there are differences between poor mental health and mental disorders. Even if a person is not diagnosed with a mental illness, they may still experience physical, psychological, and social unwellness (National Center for Chronic Disease Prevention and Health Promotion, Division of Population Health, 2021). Many different psychological issues are characterized by painful thoughts, perceptions, feelings, behaviors, and relationships with others. These include depression, bipolar disorder, schizophrenia, dementia, and eating disorders. Because the determinants of mental health and mental disorders are general, it is not only people with a genetic predisposition who become ill. Stress, diet, life experience, chronic illness, drugs, or loneliness can also lead to mental disorders (WHO, 2019).

2.2.2. EVOLUTION

Mental health is crucial for individual well-being and social and economic participation. In 2016, more than one in six people in EU countries had a mental health issue (OECD, 2018).

Mental disorders are more present than ever. Worldwide statistics about psychological health show that mental disorders have increased significantly over the past decade. These illnesses are one of the leading reasons for disability worldwide and the leading cause in the United States of America. Today, over 970 million people worldwide are affected by at least one of 200 forms of mental illness (SingleCare, 2021).

Anyone can suffer from mental health disorders, and they can impact a person's life as much as physical illnesses. The most commonly diagnosed mental conditions include depression, anxiety, and eating disorders. About a quarter of the population reported suffering from at least one mental illness (Stewart, 2021).

Thirty-four percent of Generation Z reported that their mental health deteriorated during the pandemic (American Psychological Association, 2020). An ongoing study funded by the National Science Foundation, NORC at the University of Chicago shows that younger people had more difficulty coping with the limitations resulting from the coronavirus and had higher levels of depression and anxiety (2020). Considering that quarantine has already affected people's behavior, a new phobia, corona phobia, emerged in 2020, with panic, anxiety, depression, paranoia, and obsessive-compulsive behavior (Brauser, 2020). Fifty-one percent of people in Europe reported that their mental health problems had worsened due to the COVID-19 pandemic. The age group most affected by poor mental health due to the pandemic is 18- to 24-year-olds (Stewart, 2021). Besides COVID-19, racism, prejudices, and bullying are still serious factors that impact people’s mental health. Despite increasing attention to equality, the National School Climate Survey shows that LGBTQ+ adults are at increased risk for psychological health issues because of stigmatization and marginalization (2019).

Furthermore, there are differences in the number of people affected depending on gender. Women are at higher risk of experiencing psychological health disorders. Domestic violence, income, socioeconomic inequality, and social status are why more women than men suffer from depression and other psychological diseases (Statista, 2019). According to the latest global mental health statistics, about 9% of people suffer from disordered eating habits. Anorexia and bulimia are the two most frequent diseases (Deloitte Access Economics, 2020). Previous studies prove a correlation between eating disorders behavior and depression. Therefore, people affected by eating disorders are more likely to suffer from depression. Health statistics suggest that 36-50% of patients with bulimia nervosa also have a major depressive disorder (Levy , 2020).

Although people's mental health is a huge concern today; only 2% of the global budget is spent on its treatment, representing $1 trillion per year. The World Economic Forum estimated $16 trillion to treat all mental disorders by 2030 (World Economic Forum).

2.2.3. INFLUENCING FACTORS

Mental illness is becoming one of the most prevalent public health problems worldwide and a challenge in our society today. It is impacted by various determinants, including genetic predisposition, socioeconomic background, adverse childhood experiences, chronic illness, or substance abuse (European Commission, 2021). Young adults, called Gen Z, are affected by mental health disorders. In a study of current APA stress in America from 2019, more than nine in 10 Gen Z adults reported an experience in at least one physical or emotional symptom due to stress, such as feeling depressed or sad, having no interest, motivation, or energy. This is attributed to money, work, the political climate, and climate change (APA, 2019).

A study published in the Journal of Abnormal Psychology shows that depression rates among young adults increased significantly between 2009 and 2017. Based on the Centres for Disease Control and

Prevention database, suicide rates among 15- to 24-year-olds rose in 2017 to the highest level since 2000 (Miron et al., 2019). These high numbers can be explained by various factors, three of the most important factors which especially people nowadays have to deal with are stigmatization, COVID-19 and stigmatization (Gao et al., 2020).

Stigmatization

Negative attitudes and beliefs toward people who have mental illness are widespread. Mental disorders lead to more negative judgments and stigma than any other illness. Stigma can cause discrimination, such as negative comments about mental illness or treatment. Many patients bear from social exclusion, prejudice, and experience bullying, physical violence, or harassment (Rössler, 2016). InIn conclusion, individuals with psychological disorders are deprived of the opportunities that make up a good life: good jobs, safe housing, and adequate health care (Corrigan & Watson, 2002).

Even though the middle ages are long gone, the general population is ignorant about mental health disorders, and fear of the mentally ill remains widespread (Rössler, 2016). Public stigma is the general population's reaction to people with mental diseases. Self-stigma is the prejudgement that individuals with psychological disorders direct against themselves. Stereotypes, prejudice, and discrimination drive public stigma and self-stigma. Stereotypes, in particular, has a significant impact because most members learn them of a social group (Hilton, 1996; Watson et al., 2006). The public stigma attached to mental illness is pervasive. There is no country or society where people with mental illnesses have the same social status as people without mental disorders (Rössler, 2016). In a survey involving 27 different countries, nearly 50% of people with schizophrenia reported discrimination. Up to ⅔ of those affected by this psychological disease anticipated discrimination when applying for jobs (Thornicroft et al., 2009). Behavioral effects resulting from public stigma are evident in refusal of help, avoidance, coercive treatment, and segregated facilities (Weiner et al., 1988).

It is hazardous when people with mental illness internalize the stigma. Self-stigma lowers self-esteem and self-efficacy, limiting the prospects for recovery. This can usually happen before or when people are not affected by mental disorders. People typically learn and internalize culturally prevalent stereotypes without even getting into contact with such conditions (Rössler, 2016).

Social Media

Another stressor people have to deal with is the immense use of social media. Social media has nowadays become essential in people's daily activities. Many individuals spend hours on platforms like Instagram, Facebook, and TikTok (Bartosik-Purgat et al., 2017).

Social media are interactive online and mobile networks through which people and communities share, create, or spread information, pictures, or short clips on a platform. Social networks are an essential form of communication in many people's lives and continue to grow (Berger et al., 2005). The use of applications such as Instagram, YouTube, and TikTok has become enormously popular for social interactions. They have become much more important than traditional media, especially in young adults' lives (Michikyan & Suárez-Orozco, 2016).

Social contact with others can alleviate stress, anxiety, and depression facilitated through social media. In today's world, many of us rely on social media platforms like Facebook, Twitter, Snapchat, YouTube, and Instagram to socialize and connect. Even if each of these platforms has an advantage, it's important to remember that social media can never be a substitute for genuine human relationships. Face-to-face contact with other human beings is necessary to trigger the hormones which causes happiness and positivity and decrease stress and anxiety. Ironically, technology that brings people closer together can make you feel even lonelier and more isolated by spending too much time online - and exacerbate mental health issues like anxiety and depression (Hunt et al., 2018). Since Social media is a relatively new technology, there is little research about the long-term consequences.

However, concerns about the impact of intensive use of these media are rising. In particular, the effect on young people's mental health can be significant (American Association for Suicidology, 2017). Some studies have already shown evidence of a link between social media use and mental health issues (Karim et al., 2020) and stated that these technologies are responsible for aggravating mental health disorders (Karim et al., 2020). A previous study on the impact of social media on mental health and well-being shows that young people perceive social media as a threat to mental well-being. It is believed to cause mood and anxiety disorders, is seen as a platform for cyberbullying, and the use itself has often been described as addictive (O'Reilly et al., 2018).

About 10 percent of teens report being bullied on social media, and many other users are subjected to abusive comments. Social networks can be hotspots for spreading hurtful rumors, lies, and name-calling that can leave lasting emotional scars. The given anonymity through the internet reduces the barriers to disrespectful interaction with others (Hasebrink et al., 2011). Several studies have shown robust associations between cyberbullying and mental health, particularly suicide and self-harm (Daine et al., 2013). Social media is often seen as a fake world. Even if people are aware of manipulated and heavily edited photos, they can still convey a sense of insecurity about one's appearance or life (Hunt et al., 2018).

Online Networks lead to constant and harmful comparison with the lives of others, which studies have identified as a risk factor for decreased well-being. A variety of studies show the link between social media use and negative self-esteem and self-image (Education Policy Institute, 2021). In particular, the idea of an idealized body image impacts self-esteem, especially among young women, with 9 out of 10 teenage girls reporting that they are dissatisfied with their bodies (Karslidou & Thomas, 2021). Manipulated images on social media platforms lead to unrealistic expectations for young people. Online advice and information risks trivializing and normalizing unhealthy behaviors and can lead to conditions such as eating disorders (Bell, 2007).

The constant comparison with other individuals and other individuals' lives can also lead to the fear of missing out. This phenomenon has been around for much longer, but social media's significance impacted it. According to Przybylski et al. (2013), FOMO is a pervasive fear that others may have rewarding experiences from which one is absent. It is characterized by a desire to stay connected to what others are doing. As people share photos of their supposed highlights, others may think they are missing out on certain things. This can affect an individual's self-esteem or cause anxiety. FOMO can lead to heavy social media use, restless nights, or dangerous accidents when people look at their cell phones even while driving (Karslidou & Thomas, 2021). The fear can lead not only to intensive use of social media but also to addiction. Social Media are intended to be addictive, and using them activates the brain's reward system by releasing dopamine. About 5% of adolescent users are considered more addicted to social media than alcohol and cigarette use (Jenner, 2015).

According to the OECD, extreme Internet users have lower overall life satisfaction than moderate users. Some studies have found that introverted young adults develop an addiction to further feedback on social media. This addiction can lead to poor sleep patterns or impaired performance on exams (OECD, 2016). Especially in the last two years since the COVID-19 pandemic outbreak, the use of social media has increased, and therefore its impact can be observed. A 2020 study conducted in China showed a high prevalence of mental health problems positively associated with frequent social media use during the COVID-19 outbreak (Gao et al., 2020). Another study at the University of Pennsylvania confirmed the link between feelings of loneliness and social media use. Therefore, reducing Facebook, Snapchat and Instagram can make people feel less lonely and isolated and improve their overall well-being (Hunt et al., 2018).

COVID-19

Another stressor people have to deal with today is COVID-19. Since the coronavirus in 2019, the global community has been concerned about the long-term physical and economic impact and the psychological impact. The newly identified coronavirus, first reported in Wuhan, China, spread rapidly across the globe, causing numerous infections and deaths, especially among the elderly and vulnerable (Wang et al., 2020). Although efforts to control and limit the spread of the pandemic in the community are relatively straightforward to follow, prejudices and fears appear to be jeopardizing response efforts (Ren et al., 2020).

Currently, governments worldwide are focused on testing, treating infected individuals, developing drugs, vaccines, and treatment protocols. Although one might think that the pandemic is under control after almost two years, this is not the case. And most importantly, the long-term consequences and impact on people's mental health cannot be predicted (WHO, 2020d). Public health emergencies can affect individuals' and communities' health, safety, and welfare (Pfefferbaum & North, 2020). People tend to feel anxious and uncertain when the environment changes. When there are outbreaks of infectious diseases where the cause or course of the disease and the consequences are unclear, rumors and a narrow-minded attitude develop (Ren et al., 2020).

