An Evaluation of Educators in Canada's Acceptance of Digital Mental Health Tools

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Abstract

Children and youth in Canada are experiencing rising mental health concerns, which increases their risk for further mental and physical health problems throughout their life (Beauchaine & Cicchetti, 2019). Given the varying severity of mental health difficulties in children and youth, it is imperative that mental health promotion and prevention efforts address these mental health difficulties before they progress or worsen. Mental health promotion and prevention interventions can strengthen one's ability to regulate emotions, build resiliency, and promote positive social environments and networks (World Health Organization, 2024). Schools provide a community that can act as a venue for mental health promotion and delivery of care (Hoover & Bostic, 2021; Short et al., 2022; Vaillancourt, 2021). A possible cost-effective and innovative solution for mental health services in schools are digital mental health technologies (DMHTs). DMHTs can offer an easily accessible tool to increase mental health literacy and education to complement the mental health efforts already in place in schools (Wiguna et al., 2025). Currently, there is a lack of research examining educators' perspectives on these DMHTs and their acceptance of using these tools to promote student well-being (Sakellari et al., 2021). The current study recruited 141 educators throughout Canada and evaluated their acceptance of DMHTs in their (a) professional work and (b) personal lives using the Extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework (Venkatesh et al., 2012); and examined relationships between educators' individual differences variables (e.g., demographics, attitudes towards technology, personality, well-being, and digital self-efficacy) and their acceptance of DMHTs. Partial Least Squares Structural Equation modeling analyses were conducted to test the hypothesized relationship between the UTAUT2 constructs and acceptance of DMHTs in educators' professional work and personal lives. We found that the constructs of

Habit and Hedonic Motivation significantly predicted acceptance in their professional work, with age having a moderating effect with Habit on acceptance. Performance Expectancy was a significant and positive predictor of intent to use DMHTs in their personal lives. Regression analyses revealed that digital self-efficacy was a significant predictor of acceptance in both educators' professional work and personal lives. General attitudes towards technology also predicted Behavioural Intention to use DMHTs in educators' professional work. This study has the potential to inform future development and integration of DMHTs to promote well-being and emotion regulation within schools.

Keywords: youth mental health; well-being; schools; digital mental health; electronic mental health; educators; mental health prevention and promotion

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Youth Mental Health (MH)

Children and youth (aged 3 to 17 years) in Canada are experiencing rising mental health concerns (Saunders et al., 2022; Statistics Canada, 2025). Mental health (MH) refers to an individual's emotional and psychological well-being (Statistics Canada, 2020). It plays an important role in maintaining one’s overall health. This increase in poor mental health is complex and attributed to interactions of various factors such as the COVID-19 pandemic, discrimination, the climate crisis, and problematic social media use (Public Health Agency of Canada, 2024). Considering that children and youth undergo various academic, personal, and social pressures (Acharya et al., 2018; Moltrecht et al., 2021; Wiens et al., 2020), mental health difficulties during this important life stage can impact an array of life events. These include forming relationships, academic achievements, physical health, identity development, gaining autonomy, and financial independence (Izard et al., 2001; Catalino & Fredrikson, 2011; McGorry et al., 2022; Moltrecht et al., 2021).

There are serious economic, societal, and social impacts from the early onset of mental health difficulties or lack of adequate interventions for children, youth, and their families (Kessler et al., 2008; Malla et al., 2018). Without access to mental health interventions, youth are at increased risk of missing out on educational and employment opportunities. This is evident in the fact that mental health difficulties account for 60–70% of disability-adjusted life years (Malla, 2018; Patel et al., 2007). In addition, childhood mental health difficulties are associated with a greater severity of the disorder and poorer prognosis across the lifespan (Copeland et al., 2015; Erkstine et al., 2016; Milraney et al., 2021). With lasting adverse social and economic impacts on society, their families, and themselves (Kessler et al., 2008; Malla et al., 2018), prevention and investments into adequate mental health support is crucial, which is why the mental health of young people[1] in Canada has become a public health priority (Public Health Agency of Canada, 2024).

MH Care for Children and Youth

Given the varying severity of mental health difficulties in children and youth, it is imperative that mental health promotion and prevention efforts address these mental health difficulties before they progress or worsen. Mental health promotion aims to empower individuals to take control of their own well-being and to cope with adversity by enhancing their strengths, capacity, and resources (Kalra et al., 2012; Min et al., 2013). Mental health prevention focuses on reducing risk factors and/or increasing protective factors through interventions aimed at early identification, early treatment, and rehabilitation (Sakellari et al., 2021). The two concepts of mental health promotion and prevention are interrelated and target all individuals, not just those experiencing mental health difficulties. Mental health promotion and prevention interventions can strengthen one's ability to regulate emotions, build resiliency, and promote positive social environments and networks (World Health Organization, 2024). An abundance of studies have supported that mental health promotion interventions increase factors that promote well-being and resiliency, leading to better outcomes compared to those with mental illnesses, and prevent the development of mental illness (Burton et al., 2010; Jané-Llopis et al., 2005; Kalra et al., 2012; Singh et al., 2022). Additionally, mental health promotion and prevention efforts are socioeconomically beneficial, decreasing disability-adjusted life years, and lowering the risk of developing further mental and physical health problems throughout individuals' lives

[1] The current study refers to young people in Canada as individuals' aged 3-17 years of age.

(Colizi et al., 2020; Singh et al., 2022). With poor or late access to interventions a common challenge for youth in Canada (Gravel & Béland., 2005; Malla et al., 2018), it is recommended that a continuum of care between interventions promoting positive mental health, interventions preventing the onset of mental health disorders, and interventions aimed at early identification and treatments be used (Colizi et al., 2020; Dua et al., 2011). To effectively target children and youth, promotion programs often involve a multi-level approach that varies in service delivery, such as digital media, health care settings, and school settings (WHO, 2024).

MH Care for Students

Schools provide a community that can act as a venue for mental health promotion and delivery of care (Hoover & Bostic, 2021; Short et al., 2022; Vaillancourt, 2021). Since educators interact with students every day, they have the ability to positively influence their well-being. For this reason, schools have been argued as an optimal environment for health-related interventions (Inchley et al., 2007; Pulimeno et al., 2020). A health promoting school is one that focuses on educating youth to take responsibility for their health decisions and control over their circumstances. Effective school-based health promotions are successful if the whole school is engaged (i.e., embedded in school policies and curriculum), as well as being collaborative with caregivers and health care providers to spread preventative efforts (Pulimeno et al., 2020).

A systematic review by Salerno et al. (2016) evaluated the literature on the effectiveness of mental health awareness programs in United States (U.S.) schools, from Kindergarten to Grade 12. They included 15 studies in their review and found that these prevention programs improved mental health knowledge, attitudes, and help-seeking behaviours among adolescents. However, a major limitation of this review was that only three studies used a randomized control design (Aseltine et al., 2004; Pinto-Foltz et al., 2011), with the majority of studies using a nonrandomized experimental design and pretest/posttest design, which have weaker internal validity and lack establishing causal-effect relationships (Salerno et al., 2016).

In another review, Clarke et al. (2021) evaluated the effectiveness of school-based mental health interventions for adolescents (aged 12 to 18) in the United Kingdom (UK). 34 systematic reviews along with 97 primary published journal articles were included in the review. Universal interventions, specifically those that target social-emotional learning (e.g., social and emotional well-being) were effective for all students to build resiliency and promote a mentally healthy school environment. Overall, the literature reports positive outcomes of these school-based mental health awareness programs by enhancing mental health care seeking and adherence for students (Clarke et al., 2021; Salerno et al., 2016), as well as being a cost-effective option (Le et al., 2021).

School MH Initiatives

In Canada, there are school supports already provided that align with the mental health promotion and prevention approach. The Mental Health Commission of Canada (MHCC) outlines a stepped care model (MHCC, 2025) that takes a person-centered and strengths-based approach to matching supports based on the individual's needs. Implementation of effective school-based interventions target mental health needs on a tiered system; primary or universal (all children/youth), secondary (at-risk children/youth), and tertiary (children/youth with mental health needs) (Atkins et al., 2010; Eber et al., 2011; Moon et al., 2018). The interventions “step up” from the most accessible to more intensive services if needed, ensuring all receive interventions based on their specific needs. The MHCC has numerous prevention and promotion initiatives for youth and school communities that aim to improve mental health outcomes. These include: *Headstrong*, which is a peer-led, mental health leadership program for youth aged 12 and up, aimed to reduce stigma surrounding mental health (MHCC, 2021). Another MHCC initiative is the *Mental Health First Aid* program that is designed for educators, staff, parents, and youth to identify early signs of mental health issues (MHCC, 2025). A randomized control trial carried out by Jorm et al. (2010), evaluated the *Mental Health First Aid* for high school teachers and found that the program is effective at reducing stigma associated with mental health, increasing confidence and knowledge about mental health difficulties for school teachers working with high school students (Jorm et al., 2010).

Additionally, in Ontario, there are mandatory mental health literacy learning modules for students in Grades 7, 8 and 10 (Ontario Ministry of Education, 2024). These modules are teacher-led to educate students about mental health, mental illness, and stigmas associated with both. The modules are effective in increasing knowledge for mental health and reducing mental health stigma in high school students (Mcluckie et al., 2014). While Canadian educators teaching kindergarten to Grade 6 do not explicitly provide mental health promotion and prevention interventions, they promote social-emotional learning, healthy school environments, and educate students on how to deal with stress and develop healthy relationship skills (Ontario Ministry of Education, 2024). However, students have still expressed the desire for mental health promotion and prevention initiatives in their schools (School Mental Health Ontario, 2021). Students wanted greater access to tools and resources to support their mental health and cope with stress and support their friends. They felt they had the least education in how to cope with transitions and major stress, how to stay optimistic and hopeful, and how to promote positive mental health and emotional self-care (School Mental Health Ontario & Wisdom2Action, 2022).

In addition to the perceived lack of mental health promotion programs in schools, there are also structural barriers that hinder service utilization and access to mental health care for

Canadian youth. These include high wait times, high costs, and the location of services that hinder service utilization and access to mental health care (Public Health Agency of Canada, 2024). Given the barriers in school resources, limited mental health training for educators, and lack of student engagement in the current interventions, innovative and cost-effective interventions for school mental health are needed (School Mental Health Ontario & Wisdom2Action, 2022). Digital health tools have been proposed as a novel approach to complement the current health care system and fill in the gaps for services and education (Maita et al., 2024).

MH Technology in Schools

A possible cost-effective and innovative solution for mental health services in schools are digital mental health technologies (DMHTs). DMHTs encompass a range of digital tools and services that aim to support mental health and well-being through education, assessment, prevention, and treatment (MHCC, 2014; Shen et al., 2022). These digital technologies can include mobile apps, internet websites, wearable devices, video games, telephones, and virtual reality (U.S. Food and Drug Administration, 2019). Digital health technologies being utilized in schools are promising, as Generation Z (those born between 1995 and 2010) and Generation Alpha (those born from 2010 to 2024) were brought up around technology and access to the internet (Seemiller & Grace, 2017). Given that DMHTs are congruent with the habits of Gen Z and Gen Alpha, they may offer a solution to promote and educate children and youth at a large scale (Wiguna et al., 2025).

In response to the rapid and growing use of DMHTs in Canada, the MHCC proposed guidelines on DMHTs. This is to aid governments, mental health organizations and stakeholders to shape their strategies and plans around digital mental health, set priorities, and secure resources to support the development and implementation of digital mental health. They identified the following priority issues to be addressed in the planning and implementation of digital mental health services including: improving perception, awareness, and engagement in digital mental health; embedding IDEA (inclusion, diversity, equity and accessibility) in DMHTs; supporting the workforce to integrate digital mental health into their environments; developing resources for evaluating the effectiveness of digital mental health solutions and programs; addressing the quality of digital solutions and services, including privacy and data collection concerns; and reducing the barriers and addressing system challenges to digital mental health adoption (MHCC, 2024). These priority areas are important to keep in mind when integrating and evaluating DMHTs in schools. DMHTs may offer an easily accessible tool to increase mental health literacy and education to complement the mental health modules already in place in schools. They have been proposed as an innovative solution to serve youth from underserved communities to promote accessible and equitable care (Adu et al., 2024). While DMHTs encompass a broad range of tools (e.g., apps, wearables, VR, etc.), electronic mental health fits into this definition, referring more specifically to electronic and internet-based mental health tools.

Evidence for DMHTs in Schools

Electronic Mental Health (eMH), a type of DMHT, applies to electronic technologies and the use of the internet to deliver mental health resources and care (MHCC, 2014). The surge in eMH is a result of the COVID-19 pandemic and was effective in reaching youth in rural areas and youth with poor mental health (Dimitropoulos et al., 2024; Nicholas et al., 2021). Sakellari et al. (2021) conducted a systematic review to identify and review the effectiveness of mental health and well-being digital health promotion programs in primary schools, targeting both educators and students. Overall, only six studies met the inclusion criteria, highlighting the lack of research in this population. The authors reported that universal and primary prevention interventions using the internet were not available for children over nine years old (Sakellari et al., 2021; Tark et al., 2016). Studies focusing on educators mainly aimed to teach skills on how to impact students knowledge, behaviours, and attitudes. A randomized control trial was conducted in nine elementary schools in Brazil (Pereira et al., 2015) and used a web-based education program for educators to increase their knowledge and modify their beliefs and attitudes about students with mental health difficulties. Results indicated that the web-based interactive tools were more effective and acceptable than the traditional educational tools for educators gaining knowledge. Educators' knowledge regarding mental health increased, however, there were no significant improvements in educators' beliefs and attitudes towards mental health (Pereira et al., 2015). These non-significant results could have been due to low motivation and poor adherence to the study.

A feasibility study by Van Vliet & Andrews. (2009) found that for junior high students (N = 464), a universal, internet-based approach to stress management is effective and feasible. The students completed baseline questionnaires including measures of knowledge, coping, and perceived competence prior to the six-lesson web-based stress management program. The authors combined a school-based mental health teaching intervention with a digital game-based intervention and found that the impact was greater using this combination. The classroom teachings (i.e., role-play, card games, etc.) were similar to the digital game interventions, which led to an increase in students' emotional competence, communication skills, problem-solving, and empathy (Van Vliet et al., 2009). The students' completed the study measures three months later, and improvements in knowledge were sustained, however, there were no improvements in anxiety symptoms, negative thoughts and self-esteem.

In another study by Wiguna et al. (2025), the authors examined the effectiveness of a web-based mental health education module named “Genziheal”. “Genziheal” aimed to increase mental health knowledge and decrease mental health disorder symptoms among adolescent students. A quasi-experimental, pretest-posttest control group design (intervention group: N = 80; control group: N = 50) was carried out across five senior high schools in three districts within Indonesia. The intervention consisted of five structured sessions over three months, combined with four face-to-face sessions and one online session. The sessions took approximately 60-90 minutes and educated students’ on the risks of poor mental health, the benefits of self-care, and early awareness of mental health symptoms. The results revealed a significant improvement in the intervention group’s mental health knowledge. However, there were no significant changes in mental health disorder symptoms. The authors postulated that the lack of external support mechanisms, such as parental involvement, peer support, and educator engagement, may have influenced the (lack of) impact on mental health symptoms. This study highlights how a combination of in-person and digital mental health interventions can effectively promote and educate students on mental health. Similar results supporting these findings have been established in numerous studies carried out in secondary schools (Gonsalves et al., 2019; Pieris-John et al., 2020; Sakellari et al, 2021; Teeson et al., 2020).

Mobile Mental Health, or mMH, which is a type of eMH intervention, is a promising approach considering that a significant majority of youth (77%) own their own smartphone, with most receiving their first phone between the ages of 11 and to 13 (MediaSmarts, 2021). mMH aims to improve the mental health and well-being of users by utilizing mobile and wireless devices (e.g., cell phones, tablets, wearables, etc.) (Price et al., 2014). An advantage to mMH is that they allow for real-time recording of moods, behaviours, and activities, which can be shared with friends to promote engagement (Ed-Brookes et al., 2021).

In a study conducted in the UK by Moltrecht et al. (2021), the authors examined the adoption and engagement of app-based intervention aimed at supporting students aged 10-12 years (N =144) emotion regulation in schools. Students and educators from four primary schools were encouraged to use the app-based intervention in the classroom and/or at home. Using the app was a positive experience for both children and teachers. Nearly half the children (47%) also reported using the app at home to help them relax and unwind. Despite students and teachers self-reporting the app helping them relax and unwind, this study did not measure the effectiveness of promoting their well-being and emotion regulation. Given the need for early interventions to improve functioning and prevent the severity of symptoms in youth, further research is needed to address the barriers to access and service utilization.

Adoption/Implementation of DMHTs in Schools

Despite the encouraging outcomes suggesting DMHTs positively influence well-being and MH literacy, barriers related to these tools still exist among youth who do not have reliable internet, devices, or private spaces for therapy sessions (Augsberger et al., 2024; Bagley et al., 2021; Eylem et al., 2020; Misra et al., 2021). As previously discussed, Moltrecht et al. (2021) found that students largely used the stress management app at school, however, usage varied depending on educators allowance of app use in the classroom. Educators noted that barriers to using the app in their classrooms included: if the app was compatible with their existing teaching methods, and perceived natural opportunities to integrate to their teachers. The study results highlight that although mMH can be positive, barriers to usage can exist.

Edridge et al. (2020) evaluated the mMH intervention, ReZone, in a randomized controlled trial with students (N = 409), aged 10-15, in the UK. The app aimed at reducing emotional and behavioural difficulties; however, no significant results were found. The authors theorized that the non-significant findings of the app's effectiveness could be due to difficulties at the implementation and adoption level. Students' in the study used the mMH app infrequently or not at all. Barriers for students' app adoption may be dependent on variations of teacher motivation, opinions, and priorities, to use the tools in their classrooms. Additional barriers to the implementation and adoption of these tools include administrative resources, quality and amount of available support, the schools' goals and policies (Edridge et al., 2019). Further research is needed into students' and educators' use of mMH for their personal use, and if that influences and aligns with use in the classroom.

Potentials and Supports for Digital MH in Schools

Studies have shown that students are motivated and excited to use technology for learning in the classroom when they have easy access to resources, believe that it will improve their learning, and involve collaboration (Minga & Ghosh, 2024; Ungerer, 2016). Students' openness and excitement to use technology for their learning in the classroom has promising translation to utilizing technology for their mental health needs. Smartphones and social media can have positive impacts in numerous areas, such as increased access to information, identity formation, social support, and access to online support communities (CAMH, 2021; Kuss & Griffiths, 2017; Marchant et al., 2017). However, educators have raised concerns about the amount of time youth spend on digital devices, both at home and in the classroom (Muppalla et al., 2023). Educators view smartphones and tablets as a significant source of distraction in the classroom (Maqsood & Chiasson, 2021), and have concerns about cyberbullying, viewing unsafe content, and interacting with strangers (Maqsood & Chiasson, 2021). Additionally, a longitudinal survey exploring the mental health and well-being of youth in Ontario found that one third (35%) of high school students spend five or more hours daily on electronic devices (i.e., smartphones, tablets, laptops, computers, gaming consoles) in their free time, which is above the Canadian Pediatric Society's screen time recommendations (CAMH, 2021). Another study (Public Health Agency of Canada, 2021) found that 40% of Canadian youth in grades 6-10 (N = 15,184) have problematic social media use (e.g., behavioural and psychological symptoms of social media addiction). Problematic social media use is related to challenges in academic functioning, psychosocial functioning, mental health symptoms, and cyber-bullying (Betul Keles et al., 2020; Clayborne et al., 2025; Kırcaburun et al., 2019; Lachmann et al., 2016).

Although there are issues with problematic social media use and the excessive amount of time youth spend on their smartphones, there is also general excitement for technology use in the classroom from youth (Minga & Ghosh, 2024; Ungerer, 2016). This excitement might be translated to the potential of integrating digital mental health promotion and prevention efforts offered through schools. However, even though digital mental health interventions are promising, research into individual factors that influence acceptance and willingness to use these tools, especially in school contexts, is lacking.

Individual Factors Affecting Digital Mental Health Use

Taking into account the importance of educators to student well-being and the implementation of mental health education in schools, understanding educators' views on service delivery in technological formats is imperative. One way to achieve this is by examining their broader views on technology in educators' professional work, which tend to vary based on several factors (Abel et al., 2022; Nicol et al., 2018). Research has demonstrated that educators with positive views of technology thought it might aid in students' social and emotional skills. Teachers perceived that students are more engaged and empowered when using technology-facilitated learning and that it is more effective than traditional teaching materials, such as still images (Abel et al., 2022). However, technology use requires a degree of self-education and self-motivation for educators, and this can take years to develop (Nicol et al., 2018). Factors that influence teachers unfavourable views (e.g., favouring traditional teaching methods, reluctance to use technology, etc.) surrounding technology’s teaching-related advantages include the lack of digital proficiency (Abel et al., 2022; Hana et al., 2019; Sorgo et al., 2010) and feeling unprepared to handle cyberbullying and sensitive information (Hana et al., 2019). Other factors include anxiety around using digital tools and technology creating a lack of control over their classrooms (Jones et al., 2017; Mertala et al., 2019). Some teachers have a fear of technology, lack computer self-efficacy, and are unwilling to use technology, especially more senior teachers (Mertala et al., 2019). Younger teachers are more receptive to using technology and participate more in technology workshops (Abel et al., 2022; Lauricella et al., 2020). Additionally, educators' attitudes towards technology influence whether they accept or reject technology integration into their classrooms. These factors surrounding educators' broader views on technology can be translated to understanding their views of DMHTs in their personal lives and professional work.

Jacob et al. (2022) conducted a systematic review to identify factors influencing usage of mHealth apps for adults. They found that individual characteristics that had a negative effect on app adherence were privacy concerns, less education, low technology-related skills, baseline depression or anxiety, and lack of time (Aghazadeh et al., 2019; Browning et al., 2016; Potdar et al., 2020). Personal characteristics such as preferences for face-to-face interactions with health care professionals (Darcourt et al., 2021; Sin et al., 2020), less openness to change, negative or positive perceptions of mMH (Lee et al., 2019; Sin et al., 2020), lack of interest (Alwashmi et al., 2020; Qan'ir et al., 2021) and fear of technology (Nabi et al., 2020) all impacted one’s acceptance of mental health technologies. Educators’ personal well-being is another consideration that impacts their ability to support their students’ mental well-being. Gram et al. (2011) found that teachers reporting low support for their own emotional health (e.g., burnout, low morale, limited support, etc.) were less able to support their own students’ mental health. However, Manning et al. (2024) discovered that secondary school teachers' use of digital health technologies in the COVID-19 pandemic helped them turn to digital health tools to manage their work-related stress and support their own mental well-being.

Other individual factors influencing DMHTs use are personality characteristics of the users (Borghouts et al., 2021). A study examining the association between the Big Five personality variables (neuroticism, extraversion, openness, agreeableness, and conscientiousness) and interest in using a stress management app was conducted among Finnish university students (N = 366) (Ervasti et al., 2019). Students higher in neuroticism were more interested in using stress management apps, perhaps since those individuals are more sensitive to stress, and experience stress, worry, and negative emotions more easily (Ervasti et al., 2019). Thus, they are more likely to benefit from these apps, which aligns with their personal needs with the potential benefits of the app. Those high in agreeableness (i.e., those who are cooperative, empathetic and willing to try tools), were more likely to be interested in stress apps due to these individuals being cooperative in nature to try using technologies. Neuroticism and agreeableness were negatively correlated, indicating that those who are more neurotic tend to be less agreeable, and vice versa (Ervasti et al., 2019). Thus, individuals high in neuroticism could benefit most from stress apps. However, due to scoring low in agreeableness, those high in neuroticism may be less interested in using the apps.

A separate study by March et al. (2018) found that individuals high in extraversion tended to prefer in-person services and to connect with health care professionals face-to-face, leading to those higher in extraversion having a lower likelihood of using web-based mental health services (March et al., 2018). Alqahtani et al. (2021) conducted an experimental study (N = 32) to explore the relationships between personality and features of an app to promote mental and emotional well-being. The authors aimed to determine how personality traits of individuals with self-diagnosed mental illness influenced their preferences for app features. Individuals higher in openness to experience were more interested in apps that include relaxation exercises, self-monitoring, relaxation audios, and social support. Those higher in conscientiousness preferred apps that provided relaxation audios, trusted information, contact for help, suggestions, and encouragement features. These studies provide valuable information on the development of mental health apps to tailor them to unique individual characteristics/groups.

While some information regarding individual factors influencing digital mental health use in general is available, there are limited studies evaluating educators. The majority of studies that do provide information on factors affecting digital mental health acceptance in schools, group educators and other stakeholders (e.g., school administration, psychologists, social workers, etc.) together. There is a lack of specific analyses conducted on individual factors affecting acceptance of DMHTs that only focus on school educators. This is a notable gap as educators have the primary role of carrying out mental health promotion and prevention interventions and education in their classrooms (SMHO, 2024). There is also a lack of research on acceptance of DMHTs in primary school settings. A systematic review by Sakellari et al. (2021) cited only six studies examining digital mental health promotion interventions in primary (elementary and middle) schools. Further research is needed to understand the individual characteristics of educators' that might influence usage and adoption of digital mental health apps in a range of school settings (e.g., elementary to secondary schools). With mixed research about educators' views on digital technologies in their professional work, more research is needed into determining what individual factors lead someone to be interested in and use DMHTs.

Educators' Acceptance of Digital MH

Although DMHTs are promising interventions that can lead to positive clinical outcomes, are low cost, and provide better access to care, these advantages are only going to be seen if users accept and use the tools (Jacob et al., 2022). Acceptance and attitudes towards DMHTs are important, as attitudes towards and perceptions of technology are associated with the intention to use DMHTs (Gbollie et al., 2023). Understanding an individual's attitudes and acceptance of DMHTs can help inform the development and implementation of these tools by tailoring them to what individuals find most important (e.g., privacy concerns, engagement, etc.). Nadal et al. (2020) performed a scoping review exploring how technology acceptance is measured in mental health literature. Factors that affect acceptability include user experience, the tool's performance, costs and funding, relevance and appropriateness of the app's information, and personalization to the user's needs. However, the literature surrounding digital mental health acceptability is contradictory and difficult to compare due to the differences in definitions and interchanging terms used for acceptability (i.e., acceptability, acceptance, adoption) (Nadal et al., 2020). To mitigate these disadvantages in the literature, employing a theoretical framework is recommended to measure acceptance of DMHTs.

