Usability, Quality, and Factors Influencing Acceptance of a Resilience App (JoyPop™) among University Students

Ishaq Malik

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Department of Psychology

Lakehead University

Thunder Bay, Ontario, Canada

Supervisory Committee:

Supervisor: Dr. Aislin Mushquash

Second Reader: Dr. Fred Schmidt

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Abstract

Campus mental health (MH) services are struggling with increasing postsecondary student MH needs, and many students face barriers to MH care, which can have long-term negative impacts on their well-being. MH smartphone applications (apps) are one solution that can mitigate barriers to care by providing students with accessible MH support. The JoyPop™ app was designed to improve resilience and emotion regulation. While evidence suggests that using the JoyPop™ app is associated with better MH among students, factors influencing acceptance, usability, and quality must be examined to ensure a safe, engaging, and valuable user experience. The present study used the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) to examine factors that influence the acceptance and use of the JoyPop™ app. The app's overall acceptance, usability, and quality were also evaluated. Participants were 183 postsecondary students attending a Canadian University who used the app for one week. Relationships posited by the UTAUT2 were tested using partial least squares structural equation modelling (PLS-SEM). Results showed that the UTAUT2 explained substantial variance in behavioural intention and app use. Performance expectancy, hedonic motivation, and facilitating conditions predicted behavioural intention, and behavioural intention and facilitating conditions predicted app use. Age moderated the association between facilitating conditions and behavioural intention. Experience moderated the relationship between performance expectancy, hedonic motivation, and social influence on behavioural intention. Participants rated the app's acceptance, quality, and usability highly. An exploratory analysis showed that quality and usability significantly predicted use, and personality traits showed unique associations with the UTAUT2 constructs. Findings provide insight into factors influencing the acceptance of the JoyPop™ app and support its utility as a helpful tool to support the increasing MH needs of postsecondary students. Findings also provide valuable insights for developers in evaluating and optimally designing MH apps.

Usability, Quality, and Factors Influencing Acceptance of a Resilience App (JoyPop™) among University Students

Mental health (MH) difficulties are increasing and are the leading cause of disability in Canada (Mental Health Commission of Canada (MHCC), 2013; Lang et al., 2018). One in five Canadians are affected by MH problems yearly, and even more are affected in Ontario (MHCC, 2013; Statistics Canada, 2022a). The impact of rising MH concerns is demonstrated through increased consequences across personal (e.g., disability), social (e.g., familial stress), and economic domains (e.g., decreased work productivity; Hensel et al., 2016; Lang et al., 2018; MHCC, 2013).

MH concerns are even higher among emerging adults (ages 18-29; Arnett, 2000; Arnett et al., 2014), who comprise about 13% of the population in Canada and Ontario (Statistics Canada, 2022a, 2023b). Studies show that self-reported ratings of poor/fair MH, mood and anxiety disorders, suicidality, MH-related emergency department use and hospitalizations among emerging adults are higher than the general population and rapidly increasing (MHASEF, 2021; Statistics Canada, 2022a, 2023a; Wiens et al., 2020). Greater MH concerns in emerging adult populations may result from heightened instability stemming from significant life transitions (e.g., expanding agency, role exploration, changing relationships, completing education) and emotional, cognitive, social, physical, and neurodevelopmental changes (Arnett et al., 2014; MHCC, 2013). Although instability in emerging adulthood presents a crucial developmental period for growth in areas such as resilience and intellectual functioning (Arnett et al., 2014; Wood et al., 2018), the supports, experiences, and opportunities an individual has throughout emerging adulthood, and their capacity to manage instability can have a lasting detrimental or positive impact on MH and life outcome trajectories into adulthood (Miller et al., 2015; Wood et al., 2018).

Unaddressed MH difficulties in emerging adulthood can have long-lasting personal, social, and economic consequences that negatively influence the rest of an individual's life (Macleod & Brownlie, 2011; WHO; 2015; Wood et al., 2018). First, risk factors (e.g., poor emotion regulation and impulse control) can continue into adulthood and negatively impact functioning in significant life domains (educational, occupational) or increase future risk behaviours (e.g., suicide; Macleod & Brownlie, 2011; Wood et al., 2018). Second, MH concerns may negatively affect family relationships, exacerbating MH difficulties (Macleod & Brownlie, 2011). Third, MH concerns in emerging adulthood can increase vulnerability to future stressors (Macleod & Brownlie, 2011). Fourth, problematic behaviours resulting from MH difficulties may become stable and entrenched (Macleod & Brownlie, 2011). Finally, MH difficulties and challenging behaviours can reduce opportunities to develop essential skills (e.g., interpersonal skills; Arnett et al., 2014; Macleod & Brownlie, 2011; Schulenberg et al., 2004).

Postsecondary Students

Many emerging adults enter and complete postsecondary education, which can strongly influence life and MH outcome trajectories. In 2021/2022, approximately 58% and 60% of emerging adults aged 18-29 in Canada and Ontario, respectively, attended college or university (Statistics Canada, 2022b). Postsecondary education provides unique and diverse social, intellectual, and autonomous experiences that can facilitate the transition from emerging adults to caring and responsible adults (Arnett, 2016; Arnett et al., 2014). Completing postsecondary education and higher educational attainment is consistently associated with important outcomes, such as improved academic and cognitive skills, quality of life, job satisfaction, greater community engagement and less crime, and enhanced work productivity (Borgonovi, 2012; Brennan et al., 2013). Nevertheless, the path from entering to completing postsecondary education can present significant challenges and stress that can negatively impact MH.

Everyday stressors and challenges include adjusting to a postsecondary lifestyle (e.g., less parental and teacher support), academic stressors (e.g., time constraints, fear of failure), and the campus culture (e.g., diminished sense of belonging, safety concerns; Burke et al., 2016; Dinh et al., 2013; Linden & Stuart, 2020). Students often harbour concerns about the future (e.g., career security, family planning), finances (e.g., student loans), and relationships (e.g., less support from childhood friends and family members, living with new roommates, interpersonal difficulties; Linden & Stuart, 2020; Richardson et al., 2017; Welle & Graf, 2011). The high prevalence of stressors and challenges among postsecondary students is discussed in the American College Health Association's (ACHA) 2022 National College Health Assessment (NCHA) III Survey, which examined MH and health behaviours from Fall 2019 to Spring 2022 among a nationally diverse sample of students (N = 11,322, M_{age} = 23.3) across 32 Canadian colleges and universities (ACHA, 2022). Results show that within the previous year, most students experienced stressors related to procrastination (82.5%), personal appearance (63.7%), academics (60.4%), finances (55.2%), career (48%), family (47%), intimate relationships (42.8%), peers (28.2%), roommates/housemates (26.8%), and discrimination (15%). Of concern was that most students reported experiencing three or more challenges within the previous year (84.5%).

MH of Postsecondary Students

High stress and psychological distress are associated with worse student MH outcomes, particularly when students do not seek or receive adequate MH services and when critical aspects of resilience (e.g., social support, adaptive coping skills) are limited (Byrd & McKinney, 2012; Linden & Stuart, 2020). Additionally, high levels of psychological distress may remain stable throughout an academic year (Linden et al., 2023). Significant amounts of stress and psychological distress combined with inadequate MH care and support are demonstrated by high and increasing MH difficulties among students (ACHA, 2022; Linden et al., 2018, 2021), leading to a potential MH crisis among this population (Evans et al., 2018).

The ACHA (2022) survey shows that overall student stress levels are mostly moderate (47%) and high (36.7%), while many report moderate (52%) to serious (33.4%) amounts of psychological distress and high levels of loneliness (58.6%). Around 35.5% reported having screened positive for suicidal ideation, and 2.9% reported a suicide attempt within the last year. Regarding diagnosed MH disorders, 32% reported being diagnosed with an anxiety disorder, 24.6% with depression, and 20.6% had both depression and anxiety. Similar prevalence rates are found in Ontario, with approximately 38.6% of postsecondary students reporting a MH diagnosis and many experiencing subclinical MH difficulties (e.g., problem concentration, general anxiety; Moghimi et al., 2023).

There are also specific groups of postsecondary students (i.e., Indigenous populations; sexual, gender, and racial minorities; and those in rural and remote areas) who comprise a significant proportion of the student population (ACHA, 2022; Government of Ontario, 2023; Statistics Canada, 2022c, 2022d), that often face disproportionate and additional stressors that worsen MH outcomes. Students identifying as racial, sexual, and gender minorities experience additional risks and stressors, such as acculturative stress, systematic exclusion, discrimination, ridicule, racism, and violence, which negatively impact psychological health and well-being (Berry, 2006; CACUSS & CMHA, 2013; Ruzek et al., 2011; Srivastava & Srivastava, 2019). Further, although reports of fair/poor perceived MH are similar across rural and urban communities among ages 18-34 (Statistics Canada, 2022e), disproportionate rates of suicidality are found among rural Canadians (Rauch et al., 2023), which may apply to postsecondary students attending institutions located in rural areas.

Impact of MH Problems on Postsecondary Students

The impact of unresolved MH difficulties among postsecondary students is similar to those found among emerging adults (Linden & Stuart, 2020; MHCC, 2013; WHO, 2015). Unique consequences arise when considering the specific impact stressors and MH problems have on academic performance, student retention, academic probations, graduation rates, and challenges securing postgraduation employment (Bilodeau & Meissner, 2018; Eisenberg, 2009; Moghimi et al., 2023). The 2022 ACHA-NCHA survey shows that students report multiple stressors that negatively impact their academic performance, especially when stress is associated with procrastination (74.9%), faculty (62.9%), death of a loved one (49.9%), career (44%), finances (43.5%), hazing (42.6%), family (38.5%), intimate relationships (36.3%), and bullying (35.9%; ACHA, 2022). Many MH-specific problems, such as depression (67.8%), stress (64.5%), anxiety (62.5%), sleep difficulties (56.6%), and posttraumatic stress disorder (57.3%), are also reported to impede their academic performance (ACHA, 2022). Clinical and subclinical levels of anxiety and depression are also consistently associated with worse academic performance, GPA scores, postgraduation work capacity, absenteeism, dropout rates, and social engagement at school (Awadalla et al., 2020; Eisenberg et al., 2009; Lisnyj et al., 2020).

Are Postsecondary Student's MH Needs Being Met?

In response to rising postsecondary MH problems, various discrete interventions (e.g., animal therapy, mindfulness interventions) and international, national, provincial, and local initiatives have been developed and implemented across postsecondary institutions to improve the MH and well-being of students (Linden et al., 2018; MHCC, 2020; Okanagan Charter, 2015). However, despite significant efforts to support student MH in Canada, help-seeking is low, and service effectiveness is inadequate (Jaworska et al., 2016; Ogrodniczuk et al., 2021). Even when sought, many students do not find campus MH supports and services effective because of a lack of campus MH promotion and resources, insufficient psychotherapy services, and difficulties accessing support (Moghimi et al., 2023; Ogrodniczuk et al., 2021; Robinson et al., 2016). Many institutions struggle to prevent, identify and treat student MH difficulties because of uncoordinated services, lack of funding, and high resource needs (Jaworska et al., 2016; Linden et al., 2020). Services are often further strained because of increasing student psychopathology, MH severity and complexity, and high demands for counselling services (ACHA, 2022; Jaworska et al., 2016).

Barriers to MH Care Among Postsecondary Students

Low help-seeking, inadequate campus MH care, and rising MH difficulties among postsecondary students are often because of structural (e.g., accessibility) and attitudinal barriers (e.g., stigma) to care that prevent students from receiving the MH care and support they need when they need it (Andrade et al., 2014; Dunley & Papadopoulos, 2019; Moghimi et al., 2023). Students and service providers report many similar and highly prevalent structural and attitudinal barriers. Structural barriers include a lack of coordinated services and insurance coverage, minimal long-term therapy and off-site support, limited resources and long-term therapy, long wait times, fragmented services, and limited culturally appropriate services (Dunley & Papadopoulos, 2019; Linden et al., 2018). Attitudinal barriers include low MH literacy (e.g., unaware of MH problems and available supports), time and financial constraints, stigma, lack of perceived need, self-reliance, past negative experiences, and negative beliefs about service effectiveness (Dunley & Papadopoulos, 2019; Marsh & Wilcoxon, 2015; Moghimi et al., 2023).

The prevalence of student-reported barriers was highlighted by Moghimi et al. (2023), who found that only 8.3% of students (N = 448) reported no barriers to care. The most endorsed barriers to care were financial (50.5%), long wait times (47.6%), lack of resources to address their needs (38.9%), minimal time because of school commitments (34.9%), stigma (31.4%), cultural barriers (25.4%), and prior negative experiences with MH services (20.3%; Moghimi et al., 2023). Barriers explicitly reported by service providers were highlighted in a qualitative study conducted at a postsecondary institution in southwestern Ontario among 24 on-campus service providers (MacDonald et al., 2022). Frequent student-level barriers reported were stigma and lack of student awareness and motivation (i.e., not recognizing when they need help, being overwhelmed with the number of services). Structural barriers were long wait times, insufficient resources, ineffective promotion and awareness of programs, and disconnects between upper-level decision-makers and campus MH services (MacDonald et al., 2022).

Barriers to MH Care for Vulnerable Groups

Even though barriers to postsecondary student MH are shared amongst the general population of Canadian students, vulnerable student groups (i.e., visible minorities, sexual and gender minorities, Indigenous people, and students in rural and remote communities) often face additional and unique barriers that likely contribute to the disproportionate rates of MH difficulties (Faber et al., 2023; Goetz et al., 2023; Moagi et al., 2021).

Documented barriers among these groups are related to economic integration, systemic exclusion, fewer specialized supports, and Eurocentric models of education (MHCC, 2019; Moagi et al., 2021). These groups also face additional barriers associated with language (Finnigan et al., 2022; MHCC, 2019), discrimination, stigma, and racism (Khan et al., 2020; Steele et al., 2017). Indigenous people face more barriers compared to the general population, such as geographical distance, socioeconomic barriers, lack of culturally competent supports, low MH literacy, past negative experiences with healthcare, stigma, discrimination, colonialism, and racism (Cameron et al., 2014; Goetz et al., 2023; Nguyen et al., 2020). Even though most institutions have MH outreach programs targeting Indigenous and visible, sexual, and gender minorities, a national survey of 158 Canadian postsecondary institution campus MH services shows that most do not have enough specialized, ethnically diverse and culturally competent counsellors (Jaworska et al., 2016). Students in rural and remote communities also experience additional barriers to MH care than urban communities, such as limited availability and access to supports and providers, travel-related barriers (e.g., lack of transportation, geographic distance), reduced confidentiality, uncoordinated services, and underfunding (Caxaj, 2016; Dyck & Hardy, 2013).

e-Health

Considering the difficulties that campus MH services have in meeting the increasing complexity and demand of students with MH needs, changes in delivering student support are needed. No longer is the dominant model of meeting one-on-one by a highly trained MH professional able to meet students' diverse and increasing needs (Kazdin, 2017; MHCC, 2013). Novel prevention and intervention efforts that expand the reach, scalability, affordability, flexibility, and expansion of MH supports are needed (Kazdin, 2017; MHCC, 2014). One solution is through innovations that bring services to people rather than bringing people to services (Kazdin, 2017).

Electronic health (e-Health) interventions are among the most promising innovations to improve MH support (MHCC, 2014). The WHO defines e-Health as “the cost-effective and secure use of information and communications technologies in support of health and health-related fields, including health-care services, health surveillance, health literature, and health education, knowledge and research” (WHO, 2023). Health Canada has defined e-Health as “…an overarching term used today to describe the application of information and communications technologies in the health sector. It encompasses a whole range of purposes from purely administrative through to health care delivery” (Government of Canada, 2010). e-Health includes many technologies like electronic patient administration and messaging systems, telehealth services, remote vital signs monitoring systems, and patient management systems (Government of Canada, 2010). e-Mental health delivers MH support through the Internet and associated technologies (MHCC, 2014). Technologies for e-Mental health include phone and videoconferencing services, web- and mobile-based interventions, social media, and virtual reality, among others (MHCC, 2014).

In Canada, e-Mental health is touted as a practical method to reduce MH service gaps and mitigate barriers to care for emerging adults and postsecondary students (MHCC, 2012, 2014). For instance, The Changing Directions, Changing Lives, Mental Health Strategy for Canada suggests using e-Mental health technologies to increase service capacity for postsecondary institutions, improve access to MH support, and reduce disparities in risk factors present in vulnerable groups (MHCC, 2012). In 2014, the MHCC published a briefing document outlining how e-Mental health can transform the MH system by improving quality and reducing barriers to care, especially for youth, emerging adults, and Indigenous and rural and remote populations (MHCC, 2014).

mHealth

One of the fastest growing and promising e-Health technologies is mobile health (mHealth), which the WHO Global Observatory for e-Health defines as the “medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices” (WHO, 2011, p. 6). mHealth has been implemented to facilitate healthcare via patient communication, medication monitoring, care delivery, service data collection, and more (Becker et al., 2014; Tomlinson et al., 2013). mHealth is used in many forms and purposes, such as using wrist-worn wearable technology to track daily changes in stress and activity (Boateng et al., 2019), improving medication adherence through wireless medication trays (McGillicuddy et al., 2013), home-based counselling using personal digital assistants (Abroms et al., 2014), and smartphone applications (apps) to treat MH difficulties (MH apps); Firth et al., 2017).

Current Use of Smartphones and MH apps

mHealth app use is growing at an immense pace. In 2019, there were approximately 325,000 mHealth apps in major app marketplaces, cumulating in US$23 billion in revenues and a fivefold profit increase since 2013 (Messner et al., 2019; Research2Guidance, 2016; Statista, 2019). MH apps have also rapidly increased. In major app marketplaces, more than 10,000 apps are designed for MH (Torous & Roberts, 2017). Scientific interest in MH apps is also growing. From 2000 to 2020, 12,593 articles from 166 countries on mHealth and 449 articles associated with MH apps have been published. Notably, 72% of the 12,593 mHealth articles were published between 2015 and 2020 (Cao et al., 2021).

MH apps are discussed as a solution to mitigate barriers to care because of the high usage of smartphones and their ability to provide accessible 24-hour support (Price et al., 2014; Statista, 2022). About 32 million Canadians are smartphone users, and use is expected to rise from 84% to 97.53% by 2028 (Statista, 2023). MH apps can be especially useful for postsecondary students because of their openness towards using them and the overall high rates of smartphone use among this population (Bautista & Schueller, 2023; MHCC, 2014; Statistics Canada, 2023c). For instance, 97.9% of Canadians (98.7% in Ontario) between ages 15-24 report having a smartphone, and 57.5% check it at least every 30 minutes (Statistics Canada, 2021a).

Advantages of MH apps

The advantages of integrating MH apps to enhance existing MH supports are reduced costs, expanded service capacity and effectiveness (e.g., supporting current services), improved availability and access to support (e.g., removing travel-related barriers), reduced MH disparities (e.g., among vulnerable populations), improved diversity and engagement (e.g., implementing gamification), patient empowerment (e.g., allowing patients to drive their documentation), improvements in data collection (e.g., automated data tracking), better treatment adherence (e.g., real-time reminders), and reduced stigma (e.g., confidentiality when accessing therapeutic content), among others (Messner et al., 2019; MHCC, 2014; Olff, 2015; Price et al., 2014). Because stigma, self-reliance, minimal long-term supports, staff shortages, and time and financial constraints are so prevalent, MH apps can provide a timely, accessible, private, long-term, and autonomous method to support student MH (MHCC, 2014; Moghimi et al., 2023).

Research is now demonstrating reported advantages for postsecondary students and related services. For example, Wiljer et al. (2020) examined the utility of the *Thought Spot* MH app (provides a map allowing users to locate MH and wellness resources quickly) to facilitate MH and wellness help-seeking intentions in a sample of 481 postsecondary students (M_{age} = 23.1) from three Canadian postsecondary institutions. Because similar increases in help-seeking were found among groups who either used the app or who received traditional delivery methods of MH information (e.g., information pamphlets), results supported the utility of using MH apps as an additional tool to expand campus MH service capacity and effectiveness (Wiljer et al., 2022). The ability of MH apps to improve accessibility and reduce stigma was shown by Levin et al. (2018) among a sample of 200 postsecondary students (M_{age} = 21.07 [SD = 4.74]) reporting elevated distress. The authors found that fears of self-stigma were positively related to decreased help-seeking intention for those seeking in-person support but were not related to seeking self-help support (i.e., books, websites, and MH apps; Levin et al., 2018). Considering these advantages, many postsecondary student wellness and counselling centers are already recommending and implementing MH apps as a resource to support students (Johnson & Kalkbrenner, 2017; LeViness et al., 2017).

Evaluating MH apps

Effectiveness and Efficacy. The effectiveness of MH apps is determined by examining effects in conditions similar to naturalistic real-world conditions. On the other hand, efficacy examines an app's effects under more rigorous and controlled conditions (e.g., randomized controlled trials (RCTs); Flay et al., 2005). The effectiveness and efficacy of MH apps that have been evaluated is promising (Lecomte et al., 2020; Linardon et al., 2019) and is rapidly growing among postsecondary students (Choudhury et al., 2023; Leech et al., 2021). The effectiveness of MH apps for postsecondary students was shown in a rapid review by Choudhury et al. (2023) that included 15 studies (pre-post designs) across seven developed countries. Common interventions within MH apps were meditation and mindfulness (*n* = 8), Cognitive Behavioural Therapy (CBT; *n* = 5), Acceptance and Commitment Therapy (ACT; *n* = 3), metacognitive training (*n* = 2), and positive psychology (*n* = 2). Interventions lasted four to eight weeks (range = 1-10 weeks), and eight studies provided follow-up evaluations. Results showed that six out of 12 studies found significant reductions in depression, seven of 10 studies found significant improvements in anxiety, six of seven studies found significant improvements in stress, one of three studies showed improvements in sleep quality, and three of four studies found significant improvements in self-image. Further, both studies on burnout found significant improvements; one of three studies found significant improvements in quality of life, and all five studies on general health found significant improvements. The review also found that studies with more extended intervention periods (≥ seven weeks) were most effective (Choudhury et al., 2023).

The efficacy of MH apps was demonstrated in a systematic review of 19 studies (11 being RCTs) by Oliveira and colleagues (2021) in a pooled sample of 3,399 postsecondary students. Of the 11 RCTs (sample sizes ranged from 72 to 330, 14 days to three-month follow-ups), nine showed evidence of efficacy, with most having medium to large effect sizes in reducing stress, depression, anxiety, and improving general MH. For example, Newman et al. (2020) found moderate reductions in anxiety, stress, and depression vs. a no-treatment control group after three months of using the *Lantern* app (a self-help app designed for generalized anxiety disorder). Ponzo et al. (2020) found that after four weeks, the *BioBase* app (self-guided app plus a wearable device for treating anxiety) showed moderate to large effects in reducing anxiety and depression with sustained large effects for anxiety and well-being at a two-week follow-up vs. a waitlist control group. Mcloud et al. (2020) found that the *Feel Stress Free* app (used to treat depression and anxiety) showed small to moderate effects in decreasing symptoms of depression (four and six weeks) and anxiety (four weeks) compared to a waitlist control group. Bruehlman-Senecal et al. (2020) found a significant interaction between using the *Nod* app (designed to decrease loneliness during transitions to college) and baseline loneliness in reducing depression and improving sleep quality vs. a waitlist control group after four weeks. Harrer et al. (2018) showed that after using the *Studicare Stress* app (designed to improve stress management in students) for seven weeks, moderate to large effects in reducing stress, anxiety, depression, and academic impairment while improving productivity were found and sustained at a three month follow up (Oliveira et al., 2021).

Limitations on the Effectiveness and Efficacy of MH apps

Overall, research supporting the effectiveness and efficacy of MH apps for postsecondary students is growing. MH apps demonstrating effectiveness and efficacy can thus be valuable additions to traditional campus MH supports because of the advantages they can provide users and services. However, when considering current evidence and the large number of MH apps on major app marketplaces, many MH apps evaluated in the literature are not available on the marketplaces, and most marketplace apps have yet to be empirically tested for efficacy or effectiveness (Donker et al., 2013; Messner et al., 2019; Van Ameringen et al., 2017).

Evidence supporting the effectiveness and efficacy of MH apps is also mixed among postsecondary students, with some studies having nonsignificant results and no sustained effects. Further, few studies specifically evaluate these apps with diverse samples and vulnerable groups of postsecondary students (Chouhury et al., 2023; Leech et al., 2021; Oliveira et al., 2021). There are also high rates of attrition among trials, minimal high-quality RCTs with long-term follow-ups and active control groups, while examinations of harmful effects, frequency and duration of usage, and theory-based mechanisms of change are minimal (Leech et al., 2021; Torous et al., 2018). Considering the mixed evidence, it is suggested that MH apps should only be used as additions to regular treatment or with therapist guidance (Lecomte et al., 2020; Weisel et al., 2019). A meta-analysis on the efficacy of MH apps for MH problems using 66 RCTs with 77 MH apps (28 trials used community and student samples) found that effect sizes were consistently larger when participants were provided therapist guidance and reminders to engage in the app (Linardon et al., 2019). Thus, evidence suggests that MH apps are most effective and safe as additions to regular treatment. Although stand-alone apps for self-management are effective (Leech et al., 2021), caution and consideration of the complexity and severity of an individual's MH issues are needed.

It is also critical to note that despite the importance of having evidence of effectiveness and efficacy, it does not guarantee use, and the evidence base of apps is not one of the most important predictors of engagement and use (Bautista & Schueller, 2023; Jacob et al., 2022). Thus, determining important predictors of engagement and use of MH apps among postsecondary students is the focus of the current study because even if effective, the impact of MH apps will be minimal if not used by people who may benefit.

User Engagement with MH apps

Low engagement (e.g., lack of long-term uptake and poor adherence) among MH app users is a significant issue (Linardon & Fuller-Tyszkiewicz, 2019; Torous et al., 2018). Average attrition rates in RCTs examining MH apps are 24.1% and 35.5% for short and long-term follow-ups (Linardon & Fuller-Tyszkiewicz, 2019). Once downloaded, 80% of users use them less than two times, and only about 2.58% sustain active use (Fleming et al., 2018; Jacob et al., 2022). For example, a study in a sample of 742 postsecondary students found that among participants who had previously used a MH app, only 2.4% sustained use for four weeks or more (Kern et al., 2018).

Research suggests a multitude of engagement factors that are more salient in predicting engagement and use of MH apps (Bautista & Schueller, 2023; Jacob et al., 2022), such as personal and social factors (e.g., age, attitudes and preferences), technical and material factors (e.g., usefulness, user experience, technical issues), and health-related factors (e.g., type of health condition, health awareness and literacy, relation to other therapies; Jacob et al., 2022). Similar factors are found to influence engagement and use among postsecondary students, such as usefulness, suitability to current needs, overall interest, privacy concerns, available time, affordability, ease of use, user interface, credibility, customization, and attitudes (Bautista & Schueller, 2023; Melcher et al., 2022). Therefore, in addition to evaluating efficacy and effectiveness, sociotechnical factors influencing acceptance, usability, and quality must be examined and integrated into MH app evaluations to ensure ethical, engaging, and effective user experiences (Jacob et al., 2022; Torous et al., 2018).

Acceptance. Acceptance factors have regularly influenced increased and continued usage of MH apps among diverse populations, countries, and contexts (Connolly et al., 2021; Jacob et al., 2022). However, determining what factors constitute acceptance is unclear in the current literature because acceptability, acceptance, and adoption are often used interchangeably and measured using many methods (e.g., customized and standard surveys, focus groups and interviews, app-generated data) and indicators (e.g., user perspectives, adherence and usage rates, feasibility trials; Jacob et al., 2022; Nadal et al., 2020). Acceptability, acceptance, and adoption of mHealth apps are most often defined and evaluated by how useful an app is, individuals' intentions to use the app, and actual usage rates (Nadal et al., 2020).

An important method to clarify and identify important acceptance factors is to employ theoretical technology acceptance frameworks with validated acceptance measures and constructs associated with engagement and long-term uptake and used to improve the replicability, generalizability, and utility of mHealth apps (Nadal et al., 2020; Torous et al., 2018). Incorporating theoretical frameworks to examine the acceptance of MH apps is limited, especially among postsecondary students (Oliveira et al., 2022). Consequently, one of the primary purposes of the present study is to use a well-established technology acceptance framework to examine MH app acceptance.

Theoretical Frameworks. The most prominent theories examining and predicting acceptance and use of mHealth apps are the Technology Acceptance Model (TAM; Davis, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), and the extended Unified Theory of Acceptance and Use of Technology (UTAUT2; Venkatesh et al., 2012). The TAM, UTAUT, and UTAUT2 interpret acceptance as the behavioural intention to use technology (Ammenwerth, 2019; Venkatesh et al., 2012). These theories are used to better understand factors influencing technology acceptance for many technologies (e.g., mobile banking, artificial intelligence, electronic health records, social media, mHealth apps) in a variety of settings (e.g., healthcare, postsecondary institutions, businesses, hospitals, MH services), and countries (e.g., Canada, US, China, Spain, Iran; Tamilmani et al., 2017; Williams et al., 2015). They have been used independently, with other acceptance theories, or via adding external variables relevant to specific contexts (Ammenwerth, 2019; Tamilmani et al., 2021).

The TAM was developed based on the Theory of Reasoned Action (Ajzen, 1977) and proposes that technology's perceived usefulness and ease of use are critical for its acceptance. Perceived usefulness is the perception that technology will enhance performance, and perceived ease of use is the perception that it will be easy to use (Ammenerwerth, 2019; Davis, 1989). The TAM posits that perceived usefulness and ease of use determine attitudes towards using a technology, which determines behavioural intention to use the technology, which affects actual use (Ammenwerth, 2019; Davis, 1989). Reviews on the TAM's explanatory power show that it can explain 27% to 88% of the behavioural intention to use mHealth and non-mHealth technologies depending on the country, population, and setting (Tao et al., 2020; Venkatesh et al., 2003). Research examining the utility of TAM constructs in predicting behavioural intention to use MH apps among postsecondary students is mixed (Becker, 2016; Kim et al., 2022), and the TAM is criticized for being too simplistic and not considering organizational, individual, and social factors that influence technology acceptance (Malatji et al., 2020).

The UTAUT was developed by Venkatesh et al. (2003) based on eight previous technology acceptance models, such as the TAM, TAM2, the Theory of Reasoned Action, and the Diffusion of Innovation Theory (Rogers, 2003). The UTAUT combined models to create one unified model with four core constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy refers to users' expectations that a technology is useful for its purpose. Effort expectancy relates to the ease of use and user-friendliness of technology. Social influence is the degree to which important people believe they should use technology. Facilitating conditions refers to the degree to which users believe they have sufficient organizational and technical infrastructure to use technology (Venkatesh et al., 2003). The model posits that performance expectancy, effort expectancy, social influence, and facilitating conditions affect behavioural intention, influencing technology use. Facilitating conditions is also posited to influence use directly. Gender, age, experience, and voluntariness of use are posited to be moderators of behavioural intention and use (Venkatesh et al., 2003). The original study validating the UTAUT found that it explained 70% of the variance in behavioural intention to use novel technologies (e.g., online meeting manager, sales database application, business account management analyzer, public administration account system; Venkatesh et al., 2003). Studies examining its predictive power among internet- and mHealth-based MH interventions find that it explains between 40% to 81.5% of the variance in acceptance (Phillipi et al., 2021). The core constructs of the UTAUT also consistently predict mHealth acceptance (e.g., performance expectancy predicting behavioural intention; Rouidi et al., 2022).

In samples of postsecondary students, many of the core UTAUT constructs predict the use of MH apps (Holtz et al., 2023; Mitchell et al., 2022). Holtz et al. (2023) examined the acceptance of MH apps in a sample of 118 students (M_{age} = 20.43 [*SD* = 1.86]) at an American Midwestern university. Performance expectancy, effort expectancy, and facilitating conditions significantly predicted the use of MH apps. Mitchell et al. (2022) examined the acceptance of a specific MH app called *MySSP* (connects students with 24/7 free emotional health and well-being support) among university students. They found that performance expectancy and social influence significantly predicted behavioural intention to use the app (Mitchell et al., 2022).