From previous studies on the SARS outbreak in 2003, about 70% of people in Hong Kong were afraid of contracting the virus and felt more at risk, unlike other diseases (Cheng & Cheung, 2005). This fear and anxiety about infection can lead to discriminatory actions. Accordingly, at the beginning of the COVID pandemic in 2019, discriminatory behavior towards Asians was evident. People from Wuhan have been targeted and blamed for the virus outbreak using terms such as "Wuhan virus" or "China virus" (Ren et al., 2020). Necessary measures such as self-isolation and quarantine have interfered with usual activities and routines, increasing people's loneliness, anxiety, and depression (WHO, 2020c). The amount of negative news, confrontation with death, and fear of Covid have negatively impacted the psyche of many individuals. Fear is a well-known response to infection outbreaks, and people react to the perceived threat differently. It can translate into a range of emotional reactions, unhealthy behaviors, and noncompliance with public health guidelines among sufferers and the general population (Pfefferbaum & North, 2020).

In addition, millions of people have lost their jobs and family members. Over one hundred thousand people have died worldwide, and the numbers continue to rise (WHO, 2020b). Individuals, families, and communities experience feelings of hopelessness, despair, grief, loss, and profound loss of meaning due to pandemics (Levin, 2019). The feeling of losing control leads to fear and uncertainty about the course of the pandemic (Zikmund-Fisher et al., 2018). A study from 2020 conducted by the Indian Psychiatric Society shows a twenty percent increase in mental illness since the coronavirus outbreak in the country (Loiwal, 2020). Another research of 1210 respondents from 194 cities in China from January to February 2020 found that 54% rated the psychological impact of the COVID-19 outbreak as moderate or severe, 29% reported moderate to severe anxiety symptoms, and 17% reported depressive symptoms (Wang et al., 2020).

After disasters, most people are resilient and do not become psychopathological. However, depressive disorders and anxiety are significant concerns. Some groups are more vulnerable to the psychological effects of the pandemic than others. In particular, people with COVID, individuals at increased risk, and humans with pre-existing medical, psychiatric, or addiction problems are more vulnerable to adverse psychosocial effects. The burden on health care providers should not be underestimated either. The frequent contact with covid patients, overtime, and psychological stress place significant demands on them (Pfefferbaum & North, 2020). Also, the life of young adults and children changed a lot. Young people who are particularly socially active lack exchange with other individuals. Experts already predict that Gen Z will be more mentally affected by the pandemic than different generations (Glazer, 2020).

Generation Z is arguably the most socially attuned generation of all time (Chillakuri, 2020). Still, the ease of keeping up with everything going on in the world via the internet also has side effects. An APA study (2018) on American stressors found that news is a regular source of stress for young adults. Young adults are more likely than older people to be diagnosed with an anxiety disorder and report being diagnosed with depression (Goldman, 2020). People's reaction to fear and intolerance of uncertainty leads to negative social behaviors aimed at reducing uncontrolled situations that people fear (El-Terk, 2020). Domestic violence has increased worldwide because victims have no way to escape perpetrators through incarceration (Abramson, 2020). It is essential to provide psychosocial support and help gris evidently, the Covid pandemic will leave damage. Still, it is not estimable how significant the impact will be on the population's mental health (Li et al., 2020). Therefore, mental health and treatment options will play a more significant role in the future (Levin, 2019).

2.3. MENTAL HEALTH APPLICATIONS

Since mental health applications are a relatively new technological invention, it is necessary to explain. The term "mental health applications" should be defined comprehensively to understand how it originated and developed. Due to the positive market outlook regarding these technologies, it is essential to identify the determinants and influencing factors that may contribute to the acceptance and thus the adoption of these applications, keeping in mind that these factors may vary in different regions and societies.

2.3.1. DEFINITION

The term "mental health application" refers to tools that can be accessed via smartphone or mobile devices that focus on improving different aspects of mental health and well-being. These apps focus on treating or preventing various diseases by offering multiple features like journaling, meditation, or mood-tracking. They can also provide self-help tools or therapeutic activities to improve mental health (Morin, 2021). Today, several providers such as Moodfit, Calm, Happify, or Headspace differ in their functions and disorder focus. The individual's mental health should be improved by regularly using emotion-based activities such as breathing exercises, behavioral, social or thought-based activities (Morin, 2021). Mental health is the foundation for an individual's well-being and effective functioning. It is not just the absence of mental disorders but the ability to think, learn and understand one's feelings and the reactions of others. Mental health means balancing physical, psychological, social, cultural, spiritual, and other interrelated factors (WHO, 2017). Disruption of these factors can lead to severe disorders, generally characterized by abnormal thoughts, perceptions, feelings, behaviors, and relationships. The most frequent psychological disorders are depression, bipolar disorder, schizophrenia, dementia, and anxiety. Today, there are effective therapies or medical treatments to treat these disorders and ways to prevent them. However, access to medical care and social services is essential to address these issues (WHO, 2019).

2.3.2. HISTORY

Because of the broad use of smartphones and the creation of Apple's iTunes App Store and Google's Android Market that allows users to download mobile applications in 2008 (Statista, 2021), more and more mental health applications are being developed and adopted (Clay, 2021). Since the early days of mental health apps, the market has grown steadily. According to the American Psychological Association, App stores host nearly 20,000 different mental health apps today, ranging from AI chatbots and mood detectors to services like Talkspace and BetterHelp that match patients with licensed therapists (Pappas, 2020). Forecasts show that the market size of Health apps will generally increase at a compound annual growth rate (CAGR) of 17.7% from 2021 to 2028 (Grand View Research, 2021).

One of the first mental health apps available was Headspace. It was officially founded in 2010 as an event company by Andy Puddicombe, who wanted to teach others about meditation and mindfulness. Wanting to make his techniques available to anyone, anytime, anywhere, Andy and a small team around him developed the idea of the app. Today, Headspace offers guided meditations, animations, articles, and videos that bring meditation and mindfulness closer to improving health and enhancing well-being in this world. With millions of users in more than 190 countries, the company seeks to achieve its goals (Headspace, 2021).

The shift from traditional models of care to patient-centered models is expected to increase the adoption of such applications. Growing smartphone penetration, use of the Internet and social media, and the number of healthcare professionals recommending mental health apps further influence the market growth (Grand View Research, 2021). Significantly since 2020, the demand for mental health apps has increased dramatically due to the Covid-19 pandemic. According to the findings of a survey, half of Americans have experienced negative mental health impacts from the pandemic. First-time downloads of the top 20 mental health wellness apps in the U.S. increased 29 percent from January to April, reaching 4 million. Compared to previous years, these apps typically peak in January due to New Year's resolutions while decreasing in the following months, which was not the case during the pandemic (Kirzinger et al., 2020). For example, Talkspace, which offers video- and text-based therapies, saw nearly double the number of users between mid-March and early May 2020 compared with the same period in 2019 (Levy, 2020). Talkspace competitor BetterHelp also sees an unprecedented surge in demand. According to CEO Alon Matas, the number of users opting for the platform specifically to help with stress and anxiety has doubled. According to Sensor Tower, downloads increased from 50,000 in January to 80,000 in April 2020, at least in the U.S. (Herzog, 2020).

Looking at downloads and user behavior by region, differences in adoption can be seen. These variations in market share may be due to cultural differences, access to devices, interest, information, or range of applications (Lipschitz et al., 2019). In 2020, North America dominated the market with more than 38% revenue share. Forecasts show that the regional market will continue to grow at a steady CAGR from 2021 to 2028 due to smartphone usage, development of care networks, increasing prevalence of chronic diseases, and rising geriatric population (Grand View Research, 2021). Besides the current market share, the Asian region is expected to exhibit the fastest CAGR over the forecast period, justified by the high demand for connected devices. Technological advancements and increased product demand are expected to boost new companies' market entry. Moreover, strategic promotions by companies in the form of mergers and acquisitions are likely to fuel competition and drive market growth.

However, there are also challenges that companies have to face. Concerns like skepticism and mistrust regarding data privacy and security may inhibit the adoption of mobile health technology and are factors hindering market growth (Grand View Research, 2021).

2.3.3. MARKET OUTLOOK

According to Research and Markets (2021), the global mental health application market will likely grow at a CAGR of around 31% in 2021-2026. This is due to multiple factors, including a growing awareness of health applications among various industry players and increasing initiatives for collaborations by multiple governments and market players. Many players lead multiple mindfulness and meditation applications for a new global wellbeing collaboration. These initiatives and partnerships are expected to provide mental health exercises, guided meditations, and sleep content to millions of employees, corporate clients, and guests and will be made available globally in the coming years.

Although the COVID-19 outbreak hurt almost all industries worldwide, the pandemic offers immense opportunities for the growth of the mental health app market. Today, iOS is the largest Appstore and is expected to capture the largest market share in the forecast years. The Appstore contains more health apps than its competitors and adds about 100 new health apps every day. Globally, North America has dominated the mental health app market in recent years and is likely to continue to do so. Due to the growing awareness of mental health issues and the abundant availability of numerous apps, the regional market is expanding (Research and Markets, 2021).

2.3.4. BENEFITS

Mental health apps target various mental disorders and vary in design and functionality. They fall into six categories: self-management, cognition improvement, skills training, social support, symptom tracking, and passive data collection (NIMH, 2017). Mental health apps cover all phases of clinical care, including immediate crisis intervention, prevention, diagnosis, initial treatment, adjunct to personal therapy, and post-treatment condition management (Price et al., 2014).

Experts believe that these new technologies have great potential for both clients and doctors. These mobile apps are convenient because treatment can occur anytime, anywhere and can be ideal for those with difficulty with in-person appointments. Users can feel more anonymous and have access to treatment throughout the day. In addition, the cost can be lower than traditional treatment, and the services can be made available to more people (NIMH, 2017). By offering effective options to patients with milder psychiatric symptoms, the burden on traditional mental health services could be reduced. In general, cognitive apps can prevent illness or as an adjunct to conventional therapy (Newman et al., 2011).

2.3.5. DRAWBACKS

Despite the positive outlook for mental health apps, there are still some challenges that providers need to address. Despite their increasing use, the adoption of mental health apps still has room for improvement. One reason is the deficit of awareness and knowledge about these apps. People either don't know they exist, or they don't know how to find the right app for their needs (Lipschitz et al., 2019). It is often complicated and overwhelming for users to choose the right app from hundreds of apps available on the app market (Bashir, 2017).

Although there is evidence about the effectiveness of smartphone-based mental illness treatment, there is still mistrust in these new technologies (Marshall et al., 2020). There are no industry-wide standards for consumers to determine whether an app or other mobile technology has proven valid. Further research shows that the most commonly cited reasons for not using mental health apps are weak evidence of effectiveness. These findings suggest that public dissemination of information about the validation of mental health apps could improve adoption (Lipschitz et al., 2019).

Another issue is the lack of personalization. It's essential to understand whether mental health apps work for everyone and under conditions. Even though the choices are vast, it is often difficult to get an overview and choose the app that best meets personal needs (NIMH, 2017). Privacy and data autonomy concerns have also weighed on the teletherapy field. Psychological health apps deal with sensitive private information and therefore need to ensure user privacy. Mental health sensitivity can be attributed to the long-standing social stigma that prevents people from seeking mental health treatment and support (Corrigan, 2004). Previous research shows that stigma can also be an issue when using mental health applications. Some people don't want others to know that they are using a mental health app, therefore these apps should be designed discrete and be password protected (Kenny et al., 2014).

Furthermore, negative publicity increases distrust in these apps. In February 2020, Jezebel reported that BetterHelp and Talkspace shared data with third parties. This data included anonymized intake forms with sensitive information about users' mental health, sexual orientation, and suicidal thoughts (Osberg, 2020). Sharing data with third parties is pervasive. In 2019, researchers examined the data practices of 36 leading depression and smoking cessation apps and showed that more than 80 percent of the apps transferred data to Facebook and Google, often without disclosing it in their privacy policies (Huckvale et al., 2019). When developers send user data to Mix Panel or Facebook, they can aggregate and commercialize it without their knowledge. The dangerous matter is that this behavior is not even prohibited, and there is no way to prevent the data from being shared with a fourth party. More transparency and regulation must be created to create more trust in this digital therapy space (Herzog, 2020). There are significant concerns about whether these apps can adequately protect mental health information. Informing users about how data is protected within the app can increase uptake (Lipschitz et al., 2019).