Theoretical Perspective

One commonly used framework for measuring digital technology acceptance and use, is the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003). This framework explains that acceptance and use of technology are impacted by four constructs. The first is performance expectancy, which refers to how much users perceive the technology will assist them in their work. Effort expectancy is the user's perception of how easy it is to use the technology. Social influence describes the degree of one’s perceived important others believe they should use the technology. Facilitating conditions describe the user's perception of the organization and structural features of an environment to support the technology use (Venkatesh et al., 2003). Behavioural Intention to use the technology and Usage Behaviour are two dependent variables in the UTAUT model (Venkatesh et al., 2003). Usage Behaviour refers to the extent to which a user uses a technology. Behavioural Intention has been used in numerous studies to represent acceptance of digital health technologies (Khechine et al., 2014; Venkatesh et al., 2012). In 2012, Venkatesh et al. expanded the original UTAUT model to integrate constructs and relationships to adapt it for a consumer/individual use context. The UTAUT2 included three core constructs: Hedonic Motivation, Price Value, and Habit. Hedonic Motivation refers to the fun or pleasure derived from using technology (Brown & Venkatesh, 2005). Price Value is the cost and price of technology that impacts technology use (Venkatesh et al., 2012). Habit and experience are conceptualized as how much time one uses technology and the initial use of the technology. Age, gender and experience were also added and found to moderate the effects of the three core constructs on technology use and Behavioural Intention. This model is an improvement from the original UTAUT model, with variance for explaining Behavioural Intention increasing from 54% to 74% and technology use from 40 to 52% (Venkatesh et al., 2012). Using this model can aid in understanding what factors influence educators' acceptance and engagement with DMHTs.

The UTAUT2 has been used internationally, as well as being tested and accepted in various types of contexts, including educational (Salloum et al., 2019), engineering (Chatterjee et al., 2020), and management settings (Williams et al., 2015). The UTAUT model has contributed to the digital mental health literature. For example, Uncovska et al. (2023) investigated patient acceptance of mMH in Germany using the UTAUT2 to determine what factors influenced patients' intention to use and adoption of Digital Health Applications prescribed by physicians. An online survey conducted from a broad cross section of the German population (N = 1051) was completed, gathering data from participants who had prior experience with mMH apps and those who had not. There was a high general acceptance, with 76% of participants willing to use the app, however only 27% were willing to pay for the app out of pocket. Perceived self-efficacy, performance expectancy, and data security concerns were the most significant predictors of willingness to use digital health interventions. Demographic factors such as age, attitude, and e-literacy were key predictors as well. The study highlighted that the UTAUT2 is an effective model to explain mMH adoption, as well as identify what factors influence individuals' usage of these digital tools.

Related to the school context, Blackwell et al. (2013) explored how intrinsic and personal factors influence teachers' use and access of technology in early childhood education using the UTAUT framework. The authors gathered data using online surveys from early childhood educators (N = 1329) who taught children aged four and younger. Factors such as school type and students' family income predicted teachers' access to technology. Personal factors such as teachers' highest educational attainment were also predictive of technology access. Blackwell and colleagues showed that both extrinsic facilitating factors (e.g., professional development, technology policies, and student income levels) and personal attitudes both significantly predicted technology use in the classroom. However, the significance varied depending on the type of technology. Positive beliefs regarding the technology's benefits for children's learning were the strongest predictors of technology use across most tools (except for digital cameras, iPods, and e-readers). Attitudes about technology's learning benefits outweighed educators' perceived barriers (e.g., educators' confidence, lack of access and support or training, etc.) in predicting actual use of technology for learning in their professional work. Blackwell and colleagues research contributes meaningful information to the broader literature of integration of technology for early education. However, additional research is needed to understand what individual factors predict educators' technology use and acceptance for DMHTs.

Gaps in the Literature

As DMHTs focusing on mental health promotion and prevention become more readily available and validated, further research is needed to understand educators' perspectives and acceptance of these tools. This information is important given that educators have the primary role of carrying out mental health promotion and prevention interventions and education in their classrooms (Nygaard et al., 2023). Understanding the individual factors related to educators (e.g., personality, attitudes towards technology, usage in their personal lives, etc.) is necessary to inform future implementation of these tools in schools to promote mental health and well-being for students (Gbollie et al., 2023). Currently, there is a lack of research examining educators' perspectives on their acceptance of using these tools for their students' well-being (Sakellari et al., 2021). The majority of studies group educators and key stakeholders of schools together, which limits the evaluation of only educators' perspectives on what predicts their acceptance of DMHTs in their classrooms and personal lives.

Additionally, despite the rise of DMHTs available for student mental health promotion and prevention, there is a lack of literature evaluating the acceptance and perspectives of educators’ of DMHTs in various contexts (i.e., early education, primary, and middle schools), with most studies largely focusing on secondary school students (Sakelleri et al., 2021). Perspectives and attitudes of DMHTs have important implications for implementation and adoption of these tools. However, due to the differences in definitions and terms used for acceptability in the digital mental health literature, further research is needed using a well-validated theoretical framework such as the UTAUT2.

The Current Study

To address the gaps in the literature, the current study evaluated educators’ acceptance of digital mental health tools in their (a) personal lives and (b) professional work using the UTAUT2 framework; and examined the relationships between educators’ individual differences variables (e.g., demographics, personality traits, well-being, digital self-efficacy, attitudes towards technology) on acceptance of digital mental health tools. The current study aligns with specific priority areas outlined by the MHCC with respect to planning and implementation of digital mental health services: improving perception, awareness, and engagement in digital mental health; embedding IDEA (inclusion, diversity, equity and accessibility) in DMHTs; and supporting the workforce to integrate digital mental health into their environments (MHCC, 2024).

Research Questions

The current study addresses five primary research questions:

1. Do educators' accept digital mental health tools in their professional work to support the well-being and mental health of their students?

2. Do educators' accept digital mental health tools in their personal lives?

3. Does acceptance of digital mental health tools in educators' personal lives align with acceptance in their professional work?

4. Do educators' individual differences (i.e., demographics, personality traits, well-being, digital self-efficacy, attitudes towards technology) predict acceptance of digital mental health tools in their professional work?

5. Do educators' individual differences (i.e., demographics, personality traits, well-being, digital self-efficacy, attitudes towards technology) predict acceptance of digital mental health tools in their personal lives?

Hypotheses

RQ 1 & 2: Do educators accept digital mental health tools in their professional work and personal lives?

Because no study has examined educators acceptance of digital mental health tools in their personal lives and professional work, we based our hypotheses on the broader literature on educators' acceptance of digital technologies and the original UTAUT2 results (Chen et al., 2024; Singh, 2023; Venkatesh et al., 2012). We hypothesized that:

H1: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Habit will significantly predict Behavioural Intention to use digital mental health tools in both educators' personal lives and professional work.

H2: Technology Anxiety will negatively impact the Behavioural Intention to use digital mental health tools in both educators' personal lives and professional work.

H3: Age, gender, experience with digital tools (User Behaviour), and privacy concerns will moderate the relationship between UTAUT2 constructs and Behavioural Intention in both educators' personal lives and professional work.

RQ 3: Does acceptance of digital mental health tools in educators' personal lives align with acceptance in their professional work?

Based on previous literature that has found an association between educators' personal and professional use of technology (Ertmer et al., 2001), we hypothesized that:

H4: Educators' Behavioural Intention to use digital mental health tools in their personal lives will be significantly correlated with their Behavioural Intentions to use digital mental health tools in their professional work.

RQ 4 & 5: Do educators' individual differences predict acceptance of digital mental health tools for the following factors:

Digital Self-Efficacy Educators' digital self-efficacy and positive attitudes towards technology has been shown to impact acceptance and Behavioural Intention to use digital technologies in their professional work (Abel et al., 2022; Hana et al., 2019; Sorgo et al., 2010). Based on this literature, we hypothesized that:

H5: Greater digital self-efficacy will predict greater Behavioural Intention to use digital mental health tools in educators' personal lives and professional work.

Attitudes Towards Technology

H6: Positive attitudes towards technology will predict greater Behavioural Intention to use digital in educators' personal lives and professional work.

Personal Well-Being The personal well-being of educators impacts how well educators are able to support the mental health of their students (Graham et al., 2011). Educators reporting low support for their own emotional health (e.g., burnout, low morale, limited support, etc.) were less able to support their own students' mental health. Based on this literature, we hypothesized that:

H7: Greater personal well-being of educators' will predict greater Behavioural Intention to use digital mental health tools in their personal lives.

Manning et al. (2024) study examining the use of secondary school educators' use of digital health technologies in the COVID-19 pandemic found that educators turn to digital health tools to manage their work-related stress and support their mental well-being. Given the findings from this study that educators who experienced more emotional strain and heightened stress experience more motivation to try digital health tools, we hypothesized that:

H8: Lower mental well-being of educators' will predict greater Behavioural Intention to use digital mental health tools in their professional work.

Demographics Based on previous literature (Blackwell et al., 2013) showing demographic factors such as age, school type, and educators' highest educational attainment predict acceptance of digital technology use in the classroom setting, we hypothesized that:

H9: Younger age will predict greater Behavioural Intention to use digital mental health in educators' personal lives and professional work.

H10: Higher levels of education (bachelor's degree or more) will predict greater Behavioural Intention to use digital mental health tools in educators' personal lives and professional work.

Personality

Neuroticism. Because individuals higher in neuroticism have greater acceptance and engagement with digital mental health tools, such as smartphone apps to reduce stress (Borghouts et al., 2021; Ervasti et al., 2019), we hypothesized that:

H11: Higher levels of neuroticism among educators' will predict greater Behavioural Intention to use digital mental health tools in educators' personal lives and professional work.

Agreeableness. Given that individuals who are higher in agreeableness have a cooperative nature to accept new technology, and are more interested in using smartphone apps to reduce stress (Borghouts et al., 2021; Ervasti et al., 2019), we hypothesized that:

H12: Higher levels of agreeableness among educators' will predict greater Behavioural Intention to use digital mental health tools in their personal lives and professional work.

Extraversion. Given that individuals higher in extraversion prefer in-person services to connect with health professionals in person over digital mental health services (Borghouts et al., 2021; March et al., 2018), we hypothesized that:

H13: Higher levels of extraversion among educators' will predict lower Behavioural Intention to use digital mental health tools in educators' personal lives and professional work.

Conscientiousness. Based on the literature (Alqahtani et al., 2021) that individuals higher in conscientiousness are more inclined to use smartphone apps to reduce stress, we hypothesized that:

H14: Higher levels of conscientiousness among educators' will predict greater Behavioural Intention to use digital mental health tools in educators' personal lives and professional work.

Openness to Experience. Given the findings from research that individuals who scored higher on openness to experience were more engaged in digital mental health apps (Borghouts et al., 2021; Mikolasek et al., 2018), we hypothesized that:

H15: Higher levels of openness to experience among educators' will predict greater Behavioural Intention to use digital mental health tools in their personal lives and professional work.

Method

Study Design

The current study used a cross-sectional quantitative survey design.

Target Sample

Participants were eligible for the study if they were a certified teacher and taught Kindergarten to Grade 12 (K-12) in Canada and were able to understand and speak English. Participants were recruited through a variety of methods, including using paid Facebook and Instagram ads, distribution of physical flyers to public areas around Thunder Bay and Toronto (see Appendix A), emails to educators (e.g., through school mental health leads), and distribution of flyers to principals in the Lakehead District School Boards. Recruitment in public spaces and in paid Facebook and Instagram ads, used flyers with a QR code for a Qualtrics survey with an eligibility screen (see Appendix B). This was to screen for individuals who did not meet eligibility criteria, as well as individuals who were not educators.

Respondents were excluded if they originated from outside of Canada, and if a valid work email address was not submitted. Responses were also flagged and removed if the captcha response and "honey pot" questions in the eligibility screener were not met. Responses were paid particular attention if they were collected during timeframes associated with high fraudulent activity. Other studies have flagged responders who completed the study outside of typical daytime hours, as this indicates a high likelihood that they were completed by bots (Comachio et al., 2025; Leobenberg et al., 2023; Wang et al., 2023). If respondents met the screening criteria, they were emailed the link for the Qualtrics survey. Flyers in private spaces (e.g., school staff rooms, etc.) had the QR link directly to the study survey.

Sample Size Estimation

We used the inverse square root method to determine the sample size estimation for the PLS-SEM analysis (Kock & Hadaya, 2018) due to its accuracy and conservativeness. According to Hair et al. (2022), studies implementing the PLS-SEM method require a minimum sample size of 189 to detect R^2 values of at least 0.1 with a significance level of 5% (Strzelecki et al., 2024). Given that there is no research that examines the UTAUT2 framework and digital mental health acceptance on the relationships between Behavioural Intention and Usage Behaviour for educators in K-12, the sample size estimation was based on literature examining these relationships in university students. For the relationship between Social Influence and Behavioural Intention, the lowest significant path coefficient was 0.19 at the $p \leq 0.05$ level (Schomakers et al., 2022), and 0.18 for the association between neuroticism and use (Barnett et al., 2015). Hair et al. (2022) outlined that to establish the minimum sample size requirement for a minimum significant path coefficient between 0.11 and 0.20, a sample size of 155 is needed for 80% power at the 5% significance level.

To determine the sample size estimation for the multiple regression analyses for research questions four and five, the rule of thumb approach was used (Wilson Van Voorhis & Morgan, 2007). A minimum of 10 participants is recommended for every predictor variable in the regression model ($N \geq 10 \times k$), where N is the sample size and k is the predictor variable. In the current study, there are 10 predictor variables. Therefore, a minimum of 100 participants is needed.

For the current study, we planned to recruit a sample size of approximately 186 participants to account for 20% of data loss due to quality issues or attrition, as well as to adequately power all proposed analyses.

Ethical Considerations

Lakehead University's Research Ethics Board and the Lakehead District School Board provided ethics approval for this study.

Procedure

Educators reviewed the study details (see Appendix C) and completed multiple quantitative surveys that evaluated their individual characteristics and their acceptance of digital mental health tools in their personal lives and professional work. Informed consent was obtained (see Appendix D) from participants before they participated in the study. Participants received a $20 e-transfer for completion of the study.

Measures

Adapted UTAUT2 Scale

We used an adapted version of the UTAUT2 scale (see Appendix J) developed by Venkatesh et al. (2012) to measure educators' acceptance of digital mental health tool use in their professional work. The items were rated by participants on a Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). A *Not Applicable (NA)* option for participants who did not have experience using digital mental health technology was added. Our adapted UTAUT2 measures included the constructs of Performance Expectancy, Effort Expectancy, Social

Influence, Facilitating Conditions, Hedonic Motivation, Habit, User Behaviour, and Behavioural Intention (see Table 24).

The following four core constructs were added to the modified UTAUT2 scale developed by Xu et al. (2012), Xu et al. (2008), Smith et al. (1966), and Chen et al. (2024); Perceived Surveillance, Perceived Intrusion, Secondary Use of Personal Information, and Technology Anxiety (see Table 24). Perceived Surveillance, Perceived Intrusion, and Secondary Use of Personal Information have been added to the UTAUT2 model since the literature has shown that privacy concerns hinder users' intention to use health technologies that require personal data (Bélanger et al., 2011; Li, 2011; Schomakers et al., 2024; Smith et al., 2011). Only one study, Schomakers et al. (2024), has added these privacy concern constructs to the UTAUT2 model. They found no significant relationship between these privacy concerns constructs and adult users' intentions to use mMH apps. Chen et al. (2024) included Technology Anxiety to the UTAUT2 model to examine older adults' Behavioural Intention to use digital health technologies. They found that high Technology Anxiety hindered individuals' Behavioural Intention to use digital tools. Due to the limited research on the privacy concern constructs and Technology Anxiety, more research is needed to examine these constructs using the validated UTAUT2 model in various populations and contexts.

We used a slightly modified version of the above UTAUT2 scale (see Appendix M) developed by Venkatesh et al. (2012) to measure educators' acceptance of digital mental health tool use in their personal lives. The seven core constructs of the original UTAUT2 measure and the four additional constructs (Chen et al., 2024; Xu et al., 2012) were added and slightly modified to examine educators' personal use of digital mental health tools (see Table 25). Overall acceptance of DMHTs were conceptualized as scores measured by the Behavioural

Intention construct. For both the UTAUT2 personal and professional scales, scale totals were found by summing the item score constructs and finding the means, which is consistent with how this measure was originally developed (Venkatesh et al., 2012). The *Not Applicable (NA)* option was treated as missing values and not included in the mean scores. Distributions of frequency scores for each UTAUT2 construct means were created (see Figure 7 to 21).

The UTAUT2 has high internal consistency, convergent, and discriminate validity (CR > 0.7, α = > 0.7) based on findings from a study examining Kindergarten to Grade 12 students (N = 242) Behavioural Intention to adopt mobile-based assessments using the UTAUT2 model (Nikou & Economides, 2017).

Digital Self-Efficacy

The Digital Technology Self-Efficacy scale (DSE; Ulfert-Blank & Schmidt, 2021) is a measure of one's competence and competency beliefs for using digital technologies effectively (see Appendix K). The scale assesses five competency areas with 25 items, measured on a five-point Likert scale (1 = totally disagree, 5 = totally agree). The scale was adapted to fit the school context in the current study. The five competency areas include: Information and data literacy (three items; "I can evaluate whether digital content is trustworthy"), Communication and Collaboration ("I feel confident using digital tools to communicate with others"), Safety ("I know how to protect my privacy when using digital technology"), Problem-Solving ("I feel confident troubleshooting technology when they don't work properly)", and Digital Content Creation ("I create digital content"). The mean total score across all 25 items was calculated. Higher scores indicate higher levels of digital self- efficacy. The DSE scale was validated from a web-based survey in a German sample (N = 627). The scale was confirmed to have adequate convergent and discriminant validity (Ulfert-Blank & Schmidt, 2021).

Attitudes Towards Technology

The General Attitudes Towards Digital Technologies (GATT) scale (Evers et al., 2009) measures an individual's general interest in digital technologies, including items relating to pleasurable experiences using technology and perceived usefulness (see Appendix I). The original measure was adapted to fit the school context in the current study. The items were measured on a five-point Likert response format (1 = strongly disagree, 5= strongly agree) and includes items related to: interest (e.g. "I want to know more about technology"), pleasure (e.g. "I like to talk about technology to others"), usefulness (e.g. "The use of a technology is useful to me"), and ease of use (e.g. "I feel comfortable when I use technology"). The mean total score across all items was calculated. Higher total mean scores indicate more positive attitudes towards digital technologies. This scale is reliable ($\alpha = 0.78$, $\acute{\omega}_t = 0.80$) based on findings from a study examining early childhood pre-service educators' attitudes towards digital technologies and their relations to their self-perceived digital competence (Merjovaara et al., 2023).

Personal Well-Being

The World Health Organization-Five Well-Being Index (WHO-5; Topp et al., 2015; WHO, 1998) is a measure of one's self-reported current mental well-being (see Appendix F). The WHO-5 consists of five statements, each measured on a six-point Likert scale (0 = At no time, 5 = All the time). The five statements measure well-being over the past two weeks, with higher scores indicating better well-being. The five statements include "I have felt cheerful and in good spirits"; "I have felt calm and relaxed"; "I have felt active and vigorous", "I woke up feeling fresh and well rested"; and "my daily life has been filled with things that interest me". Raw scores were totaled by summing the scores for each of the five statements to create a total score. Topp et al.'s (2015) systematic review supported that the WHO-5 is a valid, reliable and highly sensitive measure of subjective well-being. The measure has high clinometric validity, ranked among the top 20 scales due to its absence of overlap with specific disease-related aspects and side effects of pharmacological treatment. The WHO-5 has high construct validity, accurately measuring well-being. The 5-item scale is unidimensional, where each item adds unique information to the level of well-being.

Demographics

A demographics questionnaire with 17 items (see Appendix E) was used to describe participant characteristics. This questionnaire modified items from the *2024: Focus on Teaching Report* (Ontario College of Teachers, 2024) to fit the current study context. The demographic items captured participants' information, including gender, age, educational level, and grade level taught. Educators' were also asked how comfortable they were using educational technologies on a 5-point Likert scale (1 = extremely uncomfortable to 5 = extremely comfortable). All categorical variables (i.e., ordinal, nominal, binary) were numerically coded prior to analyses.

The Abbreviated Big Five Inventory

We used the abbreviated Big Five Inventory (BFI; Kang et al., 2024) (see Appendix H) to measure the Big Five personality traits Neuroticism, Agreeableness, Conscientiousness, Extraversion, and Openness). There are 18 items on the scale, consisting of three items for each Big Five domain. The items are rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree): Openness ("I see myself as someone who is original"), Conscientiousness ("I see myself as someone who does a thorough job"), Extraversion ("I see myself as someone who is talkative"), Agreeableness ("I see myself as someone with a forgiving nature"), and Neuroticism ("I am someone who worries a lot") (see Appendix I). To calculate the scores for each Big Five item, the scale totals were summed and then the mean score was computed. The abbreviated BFI is a validated tool, developed by conducting factor analyses on three large samples (N = 59,797, N = 21,177, and N = 87,983). The abbreviated BFI has high convergent validity with the original 44-item BFI inventory across all traits. It has higher validity than other abbreviated scales (10-item and 5-item versions). The test-retest correlations (N = 21,177) were very high among the traits over time.

Additional Questionnaire Items

Two attention checks were included in our study (see Appendix G and Appendix L). This was to ensure that participants were paying attention throughout the study. Two qualitative, open-ended questions were also included to gather educators' opinions on DMHTs (e.g., barriers; see Appendix N).

Data Analysis

We collected our data in Qualtrics and downloaded it into an Excel file for data organization. We then transferred the data to SPSS (IBM Corp, 2021) to assess data characteristics, missing response patterns, and generate descriptive statistics for all variables. SmartPLS version 4 software (Ringle et al., 2022) was utilized to conduct Partial Least Squares Structural Equation Modelling (PLS-SEM) to test the hypothesized predictive-causal relationships (H1-H3). We performed a Pearson correlation in SPSS to evaluate if educators' personal acceptance of digital mental health tools aligns with acceptance in their professional work (H4). Multiple regression analyses were used to assess research questions four and five using SmartPLS to determine the relationship between multiple independent variables (e.g., age, attitudes, personality, etc.) and their Behavioural Intention to use DMHTs in educators' personal lives and professional work (H5-H15).

Results

Participants

The study was completed by a total of 235 participants. After data cleaning, 141 participants were included in the analyses, which is just below our target sample size.

Data Cleaning

The collected data (n = 235) were organized and cleaned in Excel and SPSS. Participants who did not complete the entire survey (n = 19), who did not meet eligibility criteria yet still completed the survey (n = 1), did not provide a valid work email address (n = 6), who had inconsistencies in their demographic information (e.g., age did not match to birth year), and/or who completed the survey during irregular times (e.g., between 2am-5am) were removed (n = 22). Participants who completed the survey in 360 seconds or less (n = 11) and those who did not meet data quality checks (n = 5) were also removed. Therefore, the total number of participants who were removed during data organization was n = 57, resulting in a sample size of 178. Participants with 15% or more of total missing data were removed by listwise deletion (n = 35). Following the removal of these participants, a Little’s MCAR test was performed and found to be non-significant. The data was missing at random for measures of digital self-efficacy, general attitudes towards technology, the Big-5 inventory, mental well-being, and the two modified UTAUT2 scales (Little's MCAR test: $X^2(6562) = 6584.297$, $p = .421$). The amount of data missing for the rest of the constructs was minimal amongst the scales (< 5%), and person-mean imputation was used for these scale items. Outliers were assessed by analyzing descriptive statistics for variables, with no scale items having Z scores greater than +/- 3.29. One participant was removed for suspicious response patterns and another for being an outlier with over three interquartile ranges (IQR) (n = 143). Multivariate outliers were assessed by calculating the Mahalanobis distance and examining the chi-squared distribution (see Figure 1). Two more outliers who had Mahalanobis distance probability values less than 0.01 (n = 141) were removed.

Skewness and kurtosis were examined in SmartPLS 4. Five items in the DSE scales and one item in the BFI had excess kurtosis and were removed from the analyses.

Demographics

The participants were majority White (72.3%), women (80.1%), taught in Urban schools (85.8%), and worked in Ontario (81.6%). The ages of the participants were evenly distributed with age ranges (M = 39.73, SD = 10.683) from 18-29 years (23.4%), 30-39 years (27.7%), 40-49 years (24.8%), 50-59 years (23.4%). Only 0.7% of the participants were over 60 years old. Almost half of the participants (49.4%) were homeroom teachers and/or subject specialists (26.9%). There was an equal split of Kindergarten to Grade 6 teachers (49.1%) and Grades 7 to 12 (49.1%), with the remaining teachers working as supply teachers or principals. 68.1% of participants' highest level of education was a bachelor's degree, with 27.7% having a Master's degree. 33.3% of teachers were from the Elementary Teachers' Federation of Ontario (ETFO), 17.7% from the Ontario Secondary School Teachers' Federation (OSSTF), and 14.2% from the Ontario English Catholic Teachers' Association (OECTA). All demographic information can be found in Table 1.

Descriptive Statistics

Means, standard deviations, and Cronbach's alpha for all measures are reported in Table 23. Our descriptive statistics are consistent with research examining the UTAUT2 constructs in educational contexts (Moorthy et al., 2019; Chen et al., 2024). The majority of our scale measures were of adequate reliability (i.e., > .70).

Partial Least Squares Structural Equation Modelling (PLS-SEM) Evaluation

PLS-SEM was chosen to assess hypothesized predictive-causal relationships over other statistical models (e.g., covariance-based SEM) since it is recommended when evaluating theoretical frameworks based on a predictive lens (Hair et al., 2022). PLS-SEM aims to explain target constructs and can evaluate complex models (Hair et al., 2022; Rigdon, 2012). Two separate PLS-SEM models were performed for this study. One model was to examine if the professional UTAUT2 constructs of Performance Expectancy, Effort Expectancy, Habit, Social Influence, Facilitating Conditions, Hedonic Motivation, and Technology Anxiety would significantly predict Behavioural Intention to use DMHTs in educators' professional work. The second PLS-SEM model was to examine the personal UTAUT2 constructs and if they predict Behavioural Intention to use DMHTs in educators' personal lives.

Measurement Models

A measurement model in PLS-SEM is used to evaluate if the indicators (i.e. the measures of a construct) accurately predict their constructs (Hair et al., 2022). The current study conducted two reflective measurement models to evaluate the reliability and validity of the indicators and constructs in our model (e.g., UTAUT2 constructs). A reflective measurement model is used when a measure represents the effects of the underlying construct (Hair et al., 2022).