Because the original UTAUT was developed for professional contexts, Venkatesh et al. (2012) extended this model to create the UTAUT2 to capture acceptance from the consumer/individual perspective. Hedonic motivation, price value, and habit were added as core constructs. Hedonic motivation refers to the fun, pleasure, and enjoyment users experience with technology. Price value examines the influence of cost and pricing structure use. Habit refers to the automaticity in which people perform behaviours because of learning. All constructs in the model are purported to influence behavioural intention. Facilitating conditions and habit are posited to influence use directly. Age, gender, and technology experience are included as moderators of core constructs on behavioural intention, and experience is a moderator between behavioural intention and use. The UTAUT2 explained more variance in behavioural intention and use of technology than the original model (75% vs. 56% and 52% vs. 40%; Venkatesh et al., 2012). The UTAUT2 and its constructs show strong predictive validity in mHealth acceptance (Calegari et al., 2023). Calegari et al. (2023) conducted a meta-analysis of 84 articles in a sample of 31,609 participants (including emerging adults and students) to estimate the overall path coefficients of UTAUT2 core constructs and theoretically predicted associations. Results show a positive relation between performance expectancy and behavioural intention (N = 26,098; β = 0.339, 77 studies), effort expectancy and behavioural intention (β = 0.232, 66 studies), social influence and behavioural intention (N = 21,358; β = 0.28, 57 studies), facilitating conditions and behavioural intention (N = 14,492; β = 0..488, 43 studies), hedonic motivation and behavioural intention (N = 6531; β = 0.115, 24 studies), habit and behavioural intention (N = 2526; β = 0.364, nine studies), facilitating conditions and use (N = 1812; β = 0.279, 5 studies), and behavioural intention and use (N = 5428; β = 0..525, 10 studies). Although some studies found a significant relationship between price value and behavioural intention, price value was the only construct without a significant overall effect (Calegari et al., 2023).

Research also shows that age, gender, and experience with technology can moderate associations between UTAUT2 core constructs and behavioural intention and between behavioural intention and use (Calegari et al., 2023; Venkatesh et al., 2012). For example, Calegari et al. (2023) found that gender was a significant moderator (indicating a more substantial effect for men) in the relationship between effort expectancy, hedonic motivation, and behavioural intention and the associations between social influence and habit on behavioural intention (Calegari et al., 2023). Studies further suggest that women are more likely to use mobile technology (Gilbert et al., 2003), and men are more likely to adopt mHealth tools but less likely to seek MH services than women (Calegari et al., 2023; Sagar-Ouriaghli et al., 2019). Age seems to exert its most potent effects among older adults, who are more affected by the complexities of technology (Calegari et al., 2023; Venkatesh et al., 2012). mHealth app experience also influences the core constructs of the UTAUT2 (Schomakers et al., 2022; Venkatesh et al., 2012). For example, individuals with more experience may be less concerned about the effort needed to use the app and more about performance and personal and emotional aspects like enjoyment and peer influences (Schomakers et al., 2022). Although the results vary for mHealth apps, it is recommended to include these moderating variables to understand better the acceptance and use of specific technologies in different populations and settings and to improve explanatory power (Chang, 2012; Venkatesh et al., 2012).

Studies examining the acceptance of mHealth apps in samples primarily comprised of postsecondary students show that UTAUT2 constructs significantly predict behavioural intention and use (Schomakers et al., 2022; Yuan et al., 2015). For example, in a sample of 278 participants (M_{age} = 29.98 [SD = 14.39]), all UTAUT2 constructs other than price value (not assessed) and facilitating conditions significantly predicted behavioural intention to use mHealth apps (Vervier & Ziefle, 2022). Gender was also a significant moderator of behavioural intention, indicating that females were more likely to use mHealth apps (Vervier & Ziefle, 2022). Research further shows that performance expectancy, hedonic motivation, price value and habit are significant predictors of behavioural intention to use health and fitness apps among college students (Yuan et al., 2015). Finally, the core constructs of the UTAUT2 were found to be useful in explaining intention to use lifestyle and therapy mHealth apps (Schomakers et al., 2022). Specifically, social influence and hedonic motivation significantly predict behavioural intention to use therapy apps, and habit and hedonic motivation predict intention to use lifestyle apps. Age, gender, and experience moderate behavioural intention to use both types of apps, with older participants and men showing lower acceptance and those with more mHealth app experience having higher acceptance levels (Schomakers et al., 2022). It is important to note that most studies are cross-sectional, rely on retrospective reports of app use, and evaluate mHealth apps in general rather than specific MH apps. These limitations informed the purpose of the present study.

In sum, although engagement and use of mHealth apps are measured using various terms and methods, findings from research using established technology acceptance models are instrumental in predicting the acceptance of mHealth technologies, such as MH apps (Rouidi et al., 2022). It is recommended that future MH app research incorporates these models into evaluations to better understand engagement and use (Hajesmaeel-Gohari et al., 2022; Oliveria et al., 2022).

Usability. Another way to address low adherence, engagement, and usage of MH apps is to evaluate usability (Torous et al., 2018). Usability has been defined as a "quality attribute that assesses how easy interfaces are to use," comprising learnability, efficiency, memorability, errors, and satisfaction (Nielsen, 2012). The International Organization for Standardization (ISO) defined it as ease-of-use or user-friendliness and "the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use" (ISO, 2018). There is no clear consensus on the definition of usability. However, usability impacts the effectiveness, long-term uptake, engagement, and risks associated with MH apps (Inal et al., 2020; Torous et al., 2018).

Usability evaluations are essential to ensure a user-centric design (tailored to user needs; Torous et al., 2018) and reveal factors reducing adherence, engagement, and use, such as unexpected crashing, functionality and syntactic errors, update and redownload issues, and problems with layout, readability, and interconnectivity (Alqahtani & Orji, 2019; Torous et al., 2018). Usability evaluations show that postsecondary students value MH apps with a convenient and intuitive design, customization, anonymity/privacy, peer-engagement, games, and options to access professionals (Montagni et al., 2020; Oti & Pitt, 2021). Therefore, in the ongoing development of MH apps, evaluating usability is critical so developers can elicit user needs, fix technical difficulties, and inform useful adaptations while examining if their MH apps currently address user needs.

Usability evaluations should include summative (current usability) and formative (informing improvements) evaluations with healthy users, patients, healthcare providers, and organizations throughout all stages of development and implementation (Inal et al., 2020; Torous et al., 2018). However, few studies gather feedback from patients and healthcare providers (Inal et al., 2020). Another critical issue in assessing the usability of mHealth apps is that most studies use measures designed for general technologies or create a unique questionnaire according to usability assessment guidelines (Zhou et al., 2019). For example, the System Usability Scale (SUS; Brooke, 1996) is most often used, and measures specifically designed to evaluate unique features influencing the usability of mHealth apps, such as the Mobile Application Usability Questionnaire (MAUQ), are rarely employed (Hajesmaeel-Gohari et al., 2022). Applying general technology measures to mHealth apps can be helpful by providing quick access to a reliable and valid measure to assess usability. However, they miss identifying factors unique to mHealth apps, such as battery issues, limited computation power, unique security and privacy challenges, and characteristics associated with small screens and portable devices (Harrison et al., 2013; Zhou et al., 2019).

To increase engagement, uptake, and use throughout the lifecycle of a MH app, using validated and standardized usability measures developed for mHealth apps to establish a common standard and simplify app comparisons is recommended (Zhou et al., 2019). App developers should also conduct usability evaluations among patients, healthy users, and healthcare providers to ensure they meet the diverse needs of all potential users (Inal et al., 2020).

Quality. Evaluating the quality (e.g., effectiveness, credibility, reliability, safety) of mHealth apps is essential because there is minimal research on the quality of available mHealth apps (Jacob et al., 2022; Messner et al., 2019). Concerningly, claims of app effectiveness and quality are not assessed consistently by regulatory bodies (Huckvale et al., 2020; Stoyanov et al., 2016), most apps do not use evidence-based strategies (Kertz et al., 2017), many lack evidence of feasibility and efficacy, and most do not include clinical recommendations from healthcare professionals during development (Sucala et al., 2017). Without proof of quality, users cannot assess the credibility and trustworthiness of MH apps and may rely on subjective star ratings despite inconsistent relationships between user ratings and an app's quality and clinical utility (Girardello & Michahelles, 2010; Kuehnhausen & Frost, 2013; Messner et al., 2019; Singh et al., 2016). Poor quality MH apps can pose more risks, particularly to users with MH issues, such as misdiagnosis, unknown side effects, physical and mental harm, and lack of protocols in case of emergencies (Albrecht & von Jan, 2016). App quality also affects engagement and use (Jacob et al., 2022). Users are more likely to use an app knowing that information is provided and endorsed by credible and trusted sources and that an app has evidence of safety and effectiveness (Jacob et al., 2022).

Several advancements and resources are now available to locate, assess, and regulate the quality of MH apps, such as app rating guidelines and platforms, which also facilitate developers and researchers to implement quality measures when developing their apps (Alon & Torous, 2023; Neary & Schueller, 2018; Stoyanov et al., 2016). For example, the PsyberGuide app rating platform has 115 rated MH apps based on their evidence, user experience, expert reviews, and data transparency (Neary & Schueller, 2018). The Mobile App Rating Scale (MARS; Stoyanov et al., 2015) is the most popular app rating guideline (Hajesmaeel-Gohari et al., 2022) and was developed to allow experts in MH to rate apps based on quality indicators from various health-related fields (e.g., human-computer interaction and mHealth; Stoyanov et al., 2015). More recently, the end-user version of the MARS (uMARS) was developed to help consumers objectively rate the quality of health-related mHealth apps without training and expertise (Stoyanov et al., 2016). App-rating guidelines and platforms can help organizations, experts, clinicians, and users assess the quality of MH apps and compare them to other apps to develop and provide users with a safe, effective, and engaging experience (Alon & Torous, 2023; Neary & Schueller, 2018).

Personality and mHealth Apps

Personalizing mHealth apps (integrating aspects of a person's characteristics to provide content tailored towards users) to promote behaviour change and effectiveness is critical to acceptance, usability, and quality (Dijkstra, 2008; Gosetto et al., 2020). Among postsecondary students, personalization is a key determinant of acceptance, usability, and use of MH apps (Oti & Pitt, 2021; Stoyanov et al., 2015). One method to improve the personalization of apps is to examine the association between user personality traits and app use throughout development and policymaking procedures to identify groups that may benefit most from an app (Aziz et al., 2023; Gosetto et al., 2020).

The five-factor (Big Five) personality model is one of the most accepted and used models in personality and technology research (Barnett et al., 2015; John et al., 2008; McCrae & Costa, 2003). This model is highly researched and validated across different measures, cultures, populations, and settings (Costa & McCrae, 1992a, 1992b; Schmitt et al., 2007). Big Five personality traits also predict important outcomes, such as MH, academic performance, and decision-making (Byrne et al., 2015; Lamers et al., 2012; Vedel, 2014). The five traits comprising the Big Five (also known as domains) each encompass six intercorrelated lower-order traits (also known as facets; See Table 1).

Technology Acceptance. The Big Five domains are assessed in many technological contexts, such as examining social media use, online gaming, and MH app use (Aziz et al., 2023; Correa et al., 2010; Delhove & Greitemeyer, 2020). Integrating individual differences, such as personality traits, into technology acceptance models like the TAM, UTAUT, and UTAUT2 has been recommended and identified as a critical future area of research to better understand technology acceptance and use (Barnett et al., 2015; McElroy et al., 2007). Although limited, the Big Five domains have been examined within technology acceptance models to understand and explain technology acceptance and use among postsecondary students (Barnett et al., 2015; Svendsen et al., 2013).

The associations between the Big Five domains and core constructs of technology acceptance models depend on the population and type of technology. For example, Barnett et al. (2015) tested the relationship between Big Five domains and the UTAUT model in the acceptance, perceived use (participants self-reported average number of visits to the website), and actual use (frequency of visits to the website tracked through the technology) of a custom-designed web-based course management system in a sample of 382 undergraduate students (M_{age} = 21.9, 58% male) at a large university in the United States (US). Conscientiousness positively predicted perceived and actual use but did not predict behavioural intention. Openness did not predict perceived or actual use. Neuroticism negatively predicted perceived and actual use. Extraversion negatively predicted actual use but did not predict perceived use. Agreeableness did not predict perceived and actual use, and behavioural intention did not partially mediate the relationship between domains and use (Barnett et al., 2015). Lakhal and Khechine (2017) examined the relationship between the Big Five domains and core constructs of the UTAUT on the acceptance of a desktop videoconferencing system among a sample of 413 undergraduate students in Canada. Neuroticism negatively predicted performance expectancy, effort expectancy, and facilitating conditions among tested relationships. Extraversion did not predict social influence, and openness did not predict performance expectancy. Agreeableness positively predicted effort expectancy and negatively predicted social influence but did not predict facilitating conditions. Conscientiousness did not predict performance expectancy but positively predicted effort expectancy (Lakhal & Khechine, 2017).

MH apps. No studies have examined the associations between Big Five domains and acceptance of MH apps using prominent technology acceptance theories. However, domains have predicted use and engagement with MH apps. Agreeableness and neuroticism positively predict stress-management apps use (Ervasti et al., 2019); individuals high in neuroticism and with moderate levels of extraversion are more likely to regularly use MH apps (Aziz et al., 2023) and students high in conscientiousness are more likely to use apps designed to improve self-esteem and less likely to use apps with games (Khwaja et al., 2021).

Notably, the relationship between domains and MH apps depends on the features within MH apps. A review of 103 MH apps in a sample of 561 participants primarily comprised of students with a bachelor's degree elucidated the association between Big Five domains and motivation/preferences to use common MH app features (e.g., relaxation exercises and audios, encouragement, reminders, social support, rewards, self-monitoring). Significant associations demonstrated that people higher in neuroticism prefer apps with relaxation exercises and audios, social support, contact for help, rewards, and a clear privacy policy. People higher in conscientiousness preferred apps with relaxation audios, encouragement, suggestions, trusted information, and contacts for help but did not prefer customization. Individuals higher in extraversion showed preferences for all features, particularly suggestions, distraction, rewards, credibility, and praise. People high in agreeableness had preferences for all feature components except for trusted information. Their preferences were strongest for features with reminders, social support, rewards, and praise. People higher in openness preferred relaxation exercises and audio, self-monitoring, and social support but did not prefer many features, especially security features, suggestions, trusted information, and encouragement (Alqahtani et al., 2021).

Overall, research on the relationship between Big Five domains, technology acceptance, and MH apps is limited. Depending on the context, app, and model used, insights into personality can help developers better understand who will use an app while improving the design, functionalities, aesthetics, and information within an app to facilitate engagement and use (Gosetto et al., 2020).

Beyond Domains and Facets. Despite domains having strong predictive capabilities across many populations and contexts, including technology acceptance, research demonstrates the increased utility of examining lower-order Big Five aspects and facets in predicting outcomes (Rozgonjuk et al., 2021; Stewart et al., 2022). However, genetic research has challenged the idea that the facet level hierarchy is the next level below the domains of the Big Five, finding that two genetic factors are required to explain covariance among each domain's six facets (Jang et al., 2002). Because only one genetic factor for each domain would be necessary to consider facets as the next level below, DeYoung and colleagues (2007) suggested and empirically derived intermediate factors below domains and above facets, otherwise known as the ten aspects of the Big Five (see Table 2).

Compared to the Big Five facets, the ten aspects are broader, more parsimonious, and theoretically driven by the Cybernetic Big Five Theory (CB5T), based on cybernetics (study of goal-directed systems that self-regulate via feedback; DeYoung, 2015), which makes them more useful in explaining how individuals differ in Big Five traits and why these domains seem to be the primary source of covariation in personality (e.g., underlying psychological and neurobiological processes; DeYoung, 2015). For example, extraversion is suggested to represent variations in individual sensitivity to reward. The two aspects comprising extraversion are individual sensitivity to either the hedonic aspects of a reward, which drives “liking” (enthusiasm) or the incentive characteristics of rewards, which drive “wanting” (assertiveness; DeYoung, 2015). The CB5T has been used to explain various phenomena, such as psychopathology and personality disorders (DeYoung et al., 2016; DeYoung & Krueger, 2018). Compared to domains, the ten aspects better predict multiple outcomes, such as well-being, positive and negative affect, intelligence, and MH (Allen et al., 2018; Anglim et al., 2020; DeYoung et al., 2014).

Because no studies have examined the associations between the ten aspects of the Big Five and constructs of popular technology acceptance models, unique and novel relationships between users’ personality and MH app acceptance and use, which could improve personalization and thus engagement, may be neglected. Therefore, one of the purposes of this study is to test the associations between the ten aspects of the Big Five and MH app acceptance.

The JoyPop™ app

Mitigating barriers to MH care and their personal, social, and economic impact in Canada is a top priority (MHCC, 2012, 2014). Considering the large gap between evidence-based MH apps and those on the market, the advantages MH apps can provide compared to traditional delivery models, and the continued need to rigorously evaluate the effectiveness, acceptance, usability, and quality, comprehensive evaluations are still required. The JoyPop™ app is one MH app being evaluated to provide users with an evidence-based, effective, usable, and quality app.

What is the JoyPop™ App?

The JoyPop™ app is a resilience-building MH app that does not require an internet connection. It was designed for youth and emerging adults (12+), utilizing a user-centred multi-method approach in its development, evaluation, and implementation (Wekerle, 2021). The app targets youth and emerging adults because of rising MH concerns and the unique barriers these groups face (CMHO, 2020; MHCC, 2014). These ages also represent an extended developmental period of risk and resilience because of significant brain development and life transitions (Howard et al., 2010; Wekerle et al., 2007) and how individuals cope with these transitions can significantly alter MH trajectories (Howard et al., 2010; Schulenberg et al., 2004). Therefore, the JoyPop™ app was developed as a timely and accessible resilience intervention to influence MH trajectories positively. It does this through multi-modal evidence-based features to help manage stress effectively while promoting engagement in positive activities and daily routines to foster emotion regulation (Wekerle, 2019).

The JoyPop™ app has particular relevance in rural and remote areas in Canada with large Indigenous populations, such as Northwestern Ontario, because these areas and populations have disproportionate rates of MH problems and barriers to care compared to more urban areas and the general population (MHCC, 2012; Rural Ontario Institute, 2022). This is especially true for postsecondary students, who currently face what some have touted as a MH crisis (Evans et al., 2018). As postsecondary students experience adversity from major life transitions and everyday daily stressors, the JoyPop™ app could provide an easily accessible, low-cost, and strength-based tool to help foster resilience, improve emotion regulation, and thus promote long-term positive outcomes (e.g., academic success).

The JoyPop™ app is conceptualized and was developed using resilience theory, which has been used to guide strength-based interventions and elucidate factors that help individuals mitigate and thrive in the face of risk factors (Zimmerman, 2013). Rather than preventing risk and reducing deficits, resilience theory focuses on increasing promotive factors (individual, social, and environmental) to decrease the likelihood that people exposed to risk progress to pathology (Zimmerman, 2013). Promotive factors are conceptualized as assets, which occur within an individual (e.g., emotion regulation), and resources that occur outside an individual (e.g., social connectedness; Zimmerman, 2013). The JoyPop™ app features were designed to facilitate individual promotive assets and resources. For example, by increasing assets like self-monitoring and self-awareness with features supporting users in learning and implementing adaptive coping skills to improve emotion regulation, others increase resources via quick access to personal social support networks (MacIsaac, 2021; Wekerle, 2021). The app's focus on resilience and emotion regulation makes it unique and valuable because most MH apps target specific disorders, and few use a strength-based approach to foster positive MH and well-being (Eisenstadt et al., 2021; Jadhakhan et al., 2022). The app also follows recommendations to focus on well-being and coping using a transdiagnostic treatment approach to MH conditions (Bakker et al., 2016; Barlow et al., 2010).

Currently, features include (see Figure 1): Rate My Mood, to help users learn and improve emotional identification and differentiation by rating four different moods (Hilt et al., 2011; MacIsaac et al., 2021); Journaling, which provides prompts that users can use to record entries (MacIsaac et al., 2021) and was designed based on research highlighting the positive outcomes associated with goal-directed and expressive writing (King, 2002; Pascual-Leone et al., 2016); Breathing exercises, which provide users preparation tips and guided diaphragmatic breathing exercises to self-regulate (Arch, 2006); SquareMoves, a Tetris-like game, based on research on the benefits of helpful distractions in times of excessive stress and gamification on app engagement (Cheng et al., 2019; Rankin et al., 2019); Art, to help users express creativity and emotions nonverbally (Andrade, 2010); SleepEase, designed to facilitate sleep preparation and quality using soothing sounds and guidelines for sleep hygiene (Schutte-Rodin et al., 2008); Circle of Trust, which allows users quick access to personal social support; Call for Help, designed to facilitate and help users access national helplines; and Calendar, for users to track journal entries and reflect on them at any time (MacIsaac et al., 2021).

Research on the JoyPop™ App

The JoyPop™ app has a growing multimethod evidence base among diverse samples of youth and young adults in clinical and non-clinical settings (Kim et al., 2023; MacIsaac et al., 2021; Malik et al., 2022; Mushquash et al., 2021). MacIsaac et al. (2021) examined the app's effectiveness among 156 undergraduates (M_{age} = 19.02, 79% female) transitioning into a Canadian University in Northwestern Ontario. App use was associated with improved emotion regulation and depressive symptoms. Students with more adverse childhood experiences showed faster improvements in emotion regulation, and reductions in depressive symptoms were greater with more frequent use (MacIsaac et al., 2021). In a qualitative study, Mushquash et al. (2021) analyzed feedback from 30 undergraduate students in the MacIsaac et al. (2021) study to examine users' perspectives on the app's utility after four weeks. Key themes were related to facilitators (e.g., opportunities to practice self-monitoring skills), barriers (e.g., lack of variety), helpful outcomes (e.g., improved emotional expression), and recommendations (e.g., enhancing features; Mushquash et al., 2021).

Kim et al. (2023) conducted semi-structured interviews with 19 adult Indigenous community members and stakeholders (Over 18 years of age, 74% female, 63% professionals working with Indigenous youth) from the most populated Indigenous reserve in Canada (Six Nations of the Grand River) to assess if the app could be helpful to youth on reserve. Overall, 53% of participants provided unprompted positive feedback on the app's overall efficacy in promoting resilience in Indigenous youth. Four major themes emerged: Incorporation of Indigenous Culture, which included positive feedback relating to the social support feature and its consistency with cultural values and recommendations to add local hotlines and traditional music sounds (e.g., drumming) into the SleepEase feature; Appreciation of Ease, which included positive perceptions on the simple design of the app, and feedback to simplify the language within the app; and Flexibility and Personalization, which included input to allow users to choose journal prompts, and having more colours and sounds tailored to youths preferences (Kim et al., 2023).

Finally, Malik et al. (2023) conducted a qualitative study exploring the acceptance of the JoyPop™ app using the TAM as a theoretical framework among a clinical sample of six female youth (50% Indigenous) and seven White female service providers working at the two largest MH agencies in Northwestern Ontario. All participants perceived the app as beneficial because it facilitated accessibility to adaptive coping skills and promoted positive outcomes or was seen as a helpful adjunct to regular pre/active/post-treatment services. All participants found the app easy to use because of its simple and intuitive design. All participants expressed positive attitudes and feelings towards the app because of the benefits it provided youth or the advantages it could provide to MH services. All service providers highlighted organizational factors influencing its acceptance, including positive aspects such as the app's alignment with their organization's values and future needs, such as ensuring it has evidence of efficacy. All participants highlighted barriers (e.g., functionality issues) and recommendations (e.g., adding games and notifications) influencing perceptions of usefulness and ease (Malik et al., 2023).

Currently, a research team at Lakehead University (Principal Investigator: Dr. Aislin Mushquash) is conducting two RCTs examining the efficacy of the JoyPop™ app on MH outcomes (e.g., emotion regulation) in a clinical and university sample of youth and young adults. Despite being evaluated in clinical and non-clinical settings and among diverse youth, young adults, and healthcare providers, research is needed on the efficacy, usability, quality, and acceptance of the JoyPop™ app, especially using well-established theoretical frameworks and validated measures designed for mHealth apps.

Research Limitations Summary

There are several limitations in the broader literature related to the acceptance, quality, and usability of MH apps. First, among the many MH apps available on major marketplaces, few have been empirically evaluated regarding their quality, usability, and acceptance (Messner et al., 2019; Torous, 2018). These evaluations are critical in informing app adaptations and ensuring users are provided with a safe, helpful, and engaging experience. Second, few studies evaluating MH apps have quantitively evaluated acceptance using well-validated theoretical models of technology acceptance (Hajesmaeel-

Gohari et al., 2022; Ng et al., 2019). To our knowledge, no study has used the core constructs of UTAUT2 to examine the acceptance of a specific MH app quantitatively. Thus, it is unclear how useful constructs and relationships in the UTAUT2 framework apply to the acceptance of MH apps.

Third, when the quality and usability of MH apps have been evaluated, a wide variety of different measures are used, and few studies use questionnaires explicitly designed to evaluate mHealth apps (Hajesmaeel-Gohari et al., 2022; Inal et al., 2020; Zhou et al., 2019). This is especially true when assessing quality from the user's perspective (Hajesmaeel-Gohari et al., 2022). Minimal use of measures designed for mHealth apps can result in missing important facets of quality and usability unique to these apps (e.g., characteristics associated with small screens). Moreover, inconsistent measures in the mHealth app literature hinder comparing results across studies and prevent a thorough understanding of what makes a quality and usable mHealth app (Ng et al., 2019; Zhou et al., 2019). Fourth, more research is needed on whether recent measures designed to evaluate the usability and quality of mHealth apps predict future app use (Ng et al., 2019). Although usability and quality are consistently shown to be important in the acceptance of mHealth apps (Jacob et al., 2022), whether they predict future use is less clear. Fifth, studies integrating personality traits into technology acceptance models are limited (Nunes et al., 2019). Studies have yet to examine the associations between the ten aspects of the Big Five and the core constructs in any of these models.

The importance of the limitations in the broader literature also applies to the several limitations and future research needs identified in previous studies evaluating the JoyPop™ app. First, the JoyPop™ app has not quantitatively evaluated its acceptance and use using an established technology acceptance model. Second, the app has yet to be assessed for quality or usability using reliable and validated questionnaires designed for mHealth apps. Third, whether the usability and quality of the JoyPop™ influences future use is unknown. Fourth, there have not been any examinations of personality characteristics that influence the app's acceptance and use.

The Present Study

The overall purpose of the present study is to evaluate the acceptance, usability, and quality of the JoyPop™ app to determine whether it can be a valuable tool to support resilience and MH among a diverse sample of postsecondary students in need of equitable access to strength-based support. We also aimed to better understand factors influencing the acceptance and use of the JoyPop™ app to inform future adaptations and iterations. Specifically, our objectives were to 1) quantitatively examine factors influencing students' acceptance of the JoyPop™ app using the UTAUT2; 2) evaluate the overall acceptance, usability and quality of the app; 3) examine the relationship between usability and quality, and app use; and 4) examine the relationships between the ten aspects of the Big Five on behavioural intention and app use.

We used the UTAUT2 model to examine factors influencing the acceptance and use of the JoyPop™ app and evaluate its acceptance. It is a well-established and highly used model in understanding and predicting the acceptance and use of mHealth apps (Calegari et al., 2023; Schomakers et al., 2022; Yuan et al., 2015). Furthermore, despite being limited, research shows that many core constructs, such as performance expectancy, effort expectancy, social influence, and facilitating conditions, significantly predict behavioural intention to use MH apps among postsecondary students (Holtz et al., 2023; Mitchell et al., 2022). By incorporating this model, we assessed whether established UTAUT2 constructs that predict engagement and use of various mHealth apps and technologies are also important in the acceptance of a MH app like the JoyPop™ app. We also used the UTAUT2 to facilitate comparisons of findings to other studies evaluating the acceptance and use of MH and mHealth apps in general.

We evaluated the usability and quality of the JoyPop™ app from the user's perspective using two recently developed measures specifically designed for mHealth apps: the MAUQ created by Zhou et al. (2019) and the uMARS developed by Stoyanov et al. (2016). By using these measures, we comprehensively evaluated established quality and usability indicators unique to mHealth apps to gather a better understanding of how quality and usability influence the use of the JoyPop™ app and facilitate comparisons of results with other mHealth apps. We incorporated the Big Five aspects to capture nuanced relationships among personality traits, behavioural intention, and app use that may not be evident using the Big Five domains.

Hypothesis Development

UTAUT2 and Core Constructs. Because no study has examined the acceptance of a specific MH app designed to improve resilience and emotion regulation, we based our hypotheses on the broader literature and the original UTAUT2 results (Calegari et al., 2023; Venkatesh et al., 2012). We did not include price value because the JoyPop™ app is currently only being used for research purposes and is free.

H1: Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit will significantly predict behavioural intention to use the JoyPop™ app.

H2: Behavioural intention, facilitating conditions, and habit will significantly predict use of the JoyPop™ app.

H3: Age, Gender, and Experience with MH apps (experience) will moderate the relationship between UTAUT2 constructs and behavioural intention.

H4: Experience will moderate the relationship between behavioural intention and use of the JoyPop™ app.

Usability, Quality, and MH app Use. Given that indicators of usability, such as usefulness, ease of use, satisfaction, and design features, and aspects of quality, such as credibility and quality of information, engagement, aesthetics, and functionality, are reliable and established barriers and facilitators to long-term use, and overall usage of MH apps (Jacob et al., 2022; Torous et al., 2018); we hypothesized that:

H5: Usability will significantly predict app use.

H6: Quality will significantly predict app use.

Personality, UTAUT2, and App Use.

Neuroticism (Volatility and Withdrawal). Because individuals higher in neuroticism are more likely to seek and use MH apps (Aziz et al., 2023) and prefer credibly sourced MH apps with many features contained within the JoyPop^{TM} app (e.g., social support, relaxation audios, and contacts for help (Alqahtani et al., 2021), we proposed:

H7: Neuroticism (Withdrawal and Volatility) will be positively associated with behavioural intention and use of the JoyPop^{TM} app.

Extraversion (Assertiveness and Enthusiasm). Given that people higher in extraversion show strong preferences for using credible MH apps with features that are found in the JoyPop^{TM} app (e.g., providing suggestions, distraction, praise, and relaxation exercises and audios (Alqahtani et al., 2021), we proposed:

H8: Extraversion (Assertiveness and Enthusiasm) will be positively associated with behavioural intention and use of the JoyPop^{TM} app.

Agreeableness (Compassion and Politeness). Given that individuals higher in agreeableness strongly prefer using MH apps with similar features to the JoyPop^{TM} app (e.g., relaxation exercises and audios, self-monitoring, praise, and social support; Alqahtani et al., 2021), we proposed:

H9. Agreeableness (Compassion and Politeness) will be positively associated with behavioural intention and use of the JoyPop^{TM} app.

Conscientiousness (Industriousness and Orderliness). Given that conscientiousness reliably influences behavioural intention and use of mHealth and MH apps (Barnett et al., 2015; Ervasti et al., 2019; Khawaja et al., 2021) and people high in conscientiousness are motivated by MH apps like the JoyPop^{TM} app with trusted information and features related to relaxation, encouragement, suggestions, and contacts for help (Alqahtani et al., 2021); we proposed:

H10: Conscientiousness (Industriousness and Orderliness) will be positively associated with behavioural intention and use of the JoyPop^{TM} app.

Openness to Experience (Openness and Intellect). Openness to experience positively affects behavioural intention and use of technology (Devaraj et al., 2008; McElroy et al., 2007). Individuals high on openness to experience are also motivated by MH apps containing features similar to the JoyPop™ app (e.g., self-monitoring, relaxation, and social support; Alqahtani et al., 2021). Thus, we proposed:

H11: Openness to Experience (Openness and Intellect) will be positively associated with behavioural intention and use of the JoyPop™ app.

Method

Design

The study was approved by the Research Ethics Board at Lakehead University. We used a quantitative within-subjects, one-week prospective design to evaluate the acceptance, usability, and quality of the JoyPop™ app and better understand factors influencing its use. We employed a quantitative methodology to fill in the highlighted gaps in the broader MH app literature and those related to the JoyPop™ app. We used a one-week prospective design to ensure students had sufficient time to use the app thereby facilitating more informed app evaluations. Technology acceptance is a temporal process with three critical evaluation phases that lie on a continuum: before use (acceptability), short-term use (acceptance), and long-term use (adoption; Nadal et al., 2020). Indicating that we are focusing on short-term use (acceptance) will help facilitate reporting, replicating, and comparing MH app acceptance studies (Nadal et al., 2020).

Participants

Participants were eligible for the study if they were a student at Lakehead University and spoke/read fluently in English. We selected this sample because the JoyPop™ app was developed for young adults, who comprise a significant portion of the university population (Statistics Canada, 2022b), and one objective of the JoyPop™ app is to be a valuable and accessible tool to support the MH of postsecondary students.