Because mental health applications deal with a sensitive topic, they differ in their acceptability from other types of technologies. For this reason, traditional technology acceptance models may not be as accurate in their application.

2.4. THEORETICAL FRAMEWORKS

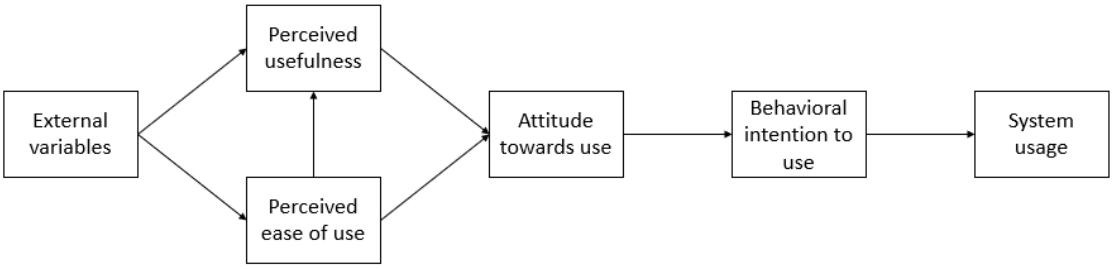
2.4.1. TECHNOLOGY ACCEPTANCE MODEL

Several influential factors stand out in reviewing the current literature on mental health app adoption. Most studies analyzing the introduction, adoption, and long-term use of mental health apps are based on the technology acceptance model which short form is TAM, the most widely used model of user acceptance, and user behavior (Holtz et al., 2020).

The TAM stems from the theory of reasoned action, which intends to describe the relationship between dispositions and behaviors within people’s actions. It is mainly used to predict how individuals behave based on their pre-existing attitudes and behavioral intentions (Taherdoost, 2017). TAM, in turn, is an information technology framework for understanding users' adoption and use of new technologies and assumes that perceived usefulness and perceived utility predict technology acceptance (Ma & Liu, 2005). Therefore, consumers are more likely to adopt new technology if it has a high-quality user experience design, and they expect to benefit from its use (Portz et al., 2019).

Figure 1

Technology acceptance model



Note: Adopted from Davis, 1985.

Since its invention, the TAM has been tested with various applications and is still the most common model to predict the acceptance of new technologies. Nevertheless, some results have statistical significance, direction, and magnitude weaknesses. Even though the correlation between usefulness and acceptability and between use and usability is strong, the relationship between usability and acceptability is weak, and its significance does not pass the fail-safe test (Ma & Liu, 2005). About mental health apps, the predictive power of TAM is also being studied. However, different studies show contradictory results, considering that they were conducted at different moment in time and countries. Research conducted in Germany in 2016 about the acceptance of mobile apps for mental health treatment shows no significant direct influence of perceived usefulness on behavioral intention regarding mental health apps. The indirect effect is present, as perceived usefulness partly reflects the population's knowledge of these apps, their effectiveness, and their ability to treat illness. While some participants indicate that mental health apps provide helpful information, most do not believe these technologies are sufficient for treating mental disorders. Regarding the usability of mental health apps, the study shows that this factor does not significantly influence usage behavior because the young German participants are experienced with smartphone use and do not consider mental health apps a challenge. Nevertheless, the study shows a positive correlation between perceived usefulness and ease of use (Becker, 2016). Another analysis focuses more on beliefs about the continued use of mental health apps after implementation confirms the direct effect of perceived ease of use on perceived usefulness. However, it states that ease of use significantly predicts satisfaction with mental health apps. Both effectiveness and ease of use significantly and positively influence intention to continue using them (Cho, 2016).

Another study shows that perceived ease of use and usefulness influence the acceptance of mental support apps. However, this study also indicates that the effect is relatively small compared to the power of subjective norms like internal motivation or subjective importance of the topic. And thus, this is not the only study that shows that the TAM is not sufficient to predict consumers' usage behavior regarding mental health apps (Lim & Wong, 2019).

2.4.2. EXTENDED TECHNOLOGY ACCEPTANCE MODEL

Since its invention, the TAM has evolved as results show that additional and more significant factors influence technology adoption. In general, demographic characteristics have been studied along with other influences. Previous research has confirmed that gender, country of origin, and age can significantly affect mental health app use (Cho, 2016).

In general, the society in which people are socialized has a significant impact on their mental health awareness. People aware of mental health are generally more likely to seek treatment. However, most people do not feel the force for mental health app usage because they consider themselves healthy and not at risk of psychological disorders (Becker, 2016).

An analysis of the technology acceptance model about e-learning reveals additional major influencing factors. The research interest focused on studying the acceptance of e-learning courses and what factors influence the adoption of such approaches. The results show that self-efficacy is the factor that most influences behavioral intention, followed by social impact (Park, 2009).

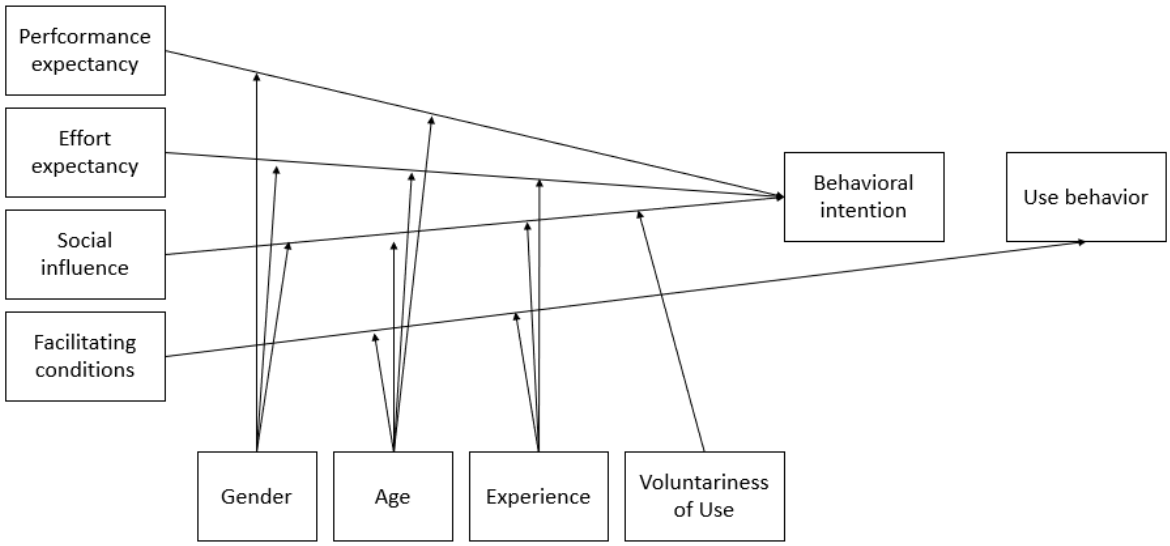
Depending on the technology and the nature of the study, the basic TAM framework was extended differently. Hsu and Chang (2013) attempted to study Moodle adoption using an extended TAM. To do so, they added the external variable perceived convenience. The results show that perceived convenience influences perceived usefulness and intention to use Moodle. Other researchers tested the TAM on other applications. Malhotra et al. considered trust as another influencing factor. Therefore, a lack of trust in the tool data security influences people's usage behavior (Malhotra et al., 2004). When using mental health apps, sensitive data about the client is collected, which can lead to privacy concerns. Researchers confirm a correlation between trust and usage behavior when using mental health apps (Becker, 2016).

2.4.3. UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY

The unified theory of acceptance and use of technology, in short UTAUT, is a model formulated by Venkatesh et al. in 2003. It aims to explain users' intentions to use an information system and subsequent usage behavior. The theory consists of four central constructs. According to them, performance expectancy, effort expectancy, social influence, and facilitating conditions influence user acceptance of technology (Venkatesh et al., 2003). In addition, the variables gender, age, experience, and voluntariness of use indirectly influence usage behavior (Abbad, 2021).

Figure 2

The unified theory of acceptance and use of technology



Note: Adopted from Venkatesh et al., 2003.

Performance expectancy refers to how people believe using the system will help them. Therefore, a high-performance expectancy increases the intention to use a particular technology. Effort expectancy refers to the degree of ease associated with using the system. Individuals who expect the system to be easy to use are more likely to use it. The third factor, social influence, represents individual perceptions of others' importance on using the technology. People who know someone who uses a specific technology recommended it or took part in a conversation about it are more likely to adopt it (Abbad, 2021).

The perceived extent to which the organizational and technical infrastructure required to support the technologies is referred to as facilitating conditions (Thomas et al., 2013). Studies have consistently shown that infrastructural and organizational aspects are essential variables to consider when implementing new information systems. The possession of a smartphone, which is necessary for using mental health apps, is part of the factor and the knowledge needed to use them or an environment that can help you (Phichitchaisopa & Naenna, 2013). Although the UTAUT has already been applied based on some technologies to predict their adoption, there are still research gaps when it comes to validity regarding the adoption of mental health apps in Europe. Yueh et al. investigated the factors influencing students' use of wikis using the UTAUT. The results show that effort expectancy and social influence have the most significant impact on use by students (2015).

Another study that focused on user experiences with mobile health applications for patients with eating disorders found that health care providers and health experts were more likely to report barriers to mobile health application adoption than facilitators, suggesting that mHealth technologies are challenging to obtain the use. Most factors influencing the adoption of mobile health applications were attributed to external factors related to the environment, such as time, rather than internal factors related to individual barriers. Nevertheless, participants reported adoption barriers such as the inability to personalize the app a lack of motivational or interactive components (Anastasiadou et al., 2019).

2.4.4. UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY 2

Nine years after the UTAUT invention, Venkatesh et al. published an extended version of the Unified theory of acceptance and use of technology. It additionally includes factors relevant to the consumer market that influence behavioral intention to use new technologies. Venkatesh et al. extracted the usage intention factor from the original UTAUT and expanded it to include three elements to improve the prediction of behavioral intention and usage behavior (2012).

The extended model additionally includes hedonic motivation, defined as the pleasure or enjoyment derived from using a technology; price value, which represents consumers' cognitive trade-off between the perceived benefits and monetary costs of operating a technology (Dodds et al., 1991); experience and habit, defined as the extent to which people tend to perform behaviors automatically based on learning. Combined with the preceding factors, they should predict people's behavioral intention (Limayem et al., 2007).

Even though the UTAUT2 is one of the most widely used technology acceptance models, studies still suggest an adjustment. Using this model, a survey of 317 participants showed that performance expectancy, hedonic motivation, and habit positively predicted users' intention to use a health and fitness app, whereas effort expectancy, social influence, facilitating conditions, and the price was entirely but not significantly associated with intent to use (Yuan et al., 2015).

2.4.5. HEALTH BELIEF MODEL

Regarding the adoption of disease treatments and prevention, other literature focuses on the health belief model, in short HBM. The HBM was invented in the early 1950s by social scientists at the U.S. Public Health Service to understand why people do not adopt disease prevention strategies or screening tests for early detection of disease. It is one of the most widely used theories in health behavior and is used as both an explanatory theory and a theory of change (Janz & Becker, 1984). The HBM assumes that a person's belief in a personal threat of disease, together with a trust in the effectiveness of the recommended health behavior or intervention, predicts the likelihood that the person will adopt the behavior (LaMorte, 2019).

The HBM is based on psychological and behavioral theories. A value-expectancy approach compares advantages and disadvantages or risks and benefits for decision-making (Franklin Health research Foundation, 2021). The basis of the model consists of two components: the desire to prevent or cure a disease and the belief that a particular action will prevent or cure a disease. In addition, the person's behavior often depends on the perception of the benefits and barriers associated with the interventions (LaMorte, 2019).