Model 1: Professional UTAUT2. The first measurement model tested included the following constructs: Hedonic Motivation, Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Habit, Technology Anxiety and Behavioural Intention. The pairwise deletion method was used to handle missing values. Indicator reliability- the measure of how much the indicators of a construct have in common- was evaluated by examining the outer loadings of the constructs (Hair et al., 2022). It is recommended that each latent variable should explain at least 50% of each indicator's variance, which is equal to an outer loading of ≥ 0.70 (Hair et al., 2022). We found inadequate indicator reliability for item four for the construct of Technology Anxiety (outer loadings <-0.739). That indicator for Technology

Anxiety was removed, as per recommendations to remove outer loadings of < 0.4 (Hair et al., 2022; e.g., Bagozzi, Yi, & Philipps, 1991; Hair, Ringle, & Sarstedt, 2011), and the model was re-run. All other loadings were adequate with loadings being above 0.70 (range = -0.738-0.976; See Table 2).

To assess discriminant validity, which is the extent to which each construct is distinct from other constructs, we evaluated the heterotrait-monotraits (HTMT) ratio of correlations (Hair et al., 2022). Values of 0.85 are used to measure conceptually distinct constructs and 0.90 for conceptually similar constructs. Ringle and Sarstedt (2015) suggest a value of 0.90 if the path model constructs are conceptually similar, which would indicate a lack of discriminant validity (Hair et al., 2022). Since our model's constructs of the UTAUT2 scale are conceptually similar, we removed any items with an HTMT over 0.90. The HTMT ratio for Performance Expectancy with Behavioural Intention was above the threshold of 0.9 (HTMT = 0.986). Therefore, discriminant validity was not met, and this construct was removed from the model. Following the removal of item four from the construct of Technology Anxiety and the construct of Performance Expectancy. The final measurement model included the constructs of Effort Expectancy, Facilitating Conditions, Social Influence, Hedonic Motivation, Technology Anxiety, and Behavioural Intention (see Figure 2). Due to the removal of Performance Expectancy, we did not examine the hypothesized relationships between Performance Expectancy and Behavioural Intention in the structural model.

We examined the internal consistency reliability of the model by evaluating Cronbach's alpha. Cronbach's alpha is used to evaluate the intercorrelations of the indicator variables (Hair et al., 2022). However, a limitation of Cronbach's alpha is that it can underestimate the internal consistency reliability due to its sensitivity to the number of items in a construct (Hair et al., 2022). To accommodate this limitation, the reliability coefficient (ρA) is recommended to be used as it lies between the lower bound of Cronbach's alpha and the upper bound of the composite reliability (ρC) (Dijkstra, 2014; Drolet & Morrison, 2001; Hair et al., 2022). Hair et al. (2022) recommend that reliability values should be ≥ 0.70 but not over 0.95, as those over 0.95 reflect redundant items, which can impact content validity (Rossiter, 2022). Therefore, we removed items with values below 0.6 and above 0.95. Our final measurement model met all indicator and internal consistency reliability criteria (see Table 2).

We then assessed the model's convergent validity, which measures the correlation with the alternate measures in the construct (Hair et al., 2022). These measures should share a high proportion of variance since the measures should explain a large variance of its indicator. The average variance extracted (AVE) is used to measure convergent validity. To meet convergent validity, each measure should have an AVE value of ≥ 0.50, meaning that each construct explains over 50% of the variance for its indicators (Hair et al., 2022). Our final measurement model met all convergent and discriminant validity criteria (see Table 5) outlined by Hair et al. (2022).

Model 2: Personal UTAUT2. The second measurement model included the following constructs for the personal UTAUT2 scales: Hedonic Motivation, Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Habit, Technology Anxiety and Behavioural Intention. Pairwise deletion was used for missing values. We found inadequate outer loadings for item 4 for technology anxiety (-0.715), and that item was removed from the model. All loadings were adequate and above 0.70 (range = -0.709-0.981; see Table 4). The final model included Effort Expectancy, Performance Expectancy, Facilitating Conditions, Social Influence, Hedonic Motivation, Technology Anxiety, and Behavioural Intention (see Figure 4).

Structural Models

Model 1: Professional UTAUT2. The structural model was performed following the confirmation that the final measurement model met all reliability and validity criteria (see Figure 4). This structural model aimed to evaluate Research Question 1 (testing H1 and H2) that the UTAUT2 constructs of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Habit would significantly predict educators' Behavioural Intention to use DMHTs in their professional work. We also hypothesized that the construct of Technology Anxiety would negatively impact Behavioural Intention. We assessed for collinearity issues by examining the variance inflation factor (VIF) values. The VIF values were below the acceptable threshold of 3 (Hair et al., 2022) (see Table 6). We performed the nonparametric bootstrap (BCa) bootstrapping method (10,000 iterations) to assess the significance of the path coefficients, as well as their *t*-values, *p*-values and 95% confidence intervals (Hair et al., 2022) (see Table 8). The structural model's explanatory power was evaluated using the coefficient of determination (R^2) value and the strength of the model's relationships was assessed using the f^2 effect size (≤ 0.02: small effect; ≤ 0.15: medium effect; ≤ 0.35: large effect). The structural model explained a significant amount of variance for Behavioural Intention, $R^2_{\text{adjusted}} = 0.619$, $p < .000$, 95% CI [0.517, 0.754]. Habit, $\beta = 0.214$, $p < .01$, $f^2 = 0.05$ (small effect size) and Hedonic Motivation, $\beta = 0.423$, $p < .000$, $f^2 = 0.258$ (medium to large effect size) significantly and positively predicted Behavioural Intention. The constructs of Effort Expectancy, Facilitating Conditions, Social Influence, and Technology Anxiety did not significantly predict Behavioural Intention. Hypothesis 1 was partially supported with Habit and Hedonic Motivation significantly predicting Behavioural Intention to use DMHTs in educators' professional work.

Model 2: Personal UTAUT2. The second structural model evaluated the constructs of Hedonic Motivation, Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Habit, and Technology Anxiety and Behavioural Intention (see Figure 5). This analysis aimed to evaluate Research Question 2 (testing H1 and H2) that the UTAUT2 constructs of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Habit would significantly predict educators' Behavioural Intention to use DMHTs in their personal lives. We also hypothesized that the construct of Technology Anxiety would negatively impact Behavioural Intention. Collinearity was assessed, and all items met the VIF criterion (see Table 10). We performed BCa bootstrapping confidence intervals and examined the *t* values, path coefficient estimates, and confidence intervals (see Table 11). The structural model explained a significant and substantial amount of variance for Behavioural Intention, $R^2_{\text{adjusted}} = 0.737$, $p < .000$, 95% *CI* [0.672, 0.828]. Performance Expectancy, $\beta = 0.660$, $p < .000$, $f^2 = 0.662$ (large effect size) significantly and positively predicted Behavioural Intention. Effort Expectancy, Facilitating Conditions, Social Influence, and Habit did not significantly predict Behavioural Intention. Hypothesis 2 was partially supported with Performance Expectancy significantly predicting educators' Behavioural Intention to use DMHTs in their personal lives to support their own well-being.

Predictive Power. We assessed the two structural models' predictive power using PLSpredict. This procedure out-of-sample predictive power, evaluating if our models' would predict similar results in another sample (Hair et al., 2022). PLSpredict was run to determine if our structural models had good predictive quality. We found that the professional Behavioural Intention model had high predictive power because, compared to the naïve LM benchmark, lower RMSEs were produced by the PLS-SEM model on all indicators (see Table 9). The personal Behavioural Intention model had a lower prediction error for the first item of Behavioural Intention, indicating that the model lacks predictive power (Hair et al., 2022). This could be a result of data or measurement model issues.

Moderation Analysis

The following moderation analyses aimed to investigate research questions one and two (testing H3) examining if the variables of age, gender, experience with digital tools, and privacy concerns are moderators for the relationship between the UTAUT2 constructs and Behavioural Intention. Moderator effects occur when a variable changes the strength or direction of the relationship between two constructs in the model (Becker, Ringle & Sarstedt, 2018; Hair et al., 2022; Memon et al., 2019). Gender moderation analyses could not be performed for both models' due to the large discrepancy in the group sample sizes (n = 107 for women, n = 27 for men), resulting in a highly skewed distribution of the gender variable.

Model 1: Professional UTAUT2. We conducted the two-stage approach to examine the moderating effects of age, privacy concerns (e.g., Perceived Intrusion, Perceived Surveillance $\alpha = 0.729$, Secondary Use of Personal Information) and experience (User Behaviour). The two-stage approach consists of analyzing our structural models without the moderator variables and then adding our moderators to the UTAUT2 variables (Chin et al., 2003; Hair et al., 2022).

Age had a significant and negative moderating interaction on the relationship between educators' perceived Habit of using these DMHTs and their intention to use these tools in their professional work, $\beta = -0.202$, $p = .028$, $f^2 = 0.051$ (small effect size). In other words, when age increases, habit has a less effect on Behavioural Intention. Additionally, we found that User Behaviour had no significant moderating effects on the UTAUT2 constructs and Behavioral Intention (see Table 13). Perceived Surveillance was removed from the model as it did not meet construct reliability and validity, ρA = -0.578, and ρC = 0.039. The constructs of Perceived Intrusion and Secondary Use of Personal Information were not significant moderators for the relationships between the UTAUT2 constructs and Behavioural Intention (see Table 19). Experience and privacy concerns do not impact the strength and/or direction of the relationships between the UTAUT2 constructs and educators' Behavioural Intention to use DMHTs in their professional work.

Model 2: Personal UTAUT2. We conducted the two-stage approach to examine the moderating effects of age, privacy concerns (e.g., Perceived Intrusion, Perceived Surveillance, Secondary Use of Personal Information) and experience (User Behaviour) on Behavioural Intention to use DMHTs in educators personal lives. Item 1 from User Behaviour was removed as it did not meet reliability criteria. After that item was removed, the model met construct and discriminant validity. The moderators of age, experience, and privacy concerns were not significant (see Table 14 and Table 20). Experience, age, and privacy did not have an effect on the relationships between the UTAUT2 constructs and Behavioural Intention to use DMHTs in educators' personal lives.

Correlation Analysis

We conducted a two-tailed Pearson Correlation analysis using SPSS to examine the strength and direction of the relationship between educators' Behavioural Intention to use DMHTs in their personal lives and their Behavioural Intention to use DMHTs in their professional work (testing H4). The results indicated a positive and strong relationship between educators' Behavioral Intention to use DMHTs in their professional work and their Behavioural Intention to use DMHTs in their personal lives, r (2) = 0.675, $p < 0.001$ (see Table 8).

Multiple Regression Analysis

We performed multiple linear regression analyses since this analysis is used to explain how a dependent variable can be predicted by various independent variables (Margalina et al., 2026). SmartPLS 4 uses the ordinary least squares estimation (OLS) approach, which calculates a line of best fit by minimizing the sum of squared distances between the values of the actual and predicted dependent variable (Margalina et al., 2026). The effect of the independent variables on the dependent variables can be evaluated by these estimated regression coefficients (Hair et al. 2019; Margalina et al., 2026).

The first regression analysis performed examined if the continuous variables of educator age, education level, digital self-efficacy ($\alpha = 0.882$), attitudes towards technology, and personal well-being predicted educators' Behavioural Intention to use technology in their professional work (research question four; H5-H11). Using an OLS method, the overall model was statistically significant, $F(4, 140) = 8.937$, $p = 0.002$, and explained 20.8% of the variance for Behavioural Intention in educators' professional work, $R^2 = 0.208$, $R^2_{\text{adjusted}} = 0.185$ (see Table 15). Both digital self-efficacy, $B = 0.251$, $\beta = 0.257$, $SE = 0.082$, $t = 3.054$, $p = 0.003$ (see Table 15), and general attitudes towards technology, $B = 0.209$, $\beta = 0.093$, $SE = 0.078$, $t = 2.613$, $p = 0.01$, were significant predictors (see Table 15). All assumptions required to perform a linear regression were met.

A second regression analysis was performed to evaluate research question five (testing H5-H11), examining if the variables of educator age, education level, digital self-efficacy, attitudes towards technology, and personal well-being predict their Behavioural Intention to use technology in their personal lives. The overall model was significant, $F(4,140) = 7.365$, $p < 0.000$, and explained 17.8% of the variance for Behavioural Intention of DMHTs in educators' personal lives, R^2=0.178, $R^2_{adjusted}$ = 0.154. Digital self-efficacy was the only significant predictor of Behavioural Intention, β = 0.381, *B*=0.377, *SE*= 0.083, *t*= 4.544, $p < 0.000$ (see Table 21). All assumptions required to perform a linear regression were met.

A multiple regression analysis was performed to examine research question five (H11-H15), testing if the Big 5 personality traits of Extraversion, Conscientiousness, Openness, Agreeableness, and Neuroticism predicted educators' Behavioural Intention to use DMHTs in their personal lives. The overall model was significant, $F(5,140) = 3.338$, $p < 0.001$ and explained 11% of the variance for Behavioural Intention of DMHTs in educators' personal lives, $R^2 = 0.110$, $R^2_{adjusted} = 0.077$. Agreeableness was a significant predictor, *B* = -0.194, β = -0.197, *SE* = 0.081, *t* = 2.389, $p = 0.018$, and Conscientiousness was another significant predictor, *B* = 0.173, β = 0.175, *SE* = 0.081, *t* = 2.127, $p = 0.035$. However, the assumption of heteroscedasticity was not met, as the Breusch-Pagan test had a p-value of less than 0.05 (p = 0.021). To correct for this assumption, we performed a multiple regression analysis in SPSS, using parameter estimates with robust standard errors. We found that Agreeableness and Conscientiousness were no longer significant predictors after using robust standard errors (see Table 18).

The last multiple regression analysis performed was to examine if the Big 5 personality traits predicted educators' Behavioural Intention to use DMHTs in their professional work (research question four; H11-H15). The overall model was significant, $F(5,140) = 3.554$, $p <$ 0.001, and explained 11.6% of the variance for Behavioural Intention of DMHTs in educators' personal lives, $R^2 = 0.116$, $R^2_{adjusted} = 0.084$. Conscientiousness, *B* = 0.171, β = 0.175, *SE* = 0.084, *t* = 2.046, $p = 0.045$, and Extraversion, *B* = 0.183, β = 0.187, *SE* = 0.081, *t* = 2.225, $p = 0.025$, were significant predictors of Behavioural Intention to use DMHTs in their professional work.

However, once again, the assumption of heteroscedasticity was not met, as the Breusch-Pagan test had a *p*-value of less than 0.05. To correct for this assumption, we performed a multiple regression analysis in SPSS, using parameter estimates with robust standard errors. However, after this adjustment, Conscientiousness and Extraversion were no longer significant predictors for the model (see Table 17).

Discussion

Educators have the unique and important role of promoting mental well-being in their professional work (Nygaard et al., 2023). On account of their integral role, and with digital mental health tools (DMHTs) being more available and accessible, understanding what factors impact educators' acceptance of these tools is crucial. Despite this need, there is still a lack of research evaluating educators' acceptance of these DMHTs for use in their own lives and their students' lives. To address this gap, our study aimed to evaluate educators' acceptance of DMHTs in their (a) professional work and (b) personal lives using the UTAUT2 framework; and examined relationships between educators' individual differences variables (e.g., demographics, personality traits, personal well-being, digital self-efficacy, attitudes towards technology) on acceptance of DMHTs.

Factors Influencing Acceptance of DMHTs in Educators' Professional Work

To understand what factors influence acceptance of DMHTs in their professional work, our study aimed to gain an understanding of if the UTAUT2 constructs significantly predicted educators' acceptance of DMHTs in their professional work to support the well-being and mental health of their students. We examined the relationships between educators' Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Technology Anxiety, Habit, and Behavioural Intention to use DMHTs in their professional work.

Our model explained 62% of variance, driven by the relationships of Habit (small effect) and Hedonic Motivation (medium-large effect) on educators’ Behavioural Intention. The other constructs in the model did not predict educators’ acceptance of DMHTs in their professional work. Hedonic Motivation being the most significant predictor of Behavioural Intention indicates that the more educators enjoyed using these DMHTs, their intention to use them in their professional work increased as well. Other studies involving educators’ technology acceptance of Artificial Intelligence (Acikgul & Nihat Sad, 2026) and other technologies in their professional work (e.g., Du & Liang, 2024; Nikolopoulou et al., 2021) showed similar results. Our results are also consistent with research by Du and Liang et al. (2024) that found that Hedonic Motivation significantly influenced educators' continued Virtual Reality usage intention in their professional work for teaching purposes. The authors posited that emotion has a critical impact on human cognitive processes, cognitive outcomes, and behavioural tendencies (Baumeister et al., 2007; Du & Liang, 2024). Research has demonstrated that when these technologies evoke more positive emotions in users, it increases their interest and adoption motivations (Nikolopoulou et al., 2020; Venkatesh et al., 2016). In our current study, we found a wide distribution of responses for Behavioural Intention (see Figure 8). This could suggest that for many educators in our study, DMHTs might be new and exciting to them, which resulted in higher usage intentions.

Another result from our PLS-SEM analysis was a small yet significant effect of Habit predicting Behavioural Intention in their professional work. Habit being a significant predictor of acceptance aligns with other studies that have evaluated the UTAUT2 constructs with educators’ acceptance of educational technology in their professional work (Arenas et al., 2015; Kumar & Bervell, 2019; Venkatesh et al., 2012). Habit is a measure of the extent of how much one believes a behaviour is automatic and has been shown to be a predictor of intention and use of technology (Nickopolous et al., 2023; Venkatesh et al., 2012). The behaviour becomes automatic due to learning from experience and usage (Venkatesh et al., 2012). Higher usage of technologies in these educational contexts is thought to lead to more active use processes (Du & Liang, 2024; Lewis et al., 2013), demonstrating that educators who are in the habit of using DMHTs in their professional work have increased acceptance of these tools. Our results align with the literature on developing health-promoting behaviours and habit formation. Habit has been shown to be a primary factor in behavioural maintenance (Gardener et al., 2023; Rothman et al., 2009). Habitual behaviours occur when a situation automatically triggers an impulse to act that is effortless and rapid due to unconscious processes (Gardener et al., 2023; Orbell & Verplanken, 2010). This situation-behaviour association is developed and learned by consistency (Gardner et al., 2023; Garder et al., 2015). Further, this habitual behaviour has been demonstrated to have an effect on various health behaviours (e.g., physical activity, diet, alcohol consumption, medication adherence, etc.) (Gardner et al., 2023; e.g., Aungeret al., 2010; Conroy et al., 2013; Gardner et al., 2012; Hagger, 2019; Hagger et al., 2020; Lin et al., 2016; Mullan et al., 2021; Phillips et al., 2013). It has been found that making health-promoting behaviours a habit is able to lower health-risk behaviours and buffer against potential motivational losses (Gardner et al., 2023; Conn & Ruppar, 2017; Orbell & Verplanken, 2020). These effects of habit on health-promotion behaviours align with our findings that when educators perceive that using DMHTs is automatic, their acceptance and intent to utilize these tools increases.

We found that Social Influence was not a significant predictor of Behavioural Intention to use DMHTs in their professional work. This suggests that social norms in the school environment did not influence educators' intention to use these tools. In El-Masri and Tarhini's (2017) study that examined the adoption of e-learning systems in the United States and Qatar, Social Influence did not influence acceptance for educators' use of these educational digital tools in the United States. However, Social Influence did significantly impact acceptance for educators' in Qatar. Similarly, Chinese educators' adoption of VR technology in their professional work was also significantly influenced by Social Influence (Du & Liang, 2024). These results could be due to the collectivist cultures of East Asia and the Middle East compared to individualist cultures such as Canada and the United States. The individualist nature of Canadian society could be thought to contribute to our non-significant findings. However, another explanation could be due to the novelty of these tools in the school environment. School management might not be encouraging use of these DMHTs yet, and as a result the educators partaking in the study were not predisposed to adopting a positive stance to use these technologies in their professional work. The frequency distribution for the construct of Social Influence in our study revealed that the majority of educators *neither agree nor disagree* with the construct (see Figure 19). It has also been argued that social influence should be further examined and re-conceptualized as research has shown that students' opinions can have a larger influence on educators' attitudes and beliefs about technology for learning in their professional work (Du & Liang 2024; Kim & Lee, 2020).

A large number of studies investigating the acceptance of educational technologies in their professional work found that Facilitating Conditions significantly impacted intention to use technology (Mistry et al., 2025). This finding indicates that when the resources and support are available for educators', adoption and acceptance of technology increases. However, the relationship between Facilitating Conditions and Behavioural Intention was not significant in our study. This null finding could be a result of once again the novelty of these DMHTs. Support and resources might not be in place in schools and therefore educators' are not aware of the resources and supports available. Consequently, educators' could not be aware of the impacts these supports and resources could have on their acceptance and use of these tools.

We found no significance of Effort Expectancy on Behavioural Intention to use DMHTs in their professional work. This finding could be because educators' currently have low exposure to various DMHTs and therefore have not yet had enough experience with these tools to observe if they are user friendly. The literature on educational technology has found that Effort Expectancy overlaps with perceived usefulness of these technologies, which then has an effect on Behavioural Intention (Meng & Wang, 2012). Thus, it's possible that educators' might perceive these DMHTs as not useful which impacts their evaluation of Effort Expectancy on Behavioural Intention. Further exploration into educators' perceived usefulness of DMHTs on their students' well-being is required.

Since the construct of Performance Expectancy was removed from our structural model, its effects on Behavioural Intention to use DMHTs in their professional work could not be evaluated. The original UTAUT2 model had four items in Performance Expectancy. However, after modifying our constructs to fit the educational context, only two items were left in the construct (e.g., "I find digital mental health tools useful in my work as an educator to support my students' mental health and well-being" and "Using digital mental health tools improves my mental health and/or productivity"). The reduction of these items from the original four to two could be why there might have been such high overlap with the construct of Behavioural Intention.

Lastly, our hypothesis (H2) that Technology Anxiety will negatively impact Behavioural Intention to use DMHTs in educators' professional work was not supported. Evaluating the frequency of results for the items in the construct of Technology Anxiety, a majority of educators chose to *disagree* and *neither agree nor disagree* with these items (see Figure 10). This construct included items such as "Using digital mental health tools in the workplace makes me feel uneasy and confused" and "Using digital mental health tools in the workplace would make me very nervous". These results indicate that educators largely have low levels of anxiety using these technologies in the workplace, and therefore it could be why it is not impacting their behavioural intention to use these tools. This low Technology Anxiety could be explained by the comfortability that the educators' in this study have using educational tools in their professional work with 36.2% of respondents feeling *extremely comfortable* and 35.5% *somewhat comfortable* using educational tools in their professional work (see Table 22). This also aligns with our findings explained below, regarding digital self-efficacy being a significant predictor of Behavioural Intention to use DMHT in in their professional work. The majority of educators in our study had high digital self-efficacy, which suggests that they were more confident and comfortable using technology and are generally not afraid to use technology in their professional work. While educators in this study had generally positive attitudes towards technology, we did not find it to be a significant predictor of their Behavioural Intention to use these tools in their personal lives. However, this could be a result of not inquiring specifically about educators' attitudes towards DMHTs.

Moderators for Acceptance of DMHTs in Educators' Professional Work

We hypothesized that age, gender, experience with digital tools (User Behaviour), and privacy concerns would moderate the relationship between UTAUT2 constructs and Behavioural Intention in educators' professional work. We used a two-stage approach in our PLS-SEM analysis to examine the moderating effects of age, privacy concerns (e.g., Perceived Intrusion, Perceived Surveillance, Secondary Use of Personal Information, and Technology Anxiety) and experience (User Behaviour) on Behavioural Intention. The only significant moderator was age. The moderator variable of gender could not be evaluated due to a large discrepancy in women educators compared to male educators. This discrepancy in gender is representative of the demographics of educators in Canada, with 76.6% of Ontario teachers identifying as female (Statistics Canada, 2025).

Age. Age has a significant interaction on Habit, indicating that when age increases, the effect of Habit on Behavioural Intention dampens. These results are not surprising as age is a well-known moderator in the UTAUT2 constructs. These results were most likely a result of older educators' having lower usage of these technologies in educational contexts. Other research has postulated that it is not age itself that impacts technology acceptance, but the exposure and experience of using technologies in their professional work (Bullen, Morgan, & Qayyum, 2011; Kennedy et al., 2007, 2009). Younger educators' were more likely to have grown up with and used technologies in their education to become an educator. Related to the DMHT context, younger educators' most likely had more exposure to DMHTs compared to their more aged peers. Increased usage of these tools is suggested to lead to increased active use processes that create habit forming behaviours (Du & Liang, 2024; Lewis et al., 2013).

User Behaviour. User behaviour was also added as a moderator in the structural model for Effort Expectancy, Technology Anxiety, Habit, Hedonic Motivation, Social Influence and Behavioural Intention. The hypothesis (H3), that User Behaviour would moderate the UTAUT2 constructs and Behavioural Intention was not supported. Although it seems contradictory to have educators' score high in Habit and low scores in User Behaviour, it is possible since educators' can have a high perception that their behaviours to use a digital tool is automatic while their actual usage of the tool can be low due to environmental barriers and/or lack of resources.

Assessing the frequency distribution of responses to the items of User Behaviour, the first item of "I have used DMHTs in the workplace" had the highest number of responses for *strongly disagree* and *strongly agree*. The median responses for all the four items were largely between *strongly disagree* and *disagree* (see Figure 12). This could explain why no moderation effect was found for these constructs, as many educators have not used or consistently use DMHTs in their lives. Despite DMHTs being widely available, these tools are still new and not readily used, which is most likely why there are no significant interaction effects between User Behaviour and the UTAUT2 constructs on Behavioural Intention.

Privacy Concerns. The constructs of Perceived Intrusion and Secondary Use of Personal Information were added as moderators to the UTAUT2 constructs and Behavioural Intention model. There were no significant interaction effects. Examining the frequencies for Secondary Use of Personal Information, it seemed as though educators' largely had no strong opinions, answering *neither agree nor disagree,* with these statements and had no concerns about these DMHTs using their students' personal information (see Figure 25). For Perceived Intrusion, educators largely chose that they *strongly disagreed* and *disagreed* with the belief that these DMHTs could be sharing information or invading their privacy (see Figure 27). The lack of concern regarding privacy could be a result of the lack of education regarding what information these DMHTs collect and who has access to it.

Factors Influencing Acceptance of DMHTs in Educators' Personal Lives

To address the research questions of if educators' accept DMHTs in their personal lives to support their own well-being and mental health, a PLS-SEM was conducted. Our hypothesis (H2) was partially supported with Performance Expectancy significantly predicting educators' Behavioural Intention to use DMHTs in their personal lives. Our studies finding that

Performance Expectancy largely predicts Behavioural Intention has been found in other studies to be a main predictor of Behavioural Intention to use mHealth apps (Hoque & Sorwar, 2017; Uncovska et al., 2023). Performance Expectancy is conceptualized as the perception that utilizing technology will be beneficial to the user and is related to the perception of usefulness (Schomakers et al., 2022; Venkatesh et al., 2012). This highlights that app developers should communicate the benefits of these tools to their target populations. A systematic review on users' engagement to use Digital Mental Health Interventions further supported the finding that users' perceived usefulness impacts their engagement with these digital mental health interventions (Bifftu et al., 2025). Users' beliefs regarding the functionality and usability are core factors influencing individuals' willingness to use these tools (Bifftu et al., 2025; Kuhn et al., 2024; Macgee et al., 2018). Researchers posit that many of digital mental health interventions are developed without including the target populations in the design of these tools and without considering users' needs and preferences (Bifftu et al., 2025; Goodwin et al., 2016; Kuhn et al., 2024).