Procedure

We recruited a convenience sample of students throughout the fall (2023) and winter (2024) academic semesters across the Lakehead University Thunder Bay campus. We recruited students with: flyers posted around campus and online (e.g., via Facebook; Appendix A – Poster); announcements made in classes (Appendix B – Class Announcement); postcards given to students across campus and after class (Appendix C – Postcard); and emails to students (e.g., through course instructors (Appendix D – Class Email)). We also posted the study online through the Department of Psychology SONA system (http://lupsych.sona-systems.com/) to recruit from the undergraduate psychology participant pool (Appendix E – SONA Ad). We took steps to increase the representativeness of our convenience sample and minimize sampling bias. First, we used various recruitment methods (e.g., posters, class emails, social media) to reach a wide range of students. Second, we had no restrictions on participant characteristics, such as year of study or program, which could improve the diversity of our sample. Third, to minimize biases of excluding those who do not have an iOS device, we provided refurbished iPhones with the JoyPop™ app for participants who did not have a suitable device of their own. There were three parts to the present study. For Part 1, we had interested students schedule an in-person orientation session with the research team (via a lab phone (text/call), email, scanning a QR code, or through Lakehead's SONA system). We emailed/texted students who contacted the research team with study details and times to schedule an orientation session (see Appendix F – Participant Recruitment (text/email)). We directed SONA students to a calendar of available orientation sessions to book a time. Once scheduled, we reminded participants of their orientation time and date (see Appendix G – Confirmation Orientation Reminder (text/email)). During the orientation, we emailed participants an ID number, SurveyMonkey link, and date to complete post-app surveys (see Appendix H - Day of Orientation Information), review study details (see Appendix I – Information Letter), and complete the informed consent form (see Appendix J – Consent Form). We reviewed the information letter and consent form with participants and gave them time to ask questions. We provided participants with contact information for MH support if they experienced distress during the study. Participants also completed pre-app measures (see Appendix K – List of Measures; Appendix L - Measures) and received information on downloading and using the app for the study. We sent reminders about booked orientation sessions one day prior (see Appendix M – Orientation Reminders (text/email)). If participants missed an orientation, we provided them opportunities to reschedule (see Appendix N – Missed Orientation Reminder (text/email)).

In Part 2, we suggested that participants use the app at least 2x/day and sent reminders to use the app at 8 am and 8 pm (see Appendix O – Daily app Use Reminders (text/email)). In Part 3, we emailed/texted a SurveyMonkey link requesting participants to complete post-app measures online on the relevant day (see Appendix P – Survey 2 Reminder (text/email)). If measures were not completed, we sent a total of three reminders (one day in between; see Appendix Q – Missed Survey 2 Reminder (text/email)). Upon completion, we reminded participants that they can continue using the app for free (see Appendix R – App Completion (text/email). Students using a loaned iPhone for the study were told to contact the research team for free access to the app if they obtained a suitable device in the future. We compensated participants via cash/e-transfer or bonus course marks towards an eligible psychology course. They received $10 for Part 1 (or one bonus point) and $20 upon completing Part 3 (1.5 bonus points).

Pre-App Measures

Demographics

We captured demographics with 13 items (see Appendix L – Measures) to describe the characteristics of the sample and conduct moderation (i.e., gender and age) and attrition analyses. One item related to MH service was a filter question to ensure that only participants who have used (or are currently using) MH services or computer-based MH services answered the preceding item (see item 12 in Appendix L – Measures). We numerically coded all categorical (i.e., ordinal, nominal, binary) variables to facilitate analysis.

MH app Experience

We collected information on participants' experience with MH apps using five items (see Appendix L – Measures) to describe the characteristics of the sample and conduct moderation and attrition analysis. We adapted items from previous measures of technology experience by Venkatesh et al. (2012) and Jabour et al. (2021) by removing ordinal response categories and replacing them with open-ended continuous response options (e.g., "For how long have you used MH-related apps? Approximate in months"). Whether participants had used app- or computer-based MH care (item one) was coded as a binary categorical variable to conduct moderation analyses (i.e., experience).

The Big Five Aspects Scale (BFAS)

We used the BFAS to measure the ten aspects of the Big Five personality traits. The BFAS is a 100-item self-report questionnaire comprised of items from the International Personality Item Pool (see Appendix L – Measures; DeYoung et al., 2007). The BFAS assesses the Big Five domains and ten lower-order aspects. Each domain scale has two 10-item aspect scales with brief statements asking participants to rate their agreement with how well a statement describes them on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree): Openness to Experience (Intellect; "Think quickly" and Openness; "Enjoy the beauty of nature"), Conscientiousness (Industriousness; "Carry out my plans" and Orderliness; "Like order"), Extraversion (Enthusiasm; "Make friends easily" and Assertiveness; "Take charge"), Agreeableness (Compassion; "Feel others' emotions" and Politeness "Respect authority"), and Neuroticism (Volatility; "Get angry easily" and Withdrawal; "Worry about things"). We calculated scores for each aspect by computing the mean of corresponding scale items and scores for each domain by taking the mean of the two aspect scores comprising a domain.

Domain and aspect scales show good convergent validity with related personality measures (e.g., Revised NEO Personality Inventory; Costa & McCrae, 1992a; 1992b) and good structural and construct validity (e.g., predicting depressive symptoms and well-being; DeYoung et al., 2007). The BFAS shows good test-retest reliability (Neuroticism = .85, Volatility = .85, Withdrawal = .81; Agreeableness = .79, Compassion = .79, Politeness = .74; Conscientiousness = .86, Industriousness = .82, Orderliness = .79;

Extraversion = .83, Enthusiasm = .73, Assertiveness = .86; Openness/Intellect = .82, Intellect = .86, Openness = .79) and high internal consistency (Neuroticism = .89, Volatility = .85-.89, Withdrawal = .80-.84; Agreeableness = .84-.89, Compassion = .84-.91, Politeness = .75-.76; Conscientiousness = .81.84, Industriousness = ..79-.82, Orderliness = .72-.80; Extraversion = .85-.88, Enthusiasm = .80-.81, Assertiveness = .84-.88; Openness/Intellect = .80-.85, Intellect = .79-.84, Openness = .72-.88) in diverse samples (e.g., clinical, community, student), including Canadian university students (Allen et al., 2017; DeYoung et al., 2007; 2016; Lyon et al., 2021; Quilty et al., 2013; Weisberg et al., 2011). The internal consistency of domain and aspect scales were suitable in the present study (Neuroticism = .90, Volatility = .89, Withdrawal = .82; Agreeableness = .82, Compassion = .83, Politeness = .72; Conscientiousness = .88, Industriousness = .86, Orderliness = .75; Extraversion = .84, Enthusiasm = .79, Assertiveness = .84; Openness/Intellect = .75, Intellect = .80, Openness = .58).

Post-App Measures

Adapted UTAUT2 Scale

We used the UTAUT2 scale developed by Venkatesh et al. (2012) to measure the seven core constructs of the UTAUT2 model with 23 items slightly adapted to fit the context of the present study (see Appendix L – Measures). While the original measure asks respondents to rate their agreement to statements related to the acceptance of mobile internet, we adapted our measure so participants rated their agreement to statements related to the acceptance of the JoyPop™ app. Items were rated on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree): Performance expectancy (three items; "I find the JoyPop™ app useful in my daily life"), Effort expectancy (four items; "Learning how to use the JoyPop™ app is easy for me"), Social influence (three items; "People who are important to me think that I should use the JoyPop™ app"), Facilitating conditions (four items; "I have the resources necessary to use the JoyPop™ app"), Hedonic motivation (three items; "Using the JoyPop™ app is fun"), Habit (three items; "The use of the JoyPop™ app has become a habit for me"), and Behavioural intention (three items; "I intend to continue using the JoyPop™ app in the future").

While most adaptations replace “mobile internet” with “the JoyPop™ app”, we also adapted one original item from Performance Expectancy “Using mobile internet increases my productivity,” to “Using the JoyPop™ app improves my mental health and/or productivity” and one original item for Habit “I am addicted to using mobile internet” to “I am immersed in using/accepting the JoyPop™ app”, which was based on a MH app adaptation by Wu et al. (2022). We calculated total scores for each construct by summing corresponding item scores and averaging them using the mean. We used participants’ scores on the behavioural intention construct scale to evaluate overall acceptance of the JoyPop™ app. To facilitate the interpretation of the app’s overall acceptance, we reported the frequencies (percentages and a frequency distribution) of participant scores (ranging from strongly disagree to strongly agree) on the construct of behavioural intention (Sullivan & Artino, 2013).

Both the original and adapted versions of the UTAUT2 scale and associated constructs show high internal consistency reliability (Cronbach’s alpha and composite reliability) and good convergent, discriminant, and construct validity across diverse samples (including university students) and technologies, including MH apps (Schomakers et al., 2022; Tamilmani et al., 2021; Venkatesh et al., 2012; Yuan et al., 2015). Among postsecondary students, strong construct and convergent validity are demonstrated with factor loadings between items and associated constructs being high: performance expectancy (.79-.83), effort expectancy (.82-.88), social influence (.86-.93), facilitating conditions (.75-.77), hedonic motivation (.83-.91), habit (.72-.83), behavioural intention (.87-.91; Nikolopoulou et al., 2020). Good discriminant validity is shown by average variance extracted estimates being greater than 0.5: performance expectancy (.64), effort expectancy (.71), social influence (.81), facilitating conditions (.58), hedonic motivation (.78), habit (.59), behavioural intention (.78; Nikolopoulou et al., 2020; Tamilmani et al., 2021). Reliability estimates are also high in samples of postsecondary students. For example, Cronbach’s alphas are good (performance expectancy = .82-.89, effort expectancy = .87-.90, social influence = .88-.89, facilitating conditions = .76-.83, hedonic motivation = .85-.89, habit = .77-.89, behavioural intention = .85-.90; Nikolopoulou et al., 2020; Tamilmani et al., 2021) and composite reliability is strong (performance expectancy = .88, effort expectancy = .91, social influence = .93, facilitating conditions = .85, hedonic motivation = .91, habit = .85, behavioural intention = .91; Nikolopoulou et al., 2020). Validity and reliability are also shown in university students using MH apps. For instance, Schomakers et al. (2022) found that the composite reliability of all constructs was greater than 0.71. The internal consistency of construct scales in the present study mostly adequate (performance expectancy = .90, effort expectancy = .74, social influence = .91, facilitating conditions = .57, hedonic motivation = .91, habit = .81, behavioural intention = .94.

The mHealth App Usability Questionnaire

The MAUQ (MAUQ; Zhou et al., 2019) assesses the usability of mHealth apps and has four versions depending on the app (interactive or standalone) and user (patient or health care provider). We used the 18-item standalone patient version of the MAUQ in the present study as it best suits the context (see Appendix L – Measures). Overall usability includes three subscales (Ease of Use, Interface and Satisfaction, Usefulness) that can be individually examined. Participants rate their level of agreement with brief statements on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree): Ease of Use (five items; “The app was easy to use”), Interface and Satisfaction (seven items; “I like the interface of the app”), and Usefulness (six items; “The app would be useful for my health and well-being”). We determined overall usability by calculating the mean of all items. We derived subscale scores by computing the mean of scores for relevant subscale items. We calculated and used the quarters for the total mean value (7) on the overall scale and each subscale to facilitate reporting and interpreting results. The range of mean values for each quarter was: 0–1.75 (poor), 1.76–3.50 (moderate), 3.51–5.25 (good), and 5.26–7 (very good).

From the initial validation sample (N = 128, 52.3% between ages 18-28, 96.1% having postsecondary education, 31.3% current students), the standalone patient version has good structural validity demonstrated by adequate factor loadings between items and subscales (Ease of Use = .42-.81, Interface and Satisfaction = .44-.84, Usefulness = .38-.68) and adequate criterion and construct validity via correlations with valid measures of technology usability (overall scale = 0.72 to 0.86, Ease of Use = .64-.81, Interface and Satisfaction = .74-.85, Usefulness = .38-.59). The MAUQ also shows adequate internal consistency (overall scale = .91, Ease of Use = .85, Interface and Satisfaction = .91, Usefulness = .72; Zhou et al., 2019). The internal consistency of the overall scale and subscales in the present study were strong (overall scale = .92, Ease of Use = .79, Interface and Satisfaction = .86, Usefulness = .85).

User Version of the Mobile Application Rating Scale (uMARS)

The uMARS (Stoyanov et al., 2016) was developed as a simple and reliable tool for end-users to assess mHealth app quality (see Appendix L – Measures). We used the uMARS to evaluate the quality of the JoyPop^{TM} app in the proposed study. The uMARS is a 27-item measure adapted from the original Mobile Application Rating Scale (MARS; Stoyanov et al., 2015) with four Objective Quality subscales (16 items: Engagement, Functionality, Aesthetics, and Information Quality), one Subjective Quality subscale (four items), and one Perceived Impact subscale (six items). The Objective Quality scales assess quality indicators based on research and expert and clinician recommendations. Users select a number most accurately representing the quality of the app they are rating on a five-point Likert scale ranging from 1 (inadequate) to 5 (excellent), with an option to select “N/A” on specific items if they are not relevant to the app: Engagement (five items; “Is the app fun/entertaining to use? Does it have components that make it more fun than other similar apps?”), Functionality (four items; “How easy is it to learn how to use the app; how clear are the menu labels, icons and instructions?”), Aesthetics (three items; “Is the arrangement and size of buttons, icons, menus and content on the screen appropriate?”), and Information (four items; “Is the app content correct, well written, and relevant to the goal/topic of the app?”). We derived each subscale scale score by calculating the mean of relevant items (items rated as N/A were omitted). We calculated the overall Objective Quality score by computing the mean score among subscales. To facilitate the interpretation of the overall Objective Quality scale and corresponding subscales, we used descriptors for different ranges of scores: 0-1 (Inadequate), 1-2 (poor), 2-3 (acceptable), 3-4 (good), and 4-5 (Excellent). These descriptors are consistent with prior studies and individual item ratings on the Objective Quality scales, which can facilitate the comparisons of apps in specific domains (Hoffman et al., 2019; Lebeau et al., 2019).

The Subjective Quality scale allows users to provide subjective quality ratings on a five-point Likert scale ranging from 1 to 5 (what numbers represent varies with each question). For example, users are asked if they would recommend the app to people who might benefit from it and provide an answer ranging from 1 (Not at all) to 5 (Definitely) or provide an overall (star) rating of the app (one star = “one of the worst apps I’ve used” to five stars = “one of the best apps I’ve used”). The Perceived Impact scale was designed to be adapted to the purpose of an app to assess its impact on user knowledge, attitudes, and intentions (i.e., The JoyPop^{TM} app was designed to impact MH and coping skills; thus, items are adapted accordingly). Users rated their level of agreement on a five-point Likert scale ranging from 1 (strongly disagree) to five (strongly agree) to examine the app’s impact on Awareness, Knowledge, Attitudes, Intention to Change, Help-Seeking, and Behaviour Change. For instance, Awareness “The JoyPop^{TM} app has increased my awareness of the importance of addressing mental health and coping skills”, and Attitudes “The JoyPop^{TM} app has changed my attitudes toward improving mental health and coping skills”. We calculated total scores by using the mean score for corresponding items on the Subjective Quality and Perceived Impact scales and reported frequencies of responses to individual items comprising each scale.

From the validation sample (N = 133, M_{age} = 19.8 [SD = 2.51], 57.9% students, 24.4% had a bachelor’s degree or higher), the overall Objective Quality scale shows excellent internal consistency (Cronbach alpha =.90) with high internal consistency among subscales (Engagement =.80, Functionality = .70, Aesthetics = .71, Information = .78) and the overall Subjective Quality scale (.78). Three month test-retest reliability estimates are good for the overall Objective Quality scale = .70 and relevant subscales (Engagement = .73, Functionality = .69, Aesthetics = .68, Information = .52) and for the Subjective Quality subscale (.71; Stoyanov et al., 2016). The internal consistency of the overall Objective Quality scale and subscales in the present study were good (Objective Quality = .89, Engagement = .77, Functionality = .75, Aesthetics = .78, Information = .79). The internal consistency of the Subjective quality and Perceived Impact scales were also good (Subjective Quality = .79, Perceived Impact = .93).

App Use

We used item two of the subjective quality scale on the uMARS (see Appendix L – Measures) to examine app use because it is conceptually similar to the original use question on the UTAUT2 questionnaire and is specifically designed to assess the frequency of prospective use of mHealth apps. This item asks users to rate "How many times do you think you would use the JoyPop™ app in the next 12 months if it was relevant to you" on a five-point scale ranging from 1 (None) to 5 (> 50 times). We also used usage data automatically tracked through the app to calculate the number of days participants used the app within a five-day period (out of a total of seven days). We selected a five-day period because all participants used the app on the first day (i.e., during an orientation session where they would familiarize themselves with it). Further, we did not include the final day participants were involved in the study because the purpose of this day was to complete post-app measures. However, we chose not to use the number of days participants used the app within this five-day period as the primary app use outcome variable because of the likelihood that there would be insufficient variation in days used.

Data Analysis

We downloaded and collected all data from Survey Monkey and then transferred it into SPSS (IBM Corp, 2021) to assess data characteristics, generate descriptive statistics for all variables, and evaluate the acceptance, usability, and quality of the JoyPop™ app. We used the SmartPLS version 4 software (Ringle et al., 2022) to conduct Partial Least Square Structural Equation Modelling (PLS-SEM) and examine hypothesized predictive-causal relationships (H1 to H11).

Data Characteristics

Prior to the analysis**,** we examined missing data, suspicious response patterns, outliers, and nonnormality. We used Little's MCAR test (Little, 1988) and observed graphs of missing value patterns to assess if missing data was missing completely at random (MCAR), missing at random (MAR), or missing not at random (MNAR). The methods we employed to deal with missing data depended on the proportion of missing data and the missing data mechanism. In line with the most recent PLS-SEM guidelines and recommendations (Hair et al., 2022), we planned to exclude indicators with > 15% missing values and respondents with > 15% missing data from the analysis (Hair et al., 2022). If data was MCAR and missing values per indicator were <5%, we planned on using mean imputation methods. PLS-SEM is highly robust when missing data is <5%, with studies showing that mean imputation in PLS-SEM does not inflate type I errors and produces minimally biased path coefficients and loading estimates (Hair et al., 2022; Kock, 2018). Although mean imputation is criticized for reducing variability and producing biased estimates, studies demonstrate that this is most relevant when approximately 10% or more of the values in the dataset are missing (Eekhout et al., 2014; Shrive et al., 2006). Thus, we planned to use person-mean imputation if the number of items missing on a scale was 20% or less and item mean substitution if greater than 20% were missing. Person-mean substitution produces less biased estimates than item-mean substitution; however, when items missing on a scale are greater than 20%, person-mean imputation tends to inflate reliability estimates (Bono et al., 2007; Downey & King, 1998).

If data were not MCAR (i.e., data is MAR or MNAR) and/or missing data were >10%, we planned to use multiple imputation with at least 40 different data sets to account for missing data because this method consistently produces unbiased parameter estimates and standard errors (Newman, 2014; Eekhout et al., 2014). Multiple imputation accounts for missing data by repeating a procedure that uses the relationships and distributions of observed variables to impute missing data, which results in many different datasets with missing data replaced. The imputed datasets are then combined and analyzed to produce results (e.g., parameter estimates; Newman, 2014). Mean imputation, on the other hand, is shown to produce biased estimates when data are missing for >10% of subjects and/or data is not MCAR (Eekhout et al., 2014; Newman, 2014).

We planned to identify and remove suspicious response patterns such as straight lining (same responses for many questions), diagonal lining (response patterns on diagonal line), and alternating extreme pole responses (responses only use extreme poles of a scale in alternating order) via visual inspection and by looking at descriptive statistics of answers per respondent (e.g., mean, variance, distributions; Hair et al., 2022).

We assessed whether there were univariate and multivariate outliers using various statistics (e.g., Mahalanobis distance) and graphs (e.g., box plots, scatterplots of Mahalanobis distance values). Although boxplots identify values 1.5 times greater or less than the IQR as outliers, this cutoff has been shown to overestimate the number of outliers (Hoaglin & Iglewicz, 1987). Thus, we classified univariate outliers as values three times greater or less than a variable's interquartile range (IQR). To identify multivariate outliers, we assessed whether significant differences exist between participants' Malahanobis distance scores (calculated from all independent variables used in the analysis) and the multivariate mean of those variables. We ranked and plotted each participant's distance scores to visually assess if multivariate outliers were extreme. We planned on retaining identified outliers with a logical explanation for their values, removing outliers resulting from suspicious response patterns, and correcting outliers resulting from data collection or entry errors (e.g., Hair et al., 2022; Sarstedt et al., 2022).

We examined whether the data is highly nonnormal by assessing if skewness and kurtosis values were greater than -2 and +2 when examining histograms of indicators and the bootstrap parameter estimate distributions (e.g., path coefficients, outer loadings; Hair et al., 2019, 2022). PLS-SEM is robust to highly nonnormal data and has no distributional assumptions (Hair et al., 2019). However, assessing for substantial nonnormality is important because highly nonnormal data prompts using the bias-corrected accelerated bootstrap (BCa) method in PLS-SEM to provide accurate and reliable results. The BCa method accounts for highly asymmetric data and skewed bootstrap parameter estimate distributions (Hair et al., 2022; Sarstedt et al., 2022).

Sample Size Estimation

The ten times rule is often used to estimate the minimum required sample size for 80% power at the 0.05 significance level for PLS-SEM models (Hair et al., 2022). This rule suggests that the sample size should equal ten times the number of independent variables in the structural model (Hair et al., 2022). However, this approach can underestimate the sample size for sufficient power and does not consider the entire model being assessed (Hair et al., 2022). We employed the inverse square root method (Kock & Hadaya, 2018) in the present study because it is a more conservative and accurate sample size estimate (Hair et al., 2022; Kock & Hadaya, 2018). This method examines the probability that the ratio of a path coefficient and its standard error will be larger than the critical value of the test statistic at the specified significance level (Kock & Hadaya, 2018). Thus, the minimum needed sample size depends on the smallest path coefficient one expects to be significant, which is determined based on prior research with similar conceptual models (Hair et al., 2022; Kock & Hadaya, 2018).

Prior research on the acceptance of MH apps using the UTAUT2 framework and research on the relationship between Big Five domains, behavioural intention, and technology use in postsecondary student samples have found that the smallest significant path coefficient at the $p \leq 0.05$ level was 0.19 in the relationship between social influence and behavioural intention (Schomakers et al., 2022) and 0.18 for the association between neuroticism and use (Barnett et al., 2015). Based on minimum sample size requirement tables derived from the inverse square root method found in Hair et al. (2022, p. 49), to detect a minimum significant path coefficient between 0.11 and 0.20, we required a minimum sample size of 155 for 80% power at the 5% significance level. Therefore, based on a similar study by MacIsaac et al. (2021), with ~12% of 156 participants not completing follow-up measures after two weeks of app use, we aimed to recruit 175 participants to account for an estimated 12% attrition throughout the study.

Partial Least Square Structural Equation Modelling (PLS-SEM)

PLS-SEM is one of two SEM methods, the other being Covariance-based SEM (CB-SEM). CB-SEM estimates model parameters to minimize the sample covariance using a common factor model (Hair et al., 2019). PLS-SEM aims to maximize the explained variance of endogenous latent variables by calculating composites of indicators representing research constructs by estimating partial model relationships via an iterative sequence of ordinary least squares regression (Hair et al., 2019, 2022). PLS-SEM was chosen for several reasons. First, although similar to multiple regression analysis (maximizing variance explained in dependent constructs), PLS-SEM focuses on maximizing variance in dependent latent constructs and increases the reliability and validity of model estimates by evaluating data quality using measurement model characteristics while minimizing measurement error by individually weighing indicators forming latent constructs (Hair et al., 2019, 2022). Second, PLS-SEM has specific advantages to CB-SEM, such as being more robust to distributional assumptions (e.g., nonnormality) and identification issues, along with having higher levels of statistical power in complex models with small sample sizes (Hair et al., 2022). Finally, and most importantly, PLS-SEM is seen as the preferred method of analysis when a study aims to test the predictive capability of a causal-predictive model based on theory and logic, when a structural model is complex with many constructs (six or more) and relationships, and when moderating effects are included (Hair et al., 2019, 2022; Liengaard et al., 2021). The causal-predictive nature makes PLS-SEM especially useful when deriving recommendations, such as informing future adaptions to the JoyPop™ app to improve acceptance (Hair et al., 2019, 2022).

We evaluated two key components within the PLS-SEM model: a measurement model (outer model), which assesses relationships between indicator variables and latent constructs and a structural model (inner model), which links constructs together and shows relationships between constructs (Hair et al., 2022). We employed a strictly reflective measurement model (measures represent an effect of an underlying construct) because among all variables in the analysis, "causal" priority went from constructs to indicators (i.e., all indicators stem from the same construct), and thus, a change in construct's scores would result in a simultaneous change on all items forming the construct (Hair et al., 2022). Throughout the measurement and structural model evaluations, we based our evaluation criteria and decision-making processes on the most recent PLS-SEM guidelines, recommendations, and research summarized by Hair et al. (2022) and Sarstedt et al. (2022).

Measurement Model Evaluation. In our measurement model evaluation, we assessed indicator reliability, internal consistency reliability, convergent validity, and discriminant validity of the indicators and constructs in the model (i.e., UTAUT2 constructs, ten aspects of the Big Five, usability, and quality). We removed indicators and constructs that did not meet reliability and validity evaluation criteria from the model to ensure that quality measures were used in the structural model (Hair et al., 2022).

We assessed indicator reliability by examining outer loadings of constructs (i.e., contribution of an indicator to the corresponding latent construct) to determine whether indicators were adequately captured by their corresponding construct. It is recommended that outer loadings should be greater than .70 because it demonstrates that a construct explains more than 50% of an indicator's variance (Hair et al., 2022; Sarstedt et al., 2022). Indicators with outer loadings below 0.40 should always be removed from their relevant construct (Hair et al., 2022). We considered indicators with outer loadings between $\geq$ 0.40 and $<$ 0.70 for removal if removing them increased the internal consistency reliability or convergent validity of a construct to recommended thresholds and did not compromise content validity. We retained indicators with outer loadings within these ranges of values if the indicator's construct met the recommended thresholds for internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2022; Sarstedt et al., 2022).

We assessed internal consistency reliability via Cronbach's alpha (Cronbach's α; reliability based on intercorrelations of observed indicator variables), composite reliability (ρ_C; reliability of construct scores based on assessing indicator loadings), and an exact reliability coefficient (ρ_A; consistent estimate of the reliability of construct scores using construct's weights rather than loadings; Dijkstra & Henseler, 2015; Hair et al., 2022; Sarstedt et al., 2022). Evaluation criteria suggest that all internal consistency estimates should be $\geq$ 0.70. This indicates strong internal consistency reliability of measured constructs in the model (Hair et al., 2022; Sarstedt et al., 2022).

We assessed convergent validity (degree to which a reflective construct explains the variance of its indicators) by computing the average variance extracted (AVE) for all items for each construct (i.e., squaring loadings of each indicator on a construct and computing the mean value). AVE's ≥ 0.50 are recommended because a construct should explain at least 50% of the variance of corresponding items (Hair et al., 2022; Sarstedt et al., 2021).

We examined the discriminant validity (degree constructs are distinct from other constructs in the model) of constructs via the heterotrait-monotrait ratio (HTMT). The HTMT estimates the true correlation between two constructs if they were perfectly measured and is a more reliable and accurate assessment of discriminant validity than other common methods, such as using the Fornell-Larcker criterion (Hair et al., 2022; Sarstedt et al., 2022). Values < 0.85 for conceptually distinct constructs and < 0.90 for conceptually similar constructs (e.g., those with commonalities among indicators) are recommended for adequate discriminant validity (Henseler, et al., 2015; Sarstedt et al., 2022). Considering the conceptual similarity among UTAUT2 constructs, the < 0.90 cut-off value was used in the present study.

Structural Model Evaluation. We examined relationships between core constructs of the UTAUT2 and behavioural intention (H1), the influence of behavioural intention, facilitating conditions, and habit on usage of the JoyPop™ app (H2), the relationships between usability and quality on use of the JoyPop™ app (H5 and H6) and the effect of the ten aspects of the Big Five on behavioural intention and use of the JoyPop™ app (H7-H11) within our structural model (see Figure 2).

We checked for collinearity among all predictor relationships in the inner model by examining the variance inflation factor (VIF). It is recommended that VIFs are ≤ 3 because this indicates no collinearity issues (Hair et al., 2022; Sarstedt et al., 2022). However, more important is that VIFs < 5 because any values greater than 5 indicate critical levels of collinearity, which then requires removing constructs or merging highly correlated constructs based on theoretical justifications (Hair et al., 2022).

We used the coefficient of determination (R^2) and adjusted R^2, which accounts for model overfit (i.e., if R^2 is too high resulting from model complexity and random noise in the sample), to examine our structural model's explanatory power (Hair et al., 2022; Sarstedt et al., 2022). R^2 values of 0.75, 0.50 and 0.25 are considered substantial, moderate and weak (Hair et al., 2019, 2022). To test hypothesized relationships in the structural model, we conducted a one-tailed test at the 5% significance level with PLS-SEM's nonparametric bootstrap procedure (10,000 iterations) to estimate path coefficients and their associated *t* values, *p* values, and confidence intervals. Guidelines suggest using 10,000 iterations in the bootstrap procedure to obtain stable results and ensure analyses are based on a solid sample distribution (Hair et al., 2022; Streukens & Leroi-Werelds, 2016). The percentile method is the recommended default option for estimating path coefficients. However, when there is data that deviates significantly from normality and when asymmetrical bootstrap distributions for parameter estimates are found, the BCa bootstrapping method is recommended over the percentile method because it provides improved stability and reduced bias in parameter estimates while yielding very low Type 1 errors (Hair & Alamer, 2022; Sarstedt et al., 2022). Thus, if highly skewed (skewness and kurtosis values beyond -2 and +2) data in the sample and among the bootstrap distributions of parameter estimates were found, we planned to use the BCa bootstrapping method (Hair et al., 2022; Sarstedt et al., 2022).

To assess the relevance of significant relationships, we examined f^2 effect sizes. The f^2 effect size helps clarify the unique impact of a predictor variable on its corresponding dependent variable by examining the change in R^2 value when a significant predictor is excluded from the model (Hair et al., 2022). We used Cohen's (1988) guidelines for interpreting the f^2 effect size, with values of 0.02, 0.15, and 0.25 representing small, medium, and large effects.

It is important to note that R^2 values are not considered true estimates of a model's predictive power (a model's utility in predicting new observations; Hair et al., 2022). R^2 is calculated by squaring the correlations of actual and predicted values. It encompasses all data used for model estimation and thus measures in-sample predictive power (Hair et al., 2019; Sarstedt et al., 2023). It does not provide a clear indication of the model's prediction power outside of the sample data included in the initial calculation of the model (Hair & Alamer, 2022; Hair et al., 2022). Novel methods to examine out-of-sample prediction power are now available to evaluate the predictive power of a structural model and its external validity across similar research design contexts (Hair & Alamer, 2022; Shmueli et al., 2016).

If our hypothesized structural model was significant, we planned to test its out-of-sample prediction power using the novel and recommended $PLS_{predict}$ procedure option in SmartPLS 4 (Hair et al., 2022; Shmueli et al., 2016). The $PLS_{predict}$ procedure estimates the predictive power of a structural model by generating estimates of model parameters using a subset of observations (training sample) and using them to predict the values of observations that have been omitted when generating parameter estimates (holdout sample; see Shmueli et al., 2019). Model estimates from the training sample are applied to values on predictor variable indicators gathered from the holdout sample to generate predictions among the dependent construct indicators within the holdout sample (Hair & Alamer, 2022; Shmueli et al., 2019). $PLS_{predict}$ examines the strength of a model's out-of-sample prediction power of dependent construct indicators by comparing prediction errors (the root mean squared errors [RMSEs]) produced by the PLS-SEM model to those made by a naïve linear regression model (LM; Hair & Alamer, 2022; Shmueli et al., 2019). The naïve LM derives predictions for the dependent variable indicators using indicators of exogenous latent variables while ignoring the specified PLS model (e.g., the measurement and structural model). Overall, this method provides valuable information about whether a theoretically established model improves (or, at minimum, does not worsen) the predictive utility of available data among indicators (Hair et al., 2022; Shmueli et al., 2019). See Table 3 for guidelines in interpreting PLSpredict results (also see Shmueli et al., 2019, for a thorough description of the $PLS_{predict}$ method).

Moderation Analysis. Consistent with the original UTAUT2 model, we examined the moderating effects of age, gender, and experience on the associations between core constructs of the UTAUT2 and behavioural intention (H3) and the moderating effect of experience on the association between behavioural intention and use of the JoyPop™ app (H4). Multigroup analysis (MGA) in PLS-SEM is recommended when assessing the influence of a moderating grouping variable (e.g., gender) across multiple relationships in a structural model (Cheah et al., 2023; Matthews, 2017). MGA is an efficient method to examine the influence of a moderating variable and provides a comprehensive assessment of the impact of a moderating variable on analysis results (Cheah et al., 2023; Hair et al., 2022). Using two identical PLS-SEM structural models, MGA examines the influence of a moderator on all modelled relationships in the structural model to test whether there are significant differences between group-specific parameter estimates (e.g., path coefficients; Cheah et al., 2023; Hair et al., 2022).