The theory includes six constructs that relate to how a person decides whether or not to engage in a particular behavior. The main factors that make up the model are perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to action, and self-efficacy (Becker, 1974).

Perceived susceptibility refers to a person's subjective perception of their risk of contracting a disease. The sense of openness to condition varies widely. Due to cognitive biases, the general public cannot assess susceptibility. For example, people generally overestimate the risks of conventional drugs while underestimating the dangers of natural products (LaMorte, 2019).

Perceived severity asks whether the outcome in question is essential or not. It indicates how serious the individual perceives the infection with a disease and includes the imposition of both the corporal and social results (Franklin Health research Foundation, 2021). An individual's perception of the effectiveness of various interventions to reduce the risk of disease is part of the perceived benefit factor. Even if individuals believe they are at serious risk of illness, they will not engage in the treatment or prevention if not perceived to be effective (LaMorte, 2019).

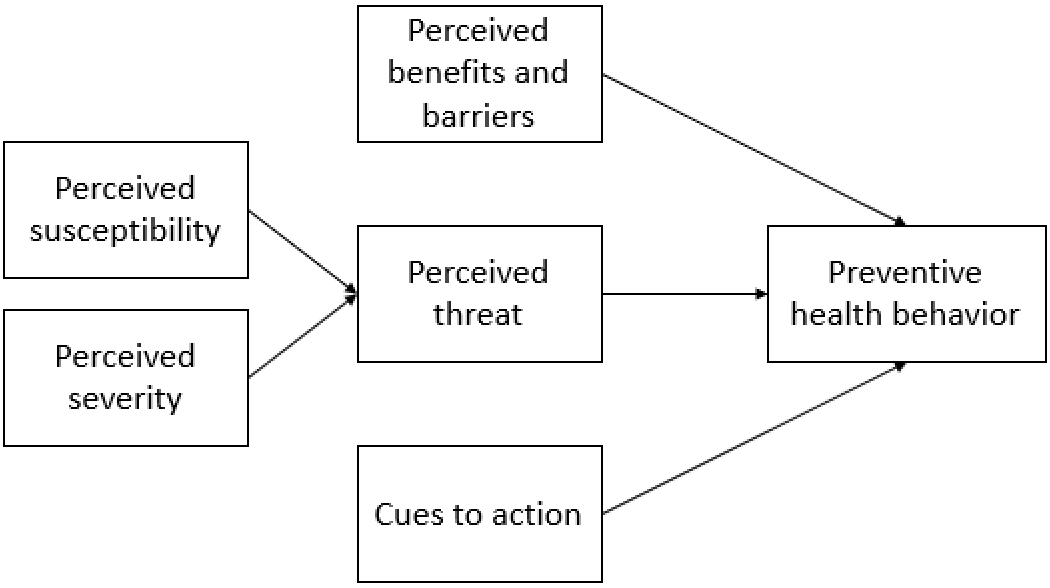
Perceived barriers represent a person's feelings about the obstacles to taking a recommended health action and lead to a cost-benefit analysis. Barriers to the activity or unshaven, including financial costs and time, social costs, physical discomfort, and other emotional costs. Stimuli for action are the stimuli needed to trigger the decision process. These stimuli can be internal, such as pain or constraint, or external, like advice from friends or advertising.

The last factor, self-efficacy, was defined by Bandura and referred to the belief that someone can perform a specific behavior (Franklin Health research Foundation, 2021). The Health belief model assumes that messages produce optimal behavior change when they successfully target perceived obstacles, benefits, self-efficacy, and threats. Although the model appears to be an ideal explanatory framework for communication research, theoretical limitations have limited its use in this field (Jones et al., 2016). Researchers have argued that the HBM does not specify the order of variables, which is essential for researchers interested in understanding communication processes (Champion & Skinner, 2008). It does not make habitual or perform behaviors for non-health-related reasons, such as social acceptance. It counterfeits that all individuals have the same access to the disease or condition information. Therefore, social influence and facilitating conditions should also be influencing factors.

The HBM is descriptive rather than explanatory and does not suggest a strategy for changing health-related actions. The individual constructs are helpful depending on the health outcome of interest. Still, for the most effective use of the model, it should be integrated with other models that consider the environmental context and suggest strategies for change (LaMorte, 2019).

Figure 3

The health belief model



Note: Adopted from Janz & Becker, 1984.

According to the acceptance of psychological health applications, the HBM can be a significant contribution to predicting the behavioral intention to use this new technology. It can complement classic technology acceptance models because it does not only focus on the adoption of new technologies but covers the health-related part. Therefore, combining both models could forecast and explain health app adoption more accurately.

3. METHODOLOGY

3.1. OVERVIEW

This chapter establishes the conceptual framework and research method for the empirical study. The methodological framework guides for choosing research methods and consists of philosophical assumptions, logical reasoning, and criteria for evaluating research findings (Scotland, 2012). Based on positivism, deductive approach, and quantitative method, a questionnaire survey is designed in this chapter. Measurement scales are designed based on previous empirical studies; data collection and analysis procedures are discussed; data quality is assessed; ethical issues are comprehensively addressed.

3.2. RESEARCH OBJECTIVES

The previous academic world has focused on the technology adoption model and the U.S. market to adopt mental health applications. However, some factors that influence end-user behavior have not yet been considered, especially in the European market. With combining the unified theory of acceptance and use of technology (Venkatesh et al., 2003) and the Health belief model(1950) as a foundation, this study contributes to research on mental health apps by providing a new approach to the topic. The results will give the academic world closer insights into the factors influencing consumers' intention to use mental health apps in the European market and may serve as a basis for further or long-term research.

3.3. CONCEPTUAL FRAMEWORK AND RESEARCH HYPOTHESIS

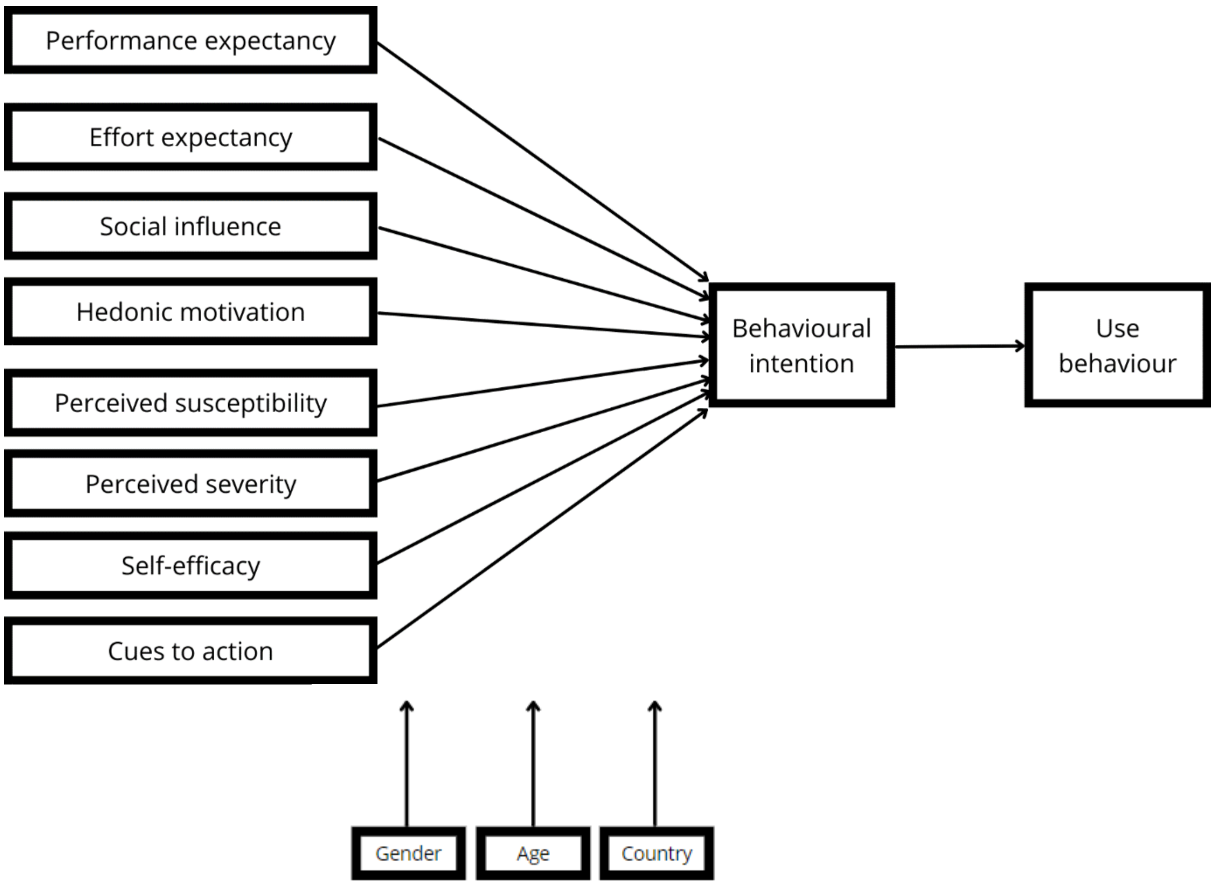
Building on the existing literature, a combination of the UTAUT 2 (Venkatesh et al., 2012) and the HBM (Janz & Becker, 1984) was chosen to serve as the basis for the conceptual framework study. The Unified

Theory of Technology Acceptance and Use has comparatively better explanatory power than other technology acceptance models. It is best suited for examining usage behavior from the consumer context rather than the organizational context (Woldeyohannes & Ngwenyama, 2017). Previous studies have demonstrated its usefulness in predicting usage intentions and adopting new technologies (Abrahao et al., 2016).

Because mental health applications are a form of health technology, it is essential to incorporate factors included in the Health belief model into the conceptual framework of this study to analyze the particular case of mental health app adoption more precisely (Abraham & Sheeran, 2015). The conceptual framework presented below (Figure 4) was conducted based on secondary research in the technology adoption field. The model includes eight factors that directly influence the behavioral intention that leads to the user behavior of the consumers and three indirect determinants, such as gender, age, and country of origin.

Figure 4

Conceptual framework



Unlike the original models UTAUT2 and HBM, the conceptual framework differs in some aspects. In contrast to the UTAUT2, the factors facilitating conditions, price value, habit, and experience were omitted (Venkatesh et al., 2012). In this study, reducing needs would primarily be represented by the ownership of smartphones. However, since it is assumed that every participant owns a smartphone or would have the opportunity to own one, the analysis of this factor would not be meaningful. This research focuses primarily on non-users of mental health apps, as they are considered a potential market. Because of this, it is essential to analyze the factors that influence their behavioral intentions to adopt these technologies. Accordingly, the elements of habit and experience can be omitted, as both can just be answered by respondents who are using a mental health app consistently. Also, the factor price value is not discussed further in this study since it results from an individual cost-benefit analysis, which is not applicable. It is also impossible to make a generalized statement about the costs and benefits of mental health apps, as they vary widely in both features and prices.

Furthermore, the factors perceived susceptibility, perceived severity, self-efficacy, and cues to action that originated from the HBM are included in the conceptual framework. The left determinants are perceived benefits and barriers, which have already been covered by combining other determinants from the UTAUT2. In addition, perceived benefits and barriers are very general factors and would therefore need to be considered more in detail. The analyzed in this study will be discussed in more detail formulate the hypotheses in the next step.

Behavioral Intention

Behavioral intention is defined as a customer's intention to adopt and use a particular tool (Venkatesh et al., 2003). According to Irani et al. (2009), most research on technology adoption has used behavioral intention to predict user behavior and, therefore, technology adoption. Behavior in this study refers to whether or not a participant intends to adopt a mental health app.