In contrast to other studies, core constructs such as Effort Expectancy on intent to use DMHTs were not found (Huang et al., 2024). This could be due to our PLSpredict model having low predictive quality. This low predictive quality indicates that our model has poor abilities at predicting out of sample observations (Hair et al., 2022). The reason that our model has low predictive quality could be due to the large amount of missing observations due to the *NA* option added to the UTAUT2 constructs. Educators in Canada might not have enough experience with using these DMHTs in their personal lives, and therefore, the UTAUT2 constructs could not be captured accurately.

Moderators for Acceptance of DMHTs in Educators' Personal Lives

We hypothesized that age, gender, experience with DMHTs (User Behaviour), and privacy concerns would moderate the relationship between the UTAUT2 constructs and Behavioural Intention in educators' personal lives. We found no significant moderators on the UTAUT2 constructs and Behavioural Intention to use DMHTs in their personal lives. This finding contrasts with studies of mHealth adoption where age is negatively correlated with intention to use these technologies (Schomakers et al., 2022; Uncovska et al., 2023). Privacy concerns not being a moderator could be due to the educators' who completed this online survey were more likely comfortable using technology to begin with. Another possibility is that our non-significant results could be due to the low predictive power of our model.

The Relationship between Educators' Behavioural Intention in their Personal Lives and Professional Work

Our hypothesis that a significant and positive correlation between educators' acceptance of DMHTs in their personal lives and professional work was supported. These results are in line with studies that found that educators' who had higher personal technology use were associated with an increase in technological resource use for tasks related to classroom preparation and administration (Almerich et al., 2024; e.g., Almerich et al., 2023; Orellana et al., 2013) and with students in their professional work (Almerich et al., 2024; e.g., Almerich et al., 2023; Becker, 2006). The literature suggests that personal use of technology is associated with technology use in their classrooms, which mirrors our findings that educators' who accept these DMHTs for their personal use are associated with their acceptance of use in their classrooms. The positive association between personal use and professional work can have meaningful implications for understanding what factors influence educators' acceptance of DMHTs and can inform future implementation procedures for DMHTs in schools. This correlation also relates to our previous finding of Habit being a predictor of Behavioural Intention in their professional work. While our structural model only examined Habit in relation to Behavioural Intention of DMHTs in their professional work, it demonstrates that those teachers who invest their time in these DMHTs have increased acceptance of these tools.

Age, Education Level, Attitudes Towards Technology, and Digital Self-Efficacy on Behavioural Intention

We performed two multiple regression analyses to examine if the variables of educator age, education level, digital self-efficacy, attitudes towards technology and personal well-being predicted educators' Behavioural Intention to use DMHTs in their personal lives and professional work. The two overall models were statistically significant, with 20.8% and 17.8% of the variation for Behavioural Intention explained by the independent variables in educators' personal lives and in their professional work.

Digital Self Efficacy. Digital self-efficacy was a significant predictor in both models, indicating that when educators have more digital self-efficacy, their Behavioural Intention to use DMHTs also increases. This finding supports hypothesis five that greater digital self-efficacy will predict greater Behavioural Intention to use digital mental health tools in educators' personal lives and professional work. Research has shown that greater computer self-efficacy has a significant impact on educators' acceptance and behavioural intention to use digital technologies for learning in their professional work (Abel et al., 2022; Hana et al., 2019; Sorgo et al., 2010). Other research on mHealth app adoption for adults found that low technology-related skills had a negative effect on app adherence and usage (Jacob et al., 2022), suggesting that educators' who are not as confident and self-sufficient using technology are less likely to use this technology for themselves as well as for their students.

Attitudes Towards Technology. General attitudes towards technology was a significant predictor of Behavioural Intention to use DMHTs in educators' personal lives, which partially supported hypothesis six. Positive attitudes towards technology have been shown to impact acceptance and use of digital mental health apps (Gbollie et al., 2023). This finding was supported by our results that more positive attitudes towards DMHTs predicted increased Behavioural Intention to use these tools in their personal lives. However, we did not find that attitudes towards technology predicted acceptance of DMHTs in their classrooms. One reason for this is that our study only inquired about general attitudes towards technology and did not inquire about educators' general attitudes specifically towards DMHTs. A study by Leem and Sung (2018) demonstrated that teachers' who had low attitudes and confidence in their abilities to enhance their teaching through digital technologies were less likely to use them in their classrooms. Future research should investigate further into the relationship between attitudes towards DMHTs and Behavioural Intention to use them in their classrooms.

Personal Well-being. Our hypotheses (H7-H8) that greater personal well-being of educators will predict greater Behavioural Intention in educators' professional work and lower well-being will predict greater Behavioural Intention to use these tools in their personal lives was not supported. While some studies (Nogueira-Leite et al., 2024) have shown that perceived stress predicted mental health app use, other studies, (Borghouts et al., 2021) only found it significant through a mediating effect of perceived need to seek help. Borghouts et al. (2021) revealed that those who had a perception of experiencing a mental health problem and had coping strategies related to digital mental health app use, were significantly and positively associated with mental health app use. Our studies non-significant findings for personal well-being and Behavioural Intention could indicate that our participants' might not have a perception that mental health promotion and prevention are important for their students' or themselves. Borghouts et al. (2021) also found a positive and significant relationship between past use of mental health services and digital mental health app use. Our study did not explicitly ask about educators' past use of services for mental health prevention and promotion. Future research should incorporate this into their research, as it could potentially be another variable that could impact the acceptance of these DMHTs.

Age. The variable of age itself did not predict Behavioural Intention in educators' personal and professional lives, which did not support our hypothesis (H9). However, we found that age did moderate the UTAUT2 construct of Habit for Behavioural Intention in their professional work. This result indicates that while age alone as a variable might not predict Behavioural Intention, it can act as a moderator through the construct of Habit. As age increases, Habit has a less effect on Behavioural Intention to use these DMHTs.

Education Level. Our hypothesis (H10), that higher levels of education (bachelor's degree or more) will predict greater Behavioural Intention to use DMHTs in educators' personal lives and professional work was not supported. The reason we might not have found significant results in education level is that the majority of our participants (68.8%) highest level of education was at the bachelor's level. We were not able to compare teachers with higher levels of education (27.7%; e.g., MA, PhD) and lower levels of education (3.5%; e.g., High-school or GED) Behavioural Intention to use these technologies. Other studies have shown that educators' with higher levels of education (i.e., graduate degrees) had more access to these technologies in their personal lives than educators with a high school degree (Blackwell et al., 2013). Educators in low-income areas and urban schools had more access to technology as well. Access to resources can impact technology habit and usage which have been associated with acceptance of technologies (Arenas et al., 2015).

Personality and Behavioural Intention. We found no significant results in personality traits predicting Behavioural Intention to use DMHTs in educators' professional work or personal lives.This is contradictory to research showing that higher levels of all five personality traits influenced acceptance and use of these DMHTs (Alquanti et al., 2018; Borghouts et al., 2021; Ervasti et al., 2019; March et al., 2018). Due to our study having a smaller sample size, as well as using a modified 18-version BFI scale instead of the original 40 version scale, our assumption of homoscedasticity was not met. Even after we corrected for homoscedasticity , our model was not significant. Our results could be a result of limited items creating our independent variables of the five personality traits, which is why there were no significant results.

Study Limitations and Future Directions

Our study had a few limitations to consider when interpreting the findings; the first being the modifications we made to our measures in order to relate them to the school context. Modifying these measures involved removing multiple items from the UTAUT2 constructs. Specifically, the construct of Performance Expectancy for the Professional UTAUT2 construct had only two items. Performance Expectancy also happened to have discriminant validity problems with Behavioural Intention. Hair et al. (2022) recommended that to handle this issue of discriminant validity, one way is to eliminate items that have low correlations with the items of the same construct. However, due to the construct of Performance Expectancy only having two items, no constructs could be removed, resulting in the entire construct being eliminated from the PLS-SEM analyses. Additionally, we used a short-form BFI scale instead of the original 40 item version to reduce the amount of time our study took to complete. Although this short-item BFI was validated, one of the BFI items had to be removed due to excess skewness. The limited number of items for each personality construct could be why no significant results were seen for personality traits and acceptance of DMHTs.

Further, although the *Not Applicable (NA)* option being added to the UTAUT2 itself was not a limitation, as we did not want educators' answering these questions if it was not relevant to them, it resulted in a large number of missing observations which contributed to a lower sample size. The educators' included in this study still had missing observations for most UTAUT2 constructs, choosing the NA option for items on the UTAUT2 scales, meaning that they were not all well-versed or had no experience using these technologies in their personal or professional lives. Participants selecting the NA option suggest that the UTAUT2 constructs still might have not captured the data for this measure accurately. Additionally, our sample was biased to predominantly White, urban, educators' located in Ontario, with a bachelors-level education. This may influence the generalizability of these findings to educators' working in rural schools and in other provinces. Additionally, we received feedback from various educators' requesting clarification of what DMHTs are. Although we included a definition of what DMHTs are at the beginning of the study, some educators' may have not understood what constitutes being a DMHT. As a result, some of our participants' may have inaccurately completed the study not having a full understanding of what a DMHT is. The confusion of what DMHTs are may have impacted our data and not accurately capture educators' perspectives. Despite these limitations, our study had promising results and contributed to the scarce literature investigating educators' acceptance of DMHTs in their professional work and personal lives. DMHTs in schools are important since DMHTs are becoming more readily available and utilized for mental health promotion. Lastly, since our study was only available online, it is a possibility that only educators who were comfortable using technology completed this survey. This limits the generalizability of our study to educators' in Canada, as it only includes educators who are comfortable with technology.

To mitigate the confusion regarding what DMHTs are, subsequent research should provide examples of DMHTs and ensure that the educators included in the study have had experience using them to capture the most accurate data. To further examine what individual factors affect acceptance of educators' intent to use DMHT, it is suggested that research include measures to capture attitudes towards DMHTs, perceived help seeking behaviours, and past use of mental health promotion and prevention strategies. To mitigate the limitation of this study of having educators' who had little to no experience using these DMHTs participate in the study, future work could provide educators with an opportunity to use DMHTs to gather more accurate information on their acceptance of these tools. In addition to this, gathering qualitative data would be useful in further understanding educators' opinions and perceptions of use of these tools within the school system.

Subsequent research could consider exploring educators' perception of their students' opinions on using these DMHTs and if that would impact their acceptance. Lastly, while evaluating educators' acceptance of these tools is important, subsequent research could gather opinions, perspectives, and perceived barriers of DMHTs from students, school administrators, and caregivers, using a more diverse population and including more rural schools.

Implications and Conclusions

The current study evaluated educators' acceptance of DMHTs in their (a) professional work and (b) personal lives using the UTAUT2 framework; and examined the relationships between educators' individual differences variables (e.g., demographics, personality traits, personal well-being, digital self-efficacy, attitudes towards technology) on acceptance of DMHTs. Our study provided key insights into what individual factors impact acceptance of DMHTs for educators, both for their personal and professional use. This is vital due to the lack of research investigating educators' acceptance of these DMHTs. In addition, our study also gathered information from educators in Canada who taught from Kindergarten to Grade 12. Currently, there is a lack of literature evaluating DMHTs in a range of school grades, with a majority of studies only focusing on secondary school students (Sakelleri et al., 2021). This allows our research to be generalizable to the early education, primary, middle schools, and high schools in Canada.

Our study found that educators' enjoyment of using DMHTs and their habits of using these tools were significant predictors of intention to use DMHTs in their classrooms. These results can inform future development and integration of DMHTs to promote the well-being of their students. To develop tools that educators would actually use, it is essential to understand and target what factors influence educators' intent and acceptance. Without educators' acceptance of these DMHTs, implementation will not be successful.

Another important individual factor that our study found was the influence of the age of the educator on acceptance of DMHTs. While age does not directly influence intent to use DMHTs in their professional work, it has an effect on the relationship between Habit and acceptance. This suggests that when educators are older, they have less exposure and experience using these DMHTs, which in turn lowers their ability to form habits of using this technology, impacting their intent to use these tools. We also found that more positive attitudes and confidence using digital tools were predictors of intent to use these tools in their professional work. Our study contributes to the understanding and knowledge of what factors school boards need to consider when integrating and developing these tools, to account for their target audience's demographics, experiences and preferences. Specifically, increasing positive attitudes and confidence in using technology could aid in mitigating the role of age in the acceptance of DMHTs.

Additionally, our study specifically focused on educators, which is important as there is a lack of research on what impacts their acceptance of DMHTs, with the majority of this research grouping educators and key stakeholders of the schools together. While other perspectives are important, it is crucial to continue expanding the literature to understand what factors impact educators' acceptance of DMHTs, as the primary role of promoting mental well-being to their students. In addition to investigating educators’ acceptance of DMHTs in their professional work, we also evaluated their acceptance in their personal lives. We found that educators’ who thought that these tools would be useful to themselves had more intent to use these tools for their own mental well-being. Their use of DMHTs in their personal life aligned with their intent to use these tools in their professional lives. This is significant, as DMHTs developers should target the benefits of these tools to their audiences. Overall, our study had promising results and contributes to the literature of DMHTs in the school context to promote educator and student well-being.