The key underlying assumption of MGA is that there is heterogeneity across groups (Henseler et al., 2016). If researchers pool data across relevant groups despite heterogeneity between groups, they risk dismissing important group-related differences in their model estimates and may produce inaccurate and unexpected results (Cheah et al., 2023; Henseler et al., 2016). To assess heterogeneity across groups, one must establish measurement invariance to ensure the validity of outcomes and that any group differences tested are not caused by different content or meanings of latent variables among the tested groups (Hair et al., 2022). The Measurement Invariance of Composite Models (MICOM) procedure in SmartPLS 4 is recommended to assess whether there is partial or full measurement invariance, and it involves three steps (Cheah et al., 2023Henseler et al., 2016). The first step is establishing configural invariance (i.e., equal parameterization and way of estimation) to ensure tested composites exist in all groups. The second step involves establishing compositional invariance (i.e., similar composite scores) to ensure composites are formed similarly across tested groups. The final step is establishing equality of composite mean values and variances. The first two steps must be established to continue with a meaningful MGA. If these first two steps are met, partial measurement invariance is confirmed, and the researcher can compare path coefficient estimates across groups. If full measurement invariance is confirmed (i.e., equal means and variances are found among composites across groups), the researcher can pool data for their analysis but must account for structural heterogeneity by including the moderator as an interaction effect (Cheah et al., 2023; Hair et al., 2022; Henseler et al., 2016).

In the present study, we had two grouping moderators that we planned to examine: gender and experience. We followed the above MICOM procedure to examine measurement invariance. If partial measurement invariance was established, we planned to compare whether path coefficients significantly differed between groups. If full measurement variance was established, we planned to pool data from groups and account for structural heterogeneity by creating interaction terms between moderating variables and relevant latent constructs using the two-stage approach (Cheah et al., 2023; Hair et al., 2022; Henseler et al., 2016). We also used this approach for the moderating variable age, a continuous variable unsuitable for MGA. We chose the two-stage approach because it provides better prediction accuracy, statistical power, and point estimation than other methods that include interaction variables, such as the product-indicator approach (Henseler & Chin, 2010; Sarstedt et al., 2022). To determine the significance of interaction terms and strength of the moderating effects, we calculated and interpreted the f^2 effect sizes (i.e., change in model and hypothesized associations R^2 with the inclusion of interaction terms; Hair et al., 2022; Sarstedt et al., 2022). The effect size of moderating effects are better interpreted with f^2 values of 0.005 (small), 0.01 (medium), and 0.025 (large) because standard cutoff values delineating f^2 effect sizes are less relevant when interpreting interaction terms (Aguinis et al., 2005; Hair et al., 2022). If significant moderating effects were found, we planned to create simple slope plots to facilitate their interpretation (Dawson, 2014; Hair et al., 2022).

Attrition Analyses

We planned to conduct an attrition analysis to compare whether there were significant differences between participants who completed post-app measures and those who only completed pre-app measures. Depending on the variable type, we planned to examine differences in demographics, MH app experience, and personality traits using either a *t*-test or a *chi-square* test.

Results

Participants

Pre-app measures were completed by 187 participants. Of these 187 participants, one did not complete post-app measures. Due to a SurveyMonkey data collection error, we lost data for three participants (on both pre- and post-app measures). Consequently, a final sample of 183 participants was included in the analysis resulting in sufficient power for the planned analyses. Considering the extremely low attrition rates, an attrition analysis was not feasible.

Data Characteristics

Among variables used in the analyses, Little's MCAR analysis demonstrated that data were missing completely at random (Little's MCAR test: $\chi 2$ (5486) = 5244.12, p = .990). Our missing value pattern analysis showed no systematic patterns among missing data. The total percentage of missing values within the dataset was 0.15%, and no indicators had more than 1.6% missing data. Because of the extremely low amounts of missing data, we did not remove any indicators or respondents from the analysis, and we used person-mean (when a scale had 20% or less of items missing) and item-mean imputation (scale had more than 20% missing) to impute missing data.

We did not find any suspicious response patterns (i.e., straight lining, diagonal lining, and alternating extreme pole responses) or data collection entries errors. We identified five univariate and four multivariate outliers. Upon inspection of individual items, we found no logical rationale to remove them (e.g., no signs of random or inconsistent responding). Furthermore, our visual inspection of statistical multivariate outliers (graphing participants' Mahalanobis distance values from highest to lowest; see Figure 3) showed that statistical outliers were not abnormally extreme compared to other multivariate data points. We found that a few indicators included in the PLS-SEM analysis had skewness and kurtosis values greater than -2 and +2 or skewed bootstrap parameter estimate distributions. Thus, we implemented the BCa method throughout the PLS-SEM analysis to account for asymmetric data and skewed bootstrap distributions.

Demographics

We present the demographic characteristics of the sample in Table 4. The majority of participants were female (82%). Ages ranged from 16-56, with a mean age of 22.60 (SD = 7.08). Participants were primarily between the ages of 16-21 (71%), 15.3% were between 22-30, and 9.8% were over 30. Regarding ethnicity, most participants identified as White (54.6%), followed by Black (18%). Of the 183 participants, the majority were full-time students (95.1%), and 42.6% of participants were in their first year of university, followed by 29.5% in their second year. When querying if participants had used MH services (currently or in the past), 42.1% answered yes. Of those that had used MH services, 10.9% had used them for 0-6 months, 3.3% for 7-11 months, 7.1% for 1-2 years, 14.8% for more than two years, and 7.1% could not recall the length of time.

MH app Experience

Regarding current or past use of app-based MH care, 80.9% of participants had not used it before. Of those who had used app-based MH care (19.1%), most used it for 0-6 months (62.9%), followed by not recalling the amount of time (20%) and 1-2 years (14.3%). Most participants reported not currently having a MH app on their phones/devices (86.3%). Of those participants, the primary reasons for not using this type of app were because they did not know about them or forgot that they are available (32.9%), they were not interested (24.1%), their MH was good and consequently did not need one (15.8%), cost concerns (7.6%), trust concerns (5.1%), and apps not being recommended by relevant others (e.g., counsellors; 5.1%). Among participants who reported having a MH app on their phone/device (13.7%), 88% had 1-3 apps, and 8% had more than seven apps. Frequency of use among these participants showed that 60% reported rarely using these apps, 12% reported using them once a week, 12% reported 2-3 times a week, and 16% used them once or twice a day. Reasons for not using MH apps among those who had one on their phone/device were forgetting to use them/getting out of the habit of using them (68%), being unsure if they are helpful (8%), not trusting them (4%), and not needing one for MH (4%); 12% reported multiple of the above reasons.

Descriptive Statistics of Primary Variables

We present means, standard deviations, domain and aspect correlations and internal consistency estimates on the BFAS in Table 5. Descriptive statistics are similar to prior research among postsecondary students (DeYoung et al., 2007; Weisberg et al., 2011). We found that usage data tracked through the app showed that the number of days used (*M* = 4.69, *Mdn* = 5, *SD* = 0.81) had extremely minimal variation, which confirmed our rationale for not including this as our measure of app use and using item two of the uMARS subjective quality scale as our primary measure of app use for all analyses.

Acceptance. We present means, standard deviations, and correlations among UTAUT2 construct scale scores in Table 6. Upon examining the frequencies of overall scores on the behavioural intention measure, we found that approximately 45.4% of participants indicated moderate (somewhat agree) to strong (strongly agree) acceptance of the app (range: 4.67-7), 25.1% showed low levels of acceptance (strongly disagree to somewhat disagree; range: 1-3.33), and 23% were unsure whether they intended to use the app (range: 3.67-4.33; See Figure 4).

Usability. We present descriptive statistics and further information relating to MAUQ scales, subscales, and items in Table 7. Participants rated the JoyPop™ app's overall usability as "very good" (*M* = 5.63 [*SD* = 0.85], range: 2.22-7), and 70% of the sample had scores in the "very good" range. Subscales show that, on average, participants rated the ease of using the app as "very good "(*M* = 6.37 [*SD* = 0.67], range: 3.20-7), and 92.3% of the sample reported scores in the "very good" range. Participants rated the interface and satisfaction with the app as "very good" (*M* = 5.70 [*SD* = 0.99], range: 1.57-7), and 68.9% had scores within the "very good" range. Participants rated the usefulness of the app as "good" (*M* = 4.93 [*SD* = 1.17], range: 1.50-7), with 42% of scores falling within the "good" range, followed by 38.3% of scores within the "very good" range.

Upon further examination of individual items for each subscale, we found that the average item score for each item on the ease of use subscale fell within the "very good" range. The highest score was reported for the app being easy for users to learn and use (*M* = 6.64 [*SD* = 0.55], range: 4-7). The lowest score was related to participants' ability to easily and quickly deal with mistakes when using the app (*M* = 5.96 [*SD* = 1.20], range: 1-7). On the interface and satisfaction subscale, we found that all average item scores were in the "very good" range. The highest average item score was related to the organization and simplicity of finding information on the app (*M* = 6.29 [*SD* = 0.92], range: 2-7). The lowest score was associated with users' willingness to use the app again (*M* = 5.42 [*SD* = 1.50], range: 1-7). Lastly, on the usefulness subscale, we found that all average item scores were in the "good" range. The highest average score was associated with the app being an acceptable way to receive health care services (*M* = 5.22 [*SD* = 1.45], range: 1-7). The lowest score was related to whether the app helped participants manage their health effectively (*M* = 4.52 [*SD* = 1.55], range: 1-7).

Quality. Participants rated the overall objective quality of the app as excellent (*M* = 4.06 [*SD* = 0.54], range: 1.96-5), with 60.7% of participants rating app quality as "excellent" (scores > 4) and 33.9% rating app quality as "good" (scores between ≥ 3 to ≤ 4). Our examination of subscales showed that participants rated the app's functionality (i.e., app performance, ease of use, navigation, and gestural design) to be "excellent" (*M* = 4.47 [*SD* = 0.52], range: 2.75-5; 74.3% of scores ≥ 4). Participants rated the app's aesthetics (i.e., graphic design, overall visual appeal, colour scheme, and stylistic consistency) as "excellent" (*M* = 4.17 [*SD* = 0.67], range: 1-5; 55.2% of scores ≥ 4, 21.2% between ≥ 3 and < 4). Closely behind Aesthetics were participants ratings of the app's information (i.e., high-quality information from a credible source), which fell within the "excellent" range (*M* = 4.14 [*SD* = 0.71], range: 1-5; 58.2% of scores ≥ 4, 21.5% between ≥ 3 and < 4). Participants rated the app's engagement (i.e., fun, interesting, customizable, interactive, has prompts) as the lowest of all ratings, falling in the "good" range (*M* = 3.48 [*SD* = 0.72], range: 1-5; 40.4% of scores between ≥ 3 and < 4, 18.6% ≥ 4). We present means and standard deviations for the objective quality scale and subscales in Table 8.

In our analysis of the subjective quality scale, we found that the most frequent star rating of the app was four stars (50.3%), followed by three stars (33.9%). For our measure of app use, which asked how often participants would use the app in the next 12 months, 42.1% reported 10-50 times, 24%

reported 3-10 times, and 19.1% reported > 50 times. We found that 33.9% of participants said they would definitely recommend the app to everyone, and 26.8% said there are many people they would recommend it to. Only 1.1% of participants reported that they would definitely pay for the app. Most reported they would definitely not (44.8%) and probably not (27.3%) pay for the app. We present means, standard deviations, and frequencies of responses for the subjective quality scale and individual items in Table 9.

We found that the overall impact of the app on participants' MH and coping skills was moderate (M = 3.48 [SD = 0.88], range: 1-5). Regarding frequencies, most participants rated the app as having a moderate impact (30% of scores between ≥ 3 and < 4), followed by a strong impact (24.6% of scores ≥ 4) and no impact (23.5% < 3). The majority of participants agreed that the app had a positive impact on their awareness (42.6%), use (47%), knowledge/understanding (44.3%), and attitudes to improve (42.6%) MH and coping skills. Further, most agreed that the app had a helpful impact on their intention/motivations to address MH and coping skills (42.1%) and their willingness to seek further help for MH and coping skills if needed (43.7%). We present means, standard deviations and frequencies of responses to the perceived impact scale and individual items in Table 10.

PLS-SEM Evaluation

Measurement Model. We examined the outer loadings, reliability, and validity for all variables involved in the proposed model to test H1-11 to ensure the adequacy of measures and constructs for the structural model evaluation. We found inadequate indicator reliability for our measures of app quality (uMARS; Objective Quality scale) and usability (MAUQ). The uMARS had 12 outer loadings < 0.70 (range: 0.38-0.68), and the MAUQ also had 12 outer loadings < 0.70 (range = 0.44-0.67). Similarly, on measures of each Big Five aspect personality construct, we found poor indicator reliability (number of items with outer loadings below thresholds ranging from 5 to 10) and convergent validity (AVEs ranging from 0.16 to 0.44). When we removed items with the lowest outer loadings among the measures of usability, quality, and personality constructs, the convergent validity of the corresponding construct was not improved to the recommended thresholds (≥ 0.50). Consequently, we removed these constructs from the model. We found two indicators on the facilitating conditions construct with outer loadings below 0.70 (0.39 and 0.66). We removed these items, which improved reliability and convergent validity of the measure to recommended thresholds, and thus we retained the construct. We retained one indicator on the effort expectancy construct with an outer loading of 0.64 because the construct met all evaluation criteria for reliability and convergent validity. Finally, we identified that discriminant validity was not established for the habit construct (HTMT of 0.98 with behavioural intention, HTMT of 0.91 with performance expectancy). We removed the construct from the model as there was no theoretical justification for merging habit with behavioural intention or performance expectancy.

Our final model included performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, behavioural intention, and use (see Figure 5). Considering this model, we did not examine the hypothesized relationships (shown in Figure 2) between habit and behavioural intention (part of H1), habit and use (part of H2), usability and use (H5), quality and use (H6), and personality traits and behavioural intention (H7-H11), in the structural model. All constructs in the final model met the measurement model evaluation criteria for indicator and internal consistency reliability and convergent and discriminant validity. We present the outer loadings of indicators and the internal consistency reliability and convergent validity estimates of constructs in the final model in Table 11. We present the discriminant validity results of constructs included in the final model in Table 12.

Structural Model. Once the reliability and validity of the final model construct measures were established, we systematically assessed the structural model. Our examination of VIF values showed no collinearity issues within the model (all VIFs ≤ 3; see Table 13). As a result of some indicators and bootstrap distributions of parameter estimates being highly skewed, we implemented the BCa bootstrapping method to examine all hypothesized relationships and derive parameter estimates. We present a summary of path coefficient estimates, *t* values, BCa bootstrapping confidence intervals, and the outcome of associated hypotheses in Table 14.

Overall, we found that the structural model explained a significant and substantial amount of variance in behavioural intention (R^2_{adjusted} = 0.751, p < .001, 95% CI [0.679, 0.795]). Performance expectancy (β = 0.576, p < .001, f^2 = 0.457; large effect), hedonic motivation (β = 0.334, p < .001, f^2 = 0.173; medium effect), and facilitating conditions (β = 0.181, p < .001, f^2 = 0.124; small effect) significantly and positively predicted behavioural intention. Social influence and effort expectancy did not significantly predict behavioural intention. Behavioural intention and facilitating conditions explained a moderate amount of variance in use (R^2_{adjusted} = 0.460, p < .001, 95% CI [0.367, 0.541]. Therefore, we found partial support for H1 as all UTAUT2 constructs did not predict behavioural intention as hypothesized. Behavioural intention (β = 0.725, p < 0.001, f^2 = 0.849; large effect) and facilitating conditions (β = 0.131 p < .001, f^2 = 0.038; small effect) significantly and positively predicted use. H2 was partially supported because habit was excluded from our model, and we did not examine the relative predictive importance of habit on use.

Predictive Power. Considering the significance of the structural model relationships in predicting behavioural intention and use, we assessed the model's predictive power. We found that the 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 15).

Moderation Analysis. We found partial measurement invariance for gender. Thus, we conducted a MGA to compare path coefficient estimates for groups (women and men) across hypothesized moderator relationships. We found full measurement invariance for experience. Consequently, we pooled data among participants who had experience and did not have experience with MH apps. We then included experience as a moderator via an interaction effect to account for structural heterogeneity. We employed the two-stage approach to examine the moderating effects of age and experience.

We found no significant differences in path coefficients between women and men (See Table 16). We found that age only had a significant and large positive moderating effect on the relationship between facilitating conditions and behavioural intention (β = 0.092 p = .047, f^2 = 0.032). Experience showed a significant and large positive moderating effect on the relationship between performance expectancy and behavioural intention (β = 0.824 p = .002, f^2 = 0.088) and significant and large negative effects on the relationships between hedonic motivation and behavioural intention (β = -0.513 p = .005, f^2 = 0.059) and social influence and behavioural intention (β = -0.360 p = .009, f^2 = 0.040). Table 17 presents the full results of the moderating effects of age and experience. Considering that we found no moderating effects for gender and that experience and age did not moderate all proposed hypothesized relationships between UTAUT2 constructs and behavioural intention, H3 was partially supported. We also found that experience did not moderate the relationship between behavioural intention and use. Thus, H4 was not supported.

We created simple slope plots of significant interaction effects to support the interpretation of the moderation results and observe how the moderator changes the relationships. Results in Figure 6 show that as age increases, the positive relationship between facilitating conditions and behavioural intention becomes stronger, and as age decreases, this relationship gets slightly weaker. Results in Figure 7 show that the relationship between performance expectancy and behavioural intention was positive and stronger for those without experience using MH apps. However, among those who had experience with MH apps, the association between performance expectancy and behavioural intention was weak and negative. Figure 8 shows that due to the negative moderating effect of experience, the positive relationship between hedonic motivation and behavioural intention is stronger among those with experience with MH apps. In contrast, it is weaker among those with no prior experience. Finally, the results in Figure 9 highlight that the relationship between social influence and behavioural intention is strong and positive among those who have experience with MH apps compared to those who have no experience, in which the relationship is weak and negative.

Exploratory Analysis

In our final structural model (see Figure 5), we were unable to test the proposed hypotheses examining the relative predictive importance of usability and quality on the use of the JoyPop^{TM} app (H5 and H6) and the relative predictive importance of Big Five personality aspects on behavioural intention and use (H7-H11) because of reliability and validity issues in the PLS-SEM measurement model evaluation. However, we conducted an exploratory analysis to gather preliminary insight into the influence of usability and quality on use and associations between personality traits, behavioural intention, and use. We also examined the associations between personality traits and core constructs of the UTAUT2. Using the Benjamini-Hochberg correction (with a false discovery rate at the 0.05 alpha level) to control for type 1 error rates (Benjamini & Hochberg, 1995), we conducted a correlational analysis to examine the relationships between the Big Five domains, ten Big Five aspects, core constructs of the UTAUT2, and app use. We included the Big Five domains to help elucidate the potential unique relationships among Big Five aspects. We used a linear regression analysis to examine whether usability and quality predict the use of the JoyPop™ app.

Personality Traits, UTAUT2, and Use. Table 18 depicts the correlations between the 10 Big Five aspects and Big Five domains, core constructs of the UTAUT2, and use. After controlling for the false discovery rate, we found significant and positive relationships between volatility and hedonic motivation ($r = .18$, $p < .001$); politeness and effort expectancy ($r = .24$, $p < .001$); enthusiasm and facilitating conditions ($r = .18$, $p < .001$); industriousness and behavioural intention ($r = .18$, $p < .001$); orderliness and effort expectancy ($r = .20$, $p < .001$); and openness and effort expectancy ($r = .26$, $p < .001$). Only openness ($r = .21$, $p = .002$) had a significant and positive relationship with use. Upon examining the associations between Big Five domains and UTAUT2 constructs, we found significant and positive associations between agreeableness and effort expectancy ($r = .24$, $p < .001$); conscientiousness and performance expectancy ($r = .18$, $p < .001$); conscientiousness and behavioural intention ($r = .19$, $p < .001$); and openness/intellect and effort expectancy ($r = .23$, $p < .001$).

Usability, Quality, and Use. We conducted a simple linear regression to evaluate the extent to which usability and quality predicted use. Usability was a significant and positive predictor of use ($\beta = .508$, $t\ [181] = 7.94$, $p < .001$) and explained 25% of the variance in use ($F\ [1, 181] = 63.04$, $p < .001$,

$R^2_{adjusted}$ = .25). Quality was also a significant and positive predictor of use (β = .439, t [181] = 6.57, p < .001) and explained 19% of the variance in use (F [1, 181] = 43.18, p < .001, $R^2_{adjusted}$ = .19). Our results demonstrate that higher reported levels of usability and quality predict increased use of the JoyPop™ app.

Discussion

MH apps are novel tools that can support the increasing complexity and demand of postsecondary students with MH needs by reducing structural and attitudinal barriers to care and increasing access to supports. Despite the potential of MH apps, most have not been assessed to determine whether they are effective. Even fewer have been evaluated to determine their acceptance, usability, and quality, which are critical determinants of user engagement and long-term use. The present study aimed to better understand factors influencing the acceptance of a resilience-building MH app (JoyPop™) and evaluated its acceptance, usability, and quality. This study applied the UTAUT2 model to determine factors that predict students' acceptance of the JoyPop™ app and evaluate its acceptance. Reliable and validated measures explicitly developed to evaluate the quality and usability of mHealth apps were used. This study also aimed to provide insight into how personality traits influence acceptance and app use and whether the app's usability and quality predicted use.

Factors Influencing Acceptance of the JoyPop™ app

In the present study, UTAUT2 constructs (without the constructs of habit and price value) explained a substantial amount of variance in students' intention to use the JoyPop™ app (approximately 75%). This suggests that UTAUT2 constructs strongly influence students' intentions to use the JoyPop™ app in the future throughout their daily lives. Behavioural intention and facilitating conditions explained a moderate amount of variance in students' use of the JoyPop™ app (approximately 46%), suggesting that students' intentions and plans to use the app in the future and whether they have the resources (e.g., devices, time) to use it, impact the use of the JoyPop™ app. This pattern of results is consistent with the original evaluation of the UTAUT2 model and studies examining the associations between the UTAUT2 constructs and various mHealth app interventions (e.g., those targeting depression, chronic pain, and well-being), which show that users' intentions and plans to use a specific technology are heavily dependent on the constructs proposed by the UTAUT2 model (Duarte & Pinho, 2019; Philippi et al., 2021; Venkatesh et al., 2012). Furthermore, these studies show that users' intentions, in addition to whether they have sufficient resources and technical knowledge, moderately impact future technology use (Duarte & Pinho, 2019; Philippi et al., 2021; Venkatesh et al., 2012).

Performance expectancy was the strongest predictor of intention to use the JoyPop™ app, followed by hedonic motivation and facilitating conditions. Thus, the JoyPop™ app's usefulness in students' daily lives to provide efficient MH support has the most substantial influence on their willingness to use it in the future, followed by how fun and entertaining it is and whether they have the resources to use it. When examining the use of the JoyPop™ app, we found that behavioural intention was a significant and strong (large effect) predictor, while facilitating conditions was a significant and weak (small effect) predictor. This suggests that students' use of the JoyPop™ app primarily depends on their intentions to use it in the future. Further, whether students have other technologies compatible with the JoyPop™ app and the resources necessary to use it plays an important but less influential role in app use.

The daily utility of the JoyPop™ app in supporting productivity and MH being the strongest predictor of its acceptance, is consistent with the vast amount of research examining technology acceptance using the UTAUT2 (Calegari et al., 2023; Philippe et al., 2021). How useful a technology is for its intended purpose is routinely shown to be the most common and strongest significant predictor of mHealth app acceptance (including MH apps), even among postsecondary students (Calegari et al., 2023; Duarte & Pinho, 2019; Holtz et al., 2023). mHealth and MH app acceptance among young adults and postsecondary students is also regularly shown to be influenced by the fun and entertainment an app provides and whether users have sufficient knowledge and resources to use it (Calegari et al., 2023; Holtz et al., 2023; Tamilmani et al., 2021). Furthermore, a large body of literature examining the relationship between mHealth app acceptance and use consistently finds that users' intentions to use an app are the most important determinants of use, followed by an essential but less impactful influence of having sufficient resources and knowledge to use an app (Calegari et al., 2023; Tamilmani et al., 2021).

Together, these results have important implications for researchers and design and development teams evaluating the JoyPop™ app. Teams can focus on adapting and tailoring the app to prioritize constructs that influence app acceptance most, first, by improving the app's ability to enhance user resilience, coping skills, and well-being (i.e., performance expectancy), such as by adding a wider variety of enhanced resilience-based features (e.g., more advanced breathing exercises, a wider variety of moods to rate). Second, adaptations should enhance or ensure the app is fun, enjoyable, and entertaining (i.e., hedonic motivation), such as adding gamification aspects to different features and implementing reward systems. Third, developers would benefit from ensuring users have the resources to use the app and that it is compatible with existing user technologies (i.e., facilitating conditions), such as expanding the app to Android devices.

Our model also showed high out-of-sample predictive power, which supports the model's external validity. High predictive power aligns with research highlighting the utility of the UTAUT2 model in predicting the acceptance of various mHealth technologies across many different contexts, populations, and countries (Calegari et al., 2023; Tamilmani et al., 2021; Zhu et al., 2023). This finding is important because despite recruiting a convenience sample of students, the strong predictive power of the model in the present study and the diversity of our sample (e.g., a wide range of ethnicities, programs, and years of study) lend support for the generalizability of the tested structural model and results across other samples of postsecondary students.

Whereas past research found effort expectancy and social influence were consistent predictors of mHealth and MH app acceptance (Philippe et al., 2021; Mitchell et al., 2022; Jacob et al., 2022), it was interesting that they both did not predict behavioural intention to use the JoyPop™ app in the present study. Participants' familiarity with smartphone apps and the finding that almost all participants strongly agreed that the JoyPop™ app was easy to learn and use may explain the effort expectancy result. Because postsecondary students show some of the highest usage rates of smartphones and apps (Bautista & Schueller, 2023; MHCC, 2014; Statistics Canada, 2023c), their familiarity with apps may make them more skilled at using apps in general, and only when an app becomes significantly challenging to use does it become a determining factor in their intention to use the app. Considering the majority of participants found the JoyPop™ easy to learn and use (i.e., had high scores on effort expectancy), a ceiling effect (Ho & Yu, 2015) may have resulted in effort expectancy no longer being an important significant predictor in its acceptance, and other factors, such as performance expectancy, becoming even more relevant. This finding is important for research and development teams investigating the JoyPop™ app. For example, design and development teams can now potentially increase the complexity of features within the app at the expense of its ease of use. However, effort expectancy levels should be continuously evaluated after app adaptations to ensure that the effort needed to use the app does not reach a point at which it negatively affects app acceptance.

Three reasons might explain why social influence did not predict app acceptance. First, this may result from the shift in attitudes of how people think about and discuss MH. The importance of developing adaptive coping strategies (e.g., diaphragmatic breathing) and addressing MH needs is now widely promoted and accepted across university campuses. Second, most postsecondary students are transitioning through emerging adulthood and experiencing expanded autonomy and agency, in which they are less concerned about the opinions of others (Arnett, 2016). Therefore, students' decisions to use a MH app may depend less on the influence of significant others in their lives and more on their own choices and agency. Third, users can access MH apps privately on their own devices and use them discretely in their own time, which may reduce the likelihood that others can influence use. This aligns with prior qualitative research on the JoyPop™ app among a clinical sample, where users perceived the app to be helpful because it provided them with a safe and private tool to work on their MH (Malik et al., 2023). Qualitative studies among postsecondary students could be conducted to better understand why social influence does not influence the acceptance of the JoyPop™ app. However, our moderation analysis did provide important insight into the relationship between social influence and behavioural intention, which is discussed below.

The present study findings also deviate from more recent, although limited, empirical research on MH app acceptance regarding the constructs included in the UTAUT2 model and the predictive utility of individual constructs in determining users' intentions to use MH apps. In the present study, the impact of UTAUT2 constructs on users' intentions to use the JoyPop™ app is much larger than that of prior studies that specifically examined some of the UTAUT2 constructs in explaining acceptance of MH-related apps. For example, UTAUT2 constructs only had a minor influence on individuals' intentions to use lifestyle and therapy apps, and what was most influential was an external construct (i.e., trust) not included in the original UTAUT2 model (Schomakers et al., 2022). A study using the original UTAUT constructs found that they only had a small to moderate impact on whether postsecondary students intended to use some of the most popular MH apps (e.g., Headspace, Calm, Talkspace; Holtz et al., 2023). Further, when examining the predictive capability of individual UTAUT2 constructs, Schomakers et al. (2022) found that how valuable a MH app was for its intended purpose and whether users had sufficient knowledge and resources to use the app were not significant determinants of whether they intended to use lifestyle and therapy apps. Mitchell et al. (2022) also found that whether users had adequate resources to use a MH app did not predict their intentions to use the app.

These conflicting findings are likely explained by the study designs, MH app differences, and the temporality in which apps were evaluated. For example, studies by Schomakers et al. (2022) and Holtz et al. (2023) were cross-sectional. They also relied on retrospective reports of participants' experiences with various MH apps rather than examining users' experiences after using a specific app for a given time, akin to the present study. Schomakers et al. (2022) also included many apps that were not specifically designed for MH (e.g., blood pressure diary and diabetes apps) and the MH app evaluated by Mitchell et al. (2022) was designed to connect people to external supports (i.e., university student support programs). The JoyPop™ app, on the other hand, is designed primarily as a stand-alone app that allows autonomous use without external contact. In addition, both Mitchell et al. (2022) and Holtz et al. (2023) only examined the predictive utility of the original UTAUT constructs (e.g., did not include hedonic motivation). These findings substantiate the need for further evaluations on the acceptance of specific mHealth apps versus solely examining user acceptance among a group of MH apps. The purpose of MH apps and the features within these apps are likely to vary. Specific app evaluations can better test the relative importance of acceptance factors to the unique characteristics of MH apps.

Moderating Effects of Gender, Age, and Experience

Gender. We did not find moderating effects for gender in the present study. The literature examining the influence of gender on mHealth acceptance is mixed (Calegari et al., 2023; Jacob et al., 2022). However, despite diverging results, meta-analyses find that gender has an important pooled effect on the relationships posited by the UTAUT2 (Calegari et al., 2023; Tamilmani et al., 2021). What may explain this finding is the variety of different features offered through the JoyPop™ app and its transdiagnostic focus on emotion regulation and resilience building. Although men and women differ on average in their coping strategies (Lawrence et al., 2006), features within the JoyPop™ app allow for various ways to use active and emotion-focused coping skills to regulate emotions. The app also includes features that can be used for purposes beyond coping, such as using the Journaling feature to plan activities or set goals or the SleepEase feature to improve sleep onset and quality. Users may thus create unique ways to utilize features to facilitate their personally preferred and most effective methods to improve their MH and build resilience. Creative and personal usage patterns of the app may, therefore, influence relationships among gender and UTAUT2 constructs.

This suggestion is supported by prior JoyPop™ research in which users often discussed how they preferred specific features over others but recognized the helpfulness of unused features to other app users (Malik et al., 2023). This finding highlights the importance of the JoyPop™ app being strength-based and having a wide variety of features, which increases the likelihood that users who differ in demographics can pick and choose which features are most helpful to them rather than being forced into using a relatively limited number of features targeting a specific MH difficulty. This finding should be interpreted cautiously as there were many more women in the present sample than men. Because we could not establish full measurement invariance for gender, we could not pool results across groups (which would have increased statistical power), and the moderator analysis may have lacked sufficient power to detect significant differences among groups (Henseler et al., 2016).

Age. We found a moderating effect for age in the present study. Specifically, the relationship between facilitating conditions was stronger among older students. Older students placed a stronger emphasis on wanting the app to be compatible with other technologies they use and ensuring they have sufficient resources to use the app. This finding was inconsistent with prior studies showing that the relationship between users' knowledge and resources to use the app and their plans and intentions to use the app is independent of their age (Calegari et al., 2023; Nunes et al., 2019). This may be explained by the fact that none of the prior studies have specifically examined the moderating effect of age when evaluating MH app acceptance in samples of postsecondary students.

One interpretation of this finding is that older students may need to become more familiar with MH apps and thus place more importance on ensuring they have the resources, knowledge, and existing technology required to use the JoyPop^{TM} app effectively (Gitlow, 2014; Mitzner et al., 2010). Older students may also have more responsibilities outside of school (e.g., children) and be less inclined to use an app that is incompatible with the technologies they already use. Research finds that older adults are more hesitant about using novel technologies because they may be more inconvenienced by the effort required to use them, have more concerns about their utility, and may need more general awareness and knowledge about them (Gitlow, 2014; Mitzner et al., 2010). Thus, older adults may need more information and support related to the utility, convenience benefits, and potential technical difficulties associated with newer technology (Mitzner et al., 2010). This finding partly implies that to increase acceptance among older students, developers would benefit from ensuring that these students are provided with extra support and information about how to use the app (Mitzner et al., 2010). For example, providing detailed examples of how the differing features within the JoyPop™ app can be implemented in various situations and clearly explaining how the app can be used on multiple types of devices (i.e., iPads, iPods, and iPhones) could help increase its overall acceptance.

