Entering The Age of the Quantified Self: White Paper On uMore, The Well-Being Measurement & Tracking Application

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Problem Statement

In today's clinical landscape, mental healthcare remains underutilized as a significant proportion of the population is unaware of the transient nature of their quality of life and mental well-being. Access to such services is constrained by financial and geographical factors, and therefore access to care is not readily available to the majority of the population.

As such, we are facing an unprecedented challenge. Evidence gathered in 2016 suggests that 1 in 6 people will experience a mental health challenge within the past week. In addition to this, the Coronavirus and its lingering effects are having a profound impact on the mental well-being of individuals in today's world, with, isolation, job loss, and limited access to healthcare creating a perfect storm that could prove detrimental to the mental well-being of modern-day society as a whole.

Our Mission

We live in the age of the quantified self. Just as wearable technology has enabled users to understand their fitness and sleep patterns better, the same capabilities should be readily available for mental well-being. We wish to empower our users' knowledge of themselves through easily interpreted data insights.

We are not developing medical treatments, but rather, we are building digital solutions that enable people to become more self-aware of their own emotions, helping them understand the changes in their mental well-being over time, and giving them tools for self-care as a means of preventative support. Our tools are to be used as helping hands to medical treatment, to help users learn how to live happier and healthier lives.

Background

A Looming Mental Health Crisis

In 2001, the World Health Organisation reported that over the course of an entire lifetime, over 25% of individuals develop one or more mental or behavioral disorders (Sayers, 2001). While experimental methodologies will differ between studies, and prevalence rates will vary across regions where public health research is conducted, this figure has since been revisited in subsequent studies. More recent research reports that 1 in 6 adults in the UK had experienced a common mental health challenge within the past week (McManus et al., 2016), whereas 1 in 5 Americans will experience a mental illness in a given year (Ahrnsbrak et al., 2017). The prevalence of mental health challenges continues to rise and has seen steady increases in recent years, with rises in psychological distress and depression, observed in the US between 2005 and 2017 (Twenge et al., 2019).

Such increases in the prevalence of mental health challenges have only been further exacerbated by the effects of the Coronavirus. uMore was founded in April of 2020, a time where the effects of the Coronavirus began to significantly impact MENA, Europe, and the USA. The Coronavirus is having a profound impact on the mental well-being of individuals (Venkatesh & Edirappuli, 2020), with unemployment, isolation, and limited access to healthcare further exacerbating the prevalence of mental health challenges in society (WHO, 2020; Yao et al., 2020).

Moreover, the effects of Covid-19 have contributed to major disruptions in daily living for individuals all over the world, which has been detrimental to many psychological outcomes (Tull et al., 2020). Indeed, multiple well-being outcomes which are prevalent in society have been considered as products of daily routine decisions made by individuals, such as stress (Norris et al., 1992) and anxiety (Fox, 1999). Such well-being outcomes are influenced by the choices made by individuals, and in turn, how they experience and live their lives.

The Need For A Quantified Self To Measure & Monitor Well-Being

Self-quantification is considered the process of collecting and analyzing data pertaining to our lived experiences in order to make decisions that improve one's quality of life (Mehta, 2011). The advent of new and affordable technologies capable of gathering and analyzing data, as well as greater awareness of access to health knowledge, has allowed users to gain insight into their health status from their own homes. As technology becomes more minimally intrusive and increasingly sensitive to detecting lifestyle changes, its adoption enables users to monitor changes to their daily living and its associated health impacts.

For the many who lack suitable access to care (whether due to geographical, economic, or cultural barriers), behavioral monitoring through mobile applications newly provides a means of surveilling health outcomes where no such support exists. Moreover, remotely monitoring patients through the use of such tools may supplement electronic health records so that clinicians may better understand an individual's mental state, and plan for adequate treatment. This facilitates the ongoing shift within the sphere of mental health policy research, which is becoming more cognizant of utilizing measurement-based care within its practice, instead of solely relying on clinical judgments that are less frequent by comparison (Fortney et al., 2017).

Healthcare experts have proposed that self-quantification may indeed improve clinicians' understanding, diagnosis, and treatment of illnesses (Swan, 2009). It is believed that individuals who take initiative to collaborate in the management of their healthcare are more likely to understand the treatment rationale and display greater clinical outcomes (Street, 2001).