Performance expectancy

According to UTAUT, performance expectancy refers to how users assume that using new technology will improve their effectiveness in performing specific tasks or benefit them and influences whether or not a person will adopt the behavior. These expectations are influenced by the person's gender and age (Venkatesh et al., 2003). Sun et al. (2013) suggested that effectiveness is primarily reflected in how they help users reduce health-related threats. Therefore, positive performance expectations may increase intention to use the technology, given common concerns about health-related threats.

H1: Performance expectancy positively influences behavioral intention.

Effort expectancy

Generally, effort expectancy has widely viewed how users perceive that adopting new technology will be free of effort (Gao et al., 2015). It plays a vital role in using a particular technology and is influenced by gender, age, and other experience. Dabholkar (1996) cited two main reasons to adopt technology: reducing effort and social risk. Featherman and Hajli (2016) describe social risk as consumers' belief that they will look foolish in front of others. This can be the case when consumers believe that technology is too difficult to use (Venkatesh et al., 2003), and they would not use it at all then ask for help. A more accessible application to use than another is more likely to be adopted (Pikkarainen et al., 2004). Effort expectancy refers to the ease of use and perceptions of the time required to select and use a mental health app (Venkatesh et al., 2003). This thesis means the ease of use of mental health apps.

H2: Effort expectancy negatively influences behavioral intention.

Social influence

The social influence factor reflects how individuals' decision-making is influenced by social factors such as subjective norms and the expectations of significant others (Venkatesh & Morris, 2000). Many studies based on the UTAUT model have demonstrated the importance of social influence in technology adoption and implementation (Alraja et al., 2016). Dwivedi et al. (2016) found that peer evaluation exerts normative pressure on users when mental health app adoption is visible to others. Furthermore, decision-making processes are always influenced by the personal reference group and tend to meet their expectations (Bearden & Etzel, 1982). Cultural differences may also affect this. People living in a more collectivistic society such as China may feel more social pressure and subjective norms than individuals in an inductivist society where greater importance is placed on achieving personal goals and self-image (Hofstede & Bond, 1984). The role of social influence factors in decision-making-making has been demonstrated in empirical studies (Scholz et al., 2020). Therefore, it can be hypothesized that people with positive social influence have a higher intention to use mental health applications.

H3: Social influence positively influences behavioral intention.

Perceived susceptibility

As mentioned earlier, the conceptual framework of this study is based not only on the UTAUT but also on the Health Belief Model. Therefore, perceived susceptibility is mentioned as another determinant. It is about individuals' perceived risk of developing a health impairment. The HBM predicts that individuals who perceive themselves as vulnerable to a particular health problem will participate in behaviors that decrease their health problem risk (Adhikari, 2019). In terms of mental health apps, this would imply that people who see themselves at risk of developing one are more likely to use them.

H4: Perceived susceptibility positively influences behavioral intention.

Hedonic motivation

Hedonic motivation is the enjoyment or pleasure derived from using new technology (Venkatesh et al., 2012). These factors play an essential role in technology adoption and use (Brown & Venkatesh, 2005). The decision-making process is not only controlled by cognition but also by emotions. Therefore, positive emotions positively influence the intention to use new technology (Ha & Stoel, 2009). In terms of mobile health service adoption, studies have shown that hedonic motivation varies across countries. Dwivedi et al. (2016) reported a positive influence of Bangladeshi citizens' intention to use mobile health services, while the effect was insignificant in Canada and the United States. Therefore, the role of hedonic motivation needs to be explored in more detail. This factor was included in the conceptual framework to analyze and test its predictive power for intention to use mental health apps.

H5: Hedonic motivation positively influences behavioral intention.

Perceived severity

Perceived severity, also called perceived seriousness, means the subjective assessment of the severity of a health problem and its potential consequences. HBM assumes that individuals who perceive a particular health problem to be serious are more likely to engage in behaviors that prevent the health problem from occurring (Hochbaum, 1958). Perceived seriousness includes both beliefs about the illness itself and its disease in functioning at work and in social roles. Even if a person does not perceive the disease as medically serious, they may perceive the financial or social consequences as serious. These results may relate to an anticipated happening in the future or a current condition, such as a pre-existing health problem (Rosenstock, 1974). A previous study of Pap smears for cervical cancer screening showed that the mean severity score among persons who underwent Pap smears was higher than the mean perceived severity score among persons who did not take the test. Perceived severity is higher among those who have experienced a Pap smear, indicating that those who fear the negative consequences of the disease are more likely to seek behavioral changes to prevent it (Abotchie & Shokar, 2009). This suggests that it is similar to the use of mental health apps.

H6: Perceived severity positively influences behavioral intention.

Self-efficacy

Another hypothesis is based on self-efficacy. As part of HBM, it represents self-confidence in one's ability to implement and act on a behavior. Some studies question Self-efficacy because research shows that its effects are often related to whether a person performs the desired behavior (Adhikari, 2019).

H8: Self-efficacy positively influences behavioral intention.

Cues to action

The last factor is influencing the adoption of disease prevention or treatment strategies are the cues to action. This is the incentive required to trigger the decision-making process to adopt a recommended health intervention. These incentives can be internal or external (Adhikari, 2019). Therefore, people who have previously heard about, been recommended, or seen advertisements for mental health apps are more likely to use them.

H7: Cues to action positively influence behavioral intention.

3.4. PARTICIPANTS

For this study, a sample of 309 individuals was surveyed between Nov. 28, 2021, and Dec. 31, 2021. Participants were between 18 and 70 years old, with a mean age of 32. 71.2% of respondents are between 21 and 36 years old, with an exceptionally high percentage of 21- to 29-year-olds. figureThe participants in this study are 57% female, 41.7% male, and 1.3% non-binary or third gender. In terms of country of origin, more than half of the respondents were from Portugal or Germany, as shown in table 1. The United States and Spain followed them. The other countries were only represented by less than 10 participants per country, representing 24.6% of the survey participants.

Table 1

Country	Frequency	Percentage	Cumulative percentage
Germany	78	25.2	25.2
Portugal	83	26.9	52.1
Spain	14	4.5	56.6
United States of America	58	18.8	75.4
Others	76	24.6	100
Total	309	100.0	

3.5. PROCEDURE

The data collection was conducted using a self-administered online questionnaire because it allows standardized and easily comparable data to be collected from a large population quickly, inexpensively, and in a very economical manner (Ponchio et al., 2021).

It is an appropriate strategy to measure the variables included in the hypotheses on a larger scale. The use of a questionnaire survey has the following advantages for this study. It maximizes the objectivity of the data and can be generalized to a larger population. The researchers are separated from the subjects during data collection, and the questions are highly structured and standardized, eliminating influence and confounding factors (Fricker & Schonlau, 2002). A standardized and structured format allows researchers to analyse the data more efficiently, and the use of statistical tools further reduces researcher interference (Melkert & Vos, 2010). Numerical data also provides higher accuracy, comparability of values, and graphical analysis. In addition, a questionnaire survey allows researchers to reach a large number of subjects simultaneously and collect a large sample at a relatively low cost

(Collis & Hussey, 2013). Because participants must be familiar with the Internet and social media, online questionnaires are appropriate for reaching this target audience.

However, it should be noted that an online survey also has some disadvantages. First, the standardized design offers less flexibility and less in-depth information. Respondents are not free to express their true thoughts and are limited to predetermined answers (Couper, 2008). In addition, respondents may not take the questionnaire seriously or may be inaccurate, affecting the results' reliability (Hoonakker & Carayon, 2009).

The questionnaire was developed on Qualtrics, an online platform for web-based surveys, and distributed through a link on several social networks, namely Facebook, Instagram, and LinkedIn, and individually via messaging platforms such as Messenger and WhatsApp. Confidentiality of the results was guaranteed, and it was ensured that the data collected were for purely academic purposes and would be analyzed in compliance with the GDPR. To provide the proper conduct of the research, the questionnaire was submitted, reviewed, and approved by the Research Ethics Committee of Nova IMS before it was distributed.

3.6. MEASURES

3.6.1. QUESTIONNAIRE DESIGN

This study used a questionnaire consisting of four main groups: (i) sociodemographic questions, (ii) experience with mental health applications, (iii) influencing factors, (iv) behavioral intention.

The first group was dedicated to the socio-demographic questions of the respondents, namely age, gender, and country of origin.

The second part, composed of questions about experience with mental health apps, asked respondents whether they had ever used a mental health app or were currently using a mental health app. If so, whether they could name the mental health app they were using.

The third group includes questions about the eight factors that may influence the adoption of mental health apps. Therefore, it consists of eight blocks of items. In the first block, participants answer four questions about the performance expectation of mental health apps. This is followed by questions on effort expectancy and social influence. The fourth and fifth blocks asked about hedonic motivation. They perceived susceptibility, representing perceived susceptibility to mental disorders—the following sections address perceived severity and self-efficacy, followed by the final block on cues to action.

The fourth block was dedicated to respondents' behavioral intention. It aimed to clarify whether participants intended or planned to use a mental health app.

3.6.2. MEASUREMENT SCALES

Because this study was conducted worldwide, all questionnaire questions are written in English (Appendix 1).

For this study and to standardize the measurement scales, a five-point Likert scale was used for most questions, ranging from "strongly disagree" (1) to "strongly agree" (5), to rate all main items according to the participants' level of agreement with the statements. Five-point Likert scales, which indicate a smaller range of opinions, are appropriate for measuring participants' attitudes. In addition, there is a disadvantage to selecting more options. Studies show that attention span reaches its effectiveness with six votes at a time. When assessing possible mood levels, our minds can only consider six at a time, so respondents have to invest a lot of time remembering possible choices. Five-point Likert scales have been shown to ensure that respondents do not lose interest. Analyzing the different response options is also easier for respondents because they are not tempted to select middle options or leave boxes blank. In addition, five sentiment levels provide a reasonable range of opinions that allow for a comprehensive understanding of attitudes toward the object or phenomenon being assessed (Taherdoost, 2020).

According to the overview of previous empirical studies, all the variables included in the conceptual framework of this study have been covered by previous studies. Hence, the measurements used in these studies can be borrowed by this thesis after slight modifications.

UTAUT 2 questionnaire

The research design was guided by Venkatesh et al.'s (2012) seven original constructs of technology acceptance. Sixteen items were adapted from the existing literature, with all questions relating to mental health apps. These items cover five of the nine constructs Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, and Behavioral Intention.

Health belief model questionnaire

To measure perceived susceptibility, perceived severity, self-efficacy, and cues to action, 15 items were adopted from the existing literature to assess the four constructs. These items are based on the health belief model questionnaires, which emerged from U.S public health researchers Godfrey Hochbaum, Stephen Kegels, Howard Leventhal, and Irwin Rosenstock. Later the first precise formulation of the HBM appeared in a paper by Rosenstock in 1966 and was later refined by Marshall Becker (1974).

Table 2

Measurement scales

Constructs	Number of items	Items	Sources
Performance expectancy	4	Using a mental health app would improve my mental wellbeing.	Venkatesh et al. (2012)
		Using a mental health app can satisfy my mental health care needs.	
		Using a mental health app can improve my efficacy in monitoring my mental health conditions.	
		Using a mental health app will improve the quality of my life.	
Effort expectancy	4	Choosing a mental health app would require a lot of effort.	Venkatesh et al. (2012)
		Using a mental health app would require a lot of effort.	
		Using a mental health app would require a lot of time.	
		Learning how to use a mental health app would be difficult.	
Social influence	3	People have asked me about my mental health.	Venkatesh et al. (2012)
		People have already advised me to seek mental health help.	