Experience. MH app experience moderated the relationships between performance expectancy, social influence, hedonic motivation, and behavioural intention. This pattern of results is consistent with prior research assessing how technology experience influences the relationship between core UTAUT2 constructs and behavioural intention to use mHealth technologies (Calegari et al., 2023; Venkatesh et al., 2012). It is interesting that students with prior MH app experience placed less importance on how beneficial the JoyPop™ app was in their daily lives and for their MH and more importance on the enjoyment and entertainment the app offered. One interpretation of these findings is that those with experience have already found prior MH apps helpful for the benefits they offer (e.g., increased access to support and improved MH) and have thus developed a belief that apps like JoyPop™ can be valuable. This may result in experienced users placing higher importance on whether the app provides enough pleasure and fun to keep them engaged and promote continued use. On the other hand, people with no experience using MH apps may be unsure whether JoyPop™ can fulfill its designed purpose, and rather than caring about whether it is fun and enjoyable, they may place more emphasis on whether it provides any benefit to their MH and coping skills.

Results describing the primary reasons participants did not use MH apps in the current study provide further insight into the above interpretation. For instance, 68% of participants who had experience with MH apps noted that they no longer used apps because they forgot about them or got out of the habit of using them. Approximately 57% of participants with no prior experience with these apps noted that they either did not know they were available/forgot they were available, and/or were not interested in them. Thus, lack of pleasure and fun may have resulted in experienced users forgetting or not habitually using MH apps versus those without experience who may not even know or believe they can be beneficial. Findings highlight the importance of developers focusing equally on adapting the app in ways that both increase its utility in improving resilience and its entertainment value to capture the most prioritized attributes among experienced and non-experienced users. Additionally, incorporating prior evidence supporting the effectiveness and performance of the JoyPop™ app into promotional efforts and even within the app could be helpful to increase acceptance for users with no MH app experience.

Although social influence had no significant main effect on behavioural intention, we found that social influence was moderated by experience. Specifically, those who had experience with MH apps placed a primary emphasis on the opinions of significant others in their intention to use the app compared to those with no experience, in which the opinions of others had a minimal negative effect on their willingness to use the app in the future. This result aligns with prior research demonstrating the moderating effect of experience on the relationship between social influence and behavioural intention to use mHealth technologies (Calegari et al., 2023; Venkatesh et al., 2012). Self-stigma (e.g., perceiving oneself as socially unacceptable or undesirable because they are seeking help; Vogel et al., 2006) may explain this finding. Self-stigma mediates the relationship between public stigma (i.e., societal perceptions) and help-seeking (Vogel et al., 2017). For example, individuals may have developed higher levels of self-stigma from prior use of MH apps and thus be more sensitive to the opinions of significant others in their lives versus those without experience who have not developed self-stigma from seeking MH support via apps. Those who have used MH apps in the past may have also been subjected to the opinions of others while using an app compared to those without experience who have not.

Notably, being influenced by significant others is not always negative. Family members and friends can play an essential role in whether an individual seeks MH support by acting as a critical and informal first step in help-seeking (Rickwood et al., 2007, 2015). Consequently, prior users of MH apps may be positively influenced by others who know them and have seen that MH supports, like MH apps, have been helpful for them (Rickwood et al., 2007, 2015). Significant others may then positively influence users' help-seeking behaviour by suggesting they use an app like JoyPop™ to support their MH. Although more research is needed to fully explore how others influence acceptance of the JoyPop™ app among experienced users, it is worth noting that the strength-based nature of the JoyPop™ app can reduce the potential effects of self-stigma. For instance, promotional efforts can discuss the strength-based nature of the app to help experienced users view the app as one that harnesses strengths rather than one that reduces MH difficulties, which may reduce user concerns about being socially undesirable or unacceptable.

Taken together, our findings highlight the importance of including moderating effects posited by the UTAUT2 framework to understand the acceptance of MH apps. Despite not finding some of the proposed moderating effects posited by the original UTAUT2 study (Venkatesh et al., 2012), it is important to note that findings of moderating effects posited by the UTAUT2 across mHealth acceptance studies are mixed (Calegari et al., 2023; Philippi et al., 2021). The context, sample, and setting in which apps are evaluated seem to determine what factors are influential moderators. It is also relevant that we did not find any studies that examined the moderating effects of gender, age, and experience on proposed UTAUT2 relationships when examining the acceptance of apps designed specifically for MH. This is especially true among samples of postsecondary students, which made comparisons across similar research studies difficult. Finally, many of the moderating effects of age, gender, and experience tend to occur via three-way interactions. For example, Venkatesh et al. (2012) found that the effect of facilitating conditions on behavioural intention was stronger among older women (age x gender x facilitating conditions) and that the effect of effort expectancy on behavioural intention was stronger among older women (age x gender x effort expectancy). Not including three-way interactions may have accounted for the lack of moderating effects included in the UTAUT2 framework. Future studies would benefit from examining higher-order interaction effects among specific MH apps.

Overall Acceptance of the JoyPop™ app

We found that the majority of students reported high acceptance of the JoyPop™ app. The results from the analysis of factors influencing acceptance of the JoyPop™ app facilitate the interpretation of this result. Performance expectancy, facilitating conditions, and hedonic motivation all significantly and positively predicted intention to use the app. These three constructs all had above-average scores on their relative measures (i.e., average scores > 4 on a scale with a maximum possible mean score of 7). The findings imply that in addition to believing they had the resources necessary to use the app and that the app was compatible with other technologies they use, participants intended to use the app in the future because they experienced the app as fun, entertaining, and helpful for their MH and well-being. High acceptance of the JoyPop™ app is consistent with past qualitative research on the JoyPop™ app, in which users and healthcare providers reported high acceptance levels (as assessed through acceptance indicators such as usefulness and ease of use; Au-Yeung et al., 2023; Kim et al., 2024; Malik et al., 2023). Our quantitative acceptance findings add to the multimethod evidence base of the JoyPop™ app as a potentially helpful MH tool for diverse youth and young adults across various contexts.

High acceptance levels in the present study diverge from past research examining the acceptance of digital health interventions and MH apps, which tend to have low acceptance levels (Holtz et al., 2023; Philippi et al., 2021). Conflicting results may be explained by the cross-sectional nature of studies, the grouping of various apps rather than evaluating specific apps independently, or simply because users preferred the design, usefulness, and features within the JoyPop™ app. Moreover, studies evaluating the acceptance of specific MH apps among postsecondary students using the well-established UTAUT2 framework are limited (Oliveira et al., 2021). To our knowledge, no study has evaluated the acceptance of a specific MH app using the UTAUT2 framework among postsecondary students. More evaluations of MH apps using well-established technology acceptance models, like the UTAUT2, will be helpful to better under the acceptance of MH apps across different types of apps, contexts, and users.

Usability and Quality

We found that participants rated the overall usability, ease of use, and satisfaction with the JoyPop™ app as "very good" and the app's usefulness as "good." Notably, responses to all items comprising usability subscales were in the "good" to "very good" range. High usability in the present study is consistent with past research evaluating the JoyPop™ app in which diverse samples of patients, health-care providers, and community members described the JoyPop™ as being highly usable based on common indicators of usability, such as usefulness, ease of use, and satisfaction (e.g., positive attitudes towards use; Au-Yeung et al., 2023; Kim et al., 2023; Malik et al., 2023). High usability ratings for the JoyPop™ app lend strong support to its ability to meet the diverse needs of various users in different contexts (e.g., clinical and academic settings).

Despite direct comparisons on the usability of MH apps being difficult because of the differences in measures, it is notable that a study rating the usability of many popular MH apps and Web-based MH programs available on the Google Play store showed a mean usability score of 3.34 (out of five) with a SD of 0.61, which the authors labelled as "fair" (range: fair to very good; Baumel et al., 2017). Since the mean usability rating for the JoyPop™ app was 5.63 (out of seven), with an SD of 0.82, findings suggest the JoyPop™ app has comparable to higher usability ratings than many popular MH apps on the Google Play store. This comparison should be interpreted cautiously as different measures were used in the present study (i.e., the MAUQ), which was unavailable at the time of the Baumel et al. (2017) review. It will be necessary for future research to incorporate similar MH app usability measures, such as the MAUQ, to facilitate valid comparisons. Nevertheless, the JoyPop™ app's comparable usability ratings with popular MH apps on the Google Play marketplace corroborate its usability, which is a critical factor in long-term engagement and use (Inal et al., 2020; Jacob et al., 2022).

We found that the overall objective quality of the JoyPop™, as measured by the uMARS, and the corresponding subscales functionality, aesthetics, and quality of information was rated as "excellent." The engagement of the app was rated as "good." Results are consistent with past research on the JoyPop™ app, highlighting it as an engaging MH app with strong functionality, visual design, and a variety of helpful evidence-based content (Au-Yeung et al., 2023; Kim et al., 2023; Malik et al., 2023). Akin to its usability rating, the JoyPop™ app's overall quality mean score (4.06 [*SD* = 0.54]) as rated by users on the uMARS is comparable to and often higher than many popular and publicly available MH apps on app marketplaces (e.g., Calm, PTSD Coach, SuperBetter, Destrssify) which have been rated by experts using the original MARS scale (Lau et al., 2021; Neary & Schueller, 2018). For example, among 100 apps reviewed on the PsyberGuide app rating platform, the average objective quality MARS rating is 3.79 (range 2.51-4.74; Neary & Schueller, 2018). Lau et al. (2021) also rated 19 popular consumer MH apps with research support using the MARS and showed that the average objective quality score was 3.52 (*SD* = 0.71; range: 2.22 to 4.32), with average scores on subscales being 3.98 (range: 2.30-4.80) for engagement, 3.42 (*SD* = 0.80; range: 2.00-4.63) for functionality, 3.23 (*SD* = 0.90; range: 1.67-4.67) for aesthetics, and 3.47 (*SD* = 0.69; range: 2.00-4.63) for information.

Results in Table 8 show that the JoyPop™ app falls within the upper ranges for overall objective quality and each associated subscale compared to popular and research-supported MH apps. It is important to note that evaluated apps on PsyberGuide and Lau et al. (2021) were rated by experts using the MARS rather than end-users using the uMARS, such as in the present study. However, users' and researchers' assessments of app quality often align with one another (Lau et al., 2021). The high-quality ratings of the JoyPop™ app across research-based indicators of mHealth app quality, in combination with its quality ratings compared to MH apps reviewed by experts, strongly support its safety, credibility, helpfulness, and use in postsecondary settings. Future research would benefit from compiling end-user quality evaluations of MH apps using the uMARS to facilitate more accurate and valid comparisons and having experts in mHealth evaluate the quality of the JoyPop™ app using the MARS to validate the present study's findings.

Response frequencies to items on the subjective quality scale also supported the quality of the JoyPop™ app (see Table 9). Most participants (78.7%) reported that they would recommend the app to people they know, and over half (57.4%) of participants provided a star rating ≥ 4. As mentioned above, although these are subjective ratings, the importance of these results in contributing to the quality evaluation of the JoyPop™ app is highlighted by the consistency between subjective consumer ratings of MH apps and objective expert reviews of MH apps (Lau et al., 2021). Subjective quality results also showed that most participants (72.1%) would not pay for the app. This is not surprising as research consistently shows that people are less likely to use apps that cost money (Huang & Bashir, 2017; Jacob et al., 2022).

Regarding the perceived impact of the JoyPop™ app, more than half of participants agreed that the app positively impacted their MH and coping skills in all areas queried (i.e., awareness, help-seeking, knowledge, attitudes, behaviour change, motivation; see Table 10). The broad range of areas impacted by the app is consistent with past research demonstrating the various potential benefits the app can provide to diverse samples of users (Au-Yeung et al., 2023; Kim et al., 2023; Malik et al., 2023). The results also align with prior effectiveness research on the JoyPop™ app among postsecondary students (MacIsaac et al., 2021) and provide further evidence that the JoyPop™ app delivers users an effective experience. Rigorously controlled trials examining the effectiveness of the JoyPop™ are needed to substantiate its effectiveness. However, results on the app's perceived impact can facilitate determining whether future outcomes are meaningful and impactful on MH and coping skills while providing researchers with an understanding of the potential mechanisms and reasons why the app might be effective. Perceived impact results can additionally inform outcome measures that can be assessed in rigorously controlled trials (e.g., measures of help-seeking and coping skills).

Finally, although usability and quality measures were inadequate for inclusion in the primary structural model analyses, our exploratory analysis provided insight into how they influence future use. Both quality and usability were positive predictors of using the JoyPop™ app. The results are consistent with research demonstrating the importance of quality and usability in increasing engagement, long-term uptake, and overall use of mHealth and MH apps (Alon & Torous, 2023; Inal et al., 2020; Torous et al., 2018). We also obtained preliminary evidence for the relative impact of quality and usability on use.

Interestingly, usability explained more variance in use than quality (approximately 6% more). Although the measures of quality and usability assess similar constructs (e.g., functionality, engagement, ease of use), this finding may be explained by the distinct constructs these measures capture. The uMARS overall objective quality score incorporates the credibility of app information into its total score, and the MAUQ includes the app's usefulness in its total score. Studies examining mHealth app acceptance show that the usefulness of an app is one of the strongest predictors of use, while the credibility of information is less important to users (Jacob et al., 2022; Schuller et al., 2018). It will be exciting for future research to integrate measures of usability and quality into a single model to examine their unique impact while assessing how various aspects of each construct (i.e., relevant subscales) influence the use of the JoyPop™ app and other MH apps.

Personality Traits, Acceptance, and Use

As a result of the Big Five aspect measure of personality traits being unable to meet measurement model evaluation criteria, we did not examine the relative predictive capability of personality traits on behavioural intention and use of the JoyPop™ app within the structural model. However, our preliminary and exploratory analysis of the associations between UTAUT2 constructs, personality traits, and use of the JoyPop™ app revealed some noteworthy results (see Table 18). Regarding the Big Five domains, agreeableness, conscientiousness, and openness/intellect were significantly associated with UTAUT2 constructs. This is consistent with past research highlighting the influence of Big Five domains on UTAUT2 constructs and their associations with use of different technologies and user preferences for specific features within MH apps (Alqahtani et al., 2021; Aziz et al., 2023; Barnett et al., 2015; Ervasti et al., 2019; Khwaja et al., 2021; Lakhal & Khechine, 2017).

It is important to note that many associations between Big Five domains, UTAUT2 constructs, and use in the present study differed from prior research (Aziz et al., 2023; Barnett et al., 2015; Lakhal & Khechine, 2017). The deviations with UTAUT2 constructs are likely a result of the different technologies examined in previous research (i.e., a web-based course management system and a desktop videoconferencing system; Barnett et al., 2015; Lakhal & Khechine, 2017). No studies have examined personality traits, UTAUT2 constructs, and the use of MH apps. Other studies examining associations between personality traits and the use of MH apps have found that neuroticism, conscientiousness, and extraversion predict use. However, in the present study, only openness/intellect predicted use. These results may be explained by these studies examining the relationship between Big Five domains and use among groups of MH apps in samples of users with prior experience with these apps (Aziz et al., 2023; Ervasti et al., 2019). On the other hand, our study examined a single MH app, with most participants having no prior experience with MH apps.

The present study likewise showed the importance of examining Big Five personality traits at the aspect level. Aspect level assessments were important in two ways. First, they revealed relationships not found at the level of domains. For example, although neuroticism was not associated with UTAUT2 constructs, its aspect, volatility, was significantly associated with hedonic motivation. Second, the ten aspects provided a more nuanced understanding of how personality traits influence UTAUT2 constructs and use. For instance, openness/intellect was significantly associated effort expectancy, but upon examining aspects, it was openness that accounted for this relationship. The results are consistent with aspect-level personality research demonstrating their increased predictive utility of outcomes compared to domains (Rozgonjuk et al., 2021; Stewart et al., 2022).

Taken together, results provide preliminary insight into the utility of examining personality traits within technology acceptance models to clarify factors influencing acceptance and use of the JoyPop™ app and other similar MH apps. Although these results are exploratory, they offer an understanding for developers and researchers to begin understanding who would use an app like the JoyPop™ and help facilitate optimal app design in a way that accounts for the different personality characteristics of users. It is also worth considering that personality is an individual difference that one brings into a situation (e.g., using technology), resulting in an interaction between personal and situation-level factors to influence behaviour and attitudes (Funder, 2008). Further, Big Five domains moderate the relationships between important technology acceptance model constructs (e.g., perceived usefulness) and acceptance of technologies (Deveraj et al., 2008). Investigating personality traits as moderators of relationships between UTAUT2 constructs and behavioural intention, and behavioural intention and use among MH apps is a promising future area of research (e.g., how do aspects moderate the relationship between performance expectancy and behavioural intention).

Strengths

A main strength of the present study was using a well-established theoretical model of technology acceptance to evaluate and understand the acceptance of a MH app and the impact of important moderating variables. Few studies have included all the moderating variables posited by the UTAUT2 framework when assessing the acceptance of mHealth apps. Further, to our knowledge, no studies have incorporated the UTAUT2 model when examining the acceptance of an individual MH app. The results represent the first direct demonstration of using the UTAUT2 framework to comprehensively evaluate and understand factors influencing the acceptance of a specific MH app among postsecondary students. Using the UTAUT2 model was essential because many of the constructs consistently predict the acceptance and use of mHealth apps across a wide range of populations, settings, and types of mHealth apps (Calegari et al., 2023; Duarte & Pinho, 2019; Yuan et al., 2015). Incorporating moderating variables facilitated insight into how posited UTAUT2 relationships vary depending on individual characteristics. Although many possible constructs can be included in a research model to evaluate app acceptance, well-established technology acceptance models like the UTAUT2 facilitated the selection of the most appropriate constructs. This is further supported by the large amount of variance in behavioural intention and use of the JoyPop™ app explained by the tested structural model.

Another strength was using recommended novel methods to determine a structural model's out-of-sample predictive power. Few PLS-SEM studies employ the PLSpredict procedure to determine the external validity of their model in similar contexts (Sarstedt et al., 2022). Using this method, we found strong support for the external validity of our model in predicting behavioural intention and use of the JoyPop™ app.

Another strength of the present study was using valid and reliable measures specifically designed to evaluate the usability (MAUQ) and quality (uMARS) of mHealth apps from the user perspective. Although more recent research is now employing these measures designed to evaluate mHealth apps, overall, they have been rarely used in the past (Hajesmaeel-Gohari et al., 2022). Using these measures allowed us to comprehensively and accurately assess the usability and quality of the JoyPop™ app by capturing unique usability features within mHealth apps (e.g., security and privacy challenges) and important established quality indicators (e.g., credibility of information) more than more commonly used measures (e.g., SUS; Hajesmaeel-Gohari et al., 2022; Zhou et al., 2019).

The demographics and diversity of our sample are another notable strength in the present study because they highlight the generalizability of the results, especially when combined with the external predictive validity of our structural model. Our sample included a large diversity of students from different programs and year levels. Importantly, not only were the proportions of participant age, ethnicities, and international students in the present sample consistent with those found within Lakehead University (Times Higher Education, n.d.), they were comparable to those found among postsecondary students across Ontario, where more than half of students identify as visible minorities and approximately 20% are international students (Statistics Canada, 2022c). Consequently, results may be generalizable across different postsecondary institutions in Ontario. A final strength of the present study is its prospective nature. Most studies examining the acceptance of mHealth and MH apps use cross-sectional designs and are confounded by the amount of time and how often participants have used MH apps before inquiring about factors influencing their acceptance. The present study provided all participants with an equal and sufficient number of days to use the JoyPop™ to provide accurate insight into its acceptance, usability, and quality based on their similar and recent usage experiences.

Limitations and Suggestions for Future Research

There are at least four potential limitations concerning the results of this study. The first limitation concerns excluding the habit construct from the structural model because of poor discriminant validity with other UTAUT2 constructs. Although our model explained substantial variance in behavioural intention and use of the JoyPop™ app, we could not determine the impact of the habit construct. This is important because research supports the importance of habit in predicting behavioural intention and the use of mHealth technologies (Calegari et al., 2023; Tamilmani et al., 2021). In fact, a meta-analysis of pooled path coefficients among the relationships between UTAUT2 constructs and technology use found that habit is among the strongest predictors of behavioural intention and use (Tamilmani et al., 2021). Future studies on the acceptance of the JoyPop™ app will benefit from including this construct. Our adaptations of items comprising the habit construct may have resulted in poor discriminant validity. It will be important that future studies explore whether retaining the original items is beneficial.

A second potential limitation is the one-week timeframe of the study. Although the UTAUT2 and proposed relationships have been validated over long study periods (Calegari et al., 2023), whether our results are stable over more extended periods is unknown. The strength and relative predictive importance of UTAUT2 constructs may change when students use the JoyPop™ app long-term. For example, if students conclude that the app is useful for their MH and wellbeing after using it for a week, whether it is fun and entertaining may become a stronger predictor of sustained acceptance and use. In addition, habit formation requires learning and experience (Calegari et al., 2023; Venkatesh et al., 2012). The short study period may not have been sufficient to examine the habit construct and might have compromised its discriminant validity. Future studies examining the acceptance of the JoyPop™ over longer periods are needed.

A third potential limitation is the indicator used to measure the use of the JoyPop™ app in the structural model. Although most studies employing the UTAUT2 framework use a subjective measure of usage (Tamilmani et al., 2021), more recent recommendations have suggested including actual technology usage metrics because most technology can automatically track this. Although we tracked the number of days the JoyPop™ app was used, the lack of variation among days used resulted in removing this variable from our model and solely using a subjective measure. Future studies would benefit from examining acceptance over more extended periods (i.e., greater than a week) to increase the likelihood that days used will vary enough to provide insight into the relationship between behavioural intention and actual usage of the JoyPop™ app. It would be helpful for future research to include both subjective and objective measures of app usage.

A fourth limitation of the present study is the disproportionate number of women, which can reduce the generalizability of results to men. Although we accounted for this by including gender as a moderating variable, which showed no significant differences in estimated paths, unequal sample sizes across groups warrant caution when interpreting moderating effects. The lack of men is not surprising considering research showing that women are more likely to use e-mental health programs designed to improve emotion regulation, while men prefer accessing health-related information in eHealth programs that include gamification and goal-based components (Antezana et al., 2022; Smail-Crevier et al., 2019). Future research would benefit from recruiting more balanced proportions of men and women or conducting a similar study among only men. Alternatively, the JoyPop™ app developers could consider building more gamification and goal-based components into the app to make it more attractive to men. For example, the newest version of the JoyPop™ app includes an updated mood-tracking feature. This is a step in the right direction, as men engage more often with apps with built-in tracking features (Antezana et al., 2022).

Implications

The present study provides important insight into established theoretical constructs and moderating variables influencing the acceptance of MH apps, particularly apps designed to improve resilience and emotion regulation. Findings support the applicability of the well-established UTAUT2 model to evaluate the acceptance and use of MH apps within health care and postsecondary contexts.

The proposed study also adds to the need to continuously evaluate the usability and quality of MH apps to ensure users are provided with a safe, engaging, evidence-based, and effective experience. Using the UTAUT2 framework and validated measures of usability and quality designed for mHealth apps can help facilitate comparisons across various mHealth apps, especially MH apps. If future app evaluations employ similar validated measures of acceptance, quality, and usability, simple comparisons across MH apps can be made and incorporated into a platform that helps users select the safest, most engaging and most effective apps for their needs. Although app-rating platforms are now available to help users select high-quality MH apps, further comprehensive platforms are needed to integrate usability, quality, and acceptance ratings across MH apps from both user and expert perspectives.

A key implication of this study is that it provides a valuable process for MH app developers in evaluating app acceptance, quality, and usability and better understanding factors that increase or decrease these evaluation metrics. For example, upon initial evaluations of a MH app, researchers and design and development teams can begin by examining validated constructs and moderators posited by the UTAUT2, which have previously been shown to influence app acceptance. This can facilitate an understanding of constructs that are the strongest predictive determinants of individuals' intentions to use the app and how these constructs vary across different user characteristics (e.g., gender, age, experience). Developers can then create, tailor, and implement features and supportive efforts in such a way that taps into strongly predictive constructs (e.g., features improving performance expectancy, tech support to account for the impact of facilitating conditions) and nuanced user characteristics (e.g., different versions for individuals with and without prior app experience). Further, understanding which constructs have less power in predicting behavioural intention and use allows developers to potentially sacrifice attributes of an app at the expense of constructs with stronger predictive strength (e.g., adding more complex features to improve performance expectancy at the expense of ease of use). MH app development teams can then engage in an iterative process in which they evaluate factors influencing the acceptance of their app in combination with usability and quality evaluations throughout all stages of development and implementation. This process can help stimulate optimal app design, minimize technical issues, and ensure app adaptations provide the most users with as helpful and engaging an experience as possible.

The exploratory analysis of the Big Five aspects additionally provides more nuanced details on how personality traits may influence the acceptance and use of MH apps, which has been largely neglected when designing mHealth apps. This could assist future MH app improvements via more personalized apps and features adapted to users' needs and characteristics to improve their overall impact and acceptance.

Specific to the JoyPop™ app, the present study identified critical factors influencing its acceptance, usability, and quality among Canadian postsecondary students. Results lend valuable support to the JoyPop™ app as an engaging and helpful tool for students to build resilience, improve MH and well-being, and increase access to helpful support for those who require care but face common barriers. We found high acceptance, usability, and quality in the present study, which, in combination with past evidence of effectiveness among postsecondary students (Macisaac et al., 2021), provide support that the JoyPop™ app may be a helpful and accessible support for diverse students in postsecondary education. Although evidence of efficacy is still accumulating (MacIsaac et al., 2024), results provide further evidence and support for integrating the JoyPop™ app into usual campus MH services. Integration of the app may help support the increasing need for MH-related student services and buffer resilience, increase emotion regulation skills, and improve long-term academic and life outcomes for students. Results are also essential in providing general and quantifiable information on the JoyPop™ app's acceptance, quality, and usability. This will help inform future iterations to ensure changes improve acceptance, usability, and quality (or, at minimum, do not worsen it) and facilitate the app's user-centeredness and ability to meet the diverse needs of postsecondary students.

Conclusion

MH apps are a promising tool to support the increasing MH demands of postsecondary students by mitigating barriers to needed care and promoting positive well-being. The present study sought to evaluate and better understand the acceptance, usability, and quality of a resilience-building MH app (JoyPop™). We used the well-validated UTAUT2 framework to evaluate the JoyPop™ app's acceptance and better understand the factors influencing its acceptance and use. The UTAUT2 model showed high out-of-sample predictive power and explained 75% of the variance in postsecondary students' acceptance of the JoyPop™ and 46% of the variance in app use. We found that students' intentions to use the JoyPop™ app were significantly influenced by its utility in providing helpful and efficient MH support, the enjoyment and entertainment it provided, and whether students had sufficient resources to use it. Notably, we found that how easy the JoyPop™ app was to learn and use and the opinions of significant others in students' lives did not influence app acceptance. We found moderating effects for age and MH app experience. Specifically, older students' intentions to use the app depended more on whether it was compatible with the technologies they already used and if they had the resources to use it. With regards to students' intention to use the app in the future, compared to students with no experience using MH apps, those with prior MH app experience placed less importance on the app's benefits for their MH and more importance on the opinions of significant others and the fun and enjoyment the app provided.

Overall, the JoyPop™ app had high acceptance, usability, and quality ratings among a diverse sample of postsecondary students. An exploratory analysis highlighted the unique associations of personality traits, specifically the Big Five aspects, UTAUT2 constructs, and JoyPop™ app use, which provided important information regarding the personalization of MH apps. Study findings contribute to the body of research by demonstrating the utility of the UTAUT2 framework in understanding mHealth app acceptance and represent the first direct demonstration of the UTAUT2 framework's utility in understanding the acceptance of a specific MH app. In combination with past JoyPop™ evaluations, results support its value as a helpful tool to integrate into postsecondary MH services and support student well-being. Findings contribute to the literature on the JoyPop™ app acceptance, quality, and usability.

In addition, results provide valuable information for MH app development teams and researchers on comprehensively evaluating MH apps to facilitate optimal app design and ensure an effective and engaging experience amongst a wide range of target users.

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Table 1

Big Five Personality Trait Domains

Domains	Characteristics of High Scores	Facets
Neuroticism	Frequent internalizing and externalizing negative affect	Stress, anxiety, impulsiveness, depression, anger, vulnerability
Agreeableness	Good-natured, trusting, and easy-going	Trust, compliance, altruism, straightforwardness, modesty, tendermindedness
Extraversion	Assertive, opportunistic, and reward-oriented	Warmth, gregariousness, assertiveness, activity, excitement-seeking, positive emotions
Conscientiousness	Disciplined, hardworking, achievement-orientated, and organized	Competence, order, dutifulness, achievement-striving, self-discipline, deliberation
Openness	Creative, appreciate aesthetics, and intellectually curious	Fantasy, aesthetics, feelings, actions, ideas, values

Sources: Costa & McCrae, 1992a and Digman, 1990

Table 2

The Ten Aspects of the Big Five Personality Traits

Domain	Aspect	Characteristics
Neuroticism	Volatility	Tendency towards externalized negative affect like anger and irritability
	Withdrawal	Tendency toward internalized negative affect, such as sadness and anxiety
Agreeableness	Compassion	Tendency towards compassionate emotional affiliations with others
	Politeness	Tendency of reasoned or cognitive considerations of others and respecting their needs and desires
Conscientiousness	Industriousness	Tendency towards reliability, persistence, and achievement striving
	Orderliness	Tendency towards tidiness, meticulousness, and scrupulousness
Extraversion	Enthusiasm	Tendency towards positive emotion and friendliness or sociability
	Assertiveness	Tendency towards dominance, leadership, and boldness
Openness/Intellect	Intellect	Tendency towards quickness, ingenuity, ideas
	Openness	Tendency towards aesthetics, imagination, fantasy

Sources: DeYoung, 2015 and DeYoung et al., 2007

Table 3

PLSPredict Guidelines for Determining Strength of Predictive Power

Predictive Power	PLS-SEM model vs. Naïve LM Benchmark Prediction Error Comparison
High	Lower RMSEs produced by PLS-SEM model on all indicators
Medium	Lower RMSEs produced by PLS-SEM model on majority of indicators
Low	Lower RMSEs produced by PLS-SEM model on minority of indicators
Poor	Lower RMSEs produced by PLS-SEM model on none of indicators

Note. PLSPredict determines predictive power by comparison Root Mean Squares Errors (RMSEs) produced by the PLS-SEM model on all dependent construct indicators to those of a naïve linear regression model (LM) benchmark.