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Figure 1

Chi-Square Q-Q Plot of Mahalanobis Distances

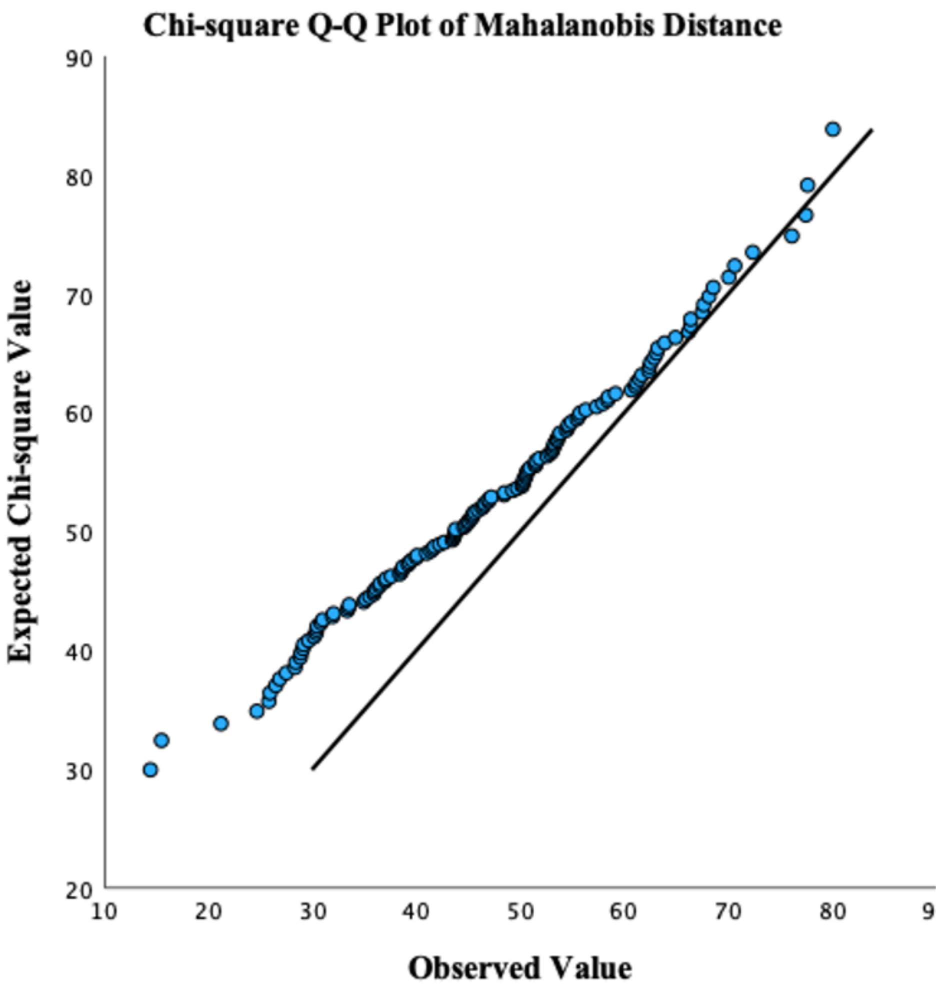


Figure 2

Measurement Model of Professional UTAUT2 Constructs

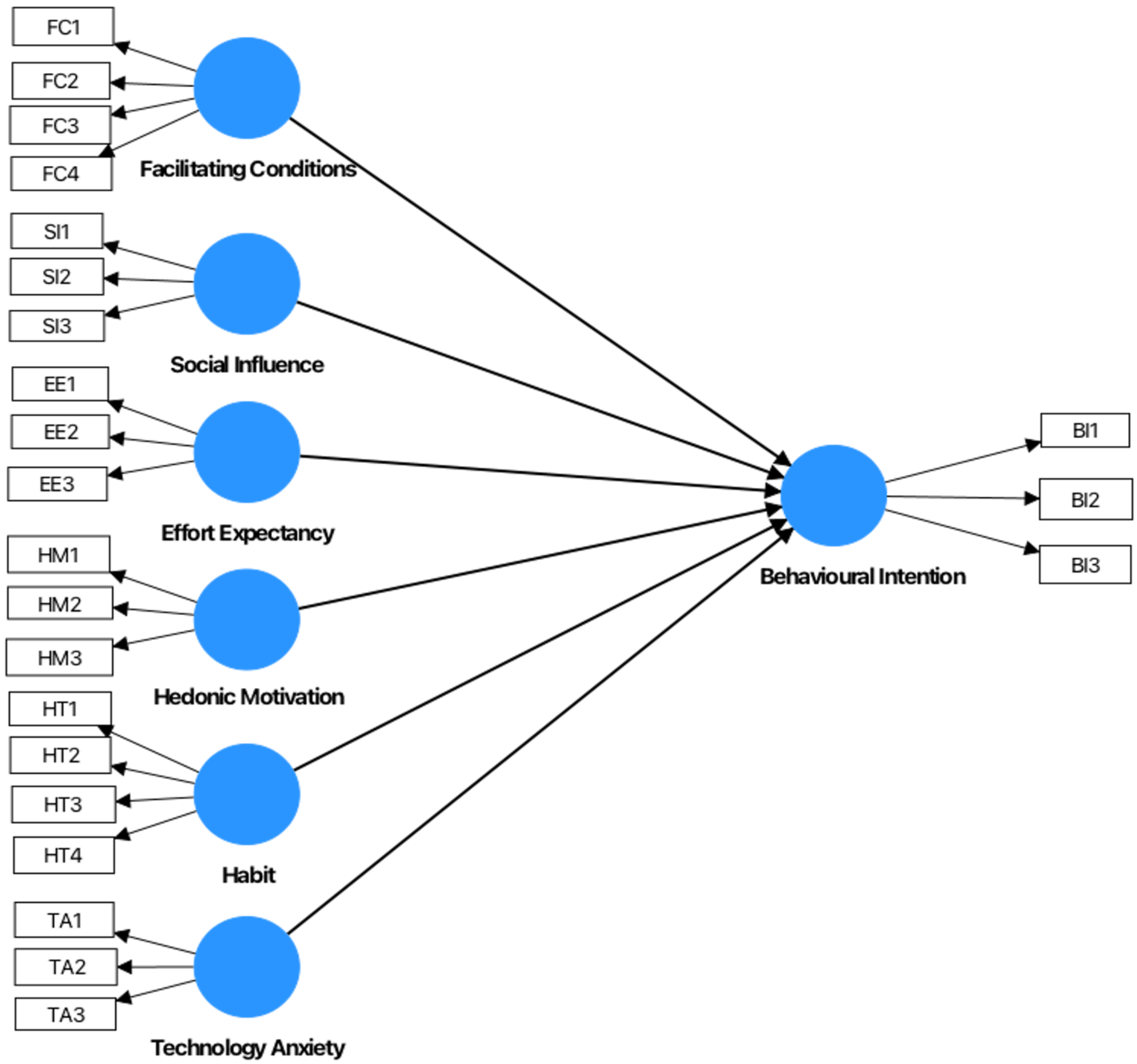


Figure 3

Measurement Model of Personal UTAUT2 Constructs

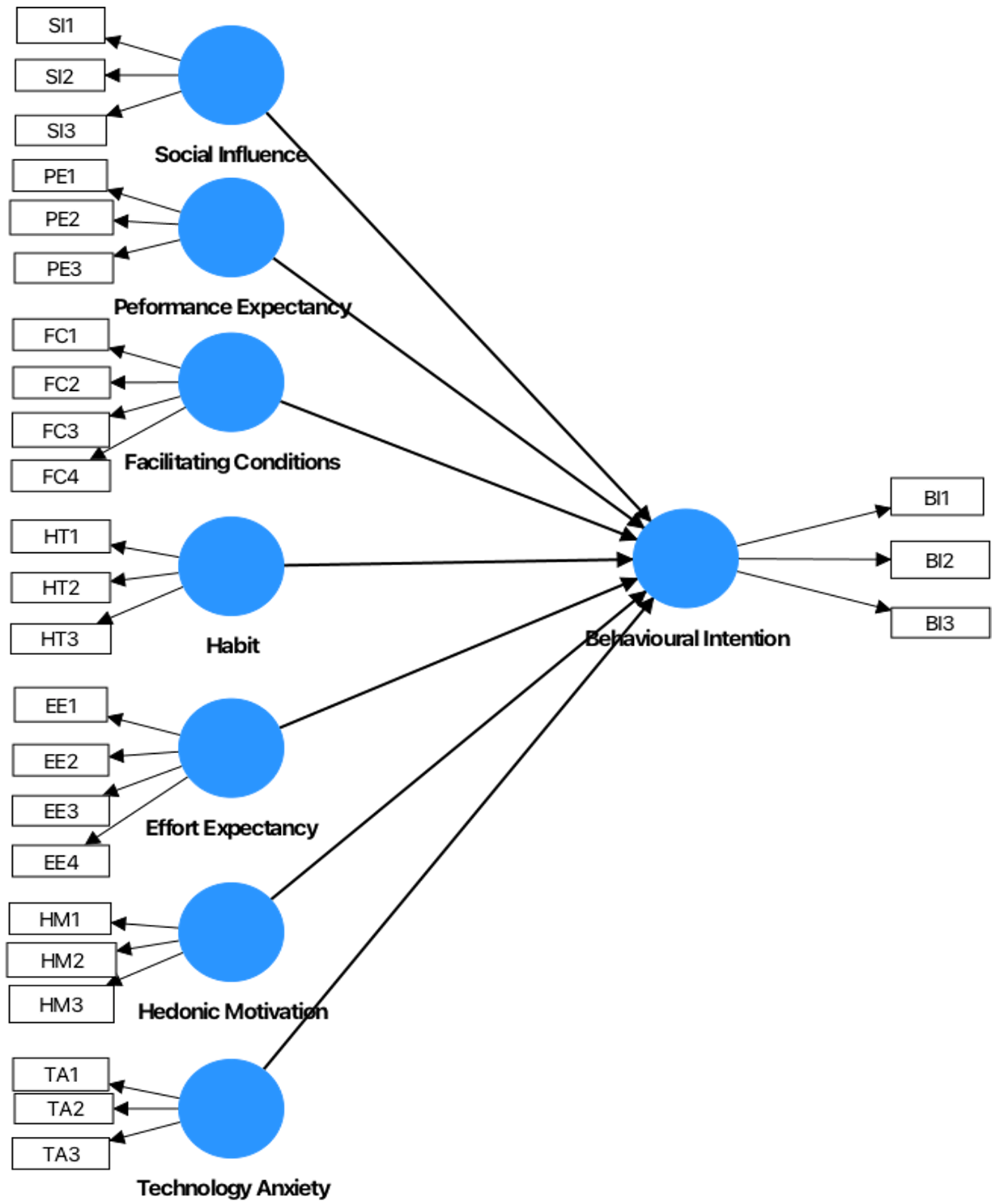


Figure 4

Structural Model of Professional UTAUT2 Constructs

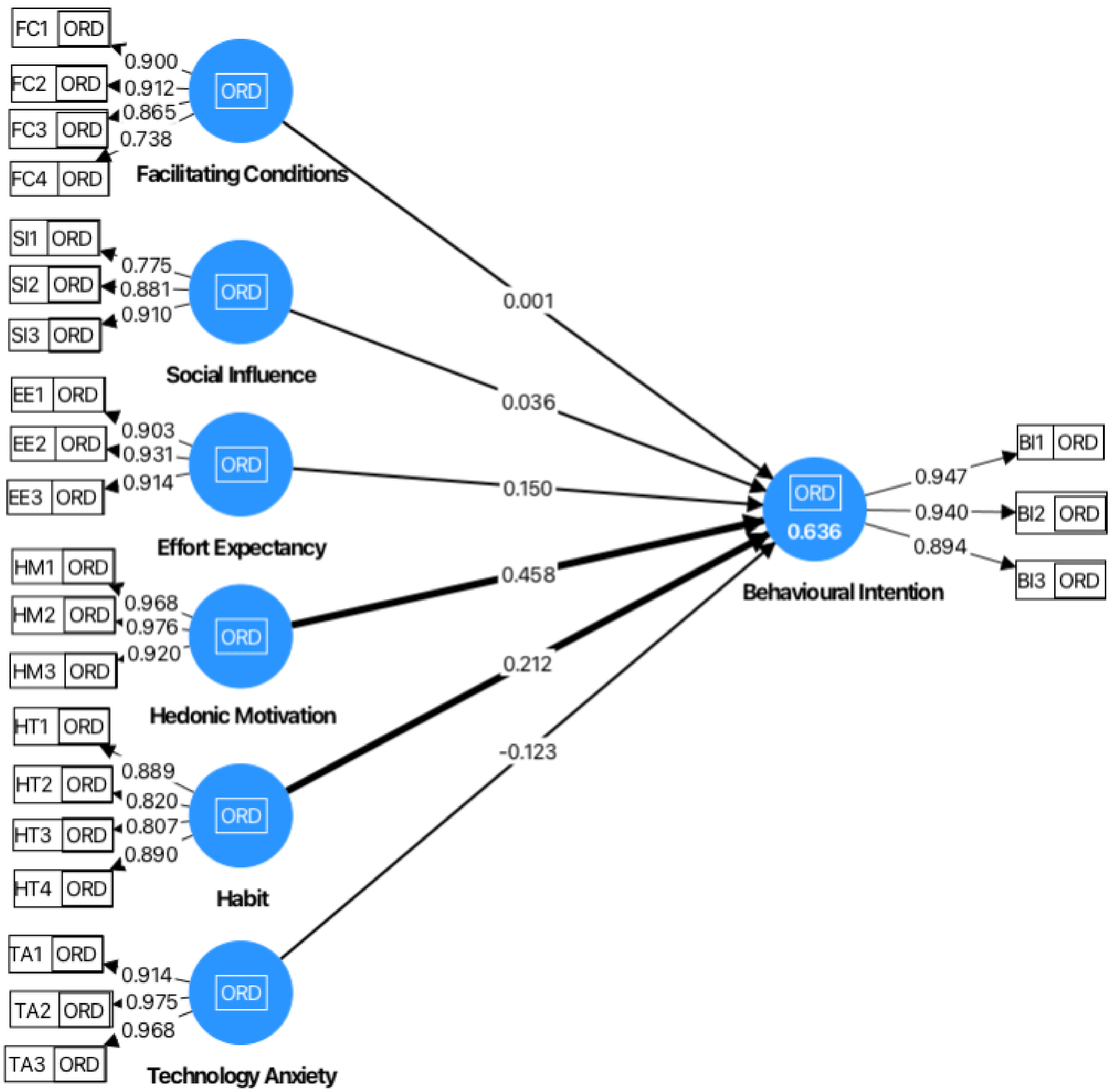


Figure 5

Structural Model of Personal UTAUT2 Constructs

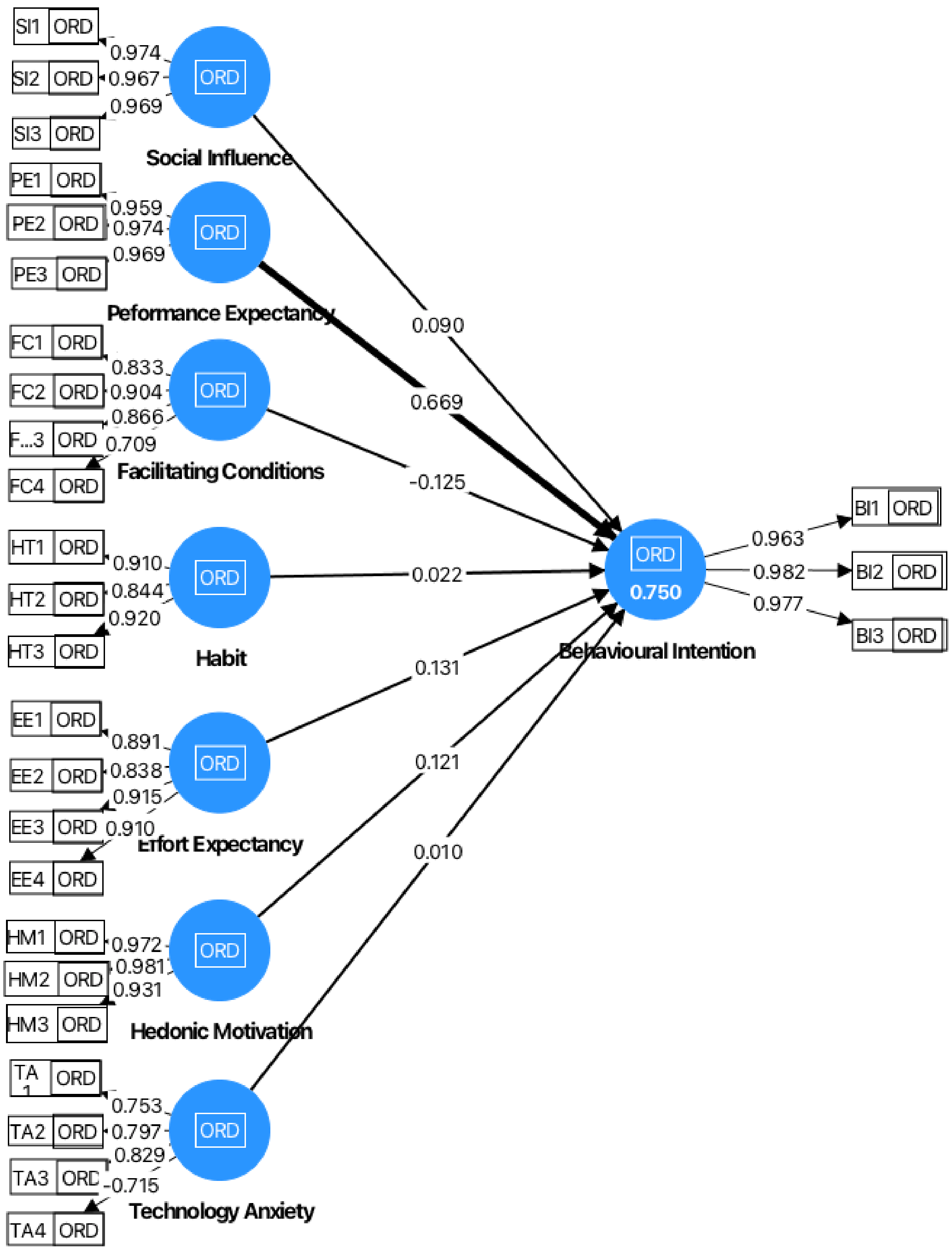


Figure 6

Moderation Graph of Age on Professional Behavioural Intention

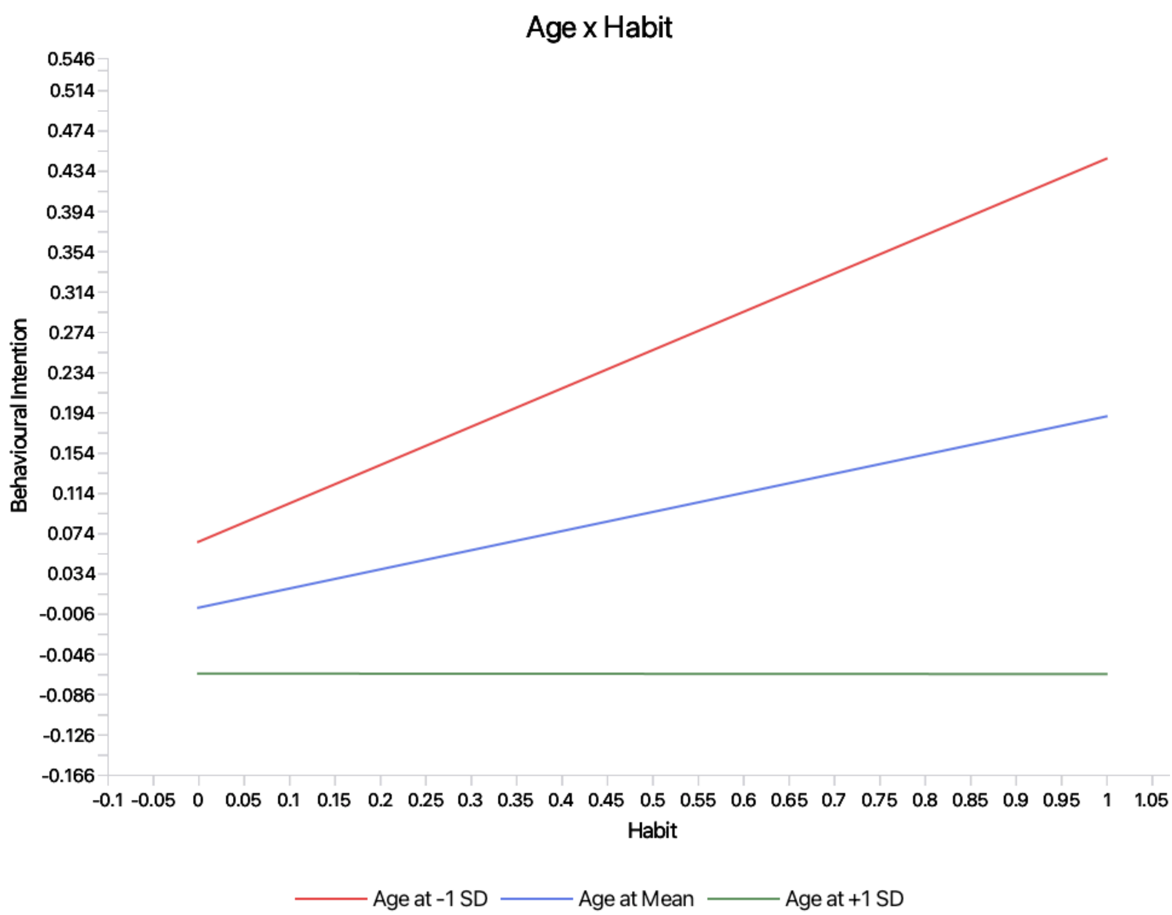


Figure 7

Frequency Distribution for Professional Behavioural Intention (BI) Construct

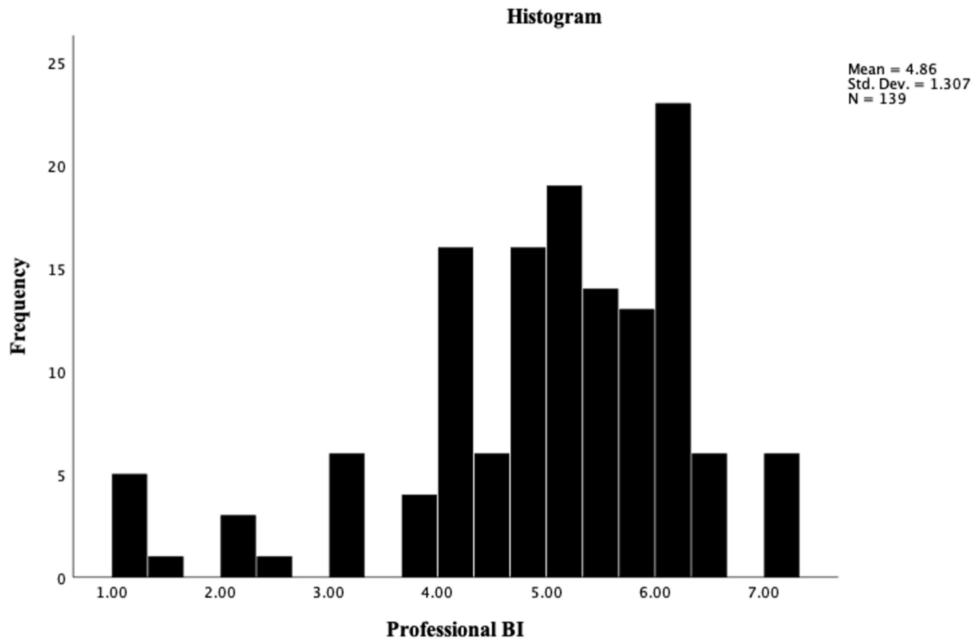


Figure 8

Frequency Distribution for Professional Habit (HT) Construct

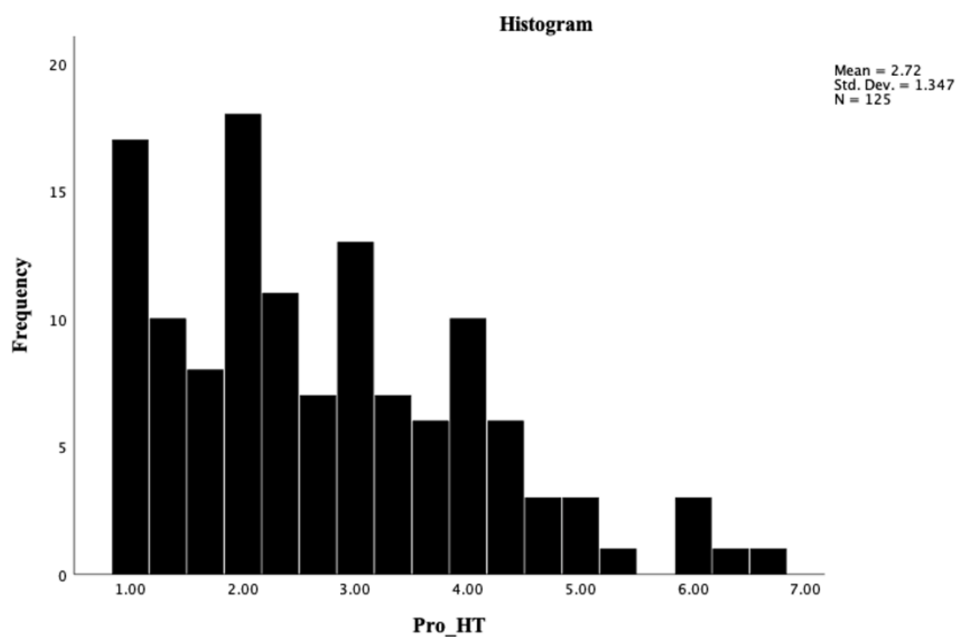


Figure 9

Frequency Distribution for Professional Effort Expectancy (EE) Construct

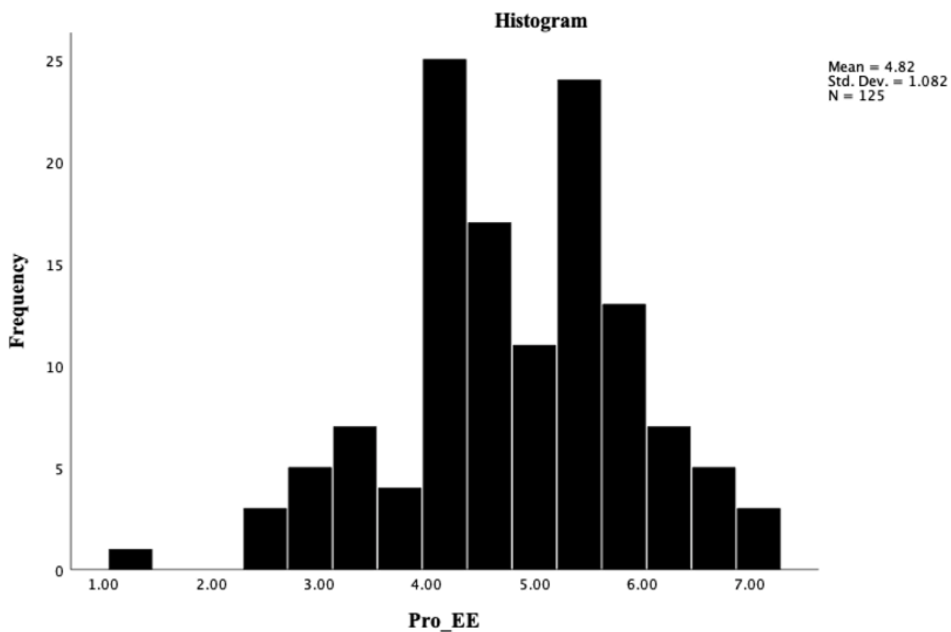


Figure 10

Distribution of Responses for the Professional UTAUT2 Construct of Facilitating Conditions (FC)

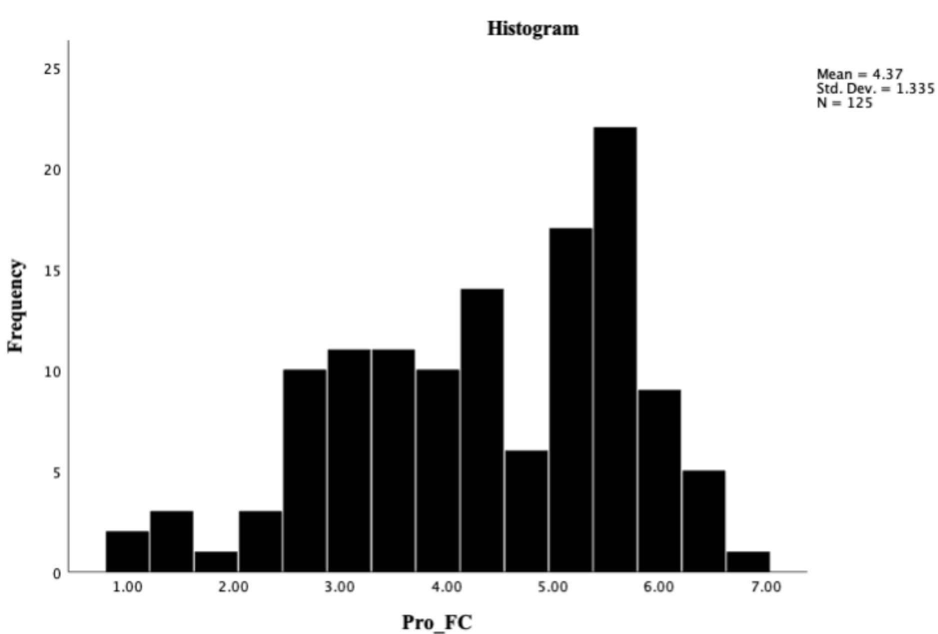


Figure 11

Distribution of Responses for the Professional UTAUT2 Construct of Hedonic Motivation (HM)

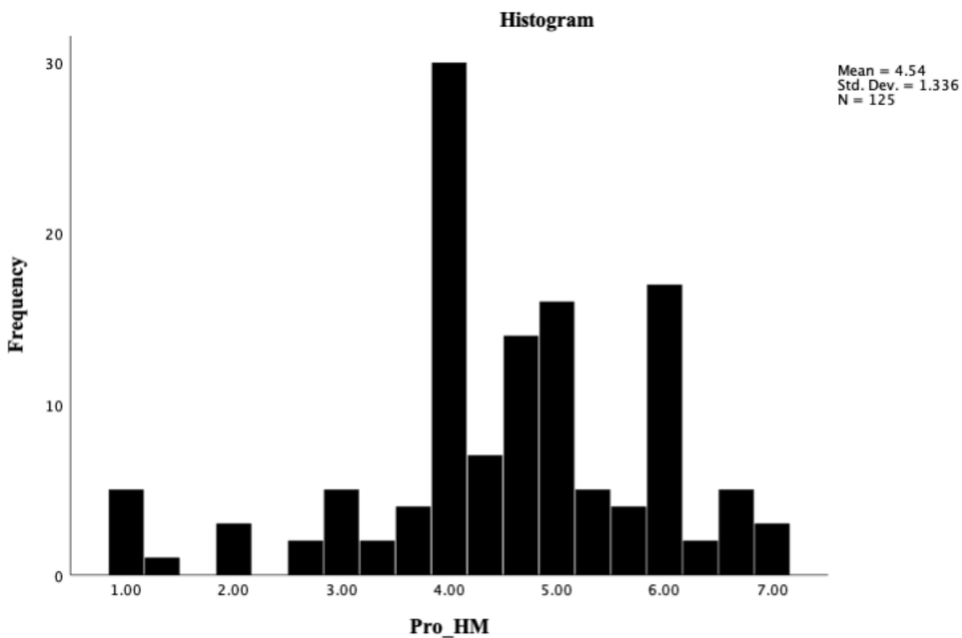


Figure 12

Distribution of Responses for the Professional UTAUT2 Construct of User Behaviour (UB)

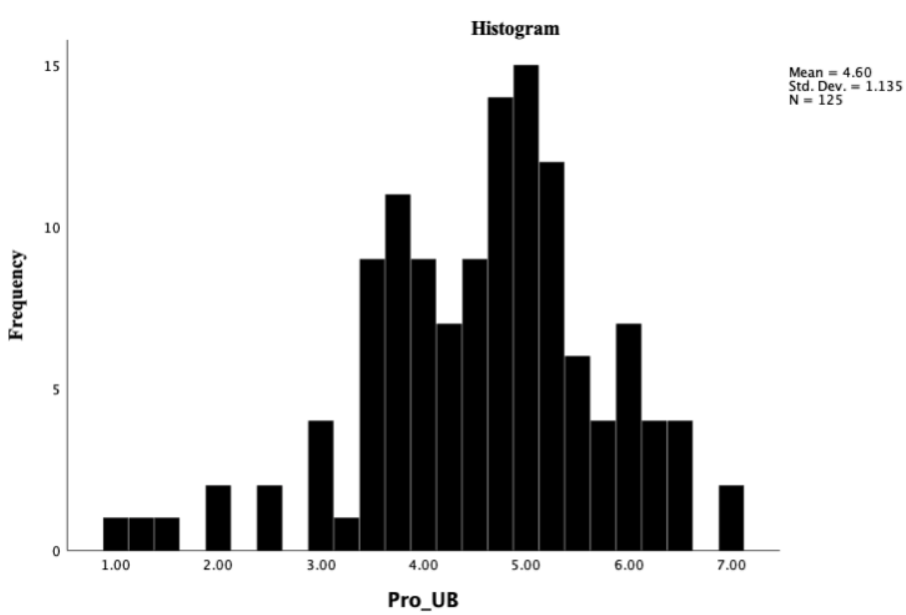


Figure 13

Distribution of Responses for the Professional UTAUT2 Construct of Performance Expectancy (PE)

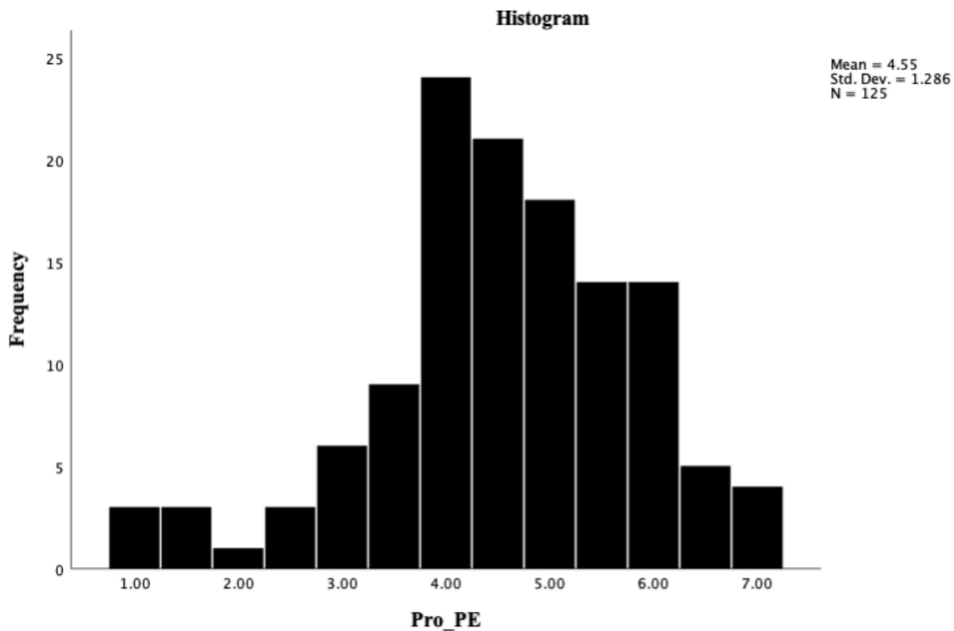


Figure 14

Distribution of Responses for the Professional UTAUT2 Construct of Social Influence (SI)

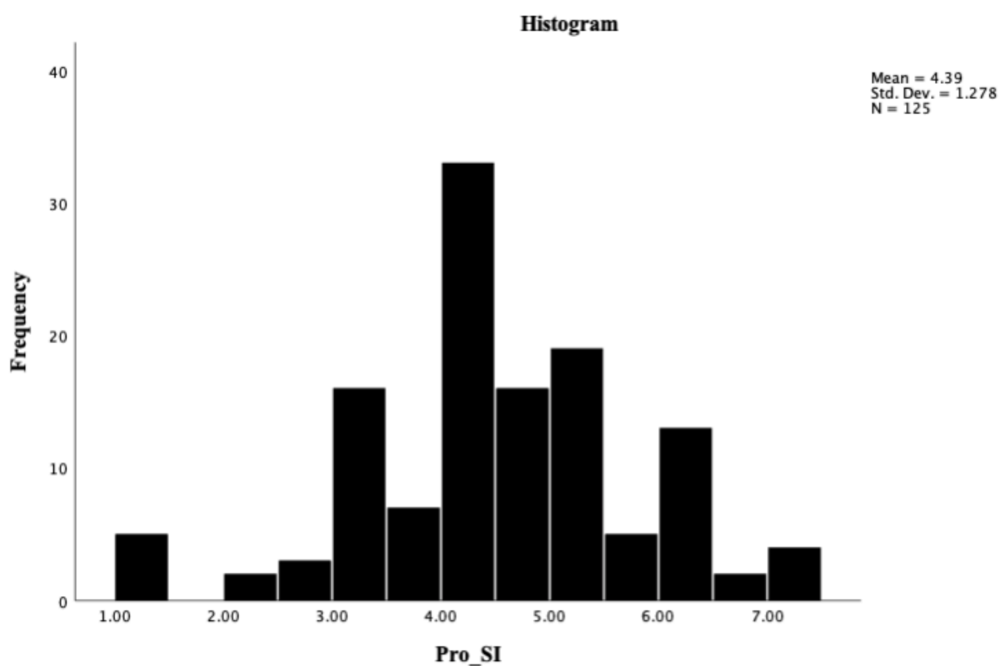


Figure 15

Distribution of Responses for the Personal UTAUT2 Construct of Behavioural Intention (BI)

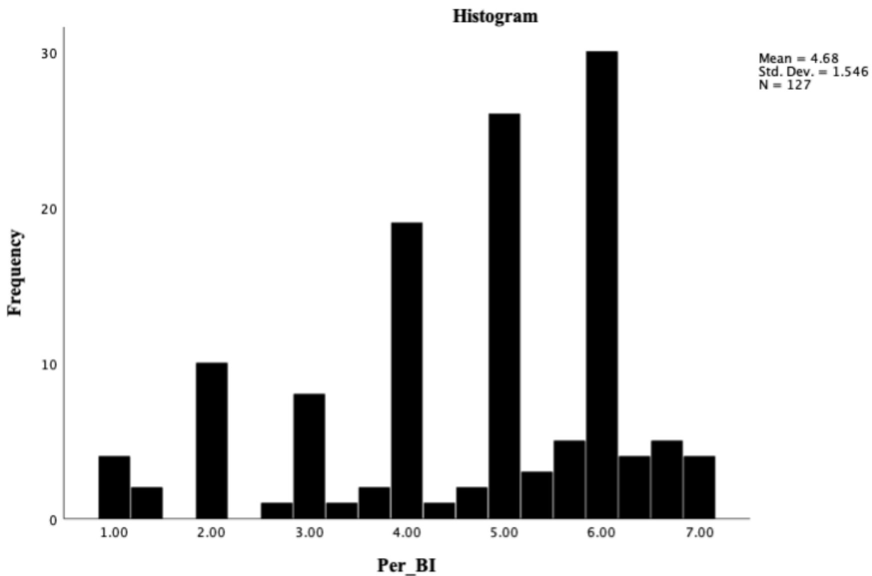


Figure 16

Distribution of Responses for the Personal UTAUT2 Construct of Habit (HT)