		People have already advised me to use a mental health app.	
Hedonic motivation	3	I think using a mental health app is fun. I think using a mental health app is entertaining, I think using a mental health app is enjoyable.	Venkatesh et al. (2012)
Behavioral intention	4	I intend to use a mental health app. I intend to check the availability of a suited mental health app. I plan to use a mental health app. It is worth using a mental health app.	Venkatesh et al. (2012)
Perceived susceptibility	4	Everybody can get a mental health disease. I am not at risk of mental health disease. I can have a mental health disease even without feeling its signs and symptoms. I am afraid of getting a mental health disease.	Becker (1974)
Perceived severity	4	Mental health diseases can lead to death. Mental health diseases can change the whole life.	Becker (1974)

		Mental health diseases can disrupt the harmony in families.	
		Mental health diseases are long lasting.	
Self-efficacy	3	I can always manage to solve difficult problem if I try hard enough.	Becker (1974)
		It is easy for me to accomplish my goals.	
		I am confident that I could deal efficiently with unexpected events.	
Cues to action	4	I heard about mental health apps before.	Becker (1974)
		I saw an advertisement about a mental health app.	
		I know at least one person who is using a mental health app.	
		Someone has already recommended a mental health app to me.	

3.7. DATA COLLECTION

This study used non-probabilistic random sampling based on the relatively easy availability of participants and is commonly used when the population to be studied too large to include. Not all individuals in the people have an equal chance of participating in this study, which influences the representativeness of the study. Still, it is the most cost-effective and least time-consuming method (Mweshi & Sakyi, 2020).

A power analysis was conducted using G-Power 3.1.9.7 software to determine the sample size required for this study. The results indicated a minimum sample size of 251 participants to achieve a statistical power of 99% for a mean effect size of 0.08 at a significance level of 1% (0.01) for the proposed model (Verma & Verma, 2020). Still, a larger sample was used to minimize the error further. In addition, Kyriazos (2018) recommends a ratio of 5 to 10 participants per item for a minimal example of 100 respondents, suggesting a selection of 195 to 390 participants for this study.

Before analyzing the results, the data were preprocessed and cleaned by identifying and deleting incomplete, irrelevant, and incorrect responses. A total of 438 participants completed the questionnaire. However, when the data was cleaned, it was found that 29.5% of the responses were incomplete and therefore removed from the data set, leaving a total of 309 completed questionnaires. Further analysis revealed no anomalies or errors. Therefore, the data set with 309 samples were used for the calculations.

4. RESULTS

4.1. OVERVIEW

For data analysis, several statistical tests were performed using IBM SPSS - Statistical Package for the Social Sciences (version 27). First, the analysis of the psychometric properties of the instruments is performed to ensure the validity and reliability of the studied constructs. Second, descriptive and differential statistics are presented to analyze the means and standard deviations of the constructs. Sociodemographic characteristics such as gender, age, and country of origin are compared concerning the use of mental health applications and the constructs mentioned in the conceptual framework. In addition, correlation analysis was performed to determine the associations and intensity between each construct. Linear multiple regression tests each hypothesis and assesses the influence of the independent variables on the dependent variables. The conceptual framework can be tested as a predictive model, and all eight ideas can be verified or falsified as appropriate. Statements can also be made about the strength of correlations. The data analysis is concluded with a goodness-of-fit test to examine whether the results can be generalized to the population.

4.2. PSYCHOMETRIC ANALYSIS

The psychometric analysis is the structured process of measuring the psychometric properties of an indicator by analyzing test data and ensuring the quality of the survey used. Because the accuracy of the results depends on the quality of the questionnaire, it is essential to analyze the psychometric properties, including the validity and reliability of the items used to measure the constructs (Jones & Thissen, 2006).

Validity explains how well the data collected cover the actual domain of investigation (Ghauri & Gronhaug, 2005). It means that an item measures what it was intended to measure (Field, 2005). There are different subtypes of validity, such as criterion validity, face validity, content validity, and construct validity. In this case, only construct validity is used. It refers to how well a construct has been transformed into an operationalization (Taherdoost, 2016).

On the other hand, reliability concerns how a measurement of a phenomenon yields stable and consistent results (Carmines & Zeller, 1979). It is concerned with repeatability, which means that a repeated samplesize produces the same results (Moser & Kalton, 1989). Reliability is measured by Cronbach's alpha coefficient, which is considered good at 0.70 or higher (Hair et al., 2018).

4.2.1. VALIDITY

The validity of the nine constructs was tested using principal component analysis (PCA). This variable reduction technique is used when a construct is measured by more than one item. PCA can therefore be used to check whether all items measure the same build and whether they can be transformed into a new variable with or without excluding one thing. (PCA)

For conducting a PCA, sample size recommendations are given by many authors, according to which the sample size of 309 participants collected for this study is considered suitable for factor analysis (Kyriazos, 2018). For this PCA, the Kaiser-Meyer-Olkin indicator (KMO indicator) and Bartlett's test of sphericity were used to assess whether the correlations between items were acceptable, which is the case for KMA values above .70 and Bartlett's test at a statistical significance of $p < .05$. Component extraction was based on Kaise-Guttmann criteria, scree plot analysis, and the percentage of variance explained, which is considered suitable for values above 60.0% (Hair et al., 2018). Only items with a factor-item correlation greater than .40 were selected in this analysis.

UTAUT2 questionnaire

A PCA was conducted to assess the validity of the items measuring performance expectancy, effort expectancy, hedonic motivation, and social influence. The KMO indicator (.81) and Bartlett's test for sphericity [χ 2 (91) = 1793.65, $p < .001$] were used to demonstrate adequate measurement of the constructs.

The eigenvalue of a factor indicates how much of the total variance of all variables is explained by that factor. The so-called "Kaiser criterion" (also "eigenvalue rule") states that only factors whose eigenvalue is more significant than 1.0 should be extracted. SPSS selects the number of factors strictly according to this criterion. As shown in Table 3, four elements have eigenvalues greater than 1.0. The middle column "Cumulated %" indicates that these four factors together explain 68.73% of the variance of all variables.

Table 3

Total variance explained

	Initial eigenvalues			Extraction sums of squared loadings		
Component	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	4.21	30.12	30.12	4.22	30.12	30.12
2	2.60	18.59	48.71	2.60	18.59	47.11
3	1.74	12.39	61.10	1.74	12.39	61.10
4	1.07	7.63	68.73	1.07	7.63	68.73
5	.85	6.03	74.76			
6	.61	4.38	79.14			
7	.49	3.49	82.63			
8	.47	3.36	85.99			
9	.42	2.97	88.96			
10	.38	2.73	91.70			
11	.33	2.36	94.05			
12	.32	2.26	96.32			
13	.28	1.99	98.31			
14	.24	1.69	100.00			

Extraction method: Principal component analysis.

The following table shows the rotated factor loadings of the data which represent both, the weighting for each factor and the correlation between the factors. A factor loading on a variable is the correlation between the variable and the element. For example, variable PE_1 and component 1 correlate at .805. The magnitude of the factor loading indicates how closely a variable is related to an element: amounts close to 0 show little correlation. The higher the value, the closer the correlation. Each variable is assigned to the factor it loads most strongly. Accordingly, it can be confirmed that the first four items measure the construct 'performance expectancy, the items HM_1, HM_2, and HM_3 can be assigned to the factor hedonic motivation, the construct effort expectancy is represented by EE_1 to EE_4, and the fourth-factor social influence is measured by the items SI_1, SI_2 and SI_3.

Table 4

Rotated component Matrix 1

	Component			
	1	2	3	4
PE_4	.805			
PE_3	.797			
PE_2	.730			
PE_1	.693			
HM_2		.864		
HM_1		.842		
HM_3		.811		
EE_3			.838	
EE_2			.820	
EE_1			.751	
EE_4			.686	
SI_2				.865
SI_1				.850
SI_3				.697

Extraction method: Principal component analysis.
Rotation method: Varimax with Kaiser normalization.
a. Rotation converged in 5 iterations.

HBM questionnaire

Considering the values of the KMO indicator (.82) and Bartlett's test for sphericity [$\chi 2$ (171) = 2680.12, $p < .001$] obtained by PCA, we can demonstrate the adequate measurement of five factors explaining 66.50% of the variance.

Nevertheless, the rotated component matrix (table 5) shows that item PSU_1 was assigned to the first factor, perceived severity, although it should be given to the construct perceived susceptibility. For this reason, it is not included in further analyses. The item PSU_2 is also excluded in the other course since it only shows a weak correlation to one of the factors.

Table 5

Rotated component matrix 2

	Component				
	1	2	3	4	5
PSE_2	.882				
PSE_3	.872				
PSU_1	.791				
PSE_1	.783				
PSE_4	.570				
BI_1		.914			
BI_3		.908			
BI_2		.904			
BI_4		.759			
CA_3			.795		
CA_2			.774		
CA_4			.709		
CA_1			.680		
SE_3				.815	
SE_2				.748	
SE_1				.722	
PSU_2	.329				
PSU_4					.821
PSU_3					.587

Extraction method: Principal component analysis.
Rotation method: Varimax with Kaiser normalization.
a. Rotation converged in 5 iterations.

After exclusion of PSU_1 and PSU_2, PCA was performed repeatedly. The results are shown in Table 6. The KMO indicator (.80) and Bartlett's test for sphericity [χ 2 (136) = 2372.14, $p < .001$] prove the adequate measurement of five factors explaining 68.98% of the variance. The first factor is composed of the items related to behavioral intention. The second component relates to perceived severity and is measured by PSE_1 through PSE_4. CA_1, CA_2, CA_3, and CA_4, the third factor, is calculated, representing action cues. Self-efficacy is the fourth factor measured by three additional items. The last construct, perceived susceptibility, is calculated by PSU_3 and PSU_4.

Table 6

Rotated component matrix 3

	Component				
	1	2	3	4	5
BI_1	.917				
BI_3	.913				
BI_2	.908				
BI_4	.752				
PSE_3		.894			
PSE_2		.883			
PSE_1		.801			
PSE_4		.637			
CA_3			.795		
CA_2			.778		
CA_4			.706		
CA_1			.685		
SE_3				.834	
SE_2				.766	
SE_1				.755	
PSU_4					.873
PSU_3					.615

Extraction method: Principal component analysis.
Rotation method: Varimax with Kaiser normalization.
a. Rotation converged in 5 iterations.

4.2.2. RELIABILITY

An essential measure of internal consistency and thus of reliability of a questionnaire is Cronbach's alpha. It indicates the extent to which the individual questions of a questionnaire agree with each other and measure the same construct. Thus, when internal consistency is high, the answers to the individual questions roughly concur. In other words, the question items all correlate positively with each other. A Cronbach's alpha above 0.7 is considered sufficient (Hair et al., 2018).

The Cronbach's alpha for the four items measuring the construct performance expectancy is .82 and for effort expectancy .78. When calculating the construct social influence (.75), one can see in table 7 that one can increase Cronbach's alpha.78 if one deletes the last item. Therefore, the third item is excluded in further analysis.

Table 7

Item-total statistics

	Scale means if Item deleted.	Scale variance if item deleted	Corrected item-total correlation	Cronbach's alpha if item deleted
SI_1	4.93	5.778	.599	.644
SI_2	5.45	5.423	.671	.555
SI_3	5.87	6.797	.476	.778

The three items measuring hedonic motivation have a reliability of .88, as shown in table 8. The construct perceived susceptibility, whose articles also showed some irregularities in the factor analysis, offers weak reliability of .25 when all items are included. If the first item is excluded, the reliability increases to .53, which is still low and must be considered critically in further analysis.

The construct perceived severity is measured with four items. If the fourth item is excluded, the reliability increases from .84 to .86. The calculation of Cronbach's alpha for self-efficacy results in a value of .71 for all three things together and .76 for the cues to action. The construct behavioral intention shows the highest internal consistency with a value of .92. If the fourth item is omitted, the reliability increases to .94.