Table 4

Participant Demographics

	n (%)
Gender	
Female	150 (82)
Male	33 (18)
Ethnicity	
White	100 (54.6)
Black	33 (18)
South Asian	20 (10.9)
Indigenous	10 (5.5)
Southeast Asian	7 (3.8)
Other (e.g., Middle Eastern, South American, Asian Canadian)	13 (7.2)
Country of Birth	
Canada	116 (63.3)
Nigeria	26 (14.2)
India	14 (7.7)
Pakistan	4 (2.2)
Phillippines	3 (1.6)
Other (e.g., Italy, Barbados, Vietnam, Sri Lanka, Uganda, China)	20 (11.1)
Program	
Nursing	66 (36.1)
Psychology	62 (33.9)
Education	10 (5.5)
Social Work	7 (3.8)
Computer Science	7 (3.8)
Biology	7 (3.8)
Other (e.g., Kinesiology, Business, Outdoor Rec, Political Science)	24 (13.1)
Year of University	
1	81 (44.2)
2	54 (29.5)
3	26 (14.2)
4	19 (10.4)
> 5	3 (1.6)

Table 5

Descriptive Statistics among the Big Five Domains and Aspects

	α	*M*	*SD*	N	A	C	E	O	Nv	Nw	Ac	Ap	Ci	Co	Ee	Ea	Oi	Oo
N	.90	3.18	.63	1.00														
A	.82	4.00	.42	.03	1.00													
C	.88	3.29	.56	-.45	.04	1.00												
E	.84	3.40	.49	-.31	-.01	.33	1.00											
O	.75	3.56	.43	-.17	.12	.16	.31	1.00										
Volatility	.89	3.03	.77	.90	-.04	-.31	-.13	-.14	1.00									
Withdrawal	.82	3.34	.66	.86	.10	-.50	-.44	-.16	.56	1.00								
Compassion	.83	4.08	.51	.11	.83	-.04	.18	.24	.08	.12	1.00							
Politeness	.72	3.91	.51	-.05	.83	.11	-.19	-.05	-.13	.06	.39	1.00						
Industriousness	.86	2.98	.70	-.60	.03	.91	.36	.19	-.44	-.64	-.05	.09	1.00					
Orderliness	.75	3.61	.57	-.15	.05	.86	.20	.09	-.07	-.21	-.02	.10	.58	1.00				
Enthusiasm	.79	3.52	.58	-.21	.23	.13	.80	.19	-.10	-.28	.35	.04	.18	.03	1.00			
Assertiveness	.84	3.28	.62	-.29	-.23	.39	.83	.32	-.11	-.43	-.04	-.34	.39	.29	.33	1.00		
Intellect	.80	3.42	.60	-.23	.06	.26	.40	.85	-.14	-.27	.20	-.09	.32	.13	.19	.45	1.00	
Openness	.58	3.69	.47	-.02	.13	-.05	.06	.73	-.08	.06	.19	.03	-.07	-.01	.10	.00	.27	1.00

Note. *Neuroticism (N); Agreeableness (A); Conscientiousness (C); Extraversion (E); Openness/Intellect (O); Volatility (Nv); Withdrawal (Nw); Compassion (Ac) Politeness (Ap); Industriousness (Ci); Orderliness (Co); Enthusiasm (Ee); Assertiveness (Ea), Intellect (Oi); Openness (Oo).*

Table 6

Means, Standard Deviations, and Correlations for UTAUT2 Variables

	M	*SD*	PE	EF	FC	SI	HT	HM	BI	App Use
PE	4.47	1.39	1.00							
EF	6.25	0.72	.39	1.00						
FC	5.67	0.94	.29	.41	1.00					
SI	4.01	1.21	.64	.24	.24	1.00				
HT	4.29	1.39	.82	.43	.33	.61	1.00			
HM	5.27	1.31	.75	.51	.33	.47	.78	1.00		
BI	4.46	1.57	.82	.37	.43	.52	.85	.76	1.00	
Use	3.55	1.61	.62	.33	.18	.50	.60	.59	.67	1.00

Note. *Performance Expectancy (PE); Effort Expectancy (EF); Facilitating Conditions (FC); Social Influence (SI); Habit (HT); Hedonic Motivation (HM); Behavioural Intention (BI).*

Table 7

Usability of the JoyPop™ app based on the mHealth App Usability Questionnaire (MAUQ)

Dimensions of Usability	*M (SD)*
Overall Usability (α = 0.92), 18 items	5.63 (0.85)
Ease of use (α = 0.79), 5 items	6.37 (0.67)
S1. The app was easy to use.	6.58 (0.66)
S2. It was easy for me to learn to use the app.	6.64 (0.55)
S3. The navigation was consistent when moving between screens.	6.37 (0.94)
S4. The interface of the app allowed me to use all the functions (such as entering information, responding to reminders, viewing information) offered by the app.	6.32 (1.04)
S5. Whenever I made a mistake using the app, I could recover easily and quickly.	5.96 (1.20)
Interface and satisfaction (α = 0.86), 7 items	5.71 (0.99)
S6. I like the interface of the app.	5.75 (1.23)
S7. The information in the app was well organized, so I could easily find the information needed.	6.29 (0.92)
S8. The app adequately acknowledged and provided information to let me know the progress of my action.	5.50 (1.45)
S9. I feel comfortable using this app in social settings.	5.84 (1.24)
S10. The amount of time involved in using this app has been fitting for me.	5.59 (1.42)
S11. I would use this app again.	5.42 (1.50)
S12. Overall, I am satisfied with this app.	5.55 (1.50)
Usefulness (α = 0.85), 6 items	4.93 (1.17)
S13. The app would be useful for my health and well-being.	5.19 (1.58)
S14. The app improved my access to health care services.	4.63 (1.62)
S15. The app helped me manage my health effectively.	4.52 (1.55)
S16. This app has all the functions and capabilities I expected it to have.	4.85 (1.71)
S17. I could use the app even when the Internet connection was poor or not available.	5.16 (1.31)
S18. This app provided an acceptable way to receive health care services, such as accessing educational materials, tracking my own activities, and performing self-assessment.	5.22 (1.45)

Table 8

Means and Standard Deviations for the uMARS Objective Quality Scales

Scales	***M (SD)***
Engagement	3.48 (0.72)
Functionality	4.48 (0.52)
Aesthetics	4.17 (6.74)
Information	4.14 (0.71)
Total Score	4.06 (0.54)

Table 9

Means, Standard Deviations, and Frequencies of uMARS Subjective Quality Scale Item Responses

Question	Response Options	*n (%)*	*M (SD)*
Would you recommend the JoyPop™ app to people who might benefit from it?	Not at all, I would not recommend this app to anyone	7 (3.8)	3.69 (1.22)
	There are very few people I would recommend this app to	32 (17.5)	
	Maybe, There are several people I would recommend this app to	33 (18)	
	There are many people I would recommend this app to	49 (26.8)	
	Definitely, I would recommend this app to everyone	62 (33.9%)	
How many times do you think you would use the JoyPop™ app in the next 12 months if it was relevant to you?	None	19 (10.4)	3.55 (1.61)
	1 to 2	8 (4.4)	
	3 to 10	44 (24)	
	10 to 50	77 (42.1)	
	> 50	35 (19.1)	
Would you pay for this app?	Definitely not	82 (44.8)	1.9 (0.98)
	Probably not	50 (27.3)	
	Unsure	40 (21.9)	
	Probably yes	9 (4.9)	
	Definitely yes	2 (1.1)	
What is your overall (star) rating of the app?	One	3 (1.6)	3.54 (0.80)
	Two	13 (7.1)	
	Three	62 (33.9)	
	Four	92 (50.3)	
	Five	13 (7.1)	
Total Score			3.17 (0.82)

Table 10

Means, Standard Deviations, and Frequencies of uMARS Perceived Impact Scale Item Responses

Items	**Response Option Frequencies, *n (%)***					***M (SD)***
	Strongly Disagree	**Disagree**	**Neither Agree or Disagree**	**Agree**	**Strongly Agree**	
Increased my awareness of the importance of addressing mental health and coping skills	7 (3.8)	28 (15.3)	41 (22.4)	78 (42.6)	29 (15.8)	3.51 (1.05)
Increased my knowledge/understanding of mental health and coping skills	10 (5.5)	26 (14.2)	44 (24)	82 (44.8)	21 (11.5)	3.42 (1.04)
Changed my attitudes toward improving mental health and coping skills	9 (4.9)	32 (17.5)	42 (23)	79 (43.1)	21 (11.5)	3.39 (1.06)
Increased my intentions/motivation to address mental health and coping skills	7 (3.8)	26 (14.2)	44 (24)	80 (43.7)	26 (14.2)	3.49 (1.02)
Would encourage me to seek further help to address mental health and coping skills	6 (3.3)	20 (10.9)	42 (23)	81 (44.2)	34 (18.6)	3.64 (1.01)
Will improve my mental health and coping skills	10 (5.5)	19 (10.4)	51 (27.9)	86 (47)	17 (9.3)	3.44 (0.99)
Total Score						3.48 (0.88)

Table 11

Outer Loadings, Internal Consistency, and Convergent Validity of Constructs in the Structural Model

Construct and Associated Indicators	Outer Loadings	α	ρA	ρC	AVE
Behavioural Intention (BI)		0.94	0.94	0.96	0.90
BI1	0.94				
BI2	0.94				
BI3	0.96				
Performance Expectancy (PE)		0.90	0.90	0.94	0.84
PE1	0.92				
PE2	0.91				
PE3	0.92				
Effort Expectancy (EF)		0.77	0.86	0.85	0.58
EF1	0.64				
EF2	0.84				
EF3	0.84				
EF4	0.70				
Facilitating Conditions (FC)		0.70	0.86	0.86	0.76
FC1	0.80				
FC3	0.94				
Social Influence (SI)		0.91	0.91	0.94	0.85
SI1	0.89				
SI2	0.93				
SI3	0.94				
Hedonic Motivation (HM)		0.92	0.92	0.95	0.86
HM1	0.93				
HM2	0.94				
HM3	0.91				

Note. Reliability Coefficient (pA); Composite Reliability (pC); Average Variance Extracted (AVE).

Table 12

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

	BI	EF	FC	HM	PE	SI
BI						
EF	0.41					
FC	0.43	0.33				
HM	0.82	0.60	0.28			
PE	0.89	0.46	0.24	0.82		
SI	0.57	0.28	0.22	0.52	0.71	
Use	0.69	0.35	0.11	0.61	0.66	0.52

Note. *Performance Expectancy (PE); Effort Expectancy (EF); Facilitating Conditions (FC); Social Influence (SI); Habit (HT); Hedonic Motivation (HM); Behavioural Intention (BI).*

Table 13

Variance Inflation Factor (VIF) Statistics for the Inner Structural Model

Model Paths	VIF
Effort Expectancy -> Behavioural Intention	1.42
Facilitating Conditions -> Behavioural Intention	1.10
Hedonic Motivation -> Behavioural Intention	2.67
Performance Expectancy -> Behavioural Intention	3.00
Social Influence -> Behavioural Intention	1.71
Facilitating Conditions -> Use	1.16
Behavioural Intention -> Use	1.16

Table 14

Structural Model Path Estimate Results

Hypothesis #	Relationship	Path Coefficient	*t*-values	CI	Decision	Overall Hypothesis
H1	PE -> BI	0.576	8.265	[0.453, 0.683]**	Supported	Partially Supported
	EF -> BI	-0.065	1.526	[-0.135, 0.004]	Not Supported	
	FC -> BI	0.181	3.801	[0.103, 0.259]**	Supported	
	SI -> BI	-0.026	0.478	[-0.119, 0.057]	Not Supported	
	HM -> BI	0.334	4.795	[0.225, 0.455]**	Supported	
	HT -> BI				Untested	
H2	BI -> Use	0.725	16.934	[0.650, 0.792]**	Supported	Partially Supported
	FC -> Use	0.131	3.649	[0.075, 0.193]**	Supported	
	HT -> Use				Untested	
H5	Usability -> Use				Untested	Unexamined
H6	Quality -> Use				Untested	
H7 to H11	Big Five Aspects -> BI and Use				Untested	Unexamined

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

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

Table 15

PLSpredict Summary

Indicators of the outcome variable	PLS model RMSE	Naïve (LM) benchmark model RMSE
BI1	**0.958**	1.011
BI2	**0.974**	1.011
BI3	**0.982**	1.020
Use	**0.907**	0.916

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 16

Multigroup Analysis Comparing Path Coefficients among Women and Men

Path Relationship	Women	Men	Difference	Lower 95%(CI)	Upper 95%(CI)	*p-Value*
EF -> BI	-0.045	-0.121	0.075	-0.218	0.192	0.234
FC -> BI	0.132	0.248	-0.116	-0.232	0.204	0.197
HM -> BI	0.284	0.563	-0.279	-0.344	0.315	0.083
PE -> BI	0.633	0.382	0.250	-0.284	0.367	0.120
SI -> BI	-0.026	0.007	-0.033	-0.262	0.236	0.444

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

Table 17

Moderating Effects of Age and Mental Health App Experience

Interaction Term Relationships	Path Coefficients	*t-Values*	Lower 95%(CI)	Upper 95%(CI)	*p-Values*
Age x EF -> BI	-0.080	0.891	-0.268	0.040	0.186
Age x FC -> BI	0.092	1.679	0.021	0.209	**0.047**
Age x FC -> Use	-0.032	0.515	-0.133	0.075	0.303
Age x HM -> BI	0.083	0.627	-0.084	0.385	0.265
Age x PE -> BI	-0.131	1.251	-0.369	0.001	0.105
Age x SI -> BI	0.095	1.167	-0.045	0.216	0.122
Experience x BI -> Use	0.085	0.496	-0.215	0.350	0.310
Experience x EF -> BI	-0.166	0.749	-0.521	0.185	0.227
Experience x FC -> BI	-0.151	1.408	-0.321	0.025	0.080
Experience x FC -> Use	0.028	0.143	-0.328	0.319	0.443
Experience x HM -> BI	-0.513	2.546	-0.804	-0.144	**0.005**
Experience x PE -> BI	0.824	2.855	0.263	1.224	**0.002**
Experience x SI -> BI	-0.360	2.366	-0.584	-0.088	**0.009**

Note. Performance Expectancy (PE); Effort Expectancy (EF); Facilitating Conditions (FC); Social Influence (SI); Habit (HT); Hedonic Motivation (HM); Behavioural Intention (BI); 95% Bootstrap Confidence Intervals (CI). Bolded p-Values represent significant interaction terms.

Table 18

Correlations among Big Five Domains and Aspects, UTAUT2 constructs, and JoyPop™ app use

	PE	EF	FC	SI	HT	HM	BI	Use
Volatility	.03	-.06	.08	-.02	.09	**.18**	.05	-.03
Withdrawal	-.04	-.04	.05	-.01	-.01	-.01	-.06	-.10
Compassion	-.10	.16	.16	-.14	-.16	-.02	-.10	-.13
Politeness	.11	**.24**	.12	.03	.09	.13	.12	.02
Industriousness	.16	.08	.13	.05	.11	.14	**.18**	.09
Orderliness	.16	**.20**	.12	.03	.12	.15	.15	.07
Enthusiasm	.08	.08	**.18**	-.02	.03	.10	.10	-.02
Assertiveness	.07	-.01	.09	.02	-.01	.04	.08	.13
Intellect	-.01	.13	.04	-.06	-.12	.01	-.08	.04
Openness	.13	**.26**	.00	.08	.06	.10	.10	**.21**
Neuroticism	.00	-.06	.08	-.01	.06	.11	-.01	-.07
Agreeableness	.01	**.24**	.17	-.07	-.04	.07	.01	-.07
Conscientiousness	**.18**	.15	.14	.05	.13	.16	**.19**	.09
Extraversion	.09	.04	.16	.00	.02	.09	.10	.07
Openness/Intellect	.06	**.23**	.02	.00	-.05	.06	.00	.14

Note. Performance Expectancy (PE); Effort Expectancy (EF); Facilitating Conditions (FC); Social Influence (SI); Habit (HT); Hedonic Motivation (HM); Behavioural Intention (BI). Bolded correlations were significant after controlling for type 1 error rates.

Figure 1

Summary and Highlights of Features in the JoyPop™ app

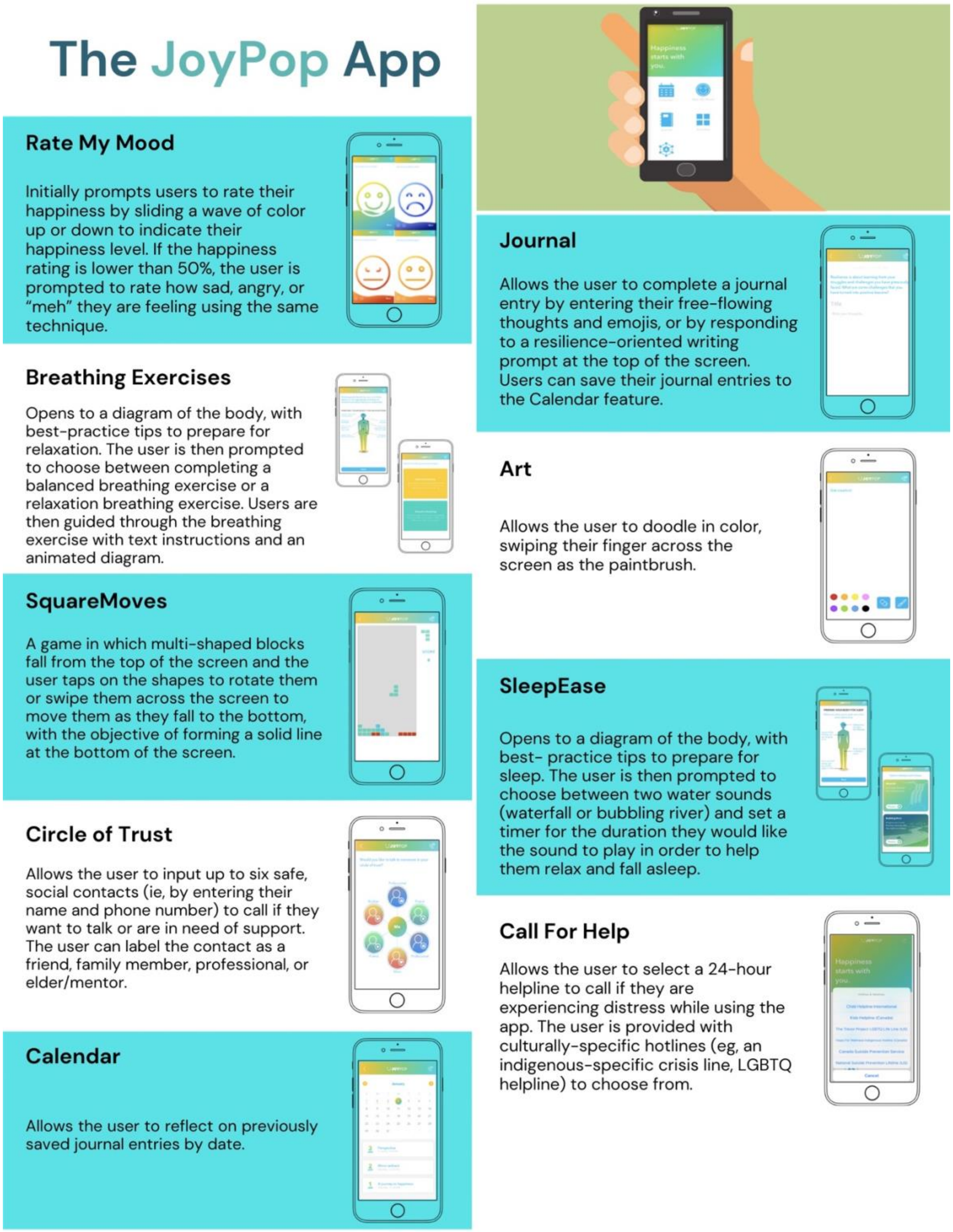


Figure 2

Structural Model and Relevant Hypotheses

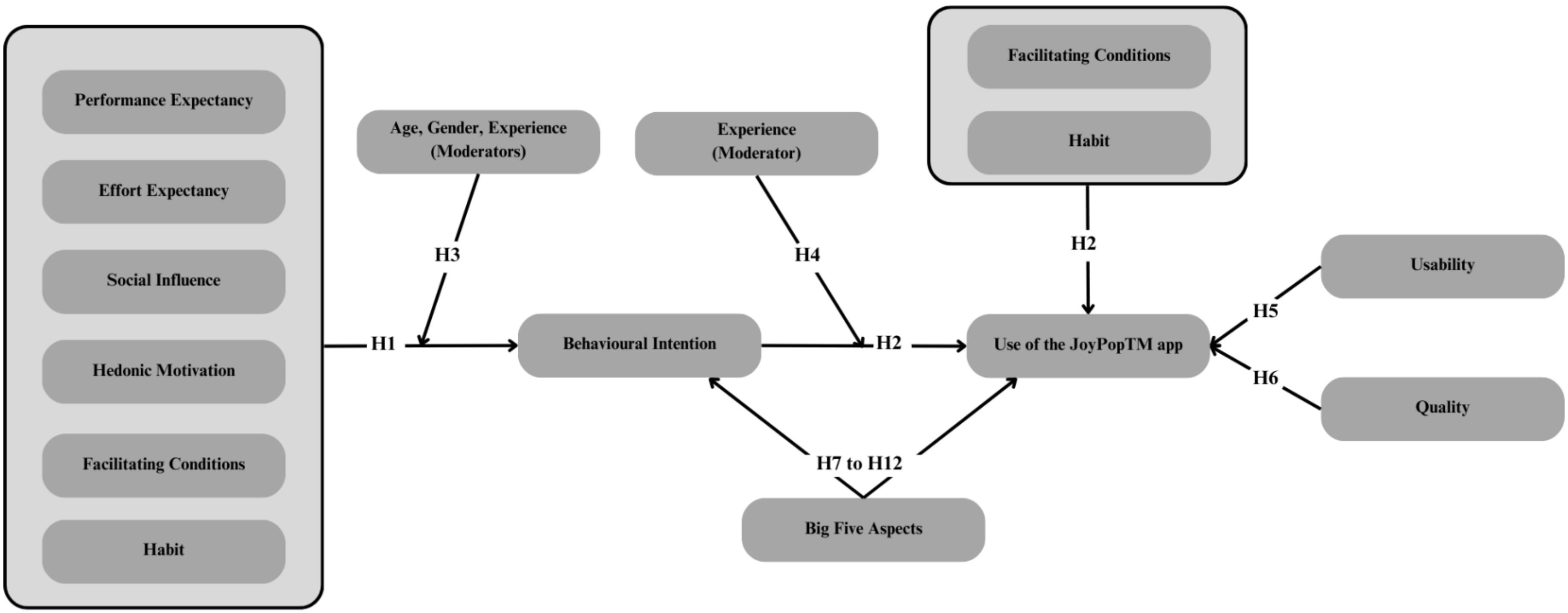


Figure 3

Mahalanobis Distance Values Ranked from Highest to Lowest

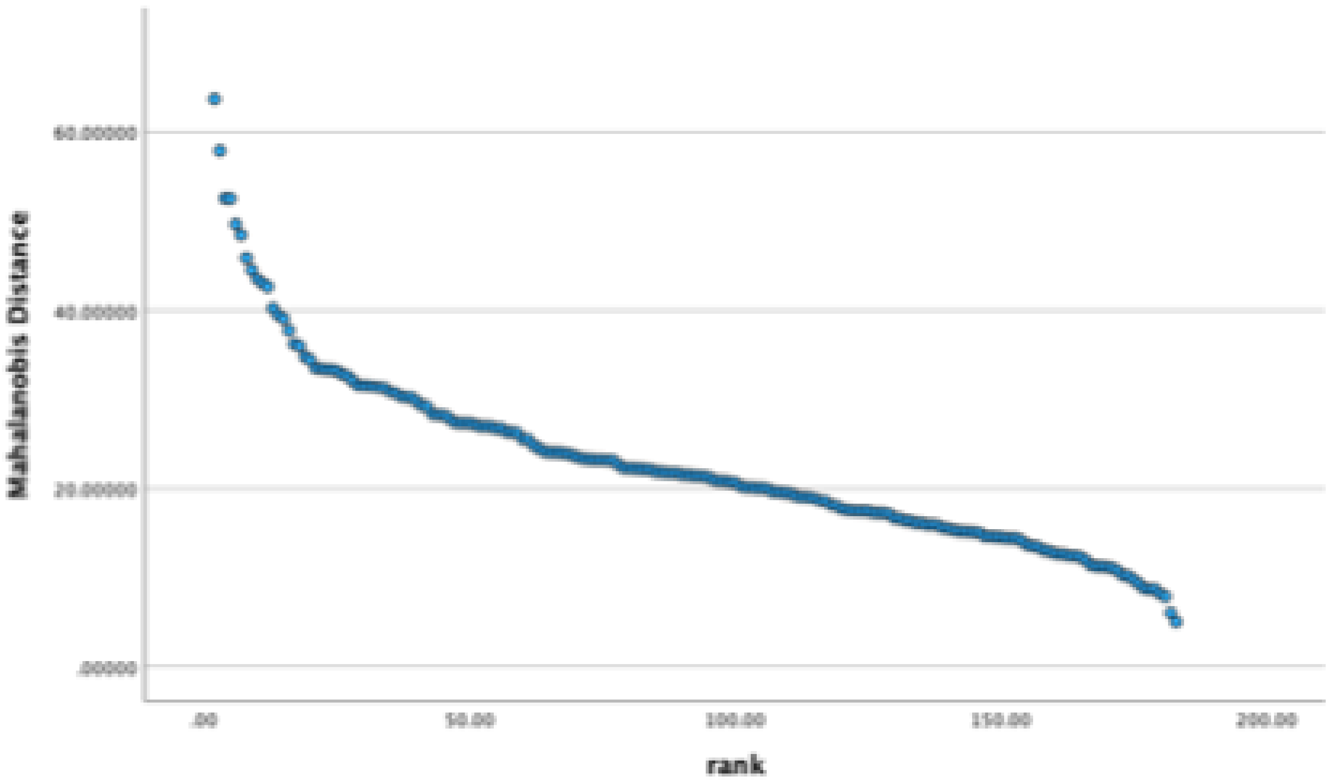


Figure 4

Frequency Distribution of Participants' Mean Scores for Behavioural Intention to Use the JoyPop™ app

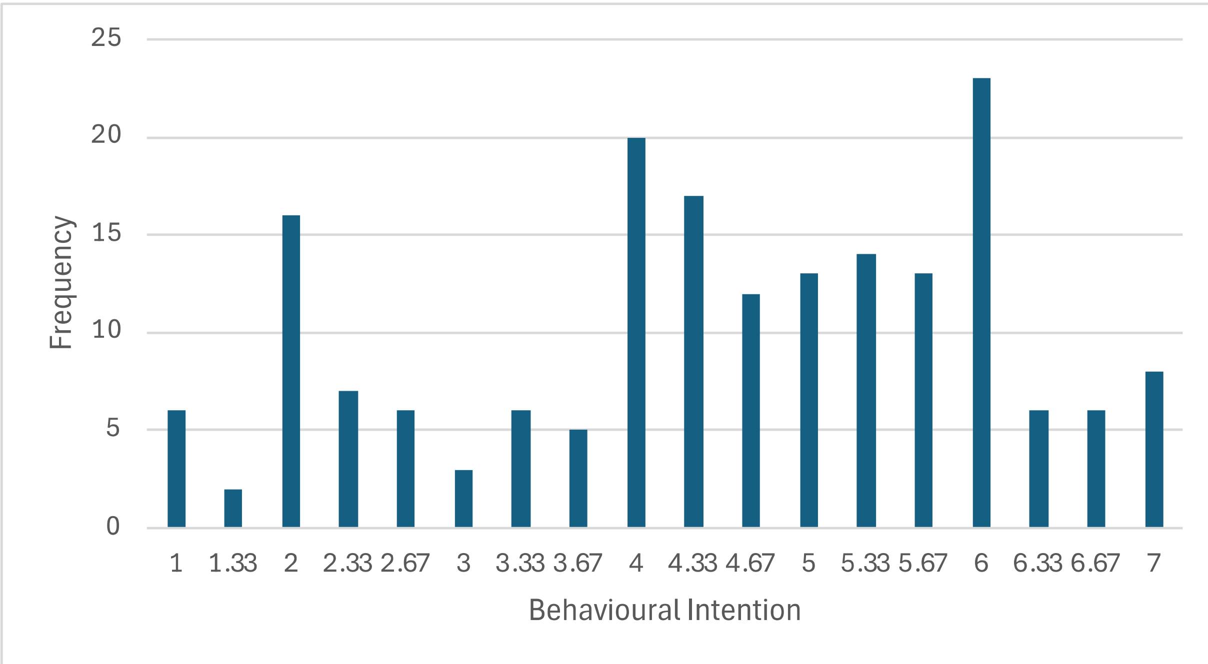


Figure 5

Final PLS-SEM Model

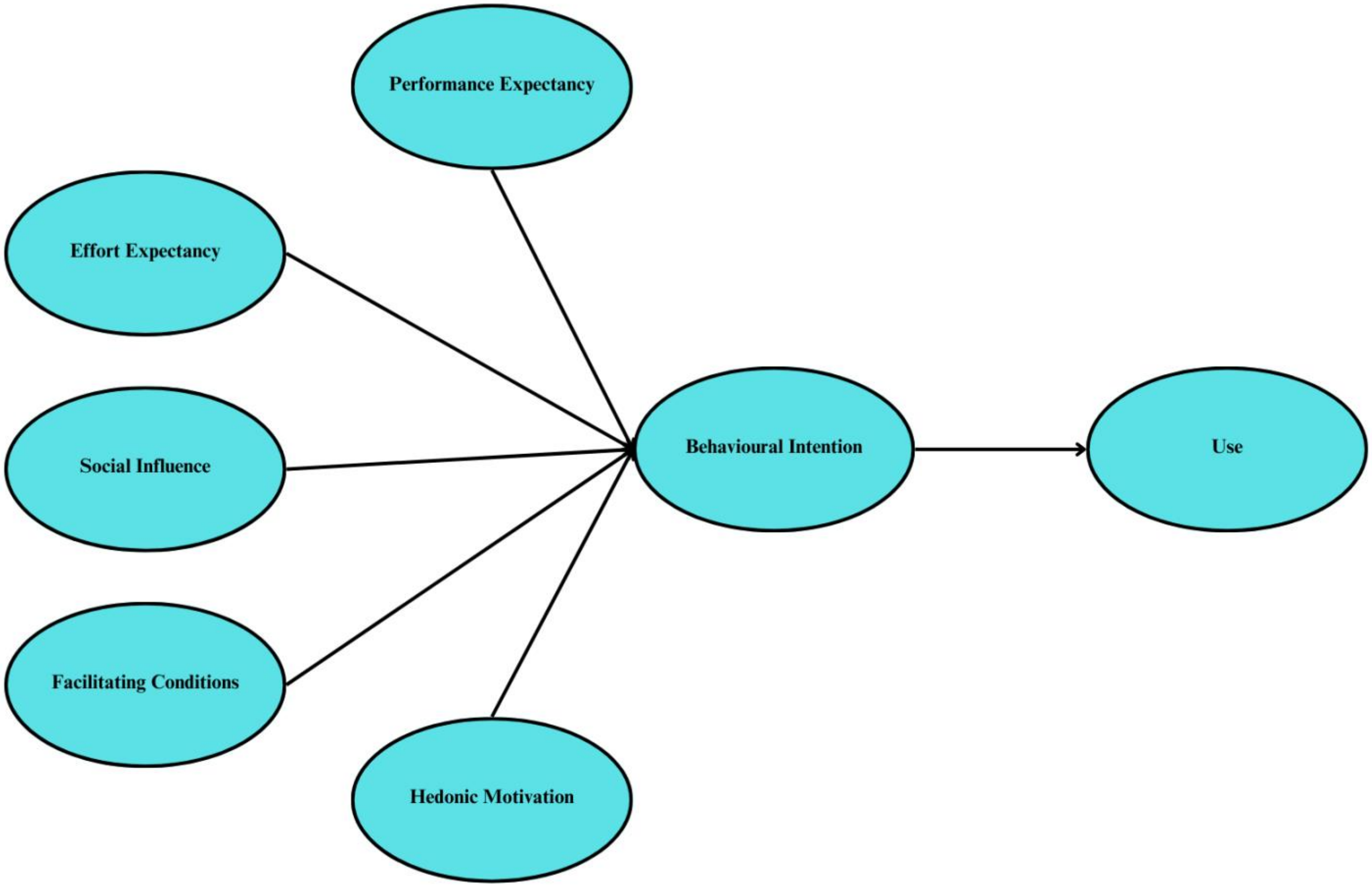


Figure 6

Moderating Effect of Age on Facilitating Conditions

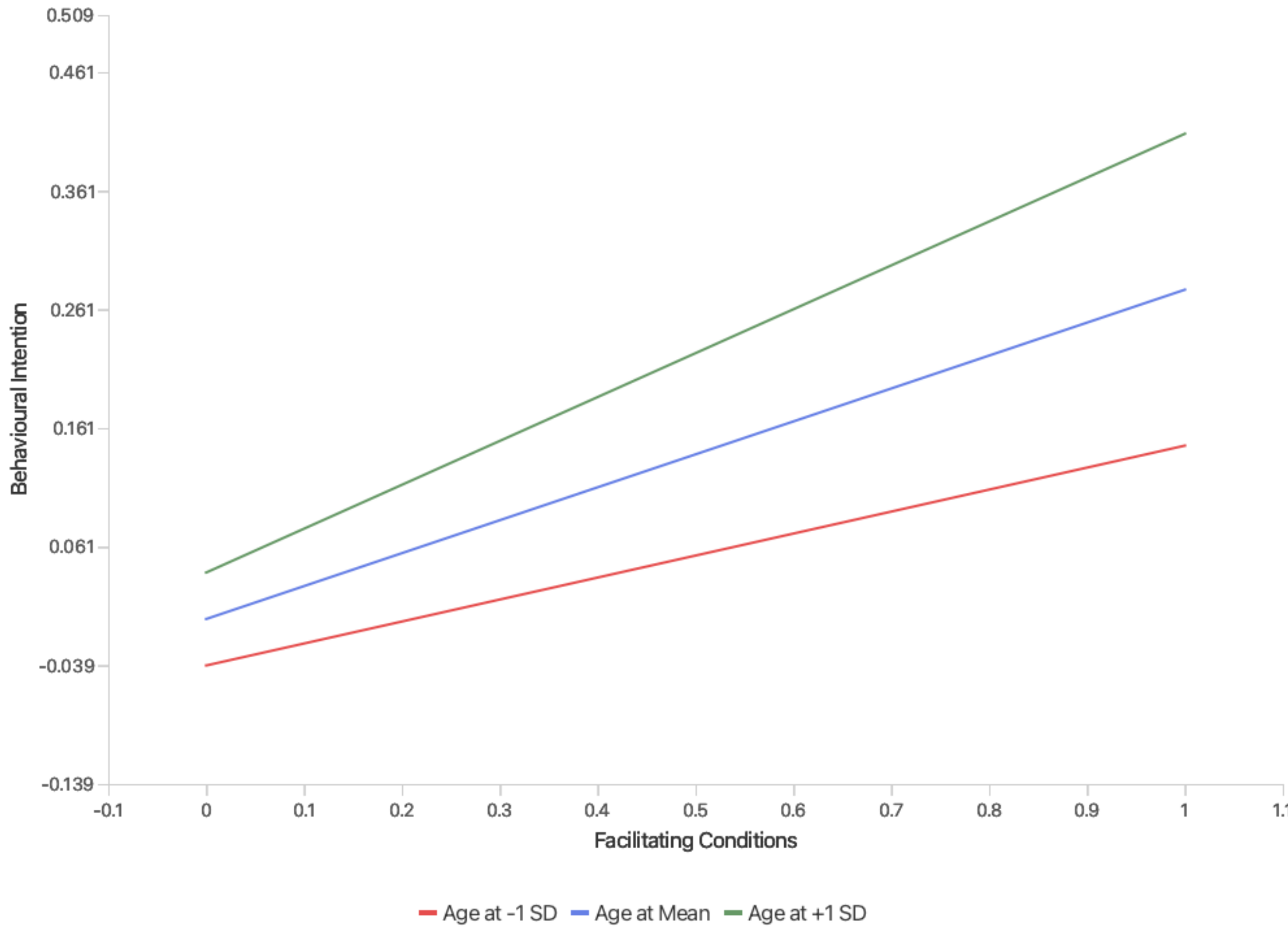
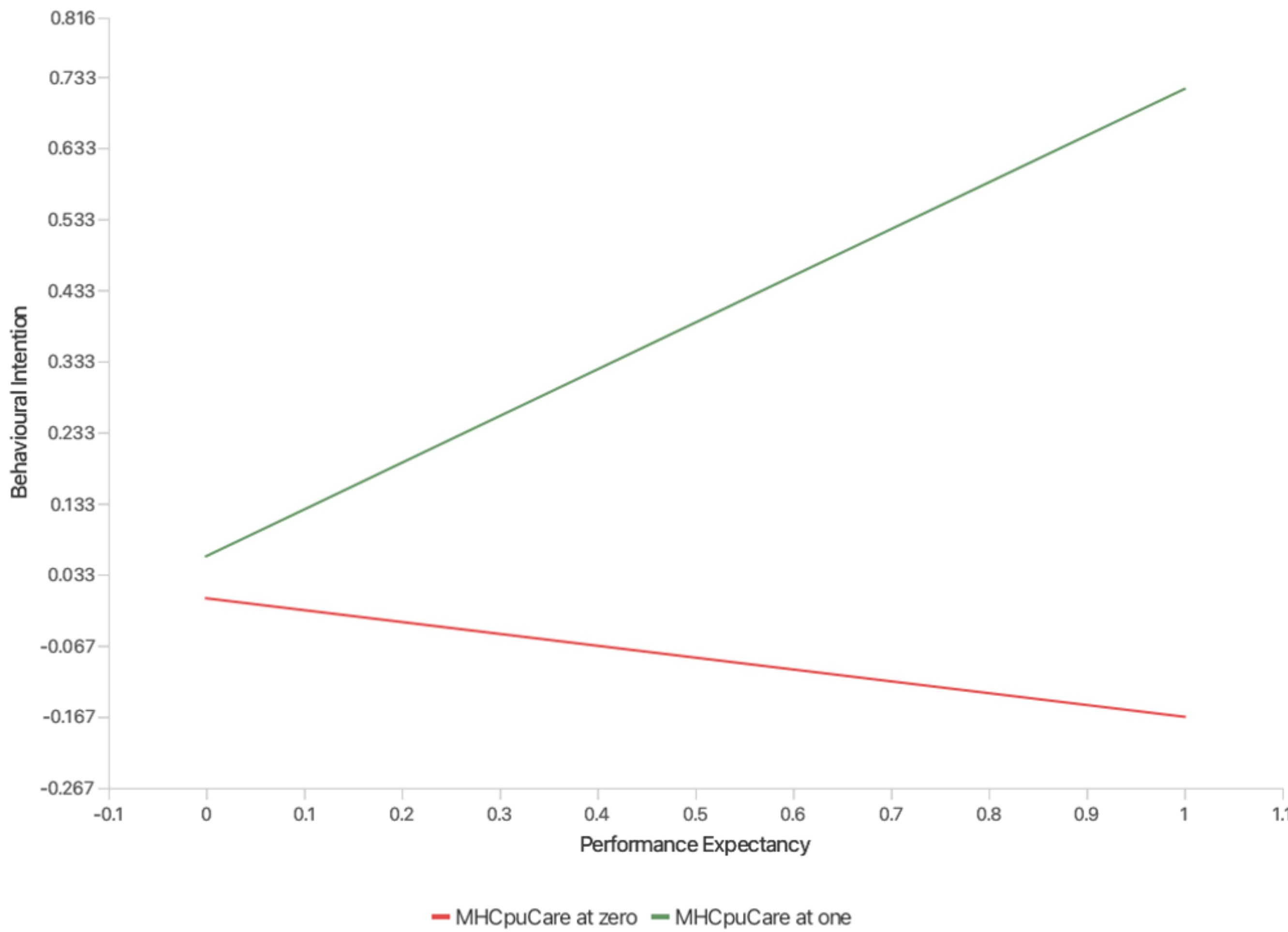