Specifically, the use of mobile applications to deliver psychological support has been considered a good choice by both clinicians and users when compared to other platforms. This has been attributed to their ease of habit, relatively low expectancy of effort to engage with, and a high level of hedonic motivation to use (East & Harvard, 2015; Yuan et al., 2015). In healthcare-centered self-quantification tools, advancements in the scope of computational analysis facilitate creating a personal self-history for users. This can be analyzed as a single case study in and of itself, improving the user's understanding of their health status and their ability to obtain self-knowledge regarding their condition (Whooley et al., 2014; Choe & Lee, 2015).

In contrast to physical diseases, which have various tools available to monitor symptoms and treatment responses, mental well-being has typically been reliant on self-reported and subjective judgments (Newnham et al., 2009). It should be considered, however, that while multiple smartphone-based applications have so far attempted to monitor features of mental health, well-being, or quality of life, researchers debate whether such existing applications adopt robust measurement methodologies, or demonstrate sufficiently high efficacy. This has been attributed to a lack of evidence-based methodologies used by these applications, as well as, the lack of studies that test their effectiveness in both clinical and non-clinical samples (Chandrashekar, 2018). There is a need for emerging mental health applications to center their design around appropriate methodological approaches, evidence-based recommendations, and easy-to-use user interfaces.

Solution

uMore is a smartphone-based application that is designed to address these pressing societal challenges through self-quantification. uMore is an AI-powered mental well-being tracker that helps users better understand their emotional well-being, track its development over time, learn how to practice positive self-care behaviors, and share their progress with loved ones and clincians.

Measurement Methodology

Through the use of empirically validated psychometric questionnaires, ecological momentary analysis, natural language processing, and digital phenotyping, uMore seeks to measure features of mental well-being.

Validity & Reliability of Patient-Reported Outcome Measures

In order to ensure high efficacy, a feature often missing in most health-centered applications (Chandrashekar, 2018), uMore uses validated psychometric questionnaires as part of its measurement methodology, in order to record patient-reported outcome measures (PROMs).

The necessity to adopt better measurements of day-to-day health improvements has led to increased interest in patient-reported outcome measures (PROMs). In 2009, the UK's National Health Service (NHS) established the widespread adoption of PROMs as measurement tools within clinical procedures. Within the NHS, using data derived from PROMs to better understand the patient is standard, while also required as part of the evidence needed for the appraisals of health technologies.

In order to measure and monitor the most commonly exhibited features of well-being, uMore seeks to target the PROMs that measure the most highly prevalent mental health challenges experienced by the general population. These include stress (Wiegner et al., 2015), anxiety (Remes et al., 2016), depression (Lim et al., 2018), burnout (Shanafelt et al., 2015) and loneliness (Beutel et al., 2017). Additionally, uMore measures aspects of flourishing and languishing, as a means of measuring improvements to the user's positive well-being (Duckworth et al., 2005).

Such PROMs are measured through the application using empirically validated psychometric questionnaires, which are used in both clinical and research settings. These consist of the Perceived Stress Scale (Cohen et al., 1994), the Generalized Anxiety Disorder-7 (GAD-7, Spitzer et al., 2006), the Patient Health Questionnaire-9 (PHQ-9, Kroenke et al., 2001), Copenhagen Burnout Inventory (Kristensen et al., 2005), and the UCLA 3-Item Loneliness Scale (Hughes et al., 2004), respectively. Each of these psychometric questionnaires has been widely adopted by clinicians. Each survey has demonstrated high internal consistency and appropriate validity to be used across a variety of populations (Lee, 2012; Spitzer et al., 2006; Kroenke et al., 2001; Kristensen et al., 2005; Hughes et al., 2004).

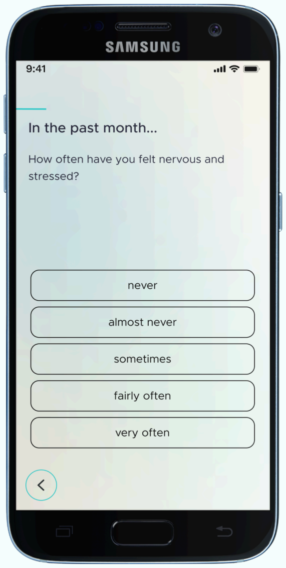

Figure 1. The user is presented with a question from the PSS-10, a psychometric measure used to assess self-perceived stress.