Table 8

Reliability statistics

Constructs	Cronbach's alpha	N of items
Performance expectancy	.82	4
Effort expectancy	.78	4
Social influence	.78	2
Hedonic motivation	.88	3
Perceived susceptibility	.53	3
Perceived severity	.86	3
Self-efficacy	.71	3
Cues to action	.76	4
Behavioral intention	.94	3

4.3. DESCRIPTIVES

After evaluating the psychometric properties of the measurement instruments, the analysis of the descriptive statistics of the variables was performed as follows. To better understand the characterization of the sample about the topic of mental health apps, several descriptive analyses were conducted.

First, about participants' experience with mental health apps, it was found that nearly 50% of participants had ever used a mental health app. Still, only 17.8% continued to use them, meaning that 54 participants in the study used a mental health app for data collection. In total, 20 different mental health apps were mentioned as used by participants. The most commonly used mental health apps are Calm and Headspace, followed by other apps that you can see in table 9.

Table 9

Mental health applications used by participants

		Frequency
Name		
	Calm	13
	Headspace	12
	Happify	3
	7Mind	3
	Sanvello	3
	Talkspace	2
	Good fit	2
	InnerHour	2
	Betterhelp	2
	GuidanceResources	2
	Balloon	1
	Breathe	1
	HealthPlix	1
	Insight Timer	1
	MindBeacon	1
	Peak	1
	Sesh	1
	Smiling Mind	1
	Woebot	1
	Wysa	1

25.6% of German participants currently use a mental health app, and 4.82% Portuguese participants. Of the participants from the USA, as many as 34.48% use a mental health app. In terms of gender, 18.75% of female participants and 17.05% of male participants currently use a mental health app.

71.2% of the respondents are between 21 and 36 years old, 211 people. 18.18% of them were using a mental health app during data collection. And 17.72% of those over 36 years old also reported using a mental health app.

Then, the descriptive analysis was conducted for the primary constructs studied. It was considered that a five-point rating scale from "strongly disagree" (1) to "strongly agree" (5) and a three-point rating scale from "no" (1) and “maybe (2) to "yes" (3) were used to measure the main questionnaire items, and that the results of each construct were calculated by adding the values assigned to each item; the higher the average value, the higher the agreement with the influencing factors. Respondents' perceptions of the influencing factors and behavioral intentions are shown below (Table 10).

Table 10

	Number of point	Mean	Std. deviation
PE	5	3.53	.77
EE	5	2.85	.88
SI	5	2.93	1.30
HM	5	3.24	.93
PSU	5	3.23	.73
PSE	5	4.43	.77
SE	5	3.50	.80
CA	3	2.14	.67
BI	5	3.18	1.11

The data show that participants have a relatively high-performance expectation of mental health apps, meaning that they believe in the effectiveness of these apps and see them as a good source of help. In terms of effort, expectations are relatively mixed below. Also, the social influence of using a mental health app does not seem to be very pronounced among participants; instead, hedonic motivation is slightly higher. It indicates how participants expect utilizing an application to be fun. Survey participants also tend to rate themselves as more prone to mental disorders. The most apparent value is that for perceived severity, which shows that mental illness is taken seriously. The value for the construct call to action also indicates that the topic of mental health is present. The behavioral intention is also slightly above average, implying increased use of mental health apps in the future.

4.4. DIFFERENTIAL STATISTICS

A comparative analysis of the results was then performed according to the socio-demographic characteristics of the respondents, such as gender, age, and country of origin. Gender group analysis revealed no significant difference between groups ($p > .05$), except for effort expectancy. (Female ($M = 2.74$, $SD = .87$, $n = 176$) participants had, on average, lower effort expectancy than males ($M = 2.98$, $SD = .85$, $n = 129$). According to Cohen (1992), the effect size is $r = .28$, corresponding to a weak effect.

In terms of age, participants were divided into two groups depending on the average age of the respondents. Group one consisted of those 18 to 32 years old. Group two included those aged 33 to 70. These two groups showed significant differences in social influence ($t(307) = 3.42$, $p = .001$), perceived severity ($t(307) = 44.44$, $p < .001$), and calls to action ($t(307) = 3.10$, $p = .002$). The Cohen (1992) effect size for social influence is $r = .40$, corresponding to a medium effect. For perceived severity, it is $r = .53$, which corresponds to a strong effect. For cues to action, it is $r = .37$, which means that the younger group perceives mental illness as more severe, was more often asked about their mental health by their environment, and already had more contact with the topic of mental health apps.

The last mean comparison is between German and Portuguese respondents due to the high participation. Looking at the data, some significant differences emerge. First, the experience of using a mental health app is significantly higher among German participants ($M = 1.55$, $SD = .501$, $n = 78$) than among Portuguese participants ($M = 1.30$, $SD = .46$, $n = 83$); second, more German respondents currently use a mental health app. The two groups also differ significantly in performance expectancy ($t(159) = 2.27$, $p = .024$), calls to action ($t(159) = 3.83$, p = < .001), and behavioral intention ($t(159) = 2.56$, $p = .012$). This means that German participants believe more in the effectiveness of mental health apps, that the topic is more present in their social environment, and that they are more inclined to use one of these apps.

4.4.1. CORRELATIONS

Subsequently, the correlations between the variables were analyzed using the Pearson correlation coefficient. A significant moderate positive correlation was demonstrated between the construct hedonic motivation and performance expectancy ($r = .589$, $p < .001$) (r between .30 and .70). Similarly, between the variables hedonic motivation and perceived receptivity ($r = .315$, $p < .001$), performance expectancy and self-efficacy ($r = .310$, $p < .001$), hedonic motivation and self-efficacy ($r = .323$, $p < .001$ and perceived receptivity and self-efficacy ($r = .248$, $p < .001$). Furthermore, a correlation is found between behavioral intention and performance expectancy ($r = .619$, $p < .001$), hedonic motivation ($r = .618$, $p < .001$), and cues to action ($r = .363$, $p < .001$). As shown in table 11, the higher the performance expectancy, hedonic motivation, and cues to action, the higher the behavioral intention to use a mental health app.

Table 11

Item correlations

	PE	EE	SI	HM	PSU	PSE	SE	BI
PE								
EE	-.017							
SI	.138*	.153**						
HM	.589**	.021	.075					
PSU	.295**	.174**	.075	.315**				
PSE	.111	-.033	-.026	-.003	.174**			
SE	.310**	.064	-.091	.323**	.248**	.025		
BI	.619**	-.059	.207**	.618**	.181**	-.022	.169**	
CA	.287**	-.104	.194**	.270**	.117*	.060	.129*	.363**

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

4.4.2. LINEAR MULTIPLE REGRESSION

Considering the previous results, multiple regression was performed using the enter method to examine the effects of each factor on the intention to use a mental health application. Regression indicates the directional linear relationship between two or more variables. The so-called coefficient of determination (R^2) expresses how well the regression line reflects the relationship between the independent and dependent variables and should be between zero and one (table 12). The dependent variable is behavioral intention, the predictors are performance expectancy, effort expectancy, social influence, hedonic motivation, perceived susceptibility, perceived severity, self-efficacy and cues to action.

Table 12

Linear multiple regression model summary

Model	R	R Square	Adjusted R Square	Std. The error of the Estimate
1	.727[a]	.529	.517	.7684

a. Predictors: (constant), CA, PSE, EE, SE, SI, PSU, HM, PE

The determination of a regression function does not yet mean that the determined correlation is significant. The so-called F-test determines the significance of the regression. The results show that the linear model is statistically substantial t [$F(8, 300) = 42.15$, $p < .001$] and that the set of variables explains 24.89% of the variance in behavioral intention (Table 13).

Table 13

ANOVA results

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	199.114	8	24.889	42.150	.000[b]
	Residual	177.149	300	.590		
	Total	376.263	308			

a. Dependent variable: BI

b. Predictors: (constant), CA, PSE, EE, SE, SI, PSU, HM, PE

Additionally, the influence of each factor within the model was analyzed. It was found that within this combined group of factors, performance expectancy ($t = 7.306$, $p = <.001$), social influence ($t = 2.426$, $p = .016$), hedonic motivation ($t = 7.517$, $p = <.001$), and action incentives ($t = 3.328$, $p = <.001$) were the only constructs with a significant influence on behavioral intention (Table 14). Therefore, H1, H3, H4, and H8 could be verified.

Table 14

Linear multiple regression coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized coefficients Beta	t	Sig.
1	(Constant)	.112	.389		.289	.773
	PE	.540	.074	.375	7.306	.000
	EE	-.066	.052	-.052	-1.257	.210
	SI	.086	.035	.102	2.426	.016
	HM	.461	.061	.385	7.517	.000
	PSU	-.058	.066	-.039	-.876	.382
	PSE	-.089	.059	-.062	-1.512	.132
	SE	-.092	.060	-.066	-1.522	.129
	CA	.240	.072	.143	3.328	.001

a. Dependent variable: BI

The variables effort expectancy, perceived susceptibility, perceived severity, and self-efficacy have no significant influence on behavioral intention. This means that they alone are not sufficient to predict consumer behavior. However, variables such as perceived susceptibility and self-efficacy can still correlate with behavioral intention. This only indicates the degree of relationship between the variables, which in this case is weak. For this reason, H2, H5, H6, and H7 cannot be verified.

4.4.3. REPRESENTATIVENESS OF THE RESULTS

In addition, a goodness-of-fit test was performed to determine whether the sample data corresponds to the data that would be expected in the actual population. It indicates the discrepancy between the observed values and the values that would be expected from the model in a normal distribution. Representativeness is defined as drawing accurate conclusions about a population from a sample. The results of the chi-square goodness-of-fit test show a significant impact for each variable (Table 15). This means a substantial difference between the observed data and the expected values.

Table 15

Representativeness of the results

	PE	EE	SI	HM	PSU	PSE	SE	BI	CA
Chi-Square	243.087[a]	126.343[a]	49.107[b]	194.634[c]	216.087[d]	656.709[d]	205.405[c]	103.761[c]	50.505[b]
df	16	16	8	12	11	11	12	12	8
Asymp. Sig.	.000	.000	.000	.000	.000	.000	.000	.000	.000

a. 0 cells (0,0%) have expected frequencies less than 5. The minimum expected cell frequency is 18,2.

b. 0 cells (0,0%) have expected frequencies less than 5. The minimum expected cell frequency is 34,3.

c. 0 cells (0,0%) have expected frequencies less than 5. The minimum expected cell frequency is 23,8.

d. 0 cells (0,0%) have expected frequencies less than 5. The minimum expected cell frequency is 25,8.

5. DISCUSSION

Over the years, numerous studies have been conducted on mental health apps, mainly focusing on efficacy and privacy (Marshall et al., 2019; Parker et al., 2019). However, mental health apps are a relatively new technology and are only now being explored.

Given the rise in mental disorders and the lack of treatments, there is a growing recognition of the need to explore mental health apps and their use as an alternative to traditional therapy (NIH, 2021). In this field, it is essential to understand the characteristics that most influence the adoption of these technologies to meet consumer needs and improve uptake. Considering that mental health is a sensitive issue in our society, the factors mentioned in classical models such as the Technology Acceptance Model or the Unified Acceptance Theory may not be sufficient to explain the acceptance of mental health applications. Therefore, other characteristics related to the health belief model were additionally proposed and investigated.

Accordingly, the main objective of this study was to understand which of the following factors such as performance expectancy, effort expectancy, social influence, hedonic motivation, perceived susceptibility, perceived severity, self-efficacy, and cues to action influence behavioral intention to use a mental health application. The results on the research questions of the proposal confirmed that performance expectancy, social influence, hedonic motivation, and cues to action positively influence the behavioral intention to use mental health applications. The effect of effort expectancy, perceived susceptibility, perceived severity, and self-efficacy on behavioral intention was not significantly demonstrated.