Figure 7

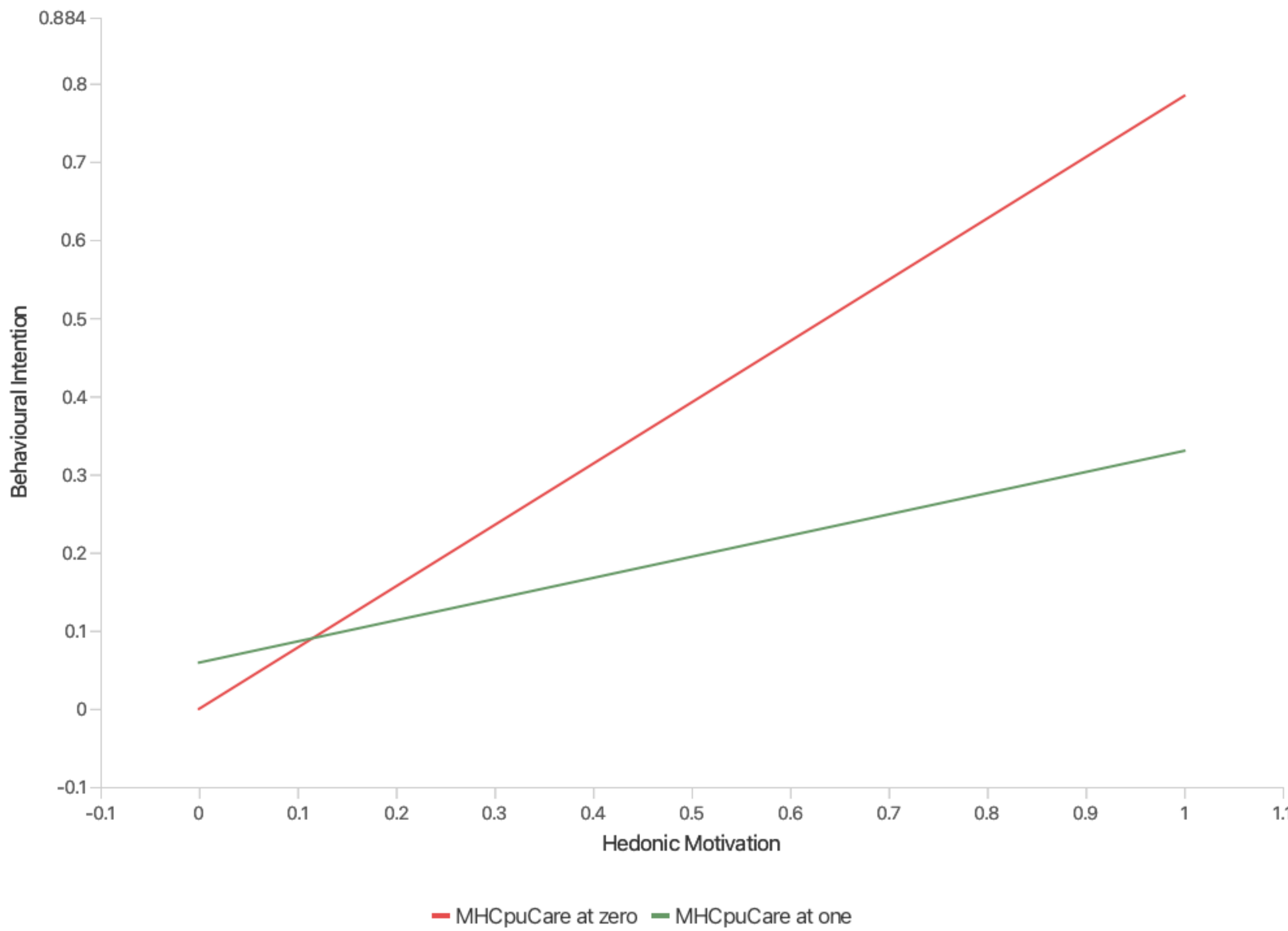
Moderating Effect of Experience on Performance Expectancy



Note. MHCpuCare at zero = Experience with MH apps; MHCpuCare at one = No Experience with MH apps

Figure 8

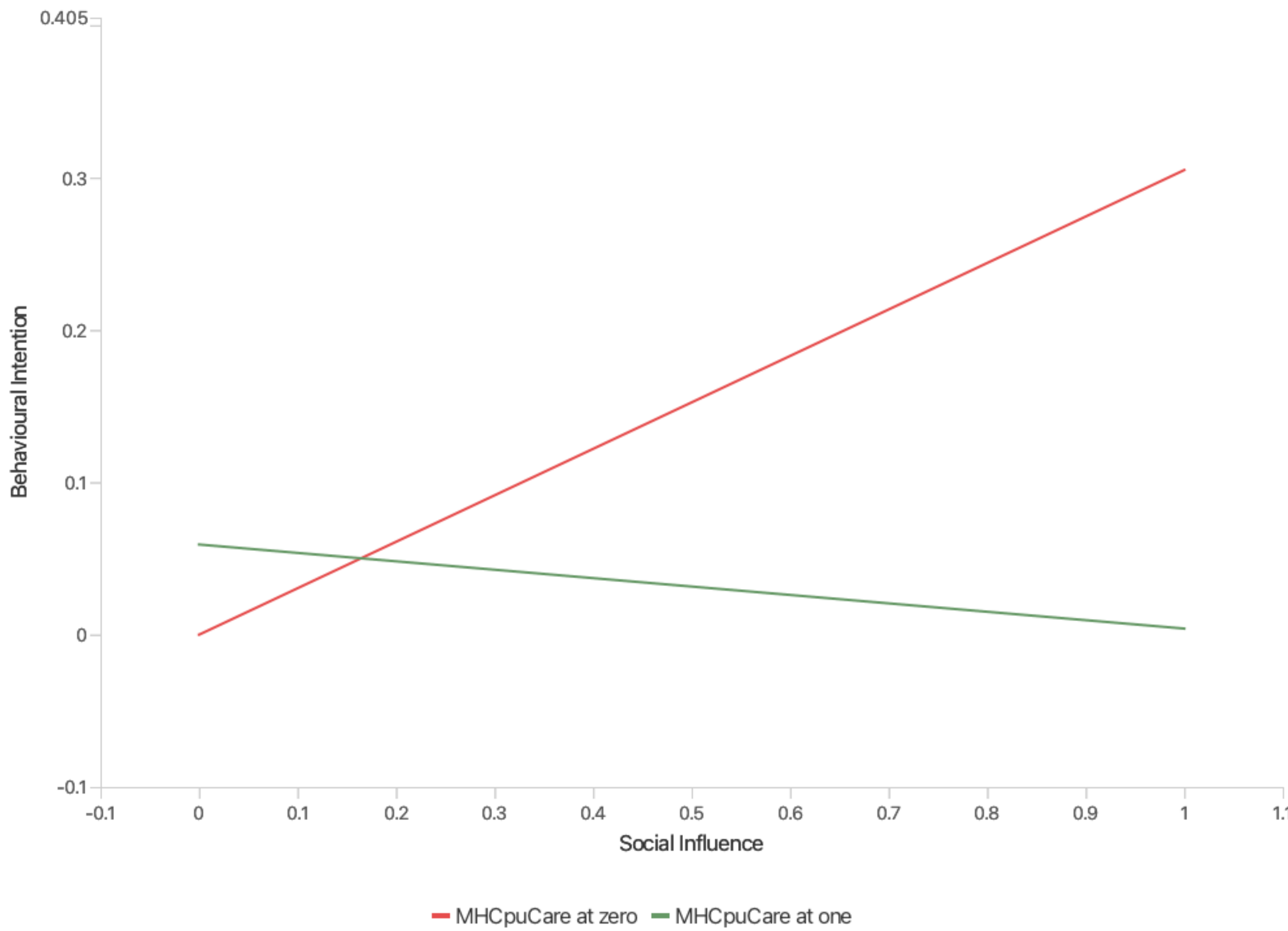
Moderating Effect of Experience on Hedonic Motivation



Note. MHCpuCare at zero = Experience with MH apps; MHCpuCare at one = No Experience with MH apps

Figure 9

Moderating Effect of Experience on Social Influence



Note. MHCpuCare at zero = Experience with MH apps; MHCpuCare at one = No Experience with MH apps

Appendix A

Poster

Appendix B

Class Announcement

Hi everyone,

My name is ____ and I am part of Dr. Aislin Mushquash's research team in the Department of Psychology. I am here to let you know about a research study we are conducting to evaluate engagement factors and the use of a resilience-building app called JoyPop™ as a tool to support university students. Resilience is defined as a characteristic of an individual and their environment that provides the resources necessary for positive development and wellbeing. The JoyPop™ app is designed to promote resilience through improved emotion regulation and has been shown to be effective in enhancing undergraduates' abilities to understand and deal with their emotions effectively. The study is designed to continue evaluating the app by further understanding students' views on its usability, acceptance, and quality to inform app improvements and effectiveness.

To qualify for the study, you must be:

- Be a student at Lakehead University
- Have an iOS device (iPhone, iPad, iPod Touch
    - *If you do not have access to an iOS device, an iPhone with only the app on it may be provided to you upon availability to use for the duration of the study.
- Speak/read fluently in English
- **NOT BE CURRENTLY** participating in the study titled: *Promoting mental health and well-being among post-secondary students with the Joypop app: A randomized controlled trial*
    - If you have participated in the above study and are finished, **YOU CAN PARTICIPATE IN OURS**

Participation will involve:

- Downloading and using the App at least twice/day for 1 week.
- Completing surveys before and after using the app

For participating, you would receive:

- Up to $40
- If you are in a psychology course that offers bonus course marks, you could earn up to 3.5 bonus course marks for an eligible psychology course.

Your participation in this study is entirely voluntary, and whether you choose to participate or not will not impact your academic standing in this or any other course. If you are interested, you can pick up a postcard from us/professor after class to access the research team contact information and/or contact our research team for more information or to sign up by emailing **imalik3@lakeheadu.ca** or texting/calling us at **807-620-7664**. If you enrolled psychology course you can sign up via SONA systems at **http://lupsych.sona-systems.com/** to participate for bonus course marks.

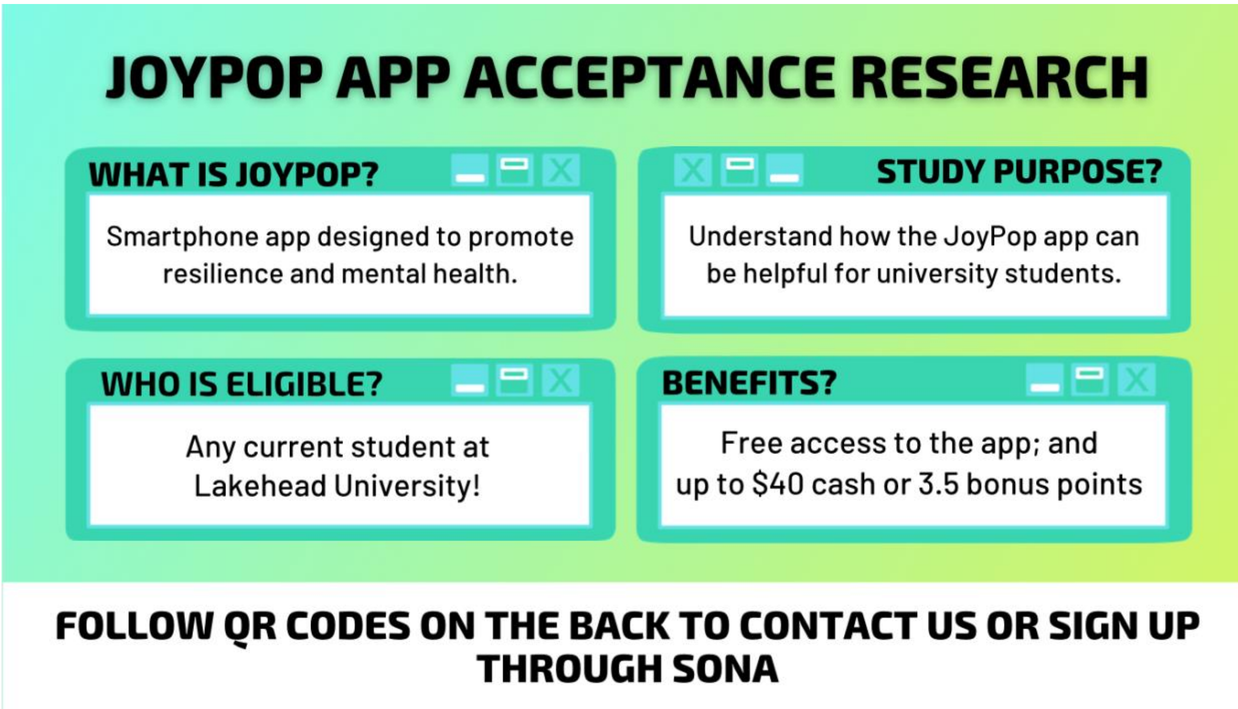
For more information about the JoyPop™ App, please follow the link below:
https://www.youtube.com/watch?v=CnDt-_4Mr2k&ab_channel=JoyPopApp

Thank you for your time.

Appendix C

Postcard

Front/Back



Appendix D

Class Email

Subject:

Research Opportunity – JoyPop™ Acceptance Study

Email Body:

Hello,

My name is ____ and I am part of Dr. Aislin Mushquash's research team in the Department of Psychology. I am here to let you know about a research study we are conducting to evaluate engagement factors and the use resilience-building app called JoyPop™ as a tool to support university students.

The JoyPop™ app is designed to promote resilience through improved emotion regulation and has been shown to be effective in enhancing undergraduates' abilities to understand and deal with their emotions effectively. The study is designed to continue evaluating the app by further understanding students' views on its usability, acceptance, and quality to inform app improvements and effectiveness.

To qualify for the study, you must be:

- A student at Lakehead University
- Have an iOS device (iPhone, iPad, iPod Touch).
    - *If you do not have access to an iOS device, an iPhone with only the app on it may be provided to you upon availability to use for the duration of the study.
- Speak/read fluently in English
- **NOT BE CURRENTLY** participating in the study titled: *Promoting mental health and well-being among post-secondary students with the Joypop app: A randomized controlled trial*
    - If you have participated in the above study and are finished, **YOU CAN PARTICIPATE IN OURS**

Participation will involve:

- Downloading and using the app at least twice/day for 1 week
- Completing surveys before and after using the app

For participating, you would receive:

- Up to $40
- If you are in a psychology course that offers bonus course marks, you could earn up to 3.5 bonus course marks for an eligible psychology course.

Your participation in this study is entirely voluntary, and whether you choose to participate or not will not impact your academic standing in this or any other course.

If you are interested, you can contact us at **imalik3@lakeheadu.ca** or **807-620-7664 (text/call)**. If you enrolled psychology course you can sign up via SONA systems at **http://lupsych.sona-systems.com/** to participate for bonus course marks.

For more information about the JoyPop™ App, please follow the link below:
https://www.youtube.com/watch?v=CnDt-_4Mr2k&ab_channel=JoyPopApp

Thank you for your time.

Principal Investigator:
Dr. Aislin Mushquash, Ph.D., C.Psych.
Associate Professor, Department of Psychology
Lakehead University
955 Oliver Road
Thunder Bay, ON P7B5E1
t: (807) 343-8010 ext 8771
f: (807) 346-7734
w: aislinmushquash.com
e: aislin.mushquash@lakeheadu.ca

Appendix E

SONA Ad

You are invited to participate in a study evaluating engagement factors and the use of a resilience-building app (JoyPop™) as a tool to support university students. The app is designed to promote resilience through improved emotion regulation and has been shown to be effective in enhancing undergraduates' abilities to understand and deal with their emotions effectively.

Eligibility criteria:

- Lakehead University student
- Have an iOS device (iPhone, iPad, or iPod Touch)
    - *If you do not have access to an iOS device, an iPhone with only the app on it may be provided to you upon availability to use for the duration of the study (if this is the case please contact the research team at **imalik3@lakeheadu.ca or 807-620-7664 (text/call).**
- Speak/read fluently in English.
- **NOT BE CURRENTLY** participating in the study titled: *Promoting mental health and well-being among post-secondary students with the Joypop app: A randomized controlled trial*
    - If you have participated in the above study and are finished, **YOU CAN PARTICIPATE IN OURS**

Participation will involve:
Downloading and using the app for 1 week and completing surveys before and after using the app. For participating, you will: Receive up to 3.5 bonus course marks for an eligible psychology course or $40 cash/e-transfer. There is minimal risk associated with participating in the proposed study but some questions may be hard for some people to discuss. Participants are free to skip questions they do not feel comfortable answering. If participants feel upset during the study, we have information available on relevant supports.

This study has 3 Parts: A description, the duration, and associated compensation of each are described below.

Part 1: You will be asked to complete some surveys and receive information on the app including its features, and how to download and use it. This will take up to 1 hour and you will receive 1 bonus course mark (or $10).

Part 2: You will be asked to use the app at least twice/day for 1 week.

Part 3: You will also be asked to complete some online surveys 1 week after Part 1. This will take approximately 10min/day + 0.5 hours. You will receive 1.5 bonus course marks or $20 for completing Part 3. In total the whole study will take you 2.5 hours and you will receive either (a) 2.5 bonus course marks; or (b) $30 (cash/e-transfer).

In addition to the description above, **you will have an opportunity to participate in Part 4** which involves participating in an interview about your experiences using the app after a week.

This would occur via Zoom or in-person and would last approximately 45 minutes. Participants will receive an extra $10 or 1 bonus course mark for completing this interview.

For more information about the JoyPop™ App, please follow the link below:
https://www.youtube.com/watch?v=CnDt-_4Mr2k&ab_channel=JoyPopApp

Appendix F

Participant Recruitment (Text)

Hello [Insert name if available],

Thank you for your interest in the JoyPop™ Acceptance study.

To qualify you must be a student at Lakehead University and have an iOS device (iPhone, iPad, or iPod touch)
*If you don't have an iOS device, let us know and an iPhone with only the app on it may be provided to you upon availability to use for the study.

NOT BE CURRENTLY participating in the study titled: *Promoting mental health and well-being among post-secondary students with the Joypop app: A randomized controlled trial*

- If you have participated in the above study and are finished, **YOU CAN PARTICIPATE IN OURS**

<u>You can earn up to $40 for participating or 3.5 bonus course marks for an eligible psychology course.</u>

<u>**TO PARTICIPATE:**</u>
<u>If you are interested in</u> **cash/e-transfer compensation please complete the form through this link** (ENTER LINK) and we will contact you to confirm a date for an orientation session.

OR

If you are enrolled in an eligible psychology course, you can participate through SONA at http://lupsych.sona-systems.com/ to participate.

For more information about the JoyPop™ App, please follow the link below:
https://www.youtube.com/watch?v=CnDt-_4Mr2k&ab_channel=JoyPopApp

If you have any questions or want to arrange an orientation directly with us, please contact us at **imalik3@lakeheadu.ca or 807-620-7664 (text/call).**

Participant Recruitment (Email)

Send to interested participant. Do not need to ask for email because we will have it.

Subject: Opportunity to Participate - JoyPop™ Acceptance Study

Body:

Hello **[Insert name]**!

Thank you for your interest in the JoyPop™ Acceptance study. Your participation in this study is entirely voluntary. **If you are interested, we can schedule a time for you to attend an orientation session, during which you will learn about the JoyPop™ app and the study**.

Here is some important information about the study. To qualify for the study, you must:

- Be a student at Lakehead University
- Have on iOS device (iPhone,iPad, or iPod Touch)
    - *If you don't have an iOS device, an iPhone with only the app on it may be provided upon availability for you to use for the duration of the study
- **NOT BE CURRENTLY** participating in the study titled: *Promoting mental health and well-being among post-secondary students with the Joypop app: A randomized controlled trial*
    - If you have participated in the above study and are finished, **YOU CAN PARTICIPATE IN OURS**

For participating, you would receive:

- Access to the JoyPop™ app. This app is designed to promote resilience by helping to build adaptive coping skills.
- **Up to 3.5 bonus course marks for an eligible psychology course or $40.**

Participation in this study will involve:

1. Using the JoyPop™ app at least twice/day.
2. Completing surveys at the start and after 1 week.
3. Option to provide feedback about your experiences using the app.

TO PARTICIPATE:
If you are interested in **cash/e-transfer compensation please complete the form through this link** (ENTER LINK) and we will contact you to confirm a date for an orientation session.

OR

If you are enrolled in an eligible psychology course, you can participate through SONA at http://lupsych.sona-systems.com/ to participate

For more information about the JoyPop™ App, please follow the link below:
https://www.youtube.com/watch?v=CnDt-_4Mr2k&ab_channel=JoyPopApp

If you have any questions or want to arrange an orientation directly with us, please contact us at **imalik3@lakeheadu.ca or 807-620-7664 (text/call).**

Thank you for your time!

Dr. Aislin Mushquash, Ph.D., C.Psych.
Associate Professor, Department of Psychology
Lakehead University
955 Oliver Road
Thunder Bay, ON P7B5E1
t: (807) 343-8010 ext 8771
f: (807) 346-7734
w: aislinmushquash.com
e: aislin.mushquash@lakeheadu.ca

Appendix G

Confirmation Orientation Reminder (Text)

Send after orientation session booking:

Hi [INSERT NAME],

Thank you for signing up for the JoyPop™ Acceptance study.

This is a confirmation that you have orientation session on:
Date: [ADD DATE]
Time: [ADD TIME]
Method: [IN PERSON MEETING PLACE]
Make note whether an available loaner phone is planned to be provided based on initial contact.

If you will not be able to attend this sessions or have any questions please contact us at **imalik3@lakeheadu.ca or 807-620-7664 (text/call).**

See you then!

Confirmation Orientation Reminder (Email)

Send after the orientation session is booked.

Subject: Confirmation Orientation Reminder - JoyPop™ Acceptance Study

Hi **[insert name]**!

This is a reminder that you have an orientation session for the study titled**: Usability, Quality, and Factors Influencing Acceptance of a Resilience app (JoyPop™) among University Students: Evaluation Study** on:

Date: [add date]
Time: [add time]
Method: [add in-person meeting place]
Make note whether an available loaner phone is planned to be provided based on initial contact.

During this orientation session, you will be provided with further details about the study and app. You will also be asked to complete a survey. Upon completion, you will receive 1 bonus course mark for an eligible psychology course or $10.

If you will not be able to attend this session or have any questions, please contact us at imalik3@lakeheadu.ca or 807-620-7664 (text/call).

See You Soon,
Dr. Aislin Mushquash, Ph.D., C.Psych.
Associate Professor, Department of Psychology
Lakehead University

955 Oliver Road
Thunder Bay, ON P7B 5E1
t: (807) 343-8010 ext 8771
f: (807) 346-7734
w: aislinmushquash.com
e: aislin.mushquash@lakeheadu.ca

Appendix H

Day of Orientation Information

Email subject:

Day of Orientation Information - JoyPop™ App Acceptance Study

Email body:

Thank you for participating in our study titled: ***Usability, Quality, and Factors Influencing Acceptance of a Resilience app (JoyPop™) among University Students: Evaluation Study.***

Below is your: ID number/SurveyMonkey link/and Survey 2 Date

Copy and paste:

1. Participant ID Number: BOLDED and HIGHLIGHTED LIKE THIS
2. Link to access online information letter, consent form, and Survey 1: [ADD LINK]
3. Link to download Testflight and the JoyPop™ app:

- You will have to click or copy this link into your internet browser https://testflight.apple.com/join/6kYqZsl9. Download and open Testflight app and then install and open the JoyPop™ app.
- You will need to enter [participant ID] once you access the app.

4. Date to complete Survey 2 (you will be sent a reminder on the relevant date with a link to access the survey): [ADD SURVEY 2 DATE]

Attached is a copy of the information letter and slides on how to use the JoyPop™ app.

If you have any questions, please contact us.

Sincerely,

Coping Research Lab
imalik3@lakeheadu.ca
807-620-7664 (text/call)

Principal Investigator:
Aislin Mushquash, Ph.D., C.Psych.
Associate Professor, Department of Psychology
Lakehead University
955 Oliver Road
Thunder Bay, ON P7B5E1
t: (807) 343-8010 ext 8771
f: (807) 346-7734
e: aislin.mushquash@lakeheadu.ca

Appendix I

Information Letter

Usability, Quality, and Factors Influencing Acceptance of a Resilience app (JoyPop™) among University Students: Evaluation Study

Dear Potential Participant:

You are invited to participate in our research study titled: ***Usability, Quality, and Factors Influencing Acceptance of a Resilience app (JoyPop™) among University Students: Evaluation Study.*** Your participation in this study is entirely voluntary, and whether you choose to participate or not will not impact your academic standing at Lakehead University. Before you decide whether or not 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.

SUMMARY

- **Purpose:** Evaluate engagement factors and use of the JoyPop™ app.
- **What's Involved:** Download + use the JoyPop™ app for 1 week + complete some surveys at the start of the study and after 1 week.
- **What will I receive:** Access to the JoyPop™ app + up to 3.5 bonus course marks for an eligible psychology course or $40 cash/e-transfer

PURPOSE

The purpose of this research is to evaluate engagement factors and the use of a smartphone app designed to promote resilience in youth and young adults by supporting the development of adaptive coping skills to improve emotion regulation. Resilience is defined as a characteristic of an individual and their environment that provides the resources necessary for positive development and wellbeing. Intervening early to support resilience may help students reach their true potential and be a buffer against maladjustment.

The Principal Investigator of the research is Dr. Aislin Mushquash, Associate Professor, Department of Psychology, Lakehead University. Ishaq Malik, Lakehead University, is a graduate student Co-Investigator. Teagan Neufeld , Amelia Traer, and Jennifer Wyman are undergraduate student researchers at Lakehead University. Angela Ashley, Lakehead University, is a graduate student researcher. All graduate and undergraduate students are under the supervision of Dr. Aislin Mushquash.

WHAT IS REQUESTED OF ME AS A PARTICIPANT?

This study has 4 parts (4th part is optional). A description, the duration, and the associated compensation of each are described below.

	Description	Duration	Compensation (cash/e-transfer)
Part 1	You will receive information on the App including its features and how to use it. You will also be asked to complete some surveys.	Up to 1 hour 30-minute orientation 30 minutes for survey	$10 *Or 1 bonus course mark for an eligible psychology course
Part 2 + 3	You will be asked to use the App at least twice/day for 1 week following Part 1. You will be asked to complete a brief survey 1 week after Part 1.	10 min/day + (60 minutes) 30 minutes for survey	$20 or 1.5 course marks for an eligible psychology course
	Total	2.5 hours	$30 or 2.5 course marks for an eligible psychology course
Part 4	Optional feedback interview about your experiences using the app (in-person or Zoom)	~45	$10 or 1 bonus course mark for an eligible psychology course
	Total	3 hours	$40 or 3.5 bonus course marks for an eligible psychology course

WHAT INFORMATION WILL BE COLLECTED?

We will be collecting information from you during Parts 1, 2, and 3 of the study. Specifically, to evaluate and determine engagement and use of the app, the surveys will ask questions about demographics, experience using mobile health applications, mental health service use, personality traits,coping flexibility, and app usability, quality, and acceptance. You are not required to answer all questions and can skip questions that you are not comfortable answering. To evaluate and determine usage of the app, information will also be collected from you via the app itself. Specifically, we will receive data related to the usage of the app (e.g., which features were accessed, time spent using the app). And finally, information about experiences using the app will be collected from some participants during the optional interview (in-person or Zoom) in Part 4. Interviews will be audio recorded to ensure accurate information is obtained.

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 have the right to withdraw your data from the study up until the data collection phase of the study is complete. Beyond this point, there will be no way to connect you to your data. Your decision to participate will not affect your academic status. You will be given, in a timely manner throughout the course of the research project, information that is relevant to your decision to continue or withdraw. To withdraw from the study, contact Dr. Mushquash at aislin.mushquash@lakeheadu.ca or (807) 343-8010 ext 8771.

WHAT ARE THE RISKS AND BENEFITS?

There is minimal risk associated with participating in the proposed study. Potential transient risk may occur (e.g., discomfort and emotional reaction to a survey question) given that some questions ask participants about their personality and about whether (and how often/long) they use mental health services. You are not required to answer all questions and can feel free to skip questions that you are not comfortable answering. Should you feel upset during or after the study, we encourage you to contact any of the following support services:

Lakehead University Student Health and Counselling	Thunder Bay Counselling Centre Walk-In Counselling	Good2Talk 24-hr Student Helpline	Thunder Bay 24-hr Crisis Response
(807) 343-8361	(807) 684-1880	1-866-925-5454	(807) 346-8282

To mitigate any potential risk of information pertaining to participants' personal experiences being accessed, your name will not be included on the surveys. Only a participant ID number will be included. The list linking participant ID numbers to participant names will only be retained for the period of data collection (estimated to be approximately 6-8 months). This list will be kept in a locked filing cabinet in Dr. Mushquash's laboratory. The list will be shredded once the data collection phase of the study is complete.