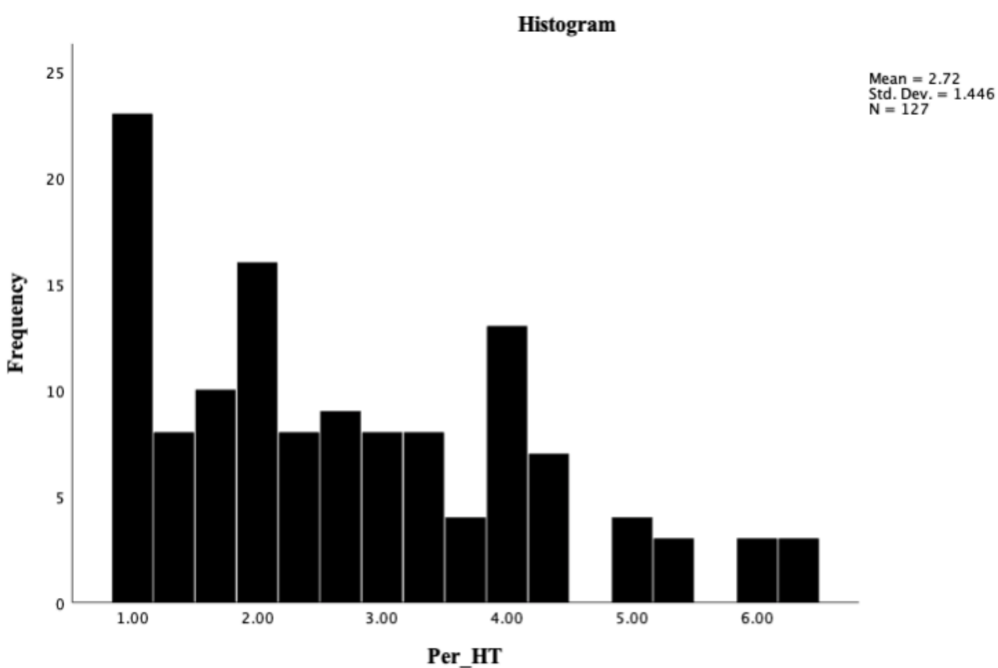


Figure 17

Distribution of Responses for the Personal UTAUT2 Construct of Facilitating Conditions (FC)

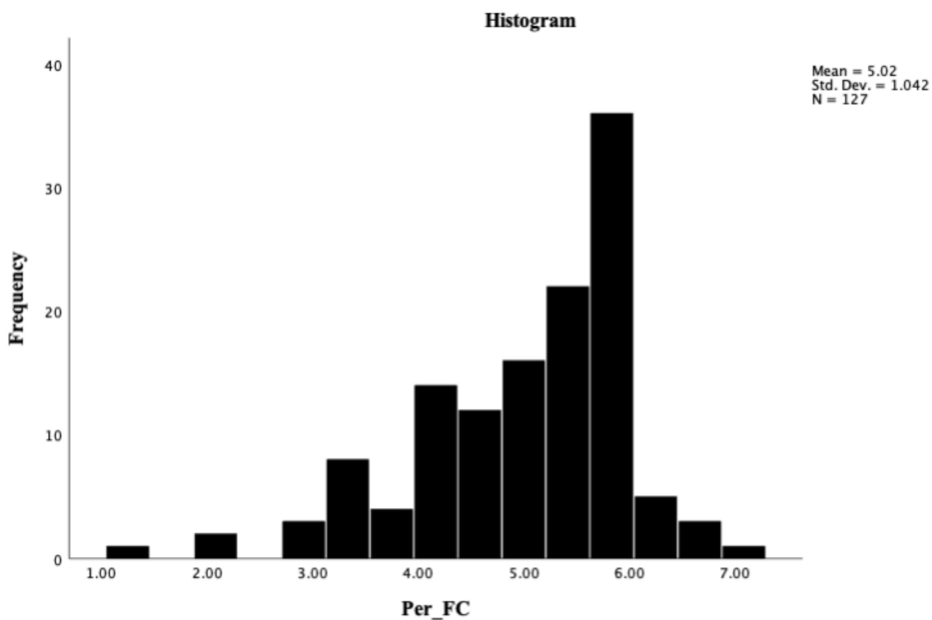


Figure 18

Distribution of Responses for the Personal UTAUT2 Construct of Technology Anxiety (TA)

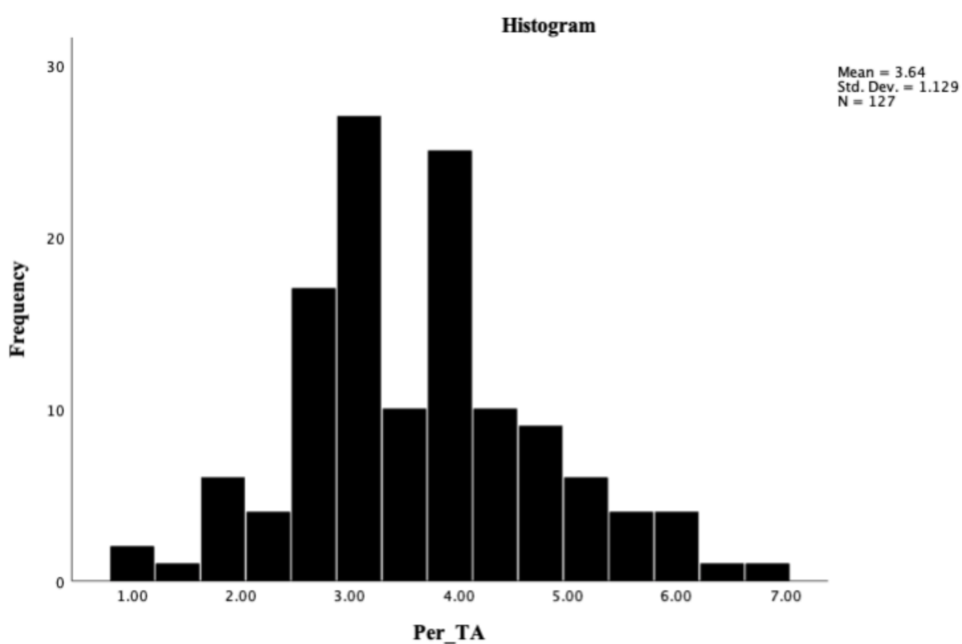


Figure 19

Distribution of Responses for the Personal UTAUT2 Construct of Social Influence (SI)

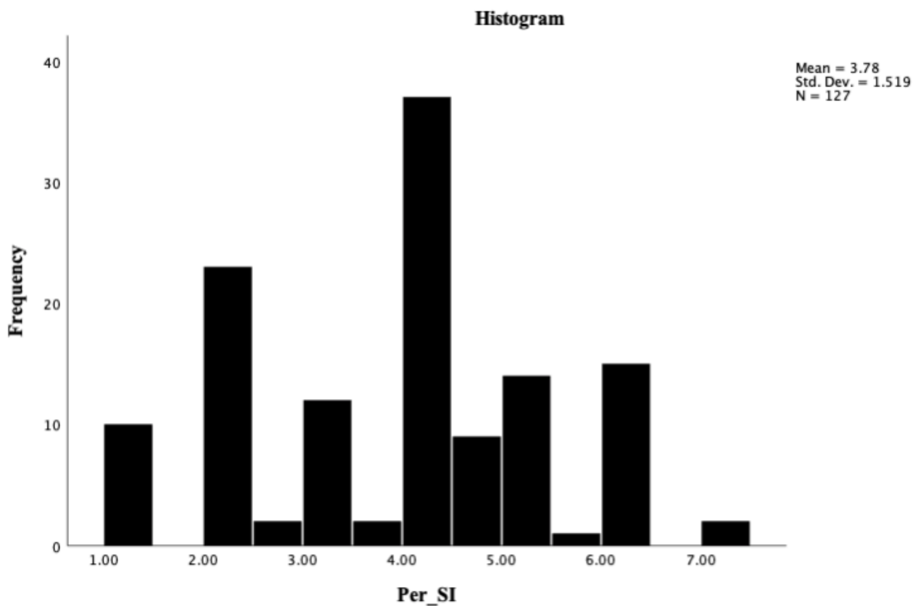


Figure 20

Distribution of Responses for the Personal UTAUT2 Construct of Performance Expectancy (PE)

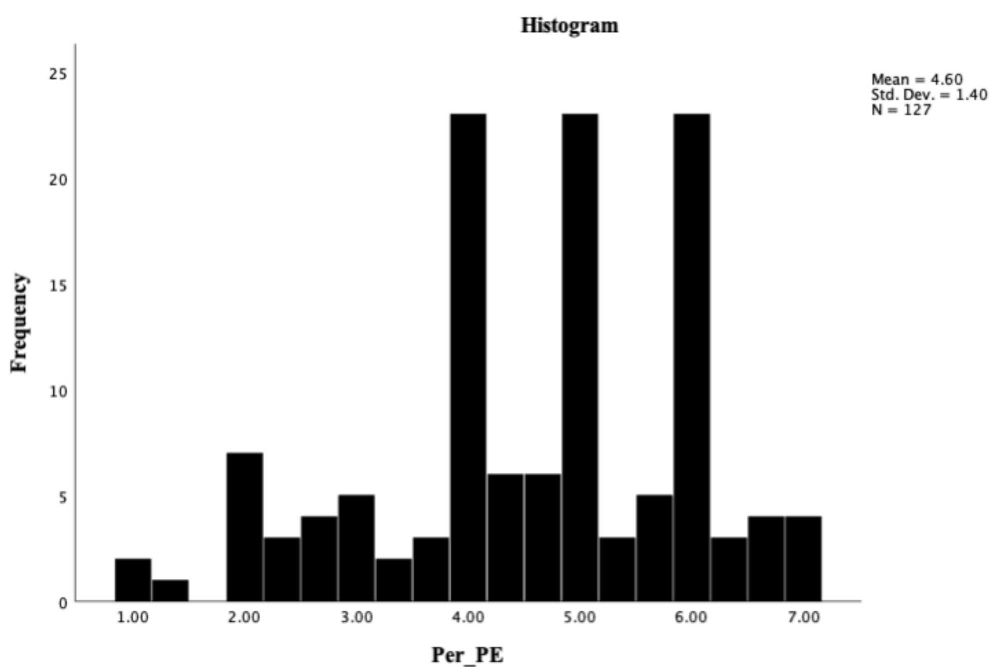


Figure 21

Distribution of Responses for the Personal UTAUT2 Construct of User Behaviour (UB)

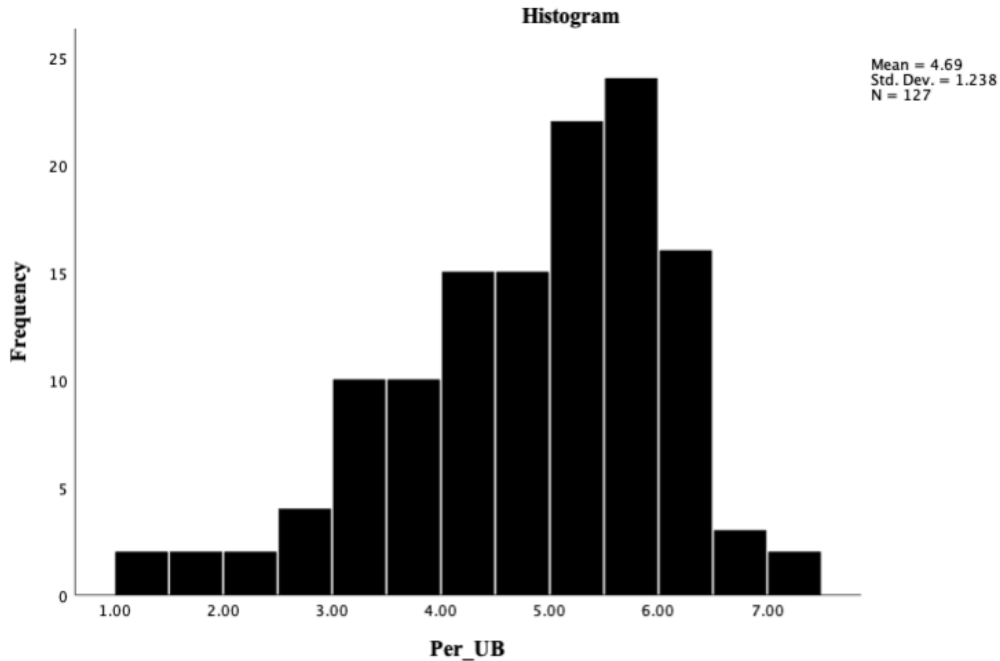


Figure 22

Distribution of Responses for the Personal UTAUT2 Construct of Hedonic Motivation (HM)

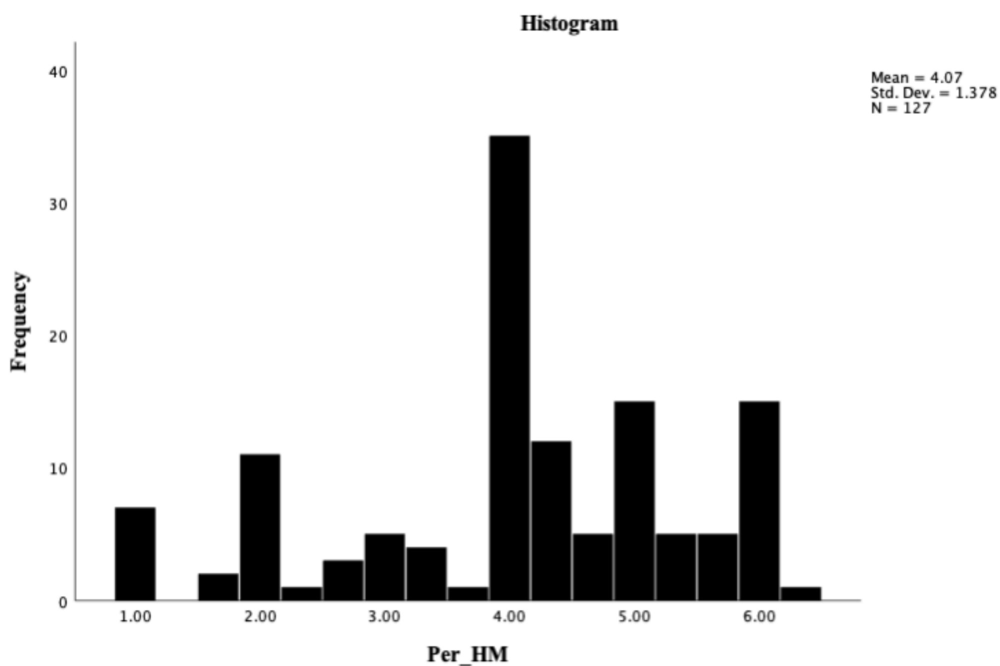


Figure 23

Distribution of Responses for the Personal UTAUT2 Construct of Perceived Intrusion (PI)

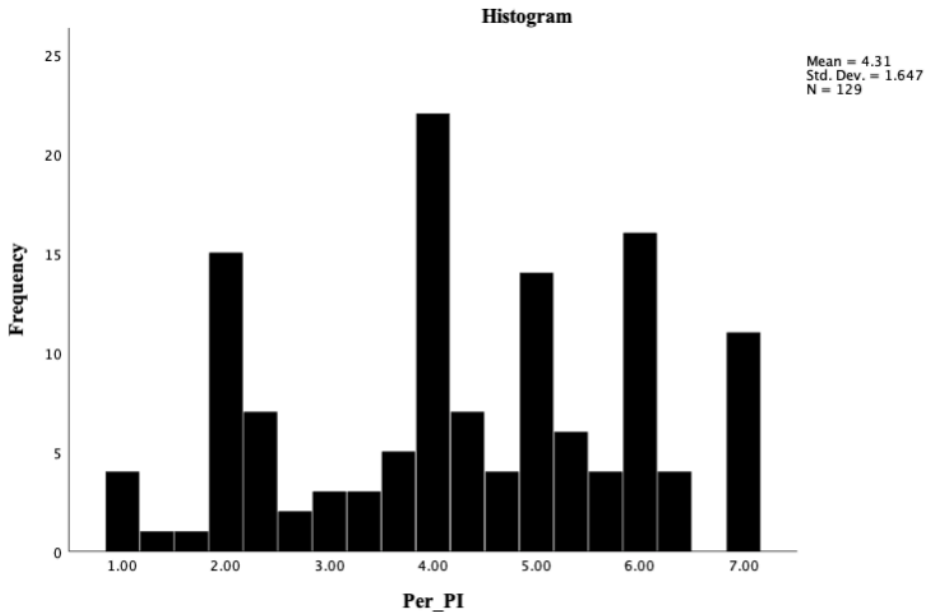


Figure 24

Distribution of Responses for the Professional UTAUT2 Construct of Secondary Use of Personal Information (SPi)

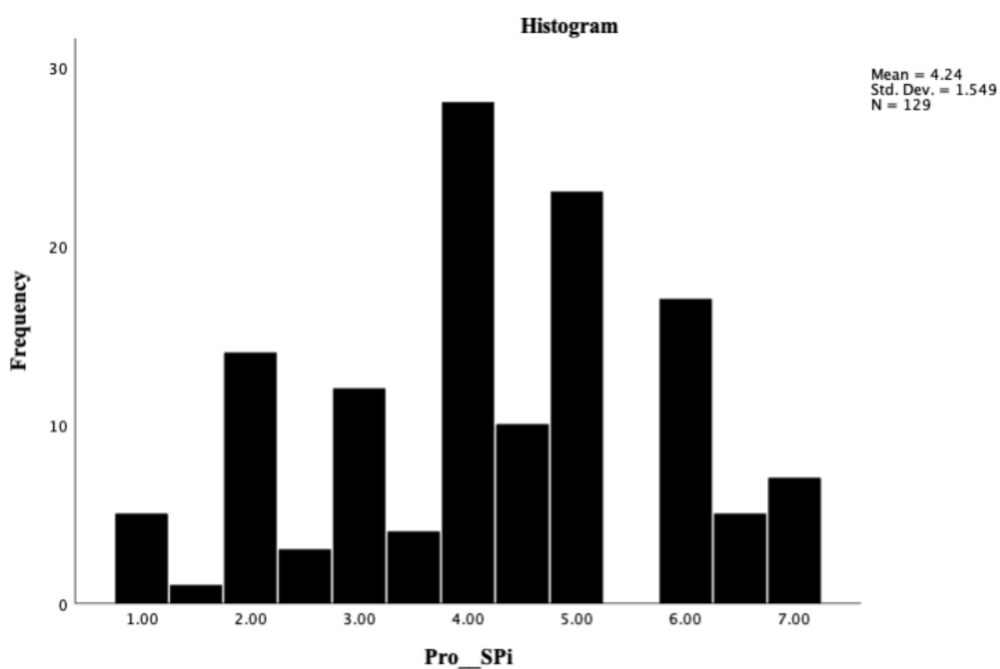


Figure 25

Distribution of Responses for the Personal UTAUT2 Construct of Secondary Use of Personal Information (SPi)

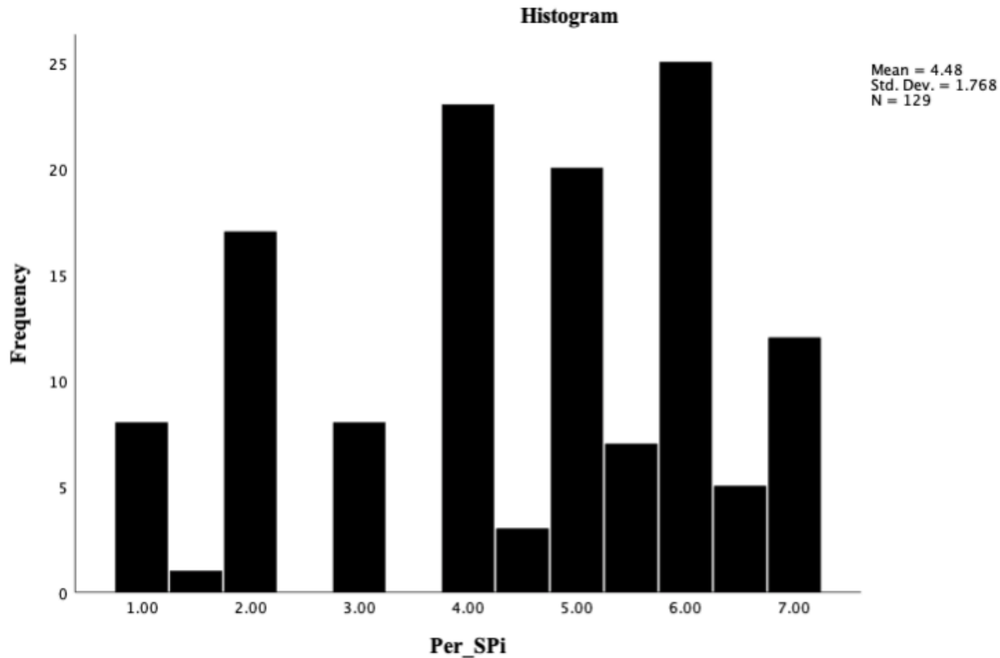


Figure 26

Distribution of Responses for the Professional UTAUT2 Construct of Perceived Intrusion (PI)

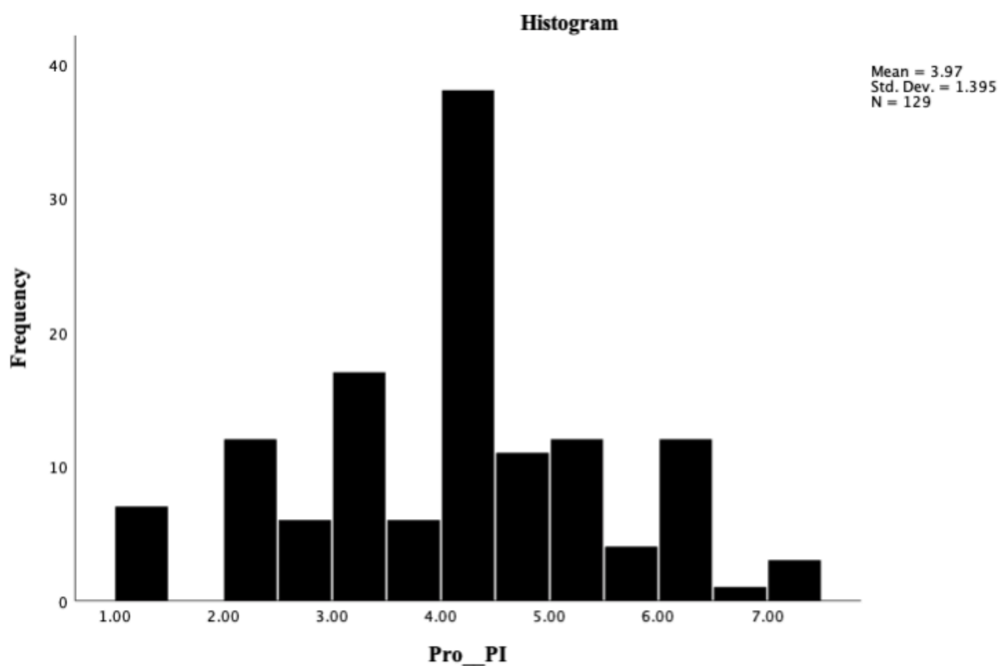


Figure 27

Distribution of Responses for the Personal UTAUT2 Construct of Perceived Surveillance (PS)

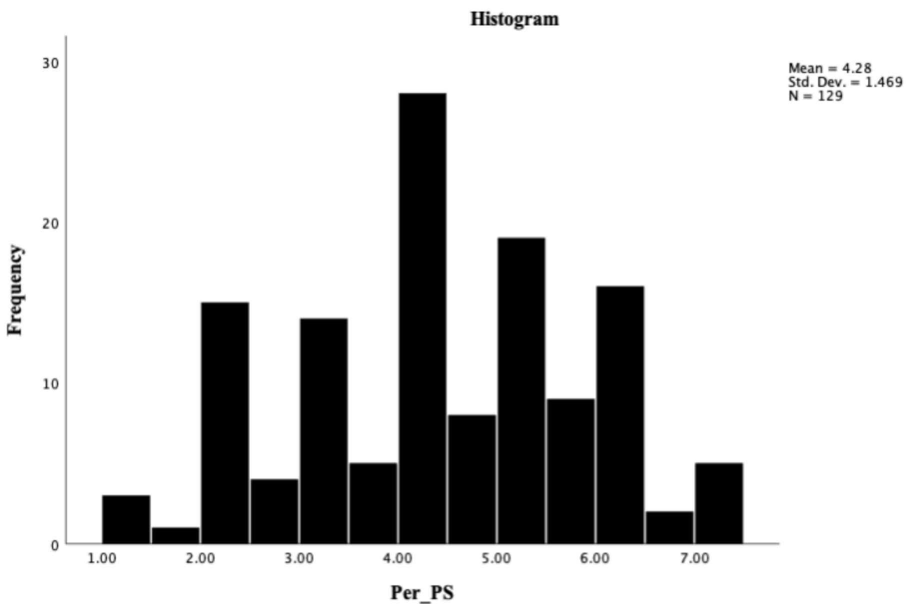


Figure 28

Distribution of Responses for the Professional UTAUT2 Construct of Perceived Surveillance (PS)

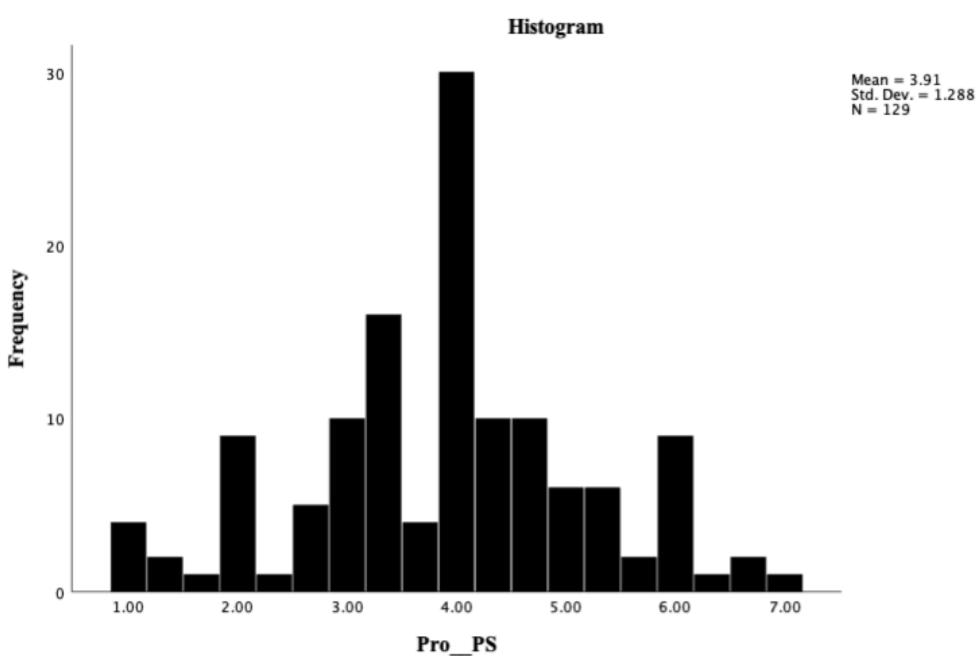


Table 1

Participant Demographic Information

	n	%
Gender		
Man	24	17.7
Woman	113	80.1
Gender Fluid	1	0.7
Non-binary	2	1.4
Sex		
Male	25	17.7
Female	116	82.3
Ethnicity		
Black	7	5.0
East Asian	12	8.5
Indigenous	3	2.1
LatinX	1	0.7
Mixed	5	3.5
South Asian	7	5.0
White	102	72.3
Undisclosed/Do not know	4	2.8
Age (years)		
18-29	33	23.4
30-39	39	27.7
40-49	35	24.8
50-59	33	23.4
60-69	1	0.7
Grades Taught		
Kindergarten to Grades 6	79	56.4
Grades 7 to 12	79	56.4
Other	3	2.1