Daily Monitoring Through Ecological Momentary Assessment

Ecological momentary assessment (EMA) describes a category of measurement methodologies that repeatedly sample an individual's real-time behaviors and experiences, within their natural environment (Shiffman & Stone, 2008). These are commonly deployed in the form of self-report questions at a specified time of day, on a daily basis. While the use of such measures warrants greater ecological validity, EMA additionally reduces the reliance on memory to self-report health experiences, as the experience is recorded in real-time (Moskowitz & Young, 2006).

EMA has been used as a methodology to measure mental health experiences in many both clinical and sub-clinical samples within the population (Moskowitz, 1994; Barge-Schaapveld et al., 1999; Bolger et al., 2003).

uMore uses EMA to capture daily changes to the user's self-reported subjective mood state. This is displayed through the use of a Likert scale consisting of 7 icons that depict a range of mood states. Users are also given the option to select from a choice of pre-prepared mood descriptors which have been based on Basic Emotional English Vocabulary (Cowie et al., 1999). Alongside this, uMore permits its users to self-report which activities they had performed that day. Examples include whether they have socialized, exercised, worked, or relaxed, among others. These are customizable, and the user is free to report what activities they had performed that day.

An internally performed analysis on a sample of over 100 participants has suggested that uMore's EMA tool correlates significantly with the PHQ9, GAD7, PSS10, other published mood assessments, and general quality of life scales.

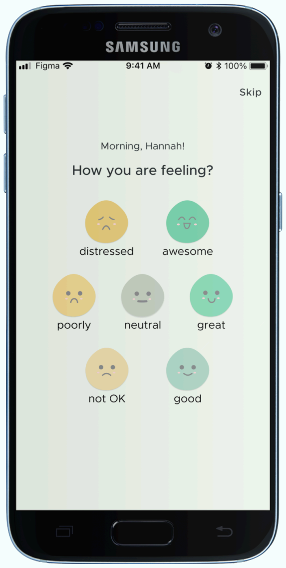

Figure 2. The user is presented with a series of questions which momentarily assess their mood state, emotions, and daily activities.

Better Understanding Mental States With Natural Language Processing

Natural language processing (NLP) is a branch of artificial intelligence that permits computer algorithms to interpret written text and make inferences about the mental state of the author. (Calvo et al., 2017). Since their inception, natural language processing systems have seen increased usage as part of computerized clinical decision support, providing healthcare providers with health-related information (Demner-Fushman et al., 2009; Velupillai et al., 2015). Texts derived from social media, online forums, doctor-patient interactions, and online therapy have all been utilized for NLP, supplying behavioral, emotional, and cognitive indicators of interest to mental health clinicians (Velupillai et al., 2018).

Using an open-response mood diary, uMore enables users to write about their lived experiences within the app. In addition to providing users with a record of their thoughts over time, the supplied text from the diary is analyzed with NLP. This allows uMore to better understand the health outcomes of the user, in relation to their own experiences.

Seamless Health Screening Using Digital Phenotyping & Application Integrations

Most measurement methodologies require initiative from the individual to self-report their own health experiences. This approach is vastly reliant on accurate recall, motivation, and adept use of language from the individual. Self-reporting is not a conducive approach to recording health data from everyone. To supplement this, psychiatry has begun to integrate digital phenotyping into the process of screening individuals for health concerns.

Digital phenotyping is a method of collecting health data passively, by recording behavior through the use of smartphone sensors and keyboard interaction (Jain et al., 2015). Digital phenotyping techniques have been developed to correlate such smartphone usage to a range of mental health challenges, including stress, anxiety, depression, and loneliness (Melcher et al., 2020). Within clinical trial research, smartphone data is often used as a health-related outcome measure (Bidargaddi et al., 2017).

In addition to smartphone sensor data, smartphone applications serve as sources of information to learn about an individual's health behaviors. Specifically, their history of usage provides an insight into the activity of the smartphone owner. Collating data from various applications facilitates the ability to obtain a holistic understanding of the individual's health-related outcomes (Li, 2011).

Similar to the models described above, uMore leverages digital phenotyping and application integrations to supplement self-reported health data. Together, a more complete picture of an individual's behavior and corresponding mental state can be pieced together.