The primary benefits of the study are for society and for the advancement of knowledge. Specifically, this study will provide information on the acceptance, quality, and usability of the App to support resilience in university students while informing App improvements.

For participating in the study, you will receive up to $40. For students in an eligible psychology course, you can receive up to 3.5 bonus course marks towards an eligible psychology course grade. See Table above for more information.

HOW WILL MY CONFIDENTIALITY BE MAINTAINED?

Confidentiality (privacy) will be maintained throughout the study. All participants will be provided an ID number at the beginning of their participation. All data (surveys and app data) will contain only this ID number.

The online survey tool used in the study, (Survey Monkey), is hosted by a server located in the USA. The US Patriot Act permits U.S. law enforcement officials, for the purpose of antiterrorism investigation, to seek a court order that allows access to the personal records of any person without the person's knowledge. In view of this we cannot absolutely guarantee the full confidentiality of your data. With your consent to participate in this study, you acknowledge this.

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 will also likely be presented at national or international scholarly conferences. All findings will be presented in summary form without identifying information of participants.

WHERE WILL MY DATA BE STORED?

The surveys will be hosted through Survey Monkey and will only be accessed by research team members. The
information systems and technical infrastructure for Survey Monkey are hosted within world-class, SOC 2
accredited data centers. Physical security controls at the data centers include 24x7 monitoring, cameras, visitor
logs, entry requirements, and dedicated cages for Survey Monkey hardware. Survey Monkey encrypts data in
transit using secure TLS cryptographic protocols. App data will be stored on a password-protected server within
Canada. App data is encrypted during transmission. Upon receipt, app data will be saved and stored on a password-protected computer in the possession of either the Principal Investigator or the Research Coordinator. All data from this study will be stored on a password-protected computer in the possession of either the Principal
Investigator or the Research Coordinator (Department of Psychology, Lakehead University). In accordance with
Lakehead University's policy, data will be retained for at least 7 years following the completion of the research.

HOW CAN I RECEIVE A COPY OF THE RESEARCH RESULTS?

If you would like to receive a summary of the findings following the completion of the study, mark 'yes' on the consent form and indicate your preferred email address. Individual results (e.g., scores on specific survey) will not be made available to participants.

RESEARCHER CONTACT INFORMATION:

For any questions, comments, or complaints about the research study, please contact the principal investigator:
Dr. Aislin Mushquash, ph.D., C.Psych
Associate Professor
Department of Psychology
Lakehead University
(807) 343-8010 ext 8771
aislin.mushquash@lakeheadu.ca
coping.research@lakeheadu.ca

RESEARCH ETHICS BOARD REVIEW AND APPROVAL:

This research study has been reviewed and approved by the Lakehead University Research Ethics Board. If you have any questions related to the ethics of the research and would like to speak to someone outside of the research team, please contact Sue Wright at the Research Ethics Board at (807) 343-8283 or research@lakeheadu.ca

Appendix J

Consent Form

Usability, Quality, and Factors Influencing Acceptance of a Resilience app (JoyPop^{TM}) among University Students: Evaluation Study

MY CONSENT:

I agree to the following:

- I have read and understand the information contained in the Information Letter
- I agree to participate
- I understand the risks and benefits to the study
- That I am a volunteer and can withdraw from the study at any time; however, I can only withdraw my data up until the data collection phase of the study is over,
- I understand that I may choose not to answer any question
- That if I participate in the interview during Part 4, my interview will be recorded to ensure accurate information is obtained
- That the data will be securely stored in a locked filing cabinet in Dr. Mushquash's laboratory and/or on a password-protected hard drive for a minimum period of 7 years following completion of the research project
- I understand that the research findings will be made available to me upon request
- That my name will not be included on my surveys but will be linked to my participant ID number until the data collection phase of the study is over
- All of my questions have been answered and I can contact the research team with further questions

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

Please note that the online survey tool used in the study, (SurveyMonkey), is hosted by a server located in the USA.
The US Patriot Act permits U.S. law enforcement officials, for the purpose of anti-terrorism investigation, to seek a
court order that allows access to the personal records of any person without the person's knowledge. In view of this we cannot absolutely guarantee the full confidentiality and anonymity of your data. With your consent to
participate in this study, you acknowledge this.

My consent has been given by clicking "CONSENT" below and continuing on to the survey.

I would like to be sent a summary of the results of this study: Yes ___ No ___

If "yes" please provide your e-mail address: ____

Appendix K

List of Measures

SELF-REPORT MEASURES

Construct	Measure	Item #	Pre-app	Post-app
Demographics	--	15	X	
Mobile Health App Experience		6	X	
Personality Traits	Big Five Aspects Scale (DeYoung et al., 2007) – **Scales(Subscales):** Neuroticism (Volatility, Withdrawal), Agreeableness (Compassion, Politeness), Conscientiousness (Industriousness, Orderliness), Extraversion (Enthusiasm, Assertiveness), Openness/Intellect (Intellect, Openness)	100	X	
App Acceptance	Adapted measure based on the extended Unified Theory of Acceptance and Use of Technology (UTAUT2- Hoque & Sorwar, 2017; Venkatesh et al., 2003; 2012) – **Subscales:** Performance Expectancy, Effort Expectancy, Social Norms, Facilitating Conditions, Hedonic Motivation, Habit, Behavioural Intention	22		X
App Usability	mHealth App Usability Questionnaire (MAUQ) for Standalone mHealth Apps Used by Patients (Zhou et al., 2019) – **Subscales:** Ease of Use, Interface and Satisfaction, Usefulness	18		X
App Quality	Mobile Application Rating Scale: user version (uMARS; Stoyanov et al., 2016) – **Subscales for overall App quality:** Engagement, Functionality, Aesthetics, Information. **Additional Scales:** Subjective Quality, Perceived Impact.	27		X
Coping Flexibility	Coping Flexibility Scale Revised (Kato, 2020) – **Subscales:** Abandonment, Re-coping, Meta-Coping	12	X	X

Appendix L

Measures

Demographics

1. Age (years): ______
2. Your biological sex (i.e., your sex assigned at birth): ______
3. Your gender: ______
4. Your sexual orientation: ______
5. The country you were born in: _____________
6. How long have you lived in Canada? _______ years
7. Your ethnicity: ___________
8. What program are you in? ____________
9. What year of study are you in? _____
    1. First
    2. Second
    3. Third
    4. Fourth
    5. Graduate School
    6. Other: ____________________________
10. Are you studying full-time or part-time? ________
11. Where do you currently live? (You can choose more than one)
    1. Residence
    2. With family members
    3. With friends
    4. Alone
    5. Group home/supportive housing
    6. On-Campus
    7. Off-Campus
    8. Other ______________
12. Have you used (or currently are using) mental health services (e.g., psychologist, social worker, counsellor)?
    1. Yes (Continue to question 15)
    2. No (Continue to next page)
13. How long have you used mental health services for?
    1. 0-6 months
    2. 7-11 months
    3. 1-2 years
    4. More than 2 years
    5. Don't remember the exact time

Mobile Health (mHealth) Application Experience

1. Have you used (or currently using) app/computer-based mental health care?
    1. Yes (Continue to question 17)
    2. No (Continue to next page)
2. How long have (did) you use app/computer-based mental health care for?
    1. 0-6 months
    2. 7-11 months
    3. 1-2 years
    4. More than 2 years
    5. Don't remember the exact time
3. Do you have any application (app) related to mental health on your smartphone/device?
    1. Yes (Continue and complete questions 3-6)
    2. No (Continue to complete question 2 and move to next page)
4. What are the reasons for not using a (mHealth) app? (You can choose more than one).
    1. Not interested
    2. They cost too much
    3. I don't trust apps to collect my data
    4. Complicated to use
    5. I don't have the ability to use them
    6. My mental health is good and I don't need one
    7. Not recommended by relevant others (e.g., friends, counsellors)
    8. Got out of the habit/forget to
    9. Other: _________
5. How many such apps do you have on your smartphone?
    1. 1-3
    2. 4-6
    3. more than 7
6. For how long have you used mental health related apps? Approximate in months ________
7. How frequently do you use these mental health related apps?
    1. Several times a day
    2. Once or twice a day
    3. 2-3 times a week
    4. Once a week
    5. Rarely used
    6. Never used
8. How much time do you spend daily using these apps? Approximate # of minutes/day __________

Big 5 Aspects Scale (DeYoung et al., 2007)

Please indicate your degree of agreement (using a score ranging from 1-5) to 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
Items from all 10 scales will be interspersed for administration

Neuroticism

Volatility

1. Get angry easily.
2. Rarely get irritated. (R)
3. Get upset easily.
4. Keep my emotions under control. (R)
5. Change my mood a lot.
6. Rarely lose my composure. (R)
7. Am a person whose moods go up and down easily.
8. Am not easily annoyed. (R)
9. Get easily agitated.
10. Can be stirred up easily.

Withdrawal

11. Seldom feel blue. (R)
12. Am filled with doubts about things.
13. Feel comfortable with myself. (R)
14. Feel threatened easily.
15. Rarely feel depressed. (R)
16. Worry about things.
17. Am easily discouraged.
18. Am not embarrassed easily. (R)
19. Become overwhelmed by events.
20. Am afraid of many things.

Agreeableness

Compassion

21. Am not interested in other people’s problems. (R)
22. Feel others’ emotions.
23. Inquire about others’ well-being.
24. Can’t be bothered with other’s needs. (R)
25. Sympathize with others’ feelings.
26. Am indifferent to the feelings of others. (R)
27. Take no time for others. (R)
28. Take an interest in other people’s lives.
29. Don’t have a soft side. (R)
30. Like to do things for others.

Politeness

31. Respect authority.
32. Insult people. (R)
33. Hate to seem pushy.
34. Believe that I am better than others. (R)
35. Avoid imposing my will on others.
36. Rarely put people under pressure.

37. Take advantage of others. (R)
38. Seek conflict. (R)
39. Love a good fight. (R)
40. Am out for my own personal gain. (R)

Conscientiousness

Industriousness

41. Carry out my plans.
42. Waste my time. (R)
43. Find it difficult to get down to work. (R)
44. Mess things up. (R)
45. Finish what I start.
46. Don’t put my mind on the task at hand. (R)
47. Get things done quickly.
48. Always know what I am doing.
49. Postpone decisions. (R)
50. Am easily distracted. (R)

Orderliness

51. Leave my belongings around. (R)
52. Like order.
53. Keep things tidy.
54. Follow a schedule.
55. Am not bothered by messy people. (R)
56. Want everything to be “just right.”
57. Am not bothered by disorder. (R)
58. Dislike routine. (R)
59. See that rules are observed.
60. Want every detail taken care of.

Extraversion

Enthusiasm

61. Make friends easily.
62. Am hard to get to know. (R)
63. Keep others at a distance. (R)
64. Reveal little about myself. (R)
65. Warm up quickly to others.
66. Rarely get caught up in the excitement. (R)
67. Am not a very enthusiastic person. (R)
68. Show my feelings when I’m happy.
69. Have a lot of fun.
70. Laugh a lot.

Assertiveness

71. Take charge.
72. Have a strong personality.
73. Lack the talent for influencing people. (R)
74. Know how to captivate people.
75. Wait for others to lead the way. (R)
76. See myself as a good leader.
77. Can talk others into doing things.
78. Hold back my opinions. (R)
79. Am the first to act.

80. Do not have an assertive personality. (R)

Openness/Intellect

Intellect

81. Am quick to understand things.
82. Have difficulty understanding abstract ideas. (R)
83. Can handle a lot of information.
84. Like to solve complex problems.
85. Avoid philosophical discussions. (R)
86. Avoid difficult reading material. (R)
87. Have a rich vocabulary.
88. Think quickly.
89. Learn things slowly. (R)
90. Formulate ideas clearly.

Openness

91. Enjoy the beauty of nature.
92. Believe in the importance of art.
93. Love to reflect on things.
94. Get deeply immersed in music.
95. Do not like poetry. (R)
96. See beauty in things that others might not notice.
97. Need a creative outlet.
98. Seldom get lost in thought. (R)
99. Seldom daydream. (R)
100. Seldom notice the emotional aspects of paintings and pictures. (R)

Adapted measure based on the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2- Hoque & Sorwar, 2017; Venkatesh et al., 2003; 2012; Wu et al., 2022)

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)

Performance Expectancy

PE1. I find the JoyPop™ app useful in my daily life.
PE2. Using the JoyPop™ app helps me accomplish things more quickly.
PE3. Using the JoyPop™ app improves my mental health and/or productivity.

Effort Expectancy

EE1. Learning how to use the JoyPop™ app is easy for me.
EE2. My interaction with the JoyPop™ app is clear and understandable.
EE3. I find the JoyPop™ app easy to use.
EE4. It is easy for me to become skillful at using the JoyPop™ app.

Social Influence

S11. People who are important to me think that I should use the JoyPop™ app.
S12. People who influence my behavior think that I should use the JoyPop™ app.
S13. People whose opinions that I value prefer that I use the JoyPop™ app.

Facilitating Conditions

FC1. I have the resources necessary to use the JoyPop™ app.
FC2. I have the knowledge necessary to use the JoyPop™ app.
FC3. The JoyPop app™ is compatible with other technologies I use.
FC4. I can get help from others when I have difficulties using the JoyPop™ app.

Hedonic Motivation
HM1. Using the JoyPop app™ is fun.
HM2. Using the JoyPop app™ is enjoyable.
HM3. Using the JoyPop app™ is very entertaining.

Habit
HT1. The use of the JoyPop app™ has become a habit for me.
HT2. I am immersed in using/accepting the JoyPop app™.
HT3. I must use the JoyPop app™.

Behavioral Intention
BI1. I intend to continue using the JoyPop app™ in the future.
BI2. I will always try to use the JoyPop app™ in my daily life.
BI3. I plan to continue to use the JoyPop app™ frequently.

Mobile Health Application Usability Questionnaire (Zhou et al., 2019)

Please indicate your degree of agreement (using a score ranging from 1-5) 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)

Ease of Use
1. The app was easy to use.
2. It was easy for me to learn to use the app.
3. The navigation was consistent when moving between screens.
4. The interface of the app allowed me to use all the functions (such as entering information, responding to reminders, viewing information) offered by the app.
5. Whenever I made a mistake using the app, I could recover easily and quickly.
6. I like the interface of the app.

Interface and Satisfaction
7. The information in the app was well organized, so I could easily find the information I needed
8. The app adequately acknowledged and provided information to let me know the progress of my action.
9. I feel comfortable using this app in social settings.
10. The amount of time involved in using this app has been fitting for me.
11. I would use this app again.
12. Overall, I am satisfied with this app.

Usefulness
13. The app would be useful for my health and wellbeing.
14. The app improved my access to healthcare services.
15. The app helped me manage my health effectively.
16. This app has all the functions and capabilities I expected it to have.
17. I could use the app even when the Internet connection was poor or not available.

18. This mHealth app provides an acceptable way to receive healthcare services, such as accessing educational materials, tracking my own activities, and performing self-assessment.

Mobile Application Rating Scale: user version (uMARS; Stoyanov et al., 2016)

Choose the number that most accurately represents the quality of the app you are rating. All items are rated on a 5-point scale from “1. Inadequate” to “5. Excellent”.
Select N/A if the app component is irrelevant.

App Quality Ratings

Engagement – fun, interesting, customisable, interactive, has prompts (e.g. sends alerts, messages, reminders, feedback, enables sharing)

1. Entertainment: Is the JoyPop^{TM} app fun/entertaining to use? Does it have components that make it more fun than other similar apps?
   - 1 Dull, not fun or entertaining at all
   - 2 Mostly boring
   - 3 OK, fun enough to entertain user for a brief time (< 5 minutes)
   - 4 Moderately fun and entertaining, would entertain user for some time (5-10 minutes total)
   - 5 Highly entertaining and fun, would stimulate repeat use
2. Interest: Is the JoyPop^{TM} interesting to use? Does it present its information in an interesting way compared to other similar apps?
   - 1 Not interesting at all
   - 2 Mostly uninteresting
   - 3 OK, neither interesting nor uninteresting; would engage user for a brief time (< 5 minutes)
   - 4 Moderately interesting; would engage user for some time (5-10 minutes total)
   - 5 Very interesting, would engage user in repeat use
3. Customisation: Does the JoyPop^{TM} app allow you to customise the settings and preferences that you would
like to (e.g. sound, content and notifications)?
   - 1 Does not allow any customisation or requires setting to be input every time
   - 2 Allows little customisation and that limits app’s functions
   - 3 Basic customisation to function adequately
   - 4 Allows numerous options for customisation
   - 5 Allows complete tailoring the user’s characteristics/preferences, remembers all settings
4. Interactivity: Does the JoyPop^{TM} app allow user input, provide feedback, contain prompts (reminders, sharing
options, notifications, etc.)?
   - 1 No interactive features and/or no response to user input
   - 2 Some, but not enough interactive features which limits app’s functions
   - 3 Basic interactive features to function adequately
   - 4 Offers a variety of interactive features, feedback and user input options
   - 5 Very high level of responsiveness through interactive features, feedback and user input options
5. Target group: Is the JoyPop^{TM} app content (visuals, language, design) appropriate for the target audience?
   - 1 Completely inappropriate, unclear or confusing
   - 2 Mostly inappropriate, unclear or confusing
   - 3 Acceptable but not specifically designed for the target audience. May be inappropriate/ unclear/confusing at times

4 Designed for the target audience, with minor issues
5 Designed specifically for the target audience, no issues found

Functionality – app functioning, easy to learn, navigation, flow logic, and gestural design of app

6. Performance: How accurately/fast do the JoyPop^{TM} app features (functions) and components (buttons/menus) work?
1 App is broken; no/insufficient/inaccurate response (e.g. crashes/bugs/broken features, etc.)
2 Some functions work, but lagging or contains major technical problems
3 App works overall. Some technical problems need fixing, or is slow at times
4 Mostly functional with minor/negligible problems
5 Perfect/timely response; no technical bugs found, or contains a 'loading time left' indicator (if relevant)

7. Ease of use: How easy is it to learn how to use the JoyPop^{TM} app; how clear are the menu labels, icons and instructions?
1 No/limited instructions; menu labels, icons are confusing; complicated
2 Takes a lot of time or effort
3 Takes some time or effort
4 Easy to learn (or has clear instructions)
5 Able to use app immediately; intuitive; simple (no instructions needed)

8. Navigation: Does moving between screens make sense; Does the JoyPop^{TM} app have all necessary links between screens?
1 No logical connection between screens at all /navigation is difficult
2 Understandable after a lot of time/effort
3 Understandable after some time/effort
4 Easy to understand/navigate
5 Perfectly logical, easy, clear and intuitive screen flow throughout, and/or has shortcuts

9. Gestural design: Do taps/swipes/pinches/scrolls make sense? Are they consistent across all components/screens?
1 Completely inconsistent/confusing
2 Often inconsistent/confusing
3 OK with some inconsistencies/confusing elements
4 Mostly consistent/intuitive with negligible problems
5 Perfectly consistent and intuitive

Aesthetics – graphic design, overall visual appeal, colour scheme, and stylistic consistency

10. Layout: Is arrangement and size of buttons, icons, menus and content on the screen appropriate?
1 Very bad design, cluttered, some options impossible to select, locate, see or read
2 Bad design, random, unclear, some options difficult to select/locate/see/read
3 Satisfactory, few problems with selecting/locating/seeing/reading items
4 Mostly clear, able to select/locate/see/read items
5 Professional, simple, clear, orderly, logically organised

11. Graphics: How high is the quality/resolution of graphics used for buttons, icons, menus and content?
1 Graphics appear amateur, very poor visual design - disproportionate, stylistically inconsistent
2 Low quality/low resolution graphics; low quality visual design – disproportionate
3 Moderate quality graphics and visual design (generally consistent in style)
4 High quality/resolution graphics and visual design – mostly proportionate, consistent in style

5 Very high quality/resolution graphics and visual design - proportionate, consistent in style throughout

12. Visual appeal: How good does the JoyPop™ app look?
    1 Ugly, unpleasant to look at, poorly designed, clashing, mismatched colours
    2 Bad – poorly designed, bad use of colour, visually boring
    3 OK – average, neither pleasant, nor unpleasant
    4 Pleasant – seamless graphics – consistent and professionally designed
    5 Beautiful – very attractive, memorable, stands out; use of colour enhances app features/menus

Information – Contains high quality information (e.g. text, feedback, measures, references) from a credible source

13. Quality of information: Is the JoyPop™ app content correct, well written, and relevant to the goal/topic of the app?
    N/A There is no information within the app
    1 Irrelevant/inappropriate/incoherent/incorrect
    2 Poor. Barely relevant/appropriate/coherent/may be incorrect
    3 Moderately relevant/appropriate/coherent/and appears correct
    4 Relevant/appropriate/coherent/correct
    5 Highly relevant, appropriate, coherent, and correct
14. Quantity of information: Is the information within the JoyPop™ app comprehensive but concise?
    N/A There is no information within the app
    1 Minimal or overwhelming
    2 Insufficient or possibly overwhelming
    3 OK but not comprehensive or concise
    4 Offers a broad range of information, has some gaps or unnecessary detail; or has no links to more information and resources
    5 Comprehensive and concise; contains links to more information and resources
15. Visual information: Is visual explanation of concepts – through charts/graphs/images/videos, etc. – clear, logical, correct?
    N/A There is no visual information within the app (e.g. it only contains audio, or text)
    1 Completely unclear/confusing/wrong or necessary but missing
    2 Mostly unclear/confusing/wrong
    3 OK but often unclear/confusing/wrong
    4 Mostly clear/logical/correct with negligible issues
    5 Perfectly clear/logical/correct
16. Credibility of source: does the information within the JoyPop™ app seem to come from a credible source?
    N/A There is no information within the app
    1 Suspicious source
    2 Lacks credibility
    3 Not suspicious but legitimacy of source is unclear
    4 Possibly comes from a legitimate source
    5 Definitely comes from a legitimate/specialised source

<u>App Subjective Quality</u>

17. Would you recommend the JoyPop™ app to people who might benefit from it?
    1 Not at all I would not recommend this app to anyone
    2 There are very few people I would recommend this app to
    3 Maybe There are several people I would recommend this app to
    4 There are many people I would recommend this app to
    5 Definitely I would recommend this app to everyone

18. How many times do you think you would use the JoyPop^{TM} app in the next 12 months if it was relevant
to you?

1 None
2 1-2
3 3-10
4 10-50
5 >50

19. Would you pay for this app?

1 Definitely not
2
3
4
5 Definitely yes

20. What is your overall (star) rating of the app?

1 * One of the worst apps I've used
2 **
3 *** Average
4 ****
5 ***** One of the best apps I've used

Perceived Impact

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

21.*Awareness* – The JoyPop^{TM} app has increased my awareness of the importance of addressing mental health and coping skills

22. *Know*ledge – The JoyPop^{TM} app has increased my knowledge/understanding of mental health and coping skills

23. *Attitudes* – The JoyPop^{TM} app has changed my attitudes toward improving mental health and coping skills

24. *Intention to change* – The JoyPop^{TM} app has increased my intentions/motivation to address mental health and coping skills

25. *Help seeking* – The JoyPop^{TM} app would encourage me to seek further help to address mental health and coping skills (if I needed it)

26. *Behaviour change* – Use of the JoyPop^{TM} app will improve my mental health and coping skills

27. Further comments about the JoyPop^{TM} app? _________

Appendix M

Orientation Reminder (Text)

Reminder - JoyPop™ orientation coming up!

Date: [ADD DATE]
Time: [ADD TIME]
Method: [IN-PERSON MEETING PLACE]
Make note whether an available loaner phone is planned to be provided based on initial contact.

Upon completion, you will receive 1 bonus course mark toward an eligible psychology course or $10.

If you will not be able to attend this session or have any questions, please contact us at imalik3@lakeheadu.ca or 807-620-7664 (text/call).

See you then!

Orientation Reminder (Email)

Subject: JoyPop Orientation Coming Up - JoyPop™ Acceptance Study

Hi **[insert name]**!

This is a reminder that you have an orientation session tomorrow for the study titled: ***Usability, Quality, and Factors Influencing Acceptance of a Resilience app (JoyPop™) among University Students: Evaluation Study.***

Date: [ADD DATE]
Time: [ADD TIME]
Method: [IN-PERSON MEETING PLACE]
Make note whether an available loaner phone is planned to be provided based on initial contact.

During this orientation session, you will be provided with further details about the study. You will also be asked to complete a survey. Upon completion, you will receive 1 bonus course mark for an eligible psychology course or $10.

If you will not be able to attend this session or have any questions, please contact us at imalik3@lakeheadu.ca or 807-620-7664 (text/call).

See you then!

Dr. Aislin Mushquash, Ph.D., C.Psych.
Associate Professor, Department of Psychology
Lakehead University
955 Oliver Road

Thunder Bay, ON P7B 5E1
t: (807) 343-8010 ext 8771
f: (807) 346-7734
w: aislinmushquash.com
e: aislin.mushquash@lakeheadu.ca

Appendix N

Missed Orientation Reminder (Text)

Hi [INSERT NAME],

You were signed up to participate in the JoyPop^{TM} App Acceptance Study orientation session on [insert date/time]

We welcome you to reschedule your appointment for another time. **Please reply to this text or contact us at imalik3@lakeheadu.ca or at 807-620-7664 (text/call).**

We look forward to hearing from you.

Missed Orientation Reminder (Email)

Subject:

Missed Orientation Reminder - JoyPop^{TM} App Acceptance Study

Email Body:

You are currently signed up to participate in the study titled: **Usability, Quality, and Factors Influencing Acceptance of a Resilience app (JoyPop^{TM}) among University Students: Evaluation Study.** You were scheduled for an orientation session on [insert date/time].

We welcome you to reschedule your appointment for another time. **Please reply to this email or contact us at imalik3@lakeheadu.ca or at 807-620-7664 (text/call).**

During this orientation, you will be asked to complete some online surveys and will receive your compensation for this portion of the study (i.e. 1 bonus course mark for an eligible psychology course or $10, see table below). We look forward to hearing from you.

	Description	Duration	Compensation (cash/e-transfer)
Part 1	You will receive information on the App including its features and how to use it. You will also be asked to complete some surveys.	Up to 1 hour 30-minute orientation 30 minutes for survey	$10 *Or 1 bonus course mark for an eligible psychology course
Part 2 + 3	You will be asked to use the App at least twice/day for 1 week following Part 1. You will be asked to complete a brief survey 1 week after Part 1.	10 min/day + (60 minutes) 30 minutes for survey	$20 or 1.5 bonus course marks for an eligible psychology course

	Total	2.5 hours	$30 or 2.5 course marks for an eligible psychology course
Part 4	Optional feedback interview about your experiences using the app	~45 min	$10 or 1 bonus course mark toward an eligible psychology course
	Total	3 hours	$40 or 3.5 bonus course mark for an eligible psychology course

You can also sign up again via SONA systems at http://lupsych.sona-systems.com/ if participating for bonus course marks for an eligible psychology course..

If you have any questions or concerns, please contact the research team at **imalik3@lakeheadu.ca, or 807-620-7664 (text/call).**

We look forward to hearing from you.

Dr. Aislin Mushquash, Ph.D., C.Psych.
Associate Professor, Department of Psychology
Lakehead University
955 Oliver Road
Thunder Bay, ON P7B5E1
t: (807) 343-8010 ext 8771
f: (807) 346-7734
w: aislinmushquash.com
e: aislin.mushquash@lakeheadu.ca

Appendix O

Daily App Use Reminder (Text)

JoyPop™ reminder - don't forget to use the app this [morning/evening].

Daily App Use Reminder (Email)

Email Sent in both morning (8am) and evening (8pm) to participants.

Subject: Reminder to use the app - JoyPop™ App Acceptance Study

Body:

You are currently enrolled in our study titled: ***Usability, Quality, and Factors Influencing Acceptance of a Resilience app (JoyPop™) among University Students: Evaluation Study.***

This is a reminder to log on and use the JoyPop™ app at the **[start/end]** of your day. Remember that the app can be used when you:

- Wake up and before you go to sleep
- Want to collect your thoughts, figure out your feelings, or express yourself
- Want to play a game
- Want to connect to your support network

If you have any questions or concerns, please contact us at **imalik3@lakeheadu.ca** **or 807-620-7664 (text/call).**

Principal Investigator:
Aislin Mushquash, Ph.D., C.Psych.
Associate Professor, Department of Psychology
Lakehead University
955 Oliver Road
Thunder Bay, ON P7B5E1
t: (807) 343-8010 ext 8771
f: (807) 346-7734
e: aislin.mushquash@lakeheadu.ca

Appendix P

Survey 2 Reminder (Text)

Sent at 8am on the relevant date.

This is a reminder that you are scheduled to complete the JoyPop^{TM} Survey 2 today. Please follow the link below. Make sure to enter your Participant ID: **#####.**

Survey 2 link:

Upon completion, you will receive $20 or 1.5 bonus course marks for an eligible psychology course.

Survey 2 Reminder (Email)

Subject:

Survey 2 Reminder! - JoyPop^{TM} App Acceptance Study

Email Body:

You are currently enrolled in the App Research Study titled: ***Usability, Quality, and Factors Influencing Acceptance of a Resilience app (JoyPop^{TM}) among University Students: Evaluation Study.***

This is a reminder that you are scheduled to complete Survey 2 today. Please follow the link below. Make sure to enter your Participant ID: **#####.**

Survey 2 link:

Upon completion, you will receive $20 or 1.5 bonus course marks for an eligible psychology course.

If you have any questions please contact us at **imalik3@lakeheadu.ca or 807-620-7664 (text/call).**

Principal Investigator:
Dr. Aislin Mushquash, Ph.D., C.Psych.
Associate Professor, Department of Psychology
Lakehead University
955 Oliver Road
Thunder Bay, ON P7B5E1
t: (807) 343-8010 ext 8771
f: (807) 346-7734
w: aislinmushquash.com
e: aislin.mushquash@lakeheadu.ca

Appendix Q

Missed Survey 2 Reminder (Text)

Reminder to complete the JoyPop™ [Survey 2] on [date]. Please follow the link below and make sure to enter your Participant ID which is ________ .

[add Survey 2 link]

Upon completion, you will receive $20 or 1.5 bonus course marks for an eligible psychology course.

Missed Survey 2 Reminder (Email)

Subject: Missed Survey 2 Reminder! - JoyPop™ App Acceptance Study

You are currently enrolled in the App Research Study titled: ***Usability, Quality, and Factors Influencing Acceptance of a Resilience app (JoyPop™) among University Students: Evaluation Study.***

You were scheduled to complete [Survey 2] on [date]. Please follow the link below and make sure to enter your Participant ID which is ________ .

[add Survey 2 link]

Upon completion, you will receive $20 or 1.5 bonus course marks for an eligible psychology course.

If you have any questions please contact us at **imalik3@lakeheadu.ca or 807-620-7664 (text/call).**

Dr. Aislin Mushquash, Ph.D., C.Psych.
Associate Professor, Department of Psychology
Lakehead University
955 Oliver Road
Thunder Bay, ON P7B5E1
t: (807) 343-8010 ext 8771
f: (807) 346-7734
w: aislinmushquash.com
e: aislin.mushquash@lakeheadu.ca

Appendix R

App Completion (Text)

You have now completed Parts 1, 2, and 3 of the JoyPop™ Acceptance Study

You may continue using the JoyPop™ App. Please note that your data will no longer be accessed when using the app.

If you are interested in participating in **Part 4: Optional feedback interview**, please contact the research team at **tmneufel@lakeheadu.ca or 807-620-7664 (text/call)** and we can set up a time and method (in-person, Zoom) that works best for you.

Thank you for your participation!

App Completion (Email)

Subject: Completion of the JoyPop™ App Acceptance Study

You have now completed Parts 1, 2, and 3 of the study titled: **Usability, Quality, and Factors Influencing Acceptance of a Resilience app (JoyPop™) among University Students: Evaluation Study**

You may continue using the JoyPop™ App. Please note that your data will no longer be accessed when using the app.

If you are interested in participating in **Part 4: Optional feedback interview**, please contact the research team a**t tmneufel@lakeheadu.ca or 807-620-7664 (text/call)** and we can set up a time and method (in-person, Zoom) that works best for you.

Upon completion, you would receive $10 or 1 bonus course mark for an eligible psychology course.

If you have any questions or concerns about the study, please contact the research team or the Principal Investigator, Dr. Aislin Mushquash.

Thank you for your participation.

Principal Investigator:
Dr. Aislin Mushquash, Ph.D., C.Psych.
Associate Professor, Department of Psychology
Lakehead University
955 Oliver Road
Thunder Bay, ON P7B5E1
t: (807) 343-8010 ext 8771
f: (807) 346-7734
w: aislinmushquash.com
e: aislin.mushquash@lakeheadu.ca