Teaching Roles		
Homeroom	77	55.0
Subject Specialist	42	30.0
Guidance	2	1.4
Special Education	15	10.7
Teacher-librarian	18	12.9
Other	2	1.4
Rural/Urban Schools		
Rural	20	14.2
Urban	121	85.8
Highest Education Level		
High school graduate (or equivalent)	2	1.4
Bachelor’s degree	96	68.1
Master’s degree	39	27.7
Doctorate degree	2	1.4
Other	2	1.4
Province Work In		
Alberta	10	7.1
British Columbia	5	3.5
Manitoba	1	0.7
New Brunswick	1	0.7
Newfoundland and Labrador	1	0.7
Nova Scotia	2	1.4
Nunavut	1	0.7
Ontario	115	81.6
Quebec	1	0.7
Saskatchewan	4	2.8
Teachers Union		
Alberta Teachers’ Association (ATA)	8	5.7
British Columbia Teachers’ Federation (BCTF)	4	2.8
Elementary Teachers of Toronto (ETT)	2	1.4

Elementary Teachers' Federation of Ontario (ETFO)	47	33.3
Lakehead Elementary Teachers of Ontario	5	3.5
Ontario English Catholic Teachers' Association (OECTA)	20	14.2
Ontario College of Teachers (OCT)	6	4.3
Ontario Secondary School Teachers' Federation (OSSTF)	25	17.7
Saskatchewan Teachers' Federation	4	2.8
Other	20	14.3
Country Born In		
Canada	122	86.5
Chile	1	0.7
China	4	2.8
India	3	2.1
Jamaica	3	2.1
Pakistan	1	0.7
South Korea	1	0.7
Taiwan	1	0.7
Ukraine	1	0.7
United Kingdom	2	1.4
United States of America	1	0.7

Table 2

Outer Loadings, Internal Consistency, and Convergent Validity of Constructs in the Professional UTAUT2 Measurement Model

Construct and Associated Indicators	Outer Loadings	α	ρA	ρC	AVE
Behavioural Intention (BI)		0.928	0.931	0.949	0.860
BI1	0.946				
BI2	0.940				
BI3	0.896				
Effort Expectancy (EE)		0.901	0.927	0.940	0.839
EE1	0.903				
EE2	0.931				
EE3	0.914				
Facilitating Conditions (FC)		0.875	0.897	0.916	0.733
FC1	0.900				
FC2	0.912				
FC3	0.864				
FC4	0.738				
Hedonic Motivation (HM)		0.903	0.908	0.95	0.905
HM1	0.968				
HM2	0.976				
HM3	0.920				

Habit (HT)		0.875	0.903	0.914	0.727
HT1	0.889				
HT2	0.820				
HT3	0.807				
HT4	0.890				
Social Influence (SI)		0.831	0.858	0.892	0.735
SI1	0.775				
SI2	0.881				
SI3	0.910				
Technology Anxiety (TA)		0.895	0.991	0.948	0.902
TA1	0.914				
TA2	0.975				
TA3	0.968				

Table 3

Discriminant Validity - Heterotrait-Monotrait-Ratios (HTMTs) of Final Professional UTAUT2 Measurement Model

	BI	EE	FC	HT	HM	SI	TA
BI							
EE	.590						
FC	.546	.664					
HT	.697	.577	.578				
HM	.809	.591	.558	.734			
SI	.554	.465	.748	.526	.570		
TA	.418	.383	.419	.176	.415	.313	

Note. Performance Expectancy (PE); Facilitating Conditions (FC); Social Influence (SI); Habit (HT); Hedonic Motivation (HM); Behavioural Intention (BI; Technology Anxiety (TA).

Table 4

Outer Loadings, Internal Consistency, and Convergent Validity of Constructs in the Personal UTAUT2 Measurement Model

Construct and Associated Indicators	**Outer Loadings**	α	**ρA**	**ρC**	**AVE**
Behavioural Intention (BI)		0.946	0.948	0.974	0.948
BI1	0.964				
BI2	0.981				
BI3	0.977				
Effort Expectancy (EE)		0.910	0.947	0.938	0.790
EE1	0.890				
EE2	0.838				
EE3	0.915				
EE4	0.910				
Facilitating Conditions (FC)		0.847	0.887	0.899	0.692
FC1	0.839				
FC2	0.905				
FC3	0.862				
FC4	0.708				
Hedonic Motivation (HM)		0.913	0.929	0.958	0.920
HM1	0.965				
HM2	0.981				

HM3	0.953				
Habit (HT)		0.877	0.954	0.921	0.795
HT1	0.910				
HT2	0.844				
HT3	0.920				
Performance Expectancy (PE)		0.936	0.937	0.968	0.937
PE1	0.964				
PE2	0.974				
PE3	0.972				
Social Influence (SI)		0.937	0.941	0.971	0.945
SI1	0.978				
SI2	0.965				
SI3	0.969				
Technology Anxiety (TA)		0.938	1.194	0.952	0.868
TA1	0.913				
TA2	0.920				
TA3	0.961				

Table 5

Discriminant Validity - Heterotrait-Monotrait-Ratios (HTMTs) of Final Personal UTAUT2 Measurement Model

	BI	EE	FC	HT	HM	PE	SI	TA
BI								
EE	.585							
FC	.399	.852						
HT	.602	.523	.375					
HM	.708	.546	.419	.694				
PE	.880	.645	.493	.631	.742			
SI	.657	.526	.424	.722	.659	.681		
TA	.202	.331	.325	.113	.162	.251	.055	

Note. Performance Expectancy (PE); Facilitating Conditions (FC); Social Influence (SI); Habit (HT); Hedonic Motivation (HM); Behavioural Intention (BI;) Technology Anxiety (TA).

Table 6

Inner VIF Scores for the UTAUT2 Professional Structural Model

Model Paths	**VIF**
Effort Expectancy → Behavioural Intention	1.884
Facilitating Conditions → Behavioural Intention	2.242
Habit → Behavioural Intention	2.152
Hedonic Motivation → Behavioural Intention	2.263
Social Influence → Behavioural Intention	1.765
Technology Anxiety → Behavioural Intention	1.363

Table 7

Pearson Correlation Table

		BI Professional	**BI Personal**
BI Professional	Pearson Correlation	1	.675**
	Sig. (2-tailed)		<.001
	N	140	139
BI Personal	Pearson Correlation	.675**	1
	Sig. (2-tailed)	<.001	
	N	139	140

** *Correlation is significant at the 0.01 level (2-tailed). Behavioural Intention (BI).*

Table 8

Path Coefficients for the UTAUT2 Professional Structural Model

Model Paths	Path coefficients	t-values	CI
EE → BI	0.150	1.553	[-0.038, 0.339]
FC → BI	0.001	0.015	[-0.177, 0.183]
HT → BI	0.212	2.548	[0.053, 0.378]*
HM → BI	0.458	4.080	[0.207, 0.648]**
SI → BI	0.036	0.355	[-0.140, 0.258]
TA → BI	-0.123	1.869	[-0.250, 0.011]

Note. Effort Expectancy (EF); Facilitating Conditions (FC); Social Influence (SI); Habit (HT); Hedonic Motivation (HM); Behavioural Intention (BI); Technology Anxiety (TA); 95% Bootstrap Confidence Intervals (CI).

* $p < 0.05$;** $p < 0.001$

Table 9

PLS Predict Summary for the UTAUT2 Professional Structural Model

Indicators of the outcome variable	PLS model RMSE	Naïve (LM) benchmark model RMSE
BI1	0.562	0.717
BI2	0.520	0.731
BI3	0.463	0.824

Note. *Bolded Root Mean Squared Errors (RMSEs) indicate better predictive power for the PLS-SEM model among an indicator of the outcome variable compared to the Naïve Linear Regression Model (LM) Benchmark; Behavioural Intention (BI).*

Table 10

Inner VIF Scores for the UTAUT2 Personal Structural Model

Model Paths	**VIF**
Effort Expectancy → Behavioural Intention	3.380
Facilitating Conditions → Behavioural Intention	2.502
Habit → Behavioural Intention	2.291
Hedonic Motivation → Behavioural Intention	2.543
Performance Expectancy → Behavioural Intention	2.649
Social Influence → Behavioural Intention	2.338
Technology Anxiety → Behavioural Intention	1.200

Table 11

Path Coefficients for the UTAUT2 Personal Structural Model

Model Paths	**Path coefficients**	***t*-values**	**CI**
EE → BI	0.123	1.117	[-0.051, 0.306]
FC → BI	-0.133	1.390	[-0.028, 0.030]
HT → BI	0.032	0.371	[-0.114, 0.169]
HM → BI	0.114	1.425	[-0.022, 0.237]
PE → BI	0.660	7.552	[0.051, 0.798]**
SI → BI	0.099	0.9234	[-0.051, 0.304]
TA → BI	-0.034	0.548	[-0.140, 0.058]

Note. Effort Expectancy (EF); Facilitating Conditions (FC); Social Influence (SI); Habit (HT); Hedonic Motivation (HM); Behavioural Intention (BI); Technology Anxiety (TA); 95% Bootstrap Confidence Intervals (CI).

** $p < 0.05$;** $p < 0.001$*

Table 12

PLS Predict Summary for the UTAUT2 Personal Structural Model

Indicators of the outcome variable	**PLS model RMSE**	**Naïve (LM) benchmark model RMSE**
BI1	**0.861**	0.846
BI2	0.862	0.975
BI3	0.933	0.999

Note: The bolded value means that this model has low predictive quality.

Table 13

Professional UTAUT2 Moderator Model

Interaction Term Relationships	**Path Coefficients**	***t*-values**	**Lower 95%(CI)**	***p*-values**
UB x EE → BI	0.056	0.218	0.277	0.827
UB x FC → BI	-0.009	0.012	0.402	9.990
UB x HT → BI	0.068	0.373	0.284	0.709
UB x HM→ BI	-0.253	1.065	-0.045	0.287
UB x SI → BI	-0.011	0.022	0.251	0.982
UB x TA → BI	-0.062	0.353	0.097	0.724
Age x EE → BI	-0.097	0.922	0.118	0.357
Age x FC → BI	0.079	9.764	0.285	0.445
Age x HM → BI	-0.202	2.205	-0.017	**0.028***
Age x SI → BI	0.181	1.346	0.408	0.178
Age x TA → BI	0.113	1.525	0.266	0.950

Note. Effort Expectancy (EF); Facilitating Conditions (FC); Social Influence (SI); Habit (HT); Hedonic Motivation (HM); Behavioural Intention (BI); Technology Anxiety (TA); 95% Bootstrap Confidence Intervals (CI).

* $p < 0.05$;** $p < 0.001$

Table 14

Personal UTAUT2 Moderator Model

Interaction Term Relationships	**Path Coefficients**	***t-Values***	**Lower 95%(CI)**	***p-Values***
Age x EE → BI	0.118	1.318	0.130	0.375
Age x FC → BI	-0.148	0.438	0.319	0.331
Age x HT → BI	-0.008	0.086	-0.002	0.466
Age x HM → BI	0.109	0.479	0.132	0.316
Age x PE→ BI	-0.001	0.013	0.256	0.495
Age x SI → BI	-0.029	0.225	0.127	0.411
Age x TA → BI	-0.112	1.524	0.169	0.064
UB x EE → BI	-0.071	0.037	0.167	0.485
UB x FC → BI	0.177	0.076	0.388	0.470
UB x HT → BI	-0.071	0.009	0.207	0.496
UB x HM → BI	-0.006	0.002	0.201	0.499
UB x PE → BI	-0.010	0.002	0.158	0.499
UB x SI → BI	0.052	0.004	0.124	0.499
UB x TA → BI	-0.061	0.079	0.033	0.469

Note. Effort Expectancy (EF); Facilitating Conditions (FC); Social Influence (SI); Habit (HT); Hedonic Motivation (HM); Behavioural Intention (BI); Technology Anxiety (TA); 95% Bootstrap Confidence Intervals (CI).

** $p < 0.05$;** $p < 0.001$*

Table 15

ANOVA Summary Table for Multiple Regression Analysis for Professional Behavioural Intention

	B	**β**	**SE**	***t*-value**	***p*- value**	**2.5 %**	**97.5%**
Age	-0.120	-0.123	0.076	1.574	0.118	-0.271	0.031
DSE	0.264	0.270	0.082	3.207	0.002*	0.101	0.426
GATT	0.207	0.212	0.079	2.619	0.010**	0.051	0.364
WHO-5	0.088	0.090	0.077	1.154	0.251	-0.063	0.240
Intercept	0.017	0.000	0.075	0.222	0.825	-0.131	0.164

*Note: Digital Self-Efficacy (DSE); General Attitudes Towards Technology (GATT); Well-being Index (WHO-5). *p<0.05, **p<0.01.*

Table 16

ANOVA Summary Table for Personal Behavioural Intention and Personality Traits

	B	**β**	**SE**	***t*** **-value**	***p-*** **value**	**2.5 %**	**97.5 %**
Agreeableness	-0.194	-0.197	0.081	2.389	0.018**	-0.355	-0.033
Conscientiousness	0.173	0.175	0.081	2.127	0.035*	0.012	0.334
Extraversion	0.120	0.122	0.083	1.444	0.151	-0.044	0.285
Neuroticism	-0.083	-0.084	0.083	1.001	0.319	-0.247	0.081
Openness	-0.156	-0.158	0.084	1.853	0.066	-0.323	0.010
Intercept	0.008	0.000	0.080	0.104	0.917	-0.150	0.167

*Note: *p<0.05, **p<0.01.*

Table 17

Parameter Estimates with Robust Standard Errors for Personality Factors and Personal BI

Parameter	B	Robust Std. Error	t	Sig	Lower Bound CI	Upper Bound
Intercept	2.281	1.232	1.851	.066	-.156	4.717
BFI_E	.290	.134	2.166	.032	.025	.555
BFI_A	.080	.209	.383	.703	-.334	.494
BFI_C	.381	.228	1.671	.097	-.070	.833
BFI_N	-.014	.151	-.092	.927	-.313	.285
BFI_O	-.048	.259	-.185	.853	-.561	.465

Note. Big Five Inventory Extraversion (BFI_E); Big Five Inventory Agreeableness (BFI_A); Big Five Inventory Conscientiousness (BFI_C); Big Five Inventory Neuroticism (BFI_N); Big Five Inventory Openness (BFI_O).

Table 18

Parameter Estimates with Robust Standard Errors for Personality Factors and Professional BI

Parameter	B	Robust Std. Errors	t	Sig.	95% CI Lower Bound	Upper Bound
Intercept	2.335	1.213	1.925	.056	-.064	4.734
BFI_E	.292	.135	2.173	.032	.026	.559
BFI_A	.084	.207	.405	.686	-.326	.494
BFI_C	.391	.232	1.684	.094	-.068	.850
BFI_N	-.016	.152	-.103	.918	-.317	.286
BFI_O	-.080	.241	-.331	.741	-.556	.396

Note. Big Five Inventory Extraversion (BFI_E); Big Five Inventory Agreeableness (BFI_A); Big Five Inventory Conscientiousness (BFI_C); Big Five Inventory Neuroticism (BFI_N); Big Five Inventory Openness (BFI_O).

Table 19

Interactions of Privacy on UTAUT2 and Professional Behavioural Intention

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Pi -> BI	-0.025	-0.207	16.308	0.002	0.999
Pi x EE -> BI	-0.360	-0.115	25.134	0.014	0.989
Pi x FC -> BI	0.240	0.037	34.556	0.007	0.994
Pi x HT -> BI	-0.109	-0.299	32.939	0.003	0.997
Pi x HM -> BI	0.274	0.601	35.192	0.008	0.994
Pi x SI -> BI	0.071	-0.108	24.657	0.003	0.998
Pi x TA -> BI	-0.017	0.008	13.208	0.001	0.999
Spi -> BI	-0.087	0.039	13.657	0.006	0.995
Spi x EE -> BI	0.277	0.007	26.350	0.011	0.992
Spi x FC-> BI	-0.274	-0.031	38.259	0.007	0.994
Spi x HT-> BI	0.108	0.343	32.676	0.003	0.997
Spi x HM -> BI	-0.086	-0.383	36.193	0.002	0.998
Spi x SI -> BI	-0.018	0.052	20.578	0.001	0.999

Note. Effort Expectancy (EF); Facilitating Conditions (FC); Social Influence (SI); Habit (HT); Hedonic Motivation (HM); Behavioural Intention (BI); Technology Anxiety (TA); Perceived Intrusion (Pi); Secondary Use of Personal Information (Spi).

Table 20

Interactions of Privacy on UTAUT2 and Personal Behavioural Intention

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
PS -> BI	-0.522	0.616	76.664	0.007	0.497
PS x EE -> BI	-0.237	-0.848	43.888	0.005	0.498
PS x HT-> BI	-0.239	0.385	28.620	0.008	0.497
PS x PE BI	-0.980	0.105	30.865	0.032	0.487
PS x Pi -> BI	-0.018	0.350	25.045	0.001	0.500
PS x Pi x SI -> BI	-0.343	-0.387	26.849	0.013	0.495
PS x SI -> BI	1.172	-0.199	40.705	0.029	0.489
PS x TA -> BI	-0.263	0.605	51.948	0.005	0.498
Pi -> BI	0.650	-0.599	73.726	0.009	0.496
Pi x EE -> BI	0.385	0.336	38.878	0.010	0.496
Pi x FC -> BI	-0.021	0.187	44.552	0.000	0.500
Pi x HT -> BI	-0.386	-1.422	89.954	0.004	0.498
Pi x HM -> BI	-0.039	0.215	57.770	0.001	0.500
Pi x PE -> BI	0.949	-0.511	71.668	0.013	0.495
Pi x SI -> BI	-0.392	1.948	139.546	0.003	0.499
Pi x TA -> BI	0.560	-0.281	42.624	0.013	0.495
SPi -> BI	0.027	0.506	27.519	0.001	0.500
SPi x EE -> BI BI	-0.428	0.030	36.414	0.012	0.495
SPi x Habit -> BI	0.720	1.133	73.474	0.010	0.496
SPi x HM -> BI	0.087	-0.519	64.854	0.001	0.499
SPi x PE -> BI	-0.080	0.087	41.488	0.002	0.499
SPi x PS -> BI	-0.238	-0.895	56.934	0.004	0.498
SPi x PS x HT -> BI	0.225	0.095	11.501	0.020	0.492

SPi x SI -> BI	-0.592	-1.025	87.702	0.007	0.497

Note. Effort Expectancy (EF); Facilitating Conditions (FC); Social Influence (SI); Habit (HT); Hedonic Motivation (HM); Behavioural Intention (BI); Technology Anxiety (TA); Perceived Intrusion (Pi); Secondary Use of Personal Information (Spi); Perceived Surveillance (PS).

Table 21

ANOVA Results for Regression Analyses for Age, Education Level, DSE, GATT, WHO-5 and Personal Behavioural Intention

	Unstandardized coefficients	Standardized coefficients	SE	T value	P value	2.5 %	97.5 %
Age	-0.039	-0.039	0.081	0.481	0.631	-0.199	0.121
DSE	0.325	0.329	0.084	3.858	0.000**	0.159	0.492
Education Level	-0.050	-0.050	0.081	0.612	0.541	-0.210	0.111
GATT	0.050	0.051	0.083	0.609	0.543	-0.113	0.213
WHO-5	0.105	0.106	0.081	1.289	0.199	-0.056	0.266
Intercept	0.008	0.000	0.078	0.105	0.916	-0.147	0.163

*Note: **p<0.01 level.*

Table 22

Descriptives of Educator Comfortability of Using Educational Tools in their Professional Work

	Frequency	**Percent**
Extremely comfortable	51	36.2
Somewhat comfortable	50	35.5
Neither comfortable nor uncomfortable	14	9.9
Somewhat uncomfortable	15	10.6
Extremely uncomfortable	11	7.8

Table 23

Means, Standard Deviations and Cronbach Alpha Values for Scale Measures (N=141)

Scale	M	SD	Cronbach's Alpha
WHO-5	15.192	4.541	0.870
DSE	105.475	14.984	0.882
GATT	19.482	3.186	0.889
UTAUT2 Professional			
UB	18.266	4.282	0.763
PE	9.0763	2.582	0.797
BI	14.671	3.827	0.930
EE	14.683	3.679	0.899
SI	13.128	3.756	0.833
FC	17.214	5.519	0.873
HM	13.496	4.045	0.956
HT	11.473	5.287	0.871
PS	11.882	3.865	0.729
Pi	11.884	4.208	0.894
SPi	8.547	3.060	0.935
TA	10.259	4.353	0.949
UTAUT2 Personal			
UB	18.948	4.619	0.854
PE	13.766	4.137	0.965
BI	14.138	4.541	0.975
EE	19.801	4.289	0.910
SI	11.139	4.614	0.966
FC	19.906	4.290	0.846
HM	12.143	4.171	0.959
HT	7.907	4.334	0.874
PS	12.881	18.747	0.879

Pi	12.913	4.811	0.952
SPi	9.028	3.495	0.982
TA	9.897	4.482	0.942
BFI			
Extraversion	9.418	2.783	0.857
Conscientiousness	12.198	1.73	0.567
Openness	19.205	2.984	0.738
Agreeableness	12.510	1.714	0.658
Neuroticism	8.659	2.452	0.762

Table 24

Adapted Professional UTAUT2 Constructs

Professional UTAUT2 Constructs	Construct Items
Performance Expectancy	1. I find digital mental health tools useful in my work as an educator to support my students' mental health and well-being. 2. Using digital mental health tools improves my mental health and/or productivity.
Effort Expectancy	1.It is easy for me to become skillful at using digital mental health tools in the workplace. 2. Learning how to use digital mental health tools in the workplace is easy for me. 3. My interaction with digital mental health tools is clear and understandable.
Social Influence	1.In general, the school managers have supported the use of digital mental health tools in the workplace. 2. People who influence my teaching behaviour think that I should use digital mental health tools in the workplace. 3. People who are important to me think that I should use digital mental health tools in the workplace.

Facilitating Conditions	1.I have the necessary resources to use digital mental health tools in the workplace. 2. I have the necessary knowledge to use digital mental health tools in the workplace. 3. Digital mental health tools are compatible with other teaching technologies and methods I use in classroom teaching activity. 4. I can get help from technical staff when I have difficulties using digital mental health tools in the workplace.
Habit	1. The use of digital mental health tools in the workplace has become a habit for me. 2. I am addicted to using digital mental health tools in the workplace. 3. I must use digital mental health tools in the workplace. 4. Using digital mental health tools in the workplace has become natural to me.
User Behaviour	1. I have used digital mental health tools in the workplace. 2. Using digital mental health tools in the workplace is a pleasant experience. 3. When my students' need to seek mental healthcare service, digital mental health tools in the workplace will be very important options for them. 4. Using digital mental health tools in the workplace helps my students to manage their mental health and well-being.

Behavioural Intention	1. I plan to keep using digital mental health tools actively as an educator in the future. 2. I plan to use digital mental health tools in my workplace. 3. I intend to recommend digital mental health tools to other educators.
Perceived Surveillance	1. I believe that the location of my students' digital mental health tools is monitored at least part of the time. 2. I am concerned that my students' digital mental health tools are collecting too much information about my students. 3. I am concerned that my students' digital mental health tools may monitor my students' activities.
Perceived Intrusion	1. I feel that as a result of my students' digital mental health tools, others know more about them than I am comfortable with. 2. I believe that as a result of my students' digital mental health tools, information about them that I consider private is now more readily available to others than I would want. 3. I feel that as a result of my students' digital mental health tools, information about them is out there that, if used, will constitute an invasion of my privacy.

Secondary Use of Personal Information	1. I am concerned that digital mental health tools may use my students' personal information for other purposes without notifying them or getting authorization. 2. I am concerned that digital mental health tools may share my students' personal information with other entities without getting their authorization.
Hedonic Motivation	1. I think that using digital mental health tools in the workplace is fun. 2. I think that using digital mental health tools in the workplace is enjoyable. 3. I think that using digital mental health tools in the workplace is entertaining.

Table 25

Adapted Personal UTAUT2 Constructs

Personal UTAUT2 Constructs	Construct Items
Performance Expectancy	1. I find digital mental health tools are useful for my mental health and well-being. 2. Using digital mental health tools helps me in improving my mental health and well-being. 3. Using digital mental health tools will improve my mental health and well-being.
Effort Expectancy	1. It is easy for me to become skillful at using digital mental health tools in my personal life. 2. Digital mental health tools are easy to use. 3. Learning how to use digital mental health tools in my personal life is easy for me. 4. My interaction with digital mental health tools in my personal life is clear and understandable.
Social Influence	1. People who are important to me think that I should use digital mental health tools. 2. People who influence my behaviour think that I should use digital mental health tools. 3. People whose opinions that I value prefer that I use digital mental health tools.