Promoting Positive Behavioral Change

Empowering Users Through Self-Quantification

In order to increase self-awareness and improve personal health outcomes, many individuals worldwide use tracking tools and data management platforms to design personal self-quantification projects. Individuals who self-quantify their health behaviors have been deemed more likely to engage with positive behavioral changes, such as improving attitudes regarding self-empowerment and goal-focus (Pettinico & Milne, 2017), as well as disclosing health concerns (Maltseva & Lutz, 2018). Additionally, self-quantification has also been associated with emotional stability (Maltseva & Lutz, 2018). These changes are considered to be prompted by the positive impact of self-quantification on anticipated motivation, which is regarded as a vital first step in behavior changes (Pettinico & Milne, 2017).

When motivated, self-quantifiers perform various activities to incur such changes. This involves acquiring, quantifying, and aggregating data pertaining to their well-being and then translating such activities into habits as part of daily living (Almalki et al., 2016). Self-monitoring tools help mediate the work performed by a self-quantified user when aimed at improving health outcomes, which is prompted by self-quantification (Gimpel et al., 2013).

Facilitating Health Activation & Self-Management

Health-focused self-quantification is considered to be comprised of two main stages of activity, where health data is recorded and transformed into actionable insights to the individual (Almalki et al., 2015). During the first stage, which focuses on data management, individuals adopt and develop consistent usage of a platform that records their objectives and health records. During the second stage, focusing on health management, such information is transformed into desired health outcomes. Here, the individual experiences patient activation, the knowledge, skills, and confidence that an individual possesses when managing their own health and healthcare (Hibbard et al., 2004).

Clinicians are reaching a growing consensus that treatment users should be more active in the healthcare process, as well as effective managers of their own health and care (Davis et al., 2005; Kilo & Wasson, 2010). Indeed, patient activation has been linked to engagement with more healthy behaviors and appropriate use of their healthcare system (Greene & Hibbard, 2012). In terms of mental healthcare, changes in self-reported patient empowerment, treatment attendance, and retention in treatment were observed following a patient activation and empowerment intervention (Alegría et al., 2008). Moreover, longitudinal studies have suggested that patient activation serves as a predictor of future health outcomes, while also being a fluid characteristic capable of developing over time (Hibbard et al., 2007; Remmers et al., 2009). Increased patient activation has also been evidenced to serve as a predictor of lower costs in healthcare settings (Greene & Hibbard, 2015).

Goal-Setting, Tracking & Facilitating Improvements In Well-Being

Learning From History & Planning For Better Health

Activity Theory states that such efforts made to improve health outcomes are mediated by the self-quantifying tools adopted by the user (Kaptelinin, 1996; Wilson, 2008), enabling them to improve health outcomes by improving behaviors. The process of setting health-improvement objectives through the use of self-quantification tools can help the user collect the data required for them to complete such objectives (Choe et al., 2014; Ancker et al., 2015). Furthermore, Activity Theory further posits that historical analysis of the user's prior activity is required to contextualize and understand their current situation (Kuutti, 1996). Each user is considered to have an objective-centered activity history of their own, whereby the self-quantifying individual develops an understanding of their context (Bedny & Karwowski, 2004).

By self-evaluating the user's health outcomes against past performance, users can compare their health status at different times in the year (Lee & Drake, 2013). By conceptualizing their changes in well-being over time, uMore users can understand when their well-being is affected over the course of a day or week, and plan behavioral changes, with the assistance of self-help exercises, to overcome the impacts of distress. As such, the variance around the usual performance or targets of the user can be used as an indication of the progress made in terms of their health measurement records.

Meaningful Health Monitoring

uMore gathers and synthesizes user data derived from a variety of measurement modalities. By allowing users to engage with a goal-setting and tracking interface centered around data visualization, uMore users are empowered to identify, adopt and rehearse healthy behaviors in response to their current state of well-being.

From data obtained through uMore's different measurement modalities, a uMore user's profile is continuously updated with well-being data. With the data that is recorded, the user's tracking interface is populated with health-related information. Such information is displayed graphically to the user, so to help them understand their current state of well-being, and how their well-being has changed over time.