First, the study results show that almost 50% of the participants have used a mental health app before, but only 17.8% continue to use it. This suggests that participants are open to using these apps but are not satisfied with them. There are also significant differences between users in different countries, such as Germany and Portugal. The study shows that there is no significant difference in use in terms of the age of the respondents. On average, participants have high-performance expectations, believe in mental health apps' effectiveness, and have positive attitudes toward these technologies. Their perceived severity and susceptibility are relatively high, indicating that they are aware of mental disorders and are more willing to use a mental health app in the future than not to use one. Strikingly, on average, respondents were not exposed to many cues of action, such as people who have recommended a mental health app to them, who know people who use such an app, or who have seen an advertisement about it.

Correlation analyses showed a significant relationship between performance expectancy, social influence, hedonic motivation, perceived susceptibility, self-efficacy, cues to action, and behavioral intention. The existence of a correlation is not sufficient to make a statement about the predictive power of the items. Therefore, multiple regression was conducted to test the hypothesis based on the conceptual framework. The first hypothesis aimed to investigate the influence of performance expectancy on behavioral intention based on the UTAUT 2 (Venkatesh et al. 2003), which was supported by the obtained results that showed a significant influence of performance expectancy on behavioral intention (H1). These results are comparable to a study about Hospital Patients’ adoption of medical apps (Chang et al., 2021).

It was then hypothesized that effort expectancy negatively influences behavioral intention (H2). Different from the UTAUT 2 model (Venkatesh et al. 2003), this study could not find a significant effect of this factor on behavioral intention. Nevertheless, social influence was shown to positively impact on behavioral intention (H3). Thus, when participants' acquaintances ask them about their mental health, advise them to seek help, or recommend using a mental health app, this positively influences their intention. The fourth hypothesis, indicating a positive influence of hedonic motivation on behavioral intention, was also confirmed (H4). Accordingly, participants who believe that using a mental health app is fun, entertaining, and enjoyable are more likely to use such an app. In contrast to the Health belief model(Becker, 1974), data from this study failed to show a significant influence of perceived susceptibility and perceived severity on behavioral intention (H5 & H6). This means that even if people feel vulnerable or take mental disorders seriously, it does not influence their behavioral choice to use a mental health app. Also, the positive influence of self-efficacy on behavioral intention could not be demonstrated in this study (H7), unlike in other studies regarding help-seeking intentions reported (Langley et al., 2017). The last hypothesis could be verified (H8). According to this hypothesis, cues to action positively influence behavioral intention. This means that participants who have heard of apps, seen an advertisement for an app or know people who use and have recommended a mental health app are more likely to use an app.

Table 16

Hypothesis overview and results

Hypothesis	Relationship	Results
H1	Performance expectancy -> behavioral intention	Supported
H2	Effort expectancy -> behavioral intention	Rejected
H3	Social influence -> behavioral intention	Supported
H4	Hedonic motivation -> behavioral intention	Supported
H5	Perceived susceptibility -> behavioral intention	Rejected
H6	Perceived severity -> behavioral intention	Rejected
H7	Self-efficacy -> behavioral intention	Rejected
H8	Cues to action -> behavioral intention	Supported

6. CONCLUSION

This study aimed to examine the influence of performance expectancy, effort expectancy, social impact, hedonistic motivation, perceived susceptibility, perceived severity, self-efficacy, and calls to action on behavioral intention to use a mental health application.

The study followed a hypothetico-deductive quantitative approach to test the research hypothesis, and data were collected using a self-administered online questionnaire consisting of four parts: (i) sociodemographic questions, (ii) experiences, (iii) influencing factors, (iv) behavioral intentions. The sample consisted of 309 participants aged between 18 and 70 years.

Results indicate moderately high scores for respondents' opinions regarding perceived severity, performance expectancy, and self-efficacy. When comparing sociodemographic, there was no significant response be concerning age or gender. There are varying degrees of mental health apps used only in terms of country. There is a substantial difference in usage and behavioral intention regarding mental health apps when comparing Germany and Portugal. Additionally, correlation analyses and multiple linear regression demonstrated a meaningful positive relationship between some factors. Finally, the research hypotheses were tested, and it was confirmed that performance expectancy, social influence, hedonic motivation, and action incentives influence the behavioral intention to use a mental health application. This analysis also revealed that participants generally have positive associations with mental health apps and intend to use them in the future.

6.1. THEORETICAL AND MANAGERIAL IMPLICATIONS

Mental health apps are one way to provide smartphone owners with low-cost, hassle-free mental health treatment. Thus, it is an opportunity to counteract the increasing trend of mental illness and close the gap between treatment needs and treatment uptake (MHA, 2021). In this context, they evaluate the factors that influence the adoption of mental health apps that yields significant results for app providers. Understanding user behavior and the perceptions consumers develop helps brands select the best features and promote their products according to the most effective and influential elements.

The ability to predict intention to use a mental health app helps companies develop marketing strategies because by understanding the psychology of how consumers are influenced to perceive a brand or product; brands can more successfully reach consumers, create positive and influential decision making toward their products, and gain competitive advantage in the marketplace (Lim et al., 2017). This means that suppliers should provide incentives for activities, such as advertising on various platforms. They should choose measures to communicate the effectiveness of these apps and ensure that people are made aware of the issue through campaigns, for example. In addition, they should speak to potential users that using mental health apps is easy and fun to appeal to hedonistic motivation. These factors have the most significant impact on behavioral intention, leading to greater adoption of mental health apps.

6.2. LIMITATIONS AND FURTHER RESEARCH

As with any research, there are several limitations to this study that may lead to recommendations for the future.

First, the sample size is relatively small to represent the population, so the data does not represent the entire target population studied. Therefore the results of this study are not sufficient to generalize the findings. Because data were collected using a random sample and an online questionnaire, most participants were between 20 and 29. Future studies may be of interest to reach a broader age group and further validate whether there are differences in perceptions and influencing factors regarding the adoption of mental health applications. It may also be speculated whether individuals who voluntarily participate in a mental health survey are generally more open to the topic and are typically part of the population segment more likely to use a mental health app.

In addition, this study did not consider some sociodemographic factors, such as income or education level. Therefore, it would be interesting to investigate possible differences in behavioral intention according to participants' income and education level in future projects. It would also be interesting to analyze the differences in usage between different countries, such as Portugal and Germany, to understand the reasons for this. Moreover, it is essential to note that the data were collected during the COVID 19 pandemic. The respondents in this crisis might have influenced the responses regarding the intention to use a mental health app due to psychological stress. Because the influencing factors and behavioral intention were assessed based on UTAUT2 and HBM factors, some other determinants could not be analyzed. Another limitation is that the study is correlational, so no causation can be concluded.

Finally, examining the long-term use of mental health apps would be essential because of the large gap between initial adoption and long-term service. Therefore, it would be interesting to find out why people stop using these apps and how to counteract this.

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8. APPENDIX

Published survey

By participating in this survey you will help me to finish my master's thesis. Thank you very much! :)

Informed consent By clicking "I agree", I declare that I am at least 18 years old and that I agree to participate in this research. I declare that I have been informed that my participation in this study is voluntary, that I can leave the survey at any time without penalty, and that all data will be kept confidential. I understand that there are no serious risks associated with this study.

○ I do not agree to participate in this survey (1)

○ I agree to participate in this survey (2)

Skip To: End of Survey If By clicking "I agree", I declare that I am at least 18 years old and that I agree to participate... = I do not agree to participate in this survey

End of Block: Informed consent

Start of Block: Introduction

Introduction Mental health apps like Headspace, Calm, or Moodfit focus on improving various aspects of mental health and well-being. They meet a range of needs and offer different functions. Some focus on meditation, mood tracking, anti-stress exercises and sleep aids, while others serve more as a diary or online therapy where you can speak with a licensed mental health professional. Apart from a few paid apps, most of them can be downloaded and used for free by any smartphone user.

End of Block: Introduction

Start of Block: Demographics

Age What's your age? (full numbers)

____

Gender What's your gender?

- ○ Female (1)
- ○ Male (2)
- ○ Non-binary / third gender (3)
- ○ Prefer not to say (4)

Country Which country are you from?

▼ Afghanistan (1) ... Zimbabwe (1357)

End of Block: Demographics

Start of Block: Experience

Usage past Have you ever used a mental health app?

- ○ No (1)
- ○ Yes (2)

Usage present Are you currently using a mental health app?

◯ No (27)

◯ Yes (28)

Page Break

Display This Question:

If Are you currently using a mental health app? = Yes

Name app Please name the mental health app/ apps you are currently using.

____

____

____

____

____

End of Block: Experience

Start of Block: Performacy expectancy

PE Please rate the following statements.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Using a mental health app would improve my mental wellbeing. (1)	○	○	○	○	○
Using a mental health app can satisfy my mental health care needs. (2)	○	○	○	○	○
Using a mental health app can improve my efficacy in monitoring my mental health conditions. (3)	○	○	○	○	○
Using a mental health app will improve the quality of my life. (4)	○	○	○	○	○

End of Block: Performacy expectancy

Start of Block: Effort expectancy

EE Please rate the following statements.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Choosing a mental health app would require a lot of effort. (1)	○	○	○	○	○
Using a mental health app would require a lot of effort. (2)	○	○	○	○	○
Using a mental health app would require a lot of time. (3)	○	○	○	○	○
Learning how to use a mental health app would be difficult. (4)	○	○	○	○	○

End of Block: Effort expectancy

Start of Block: Social influence

SI Please rate the following statements.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
People have already asked me about my mental health. (1)	o	o	o	o	o
People have already advised me to seek mental health help. (2)	o	o	o	o	o
People have already advised me to use a mental health app. (3)	o	o	o	o	o

End of Block: Social influence

Start of Block: Hedonic motivation

HM Please rate the following statements.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I think using a mental health app is fun. (1)	○	○	○	○	○
I think using a mental health app is entertaining. (2)	○	○	○	○	○
I think using a mental health app is enjoyable. (3)	○	○	○	○	○

End of Block: Hedonic motivation

Start of Block: Perceived susceptibility

PSU Please rate the following statements.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Everybody can get a mental health disease. (1)	○	○	○	○	○
I am not at risk of mental health disease. (2)	○	○	○	○	○
I can have a mental health disease even without feeling its signs and symptoms (3)	○	○	○	○	○
I am afraid of getting a mental health disease. (4)	○	○	○	○	○

End of Block: Perceived susceptibility

Start of Block: Perceived severity

PSE Please rate the following statements.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Mental health diseases can lead to death. (1)	o	o	o	o	o
Mental health diseases can change the whole life. (2)	o	o	o	o	o
Mental health diseases can disrupt the harmony in families. (3)	o	o	o	o	o
Mental health diseases are long lasting. (4)	o	o	o	o	o

End of Block: Perceived severity

Start of Block: Self-efficacy

SE Please rate the following statements.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I can always manage to solve difficult problems if I try hard enough. (1)	○	○	○	○	○
It is easy for me to accomplish my goals. (2)	○	○	○	○	○
I am confident that I could deal efficiently with unexpected events (3)	○	○	○	○	○

End of Block: Self-efficacy

Start of Block: Cues to action

CA Please rate the following statements.

	No (32)	Maybe (33)	Yes (34)
I heard about mental health apps before. (1)	○	○	○
I saw an advertisement about a mental health app. (3)	○	○	○
I know at least one person who is using a mental health app. (5)	○	○	○
Someone has already recommended a mental health app to me. (6)	○	○	○

End of Block: Cues to action

Start of Block: Behavioral intention

BI Please rate the following statements.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I intend to use a mental health app. (1)	○	○	○	○	○
I intend to check the availability of a suited mental health app. (2)	○	○	○	○	○
I plan to use a mental health app. (3)	○	○	○	○	○
It is worth using a mental health app. (4)	○	○	○	○	○

End of Block: Behavioral intention