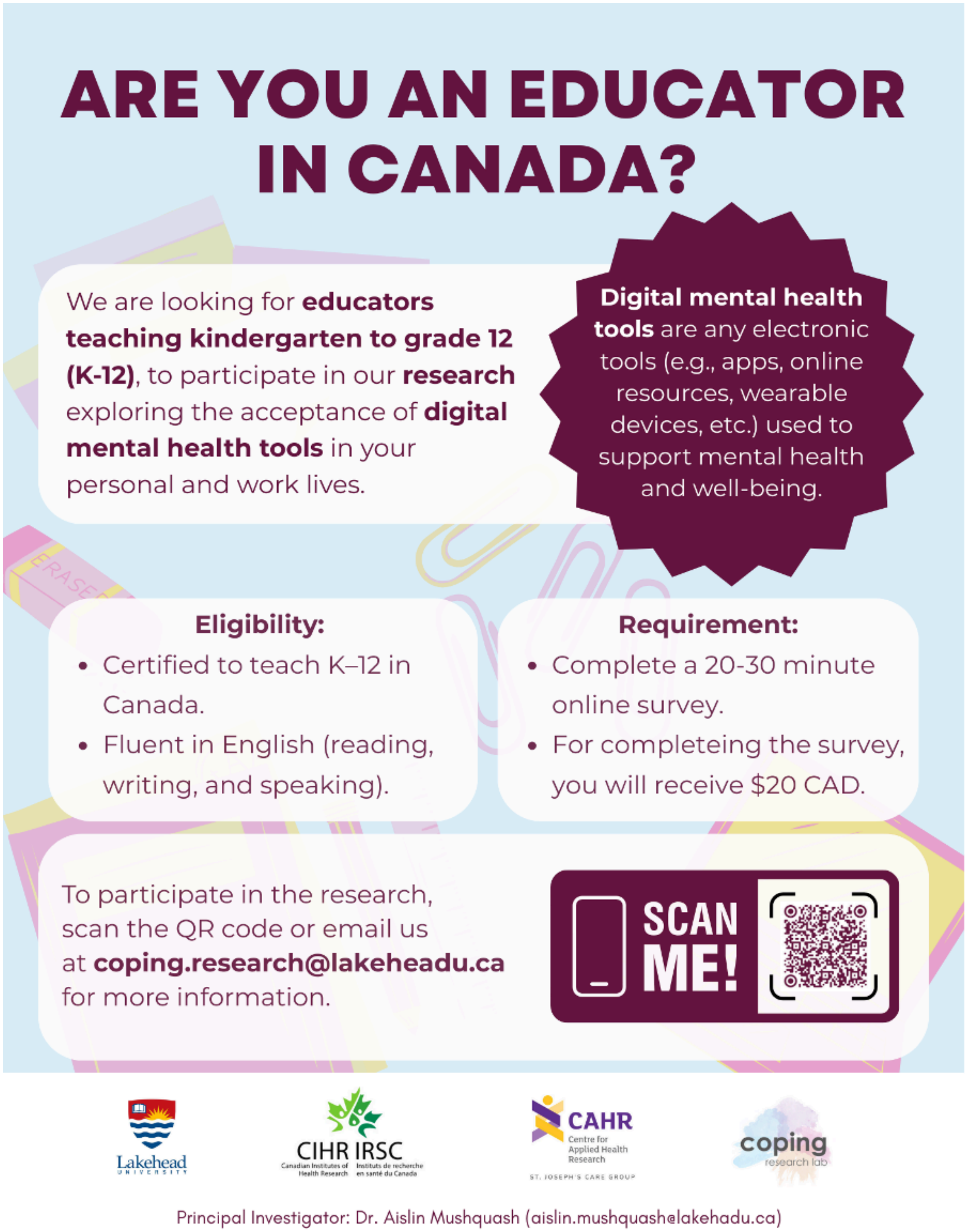
Facilitating Conditions	1. I have the necessary resources to use digital mental health tools in my personal life. 2. I have the necessary knowledge of digital mental health tools in my personal life. 3. Digital mental health tools are compatible with other technologies I use in my personal life. 4. I can get help from others when I have difficulties with digital mental health tools.
Habit	1. The use of digital mental health tools outside of work has become a habit for me. 2. I am addicted to using digital mental health tools outside of work. 3. I must use digital mental health tools outside of work.
User Behaviour	1. I have used digital mental health tools. 2. Using digital mental health tools is a pleasant experience. 3. When I need to seek mental healthcare service, digital mental health tools will be very important options for me. 4. Using digital mental health tools helps me to manage.

Behavioural Intention	1. I plan to keep using digital mental health tools in my life outside of work. 2. I plan to use digital mental health tools in my personal life. 3. I intend to use digital mental health tools in my life outside of work.
Perceived Surveillance	1. I believe that the location of my digital mental health tool is monitored at least part of the time. 2. I am concerned that a digital mental health tools device is collecting too much information about me. 3. I am concerned that digital mental health tools may monitor my activities.
Perceived Intrusion	1. I feel that as a result of my using a digital mental health tool, others know more about me than I am comfortable with. 2. I believe that as a result of my using a digital mental health tool, information about me that I consider private is now more readily available to others than I would want. 3. I feel that as a result of my using a digital mental health tool, information about me is out there that, if used, will constitute an invasion of my privacy.

Secondary Use of Personal Information	1. I am concerned that a digital mental health tool may use my personal information for other purposes without notifying me or getting my authorization. 2. I am concerned that a digital mental health tool may share my personal information with other entities without getting my authorization.
Hedonic Motivation	1. I think that using digital mental health tools outside of work is fun. 2. I think that using digital mental health tools outside of work is enjoyable. 3. I think that using digital mental health tools outside of work is entertaining.

Appendix A

Recruitment Poster



Appendix B

Eligibility Qualtrics Survey for the Public

RSVP/Signup Form

Before you proceed, please check the box below:

☐ I'm not a robot — reCAPTCHA Privacy - Terms

Thank you for your interest in the Educator Digital Mental Health Study!

Are you a school teacher (Kindergarten to Grade 12) in Canada?

- ○ Yes
- ○ No

Please specify the teachers' union or professional organization you are a member of:

Leave this field blank if you are human:

Please enter your **work** email address below to receive additional information about eligibility and study requirements:

If you do not enter a valid work email address, you will not be contacted

Email address

Your email will not be connected to your survey responses, which will remain anonymous.

Appendix C

Information Letter

An Evaluation of Educators' Acceptance of Digital Mental Health Tools

Dear Potential Participant:

You are invited to participate in our research study titled: *An Evaluation of Educators' Acceptance of Digital Mental Health Tools.* Your participation in this study is entirely voluntary. Before you decide whether you would like to take part, please read this letter carefully to understand what is involved. After you have read the letter, please ask any questions you may have.

PURPOSE

The purpose of this research is to understand educators' perspectives and acceptance of digital mental health tools in their personal and professional lives. As more digital mental health tools become available, it is important to understand educators' individual characteristics that influence their degree of acceptance of these technologies to support their students' well-being and mental health. Student mental health challenges can be expressed in two general ways: *internally* and *externally*. Internalizing challenges typically appear as anxiety, sadness, or withdrawal. These occur when students turn their struggles inward. Externalizing challenges can appear as acting out, aggression, or defiance. These arise when students' express their struggles outwardly. Both internal and external challenges are important to notice and support.

The Principal Investigator of the research is Dr. Aislin Mushquash, Associate Professor, Department of Psychology, Lakehead University. Amy Stern, Lakehead University, is a graduate student Co-Investigator/Research Coordinator under the supervision of Dr. Mushquash. Dr. Jocelyn Bel is the research staff also involved in the study. This research is supported by funding from the Canadian Institutes of Health Research- Hospital for Sick Children Foundation (SickKids) Research Grant.

WHAT IS REQUESTED OF ME AS A PARTICIPANT?

You will have an opportunity to participate in a series of questionnaires about your experiences with digital mental health tools, as well as a series of questionnaires regarding your personal characteristics, including your attitudes towards technology, personality, and digital self-efficacy. Questionnaires would take approximately 30 minutes. You will receive $20 cash/e-transfer for completion. You will not be compensated if the researchers determine that your data quality has not been met.

WHAT ARE MY RIGHTS AS A PARTICIPANT?

As a participant, you are under no obligation to participate and are free to withdraw at any time without penalty. You can skip any questions in the surveys. You have the right to leave the survey at any time until you submit by exiting the screen. After you submit, we cannot connect you to your data because it is an anonymous survey.

WHAT ARE THE RISKS AND BENEFITS?

There are no anticipated risks of participating in the study. All data will be stored on a password-protected computer in the possession of Dr. Aislin Mushquash or the Research Coordinator, Amy Stern (Department of Psychology, Lakehead University).

The primary benefits of the study are for society and for the advancement of knowledge. In particular, findings from this study will provide information on understanding educators' acceptance of digital MH tools in their classrooms.

HOW WILL MY CONFIDENTIALITY BE MAINTAINED?

All data will be completely anonymous. This means that directly identifiable information will not be collected, like your name or contact information. Some indirectly identifying information (i.e., birth year, race, etc.) data will be collected, however all data collected will be anonymized and reported in aggregate form.

We will collect your work email address and school board in an effort to ensure data quality. At the time of data analysis, this information will be removed from the data set and the remaining data will be anonymized.

Disclaimer: The Research Ethics Board may review the study records to ensure compliance with the approved research ethics guidelines. All information collected during this study, including if your personal information is on the consent forms, will remain confidential.

WHERE WILL MY DATA BE STORED?

Questionnaires will be stored on a password-protected computer at Lakehead University, Department of Psychology. In accordance with Lakehead University's policy, data will be retained for at least 7 years following the completion of the research.

Due to the use of online tools in this study, there is a small risk that your data could be accessed by third parties, including government authorities, under applicable privacy and national-security laws. While all reasonable efforts will be made to protect your confidentiality and anonymity, absolute confidentiality cannot be guaranteed when data is transmitted or stored online.

HOW CAN I RECEIVE A COPY OF THE RESEARCH RESULTS?

It is anticipated that peer-reviewed journal articles will be published based on the results of this study. Portions of the findings from the study are also likely to be presented at national or international scholarly conferences. All findings will be presented in summary form without identifying information of participants. If you would like a summary of the results, please email aislin.mushquash@lakeheadu.ca or coping.research@lakeheadu.ca

RESEARCHER CONTACT INFORMATION:

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RESEARCH ETHICS BOARD REVIEW AND APPROVAL:

The Lakehead University Research Ethics Board has reviewed and approved this research study. If you have any questions related to the research ethics and would like to speak to someone outside of the research team, please contact Sheena Beach at the Research Ethics Board at 807-343-8010 ext. 8933 or research.ethics@lakeheadu.ca.

Appendix D

Consent Form

An Evaluation of Canadian Educators' Acceptance of Digital Mental Health Tools

MY CONSENT:

I agree to the following:

- ✔ I have read and understood the information contained in the Information Letter.
- ✔ I agree to participate.
- ✔ I understand the risks and benefits of the study.
- ✔ I understand that I am a volunteer and can skip any question.
- ✔ I understand that the research findings will be made available to me upon request.
- ✔ I understand that I can stop participating and leave the study at any time until I have submitted the survey. Once I have submitted the survey, it will not be possible to remove my contributions.
- ✔ The data will be stored on a password-protected computer at Lakehead University in the Department of Psychology for at least 7 years following the completion of the research.
- ✔ I will remain anonymous.
- ✔ I agree that all my questions have been answered and I can contact the Principal Investigator with further questions.

By consenting to participate, I have not waived any rights to legal recourse in the event of research-related harm.

My consent has been given by clicking "CONSENT" below

Appendix E

Demographics Questionnaire (Ontario College of Teachers, 2024)

Our study is looking at digital mental health tools used for mental health promotion and prevention. These tools can include mobile apps, websites, and wearable devices, that aim to support one's well-being, increase mental health knowledge, and prevent the onset of mental health challenges. Examples of these tools include apps that track moods, provide self-regulation skills, and/or provide self-guided exercises. Other examples are smartwatches or apps on your phone that monitor behavioural patterns or provide reminders for self-care activities.

Q1 Please specify the teachers' union or professional organization you are a member of:

____

Q2 What is your age (in years):

____

Q3 What was your sex assigned at birth?

o Male
o Female
o Intersex
o Prefer not to say

Q4 What options best describe your gender? (*Select all that apply*)

▢ Gender fluid
▢ Woman
▢ Man
▢ Queer
▢ Two-spirit
▢ Non-binary
▢ Prefer not to answer
▢ Other: ____

Q5 The country you were born in:

____

Q6 How long have you lived in Canada? (in years):

____

Q7 When did you first start teaching in Canada?

o Within the last 5 years (2020-2025)

o Between 6 to 10 years ago (2015-2019)

o Between 11-15 years ago (2010-2014)

o Between 16-20 years ago (2005-2009)

o More than 20 years ago

o Not applicable - I have not started teaching in Canada

Q8 Which of the following best describes your employment status from September 1, 2025 to June 28, 2026 (i.e., the 2025/2026 school year)?

o Not applicable – I was not employed in education during this period

o Full-time employed: and worked in a job in education

o Full-time employed: but on leave from a job in education

o Part-time employed: not retired from educational sector

o Retired and doing occasional work in education

o Retired and not working in education

o Self employed, in education

Q9 What province/territory do you work in?

o Alberta

o British Columbia

o Manitoba

o New Brunswick

o Newfoundland and Labrador

o Nova Scotia

o Ontario

o Prince Edward Island

o Quebec

o Saskatchewan

o Northwest Territories

o Nunavut

o Yukon

Q10 Statistics Canada (2002) defines Rural schools as those located in small towns under 10, 000 people. Urban schools are located in cities with 10,000+ people, in addition to nearby towns where at least half the workforce commutes into the city. Do you teach in an urban or rural school?

o Rural

o Urban

Q11 What is your highest education level?

o High school graduate (or equivalent, e.g. GED)

o Bachelors degree

o Master's degree

o Doctorate degree

o Other: ____

Q12 Describe your race/ethnicity:

____

Q13 Which of the following best describes your current teaching role? (Select all that apply)

▢ Homeroom/classroom teacher

▢ Guidance counsellor

▢ Special education/resource teacher

▢ Subject specialist (e.g., French, Music, Physical Education, Technology, etc.)

▢ Teacher-librarian

▢ Other (please specify): ____

Q14 Which grade(s) do you currently teach or work with? (Select all that apply)

▢ Kindergarten

▢ Grade 1

▢ Grade 2

▢ Grade 3

▢ Grade 4

▢ Grade 5

▢ Grade 6

▢ Grade 7

- ▢ Grade 8
- ▢ Grade 9
- ▢ Grade 10
- ▢ Grade 11
- ▢ Grade 12
- ▢ Other (please specify): ____

Q16 What is the year of your birth?

▼ 2025 (1) ... 1930

Q17 For this question, we are asking about educational tools (e.g., computerized programs like Lexia, Prodigy, Reflex Math, Epic, UFLI, Knowledgehook etc.) not mental health related tools. How comfortable do you feel using digital educational tools in your classroom?

	Extremely uncomfortable (1)	Somewhat uncomfortable (2)	Neither comfortable nor uncomfortable (3)	Somewhat comfortable (4)	Extremely comfortable (5)
: (1)	o	o	o	o	o

Appendix F

WHO-5 Well-being Index (World Health Organization, 1998; Topp et al., 2015)

Please indicate for each of the five statements which is closest to how you have been feeling over the last two weeks.

	All of the time	Most of the time	More than half the time	Less than half the time	Some of the time	At no time
1. I have felt cheerful and in good spirits.	o	o	o	o	o	o
2. I have felt calm and relaxed.	o	o	o	o	o	o
3. I have felt active and vigorous.	o	o	o	o	o	o
4. I woke up feeling fresh and rested.	o	o	o	o	o	o
5. My daily life has been filled with things that interest me.	o	o	o	o	o	o

Appendix G

Attention Check #1

The colour test you are about to take part in is very simple. When asked for your favourite colour, you must select 'Purple'. This is an attention check. Based on the text you read above, what colour have you been asked to enter?

o Red

o Blue

o Purple

o Green

Appendix H

The Abbreviated Big Five Inventory (BFI) (Kang et al., 2024)

Please respond to each statement by marking one circle per row, indicating the extent to which you agree or disagree with that statement for the following sentences.

1=strongly disagree; 2=disagree; 3=neither agree nor disagree; 4=agree; 5=strongly agree

(R) Indicates items to be reversed scored

I see myself as someone who…..

1. is talkative
2. does a thorough job
3. is original, comes up with new ideas
4. is reserved (R)
5. is relaxed, handles stress well
6. has a forgiving nature
7. tends to be disorganized (R)
8. worries a lot
9. tends to be quiet (R)
10. is emotionally stable, not easily upset (R)
11. is inventive
12. perseveres until the task is finished
13. values artistic, aesthetic experiences.
14. is considerate and kind to almost everyone
15. likes to reflect, play with ideas
16. has few artistic interests (R)
17. likes to cooperate with others
18. is sophisticated in art, music, or literature

Appendix I

General Attitudes toward Digital Technologies (GATT; Evers et al., 2009)

Please respond to each statement by marking one circle per row, indicating the extent to which you agree or disagree with that statement for the following sentences.

	1= strongly disagree	2= disagree	3= neither agree nor disagree	4= agree	5= strongly agree
1. Working with digital technologies is very interesting to me.	o	o	o	o	o
2. The use of digital technologies is useful to me.	o	o	o	o	o
3. I would like to know a lot about digital technologies.	o	o	o	o	o
4. I think it's important to be able to use digital technologies.	o	o	o	o	o
5. I like talking to others about digital technologies.	o	o	o	o	o

Appendix J

UTAUT2 Professional; Adapted measure based on the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2- Venkatesh et al., 2003; Xu et al., 2012; Chen et al., 2024)

Please indicate your degree of agreement (using a score of 1 to 7) for the following sentences. (1=strongly disagree; 2=disagree; 3=somewhat disagree; 4=neither agree nor disagree; 5=somewhat agree; 6=agree; 7=strongly agree)

User Behaviour (UB)

UB1. I have used digital mental health tools in the workplace.

UB2. Using digital mental health tools in the workplace is a pleasant experience.

UB3. When my students' need to seek mental healthcare service, digital mental health tools in the workplace will be very important options for them.

UB4. Using digital mental health tools in the workplace helps my students' to manage their mental health and well-being.

Performance Expectancy (PE)

PE1. I find digital mental health tools useful in my work as an educator to support my students' mental health and well-being.

PE3. Using digital mental health tools improves my mental health and/or productivity.

Behavioural Intention (BI)

CI1. I plan to keep using digital mental health tools actively as an educator in the future.

CI2. I plan to use digital mental health tools in my workplace.

CI3. I intend to recommend digital mental health tools to other educators.

Effort Expectancy (EE)

EE1. It is easy for me to become skillful at using digital mental health tools in the workplace.

EE2. Learning how to use digital mental health tools in the workplace is easy for me.

EE4. My interaction with digital mental health tools is clear and understandable.

Social Influence (SI)

SI1. In general, the school managers have supported the use of digital mental health tools in the workplace.

SI2. People who influence my teaching behaviour think that I should use digital mental health tools in the workplace.

SI3. People who are important to me think that I should use digital mental health tools in the workplace.

Facilitating Conditions (FC)

FC1. I have the necessary resources to use digital mental health tools in the workplace.

FC2. I have the necessary knowledge to use digital mental health tools in the workplace.

FC3. Digital mental health tools are compatible with other teaching technologies and methods I use in classroom teaching activity.

FC4. I can get help from technical staff when I have difficulties using digital mental health tools in the workplace.

Hedonic Motivation (HM)

HM1. I think that using digital mental health tools in the workplace is fun.

HM2. I think that using digital mental health tools in the workplace is enjoyable.

HM3. I think that using digital mental health tools in the workplace is entertaining.

Habit (HT)

HT1. The use of digital mental health tools in the workplace has become a habit for me.

HT2. I am addicted to using digital mental health tools in the workplace.

HT3. I must use digital mental health tools in the workplace.

HT4. Using digital mental health tools in the workplace has become natural to me.

Perceived Surveillance (PS)

PS1. I believe that the location of my students' digital mental health tools is monitored at least part of the time.

PS2. I am concerned that my students' digital mental health tools are collecting too much information about my students.

PS3. I am concerned that my students' digital mental health tools may monitor my students' activities.

Perceived Intrusion (Pi)

Pi1. I feel that as a result of my students' digital mental health tools, others know more about them than I am comfortable with.

Pi2. I believe that as a result of my students' digital mental health tools, information about them that I consider private is now more readily available to others than I would want.

Pi3. I feel that as a result of my students' digital mental health tools, information about them is out there that, if used, will constitute an invasion of my privacy.

Secondary Use of Personal information (SPi)

SPi1. I am concerned that digital mental health tools may use my students' personal information for other purposes without notifying them or getting authorization.

SPi2. I am concerned that digital mental health tools may share my students' personal information with other entities without getting their authorization.

Technology Anxiety (TA)

TA1. Using digital mental health tools in the workplace makes me feel uneasy and confused.

TA2. Using digital mental health tools in the workplace would make me very nervous.

TA3. Using digital mental health tools in the workplace makes me feel uncomfortable.

TA4. I feel calm using digital mental health tools in the workplace.

Appendix K

Digital Self-Efficacy Scale (Ulfert-Blank & Schmidt, 2022)

We will now ask you how you use digital systems. Digital systems are digital applications (e.g., software or apps), digital devices (e.g., computers or smartphones), and digital environments (e.g., the internet or messaging services). Please respond to each item by marking one box per row.
(6= completely agree, 5= agree, 4= slightly agree, 3= slightly disagree, 2= disagree, 1= completely disagree)

Items Information and data literacy (iSE)
iSE1: I search for specific information in digital environments
iSE2: I distinguish between correct and incorrect digital information
ISE3: I store and organize digital content so that I can easily find it again

Communication and collaboration (cSE)
cSE1: I interact with others in digital environments
cSE2: I share information and data with others digitally
cSE3: I participate in public discussions and activities in digital environments*
cSE4: I defend myself and others against injustice in digital environments*
cSE5: I use digital systems to collaborate with others
cSE6: I use the proper etiquette to communicate in a digital environment
cSE7: I manage and delete the information I leave online
cSE8: I present myself the way I want in digital environments*

Digital content creation (dSE)
dSE1: I create digital content
dSE2: I change digital content in a way that new content is created
dSE3: I identify legal aspects in digital environments, such as terms of use and licenses
dSE4: I write a simple command in a programming language*

Safety (sSE)

sSE1: I protect my digital devices from unwanted access

sSE2: I protect my personal data in digital environments

sSE3: I recognize health risks associated with using digital environments

sSE4: I use digital environments to promote my health

sSE5: I recognize the impact of digital environments on nature and the climate

Problem-solving (pSE)

pSE1: I identify technical problems when using digital environments

pSE2: I find and apply various solutions to technical problems that arise

pSE3: I find the right digital system to meet non-technical challenges

pSE4: I develop novel digital solutions

pSE5: I identify and improve the digital skills I lack

Appendix L

Attention Check #2

Q142 The following question is to verify that you are a real person. Please enter the word tomato into the box below:

____

____

Appendix M

UTAUT2 Personal: Adapted measure based on the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2- Venkatesh et al., 2003; Xu et al., 2012; Chen et al., 2024)

Please indicate your degree of agreement (using a score ranging from 1-7) to the following sentences.
(1=strongly disagree; 2=disagree; 3=somewhat disagree; 4=neither agree nor disagree; 5=somewhat agree; 6=agree; 7=strongly agree)

User Behaviour (UB)

UB1. I have used digital mental health tools.
UB2. Using digital mental health tools is a pleasant experience.
UB3. When I need to seek mental healthcare service, digital mental health tools will be very important options for me.
UB4. Using digital mental health tools helps me to manage

Performance Expectancy (PE)

PE1. I find digital mental health tools are useful for my mental health and well-being.
PE2. Using digital mental health tools helps me in improving my mental health and well-being.
PE3. Using digital mental health tools will improve my mental health and well-being.

Behavioural Intention (BI)

CI1. I plan to keep using digital mental health tools in my life outside of work.
CI2. I plan to use digital mental health tools in my personal life.
CI3. I intend to use digital mental health tools in my life outside of work.

Effort Expectancy (EE)

EE1. It is easy for me to become skillful at using digital mental health tools in my personal life.
EE2. Digital mental health tools are easy to use.
EE3. Learning how to use digital mental health tools in my personal life is easy for me.

EE4. My interaction with digital mental health tools in my personal life is clear and understandable.

Social Influence (SI)

SI1. People who are important to me think that I should use digital mental health tools.

SI2. People who influence my behaviour think that I should use digital mental health tools.

SI3. People whose opinions that I value prefer that I use digital mental health tools.

Facilitating Conditions (FC)

FC1. I have the necessary resources to use digital mental health tools in my personal life.

FC2. I have the necessary knowledge of digital mental health tools in my personal life.

FC3. Digital mental health tools are compatible with other technologies I use in my personal life.

FC4. I can get help from others when I have difficulties with digital mental health tools.

Hedonic Motivation (HM)

HM1. I think that using digital mental health tools outside of work is fun.

HM2. I think that using digital mental health tools outside of work is enjoyable.

HM3. I think that using digital mental health tools outside of work is entertaining.

Habit (HT)

HT1. The use of digital mental health tools outside of work has become a habit for me.

HT2. I am addicted to using digital mental health tools outside of work.

HT3. I must use digital mental health tools outside of work.

Perceived Surveillance (PS)

PS1. I believe that the location of my digital mental health tool is monitored at least part of the time.

PS2. I am concerned that a digital mental health tools device is collecting too much information about me.

PS3. I am concerned that digital mental health tools may monitor my activities.

Perceived Intrusion (Pi)

Pi1. I feel that as a result of my using a digital mental health tool, others know more about me than I am comfortable with.

Pi2. I believe that as a result of my using a digital mental health tool, information about me that I consider private is now more readily available to others than I would want.

Pi3. I feel that as a result of my using a digital mental health tool, information about me is out there that, if used, will constitute an invasion of my privacy.

Secondary Use of Personal information (SPi)

SPi1. I am concerned that a digital mental health tool may use my personal information for other purposes without notifying me or getting my authorization.

SPi2. I am concerned that a digital mental health tool may share my personal information with other entities without getting my authorization.

Technology Anxiety (TA)

TA1. Using digital mental health tools makes me feel uneasy and confused.

TA2. Using digital mental health tools would make me very nervous.

TA3. Using digital mental health tools makes me feel uncomfortable.

TA4. I feel calm using digital mental health tools.

Appendix N

Qualitative Questions/End of Survey

Our study is looking at digital mental health tools used for mental health promotion and prevention. These tools can include mobile apps, websites, and wearable devices, that aim to support one's well-being, increase mental health knowledge, and prevent the onset of mental health challenges. Examples of these tools include apps that track moods, provide self-regulation skills, and/or provide self-guided exercises. Other examples are smartwatches or apps on your phone that monitor behavioural patterns or provide reminders for self-care activities.

Q21 Is there anything else you want to share with us about Digital Mental Health Tools?

____

____

Q22 What are the biggest barriers for your professional use of Digital Mental Health Tools?

____

____

Thank you for participating in the study!

To receive your $20 e-transfer, you will need to enter your unique participation code into the box below and email it to coping.research@lakeheadu.ca using your work email address. When emailing the code, please use the subject heading "Educator Study".

Your Code: ${rand://int/100000:9999999}

Q134 Please paste enter your code below:

____