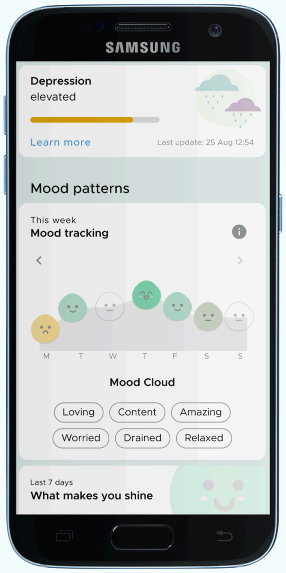

Figure 3. uMore's tracking interface, providing indications of progress and state of well-being.

uMore may detect when the well-being of a user falls below a given threshold which indicates a risk of experiencing distress, or patterns of consistent decreases in well-being. From here, uMore can provide insight into these changes in the form of data visualizations, helping the user recognize these patterns. Thereafter, self-care exercises are provided to help users make behavioral changes that support their well-being. uMore can also redirect distressed users to a database of free-to-access helplines. To our knowledge, our database of helplines is the most internationally comprehensive available on the internet.

Building Positive Habits With Self-Help Exercises

The Supporting Role of Self-Help

Numerous self-help strategies and various environmental support factors have been evidenced to assist in the mental health recovery process (Biringer et al., 2016). Indeed, digitally administered self-help programs have produced useful and efficacious results in improving mental health outcomes (de la Fuente et al., 2015). Self-help activities are considered a feasible management option for those with subthreshold mental health syndromes who lack support and also have been regarded positively by patients and clinicians alike (Collings et al., 2012).

Learning From Evidence-Based Exercises

uMore hosts a library of evidence-based psychological self-help exercises that are designed to improve the user's well-being. Each exercise is designed to help users make particular challenges associated with a range of mental health outcomes, as a preventative measure against declines in well-being. Additionally, the exercises are arranged into series that are grouped thematically by the skills they develop to facilitate positive changes in well-being. Their efficacy is tracked with the scores derived from each PROM.

Every one of uMore's evidence-based exercises is based upon a range of techniques that have been validated in psychological research. Some of these techniques include Psychoeducation (Lukens et al., 2004), Cognitive Behavioural Therapy (Rothbaum et al., 2000), Mindfulness-Based Stress Reduction (Grossman et al., 2004), Applied Relaxation (Öst, 1987), Sleep Hygiene (Irish et al., 2015) and Positive Psychology Interventions (Sin & Lyubomirsky, 2009).

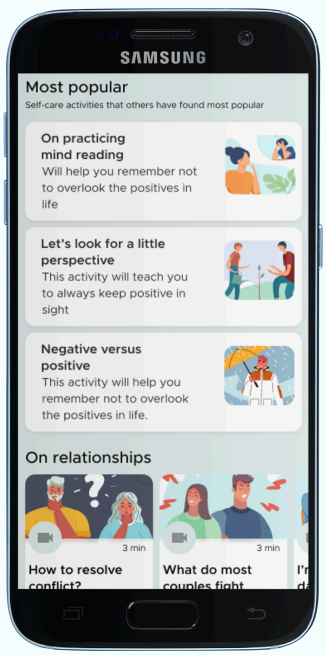

Figure 4. uMore uses elements of Cognitive Behavioural Therapy in its self-help exercises.

Sharing Progress with Others

The Importance of Self-Disclosure

Social penetration theory suggests that self-disclosure attributed to revealing experiences can help individuals gain a greater understanding of others (Altman & Taylor, 1973). Such experiential knowledge originating from interpersonal self-disclosure may improve attitudes towards mental health challenges (An & McDermott, 2014). However, concealment of the self-disclosure of mental health experiences may limit disclosure-driven interactions with the general public and familiarity of others with lived experience of mental health challenges, presenting barriers to improving societal attitudes (Bos et al., 2009). Specifically, research has suggested that the disclosure of lived emotional experiences may contribute to decreases in levels of depression, distress, and anxiety (Frattaroli, 2006).

An individual's support network has been recognized as an important feature of improvements to care provided within community mental health settings (Froland et al., 1979). Recovery from poor well-being outcomes acts as a process. Indeed, such processes which include the provision of hope and goal orientation have been associated with social support networks available to individuals (Corrigan & Phelan, 2004).

Creating The Buddies Feature

Through uMore's Buddies feature, uMore ensures that by sharing well-being outcomes with others, self-disclosure facilitates disclosure-driven actions with others which can prompt improvements in well-being outcomes. The Buddies feature is designed to allow users to bilaterally share their state of recorded well-being with their loved ones on the app, as well as with clinicians. By providing a social support network for each user, uMore ensures that users are provided with the support networks necessary to facilitate progress in well-being outcomes.

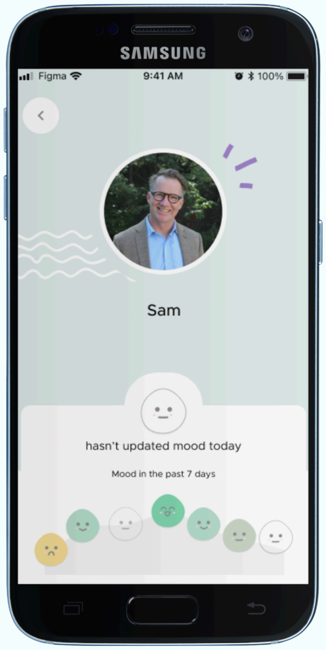

Figure 5. uMore's Buddies feature displays the current state of the well-being of loved ones on the app.

uMore High-Efficiency Design Characteristics

To effectively address challenges faced by users, mental health and well-being applications are required to be evidence-based and carefully designed (Chandrashekar, 2018). uMore carefully follows many of the recommendations provided from research into self-quantification and well-being monitoring in order to provide support to its users.

High User Engagement

Since users of well-being applications are not provided with clinical assistance to use their interfaces, uMore champions an engaging approach to maintaining user motivation. Prior research has suggested that engagement with patients can be improved through real-time engagement, usage reminders, and gamified interactions (Bakker et al., 2016; Chan et al., 2017; Fleming et al., 2017). uMore implements these design requirements through the use of real-time data visualizations, push notifications that provide insight into well-being pattern changes, and custom messages for personal improvement.

Simple UI/UX

Users who exhibit features of anxiety, depression, or psychosis may experience impaired working memory. As such, uMore designs its platform to reduce the cognitive demands required by users in order to interact with it, therefore facilitating their processes of learning. So to achieve this, Bakker and colleagues (2016) recommend the use of visual imagery in place of text, short sentences, and nonclinical terminology. uMore adopts these design requirements in its design philosophy, using simple visual imagery to show well-being outcomes, as well as explanations of well-being that accommodate all levels of mental health literacy.

Self-Monitoring Features

Tracking and providing feedback on well-being outcomes may increase emotional self-awareness. The improvement of emotional self-awareness may subsequently improve well-being and improve coping skills (Heron & Smyth, 2010; Morris et al., 2010; Kauer et al., 2012; Rickard et al., 2016). Moreover, for monitoring to be efficient, measures used within the application must be easily and quickly administered in an acceptable manner to the user (Newnham et al., 2009). Therefore, uMore uses real-time tracking features which use psychometrically validated short-item psychometric scales, each of which has been deemed acceptable by individuals and clinicians.

Class I Medical Device Classification

uMore is a risk class I medical product in the European Union according to the Council Directive 93/42/EEC Appendix IX.3 rule 12. As a monitoring and self-management application, uMore declares that it meets the provisions of Annex VII of the Council Directive 93/42/EEC for medical devices. Our European Union declaration of conformity is issued under the sole responsibility of the manufacturer.

uMore

Conclusion

uMore adopts recent developments in psychological research to provide high-quality well-being measurement and tracking solutions. With a focus on Activity Theory and self-quantification, uMore's design uses psychological research to facilitate positive behavioral change. Alongside this, it seeks to provide its users with the means to share their well-being status with social support networks. Given the global shortage of psychological care and mental health support, uMore uses its features to improve access to mental health measurement and self-management tools. Together, with its evidence-based methodology, technological features, and design principles, uMore provides a modern solution to improving access to well-being monitoring systems.

Contact

Want to get in touch? For any questions regarding what we do at uMore, visit our website, or reach out to us through the following email addresses.

- For general inquiries - info@umore.app.
- For press and media inquiries - press@umore.app.
- For research collaborations - alex@umore.app.
- For investor inquiries - finance@umore.app.
- For job openings and internships, please send your CV to - jobs@umore.app.

You can also reach us directly on Facebook, Instagram, or Twitter.

If you are experiencing a mental health crisis, do not hesitate to consult emergency support to assist you. For an international list of mental health resources, visit our database of global mental health helplines.

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