Perceived Acceptability of Wearable Devices for the Treatment of Mental Health Problems

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Abstract

Objective. This study examined the potential acceptability of wearable devices (e.g. smart headbands, wristbands and watches) aimed at treating mental health disorders, relative to conventional approaches.

Method. A questionnaire assessed perceptions of wearable and non-wearable treatments, along with demographic and psychological information. Respondents ($N = 427$) were adults from a community sample ($M_{age} = 44.6$, $SD_{age} = 15.3$) which included current (30.2%) and former (53.9%) mental health help-seekers.

Results. Perceived effectiveness of wearables was a strong predictor of interest in using them as adjuncts to talk therapies, or as an alternative to self-help options (e.g., smartphone applications). Devices were more appealing to those with negative evaluations of psychological therapy and less experience in help-seeking.

Conclusions. Interest in using wearable devices was strong, particularly when devices were seen as effective. Clients with negative attitudes to conventional therapies may be more responsive to using wearable devices as a less directive treatment approach.

Keywords:

clinical decision-making; e-mental health; patient acceptance of healthcare; patient preferences; wearable electronic devices

Perceived Acceptability of Wearable Devices for the Treatment of Mental Health Problems

Untreated psychological disorders are a major global problem. Since the 1990s there has been a growing awareness of the 'treatment gap' between those who require treatment and those who access it (Demyttenaere et al., 2004). However, despite considerable improvements in treatment resources, the gap in industrialized countries does not appear to have shifted over time (Jorm, Patten, Brugha, & Mojtabai, 2017). Improving preventive mental health, as well as targeting therapies to the most severe cases, may be important strategies in reducing the treatment gap (Jorm et al., 2017). However, a range of psychological and structural barriers prevent people from accessing traditional face-to-face mental health services, including stigma, a preference for solving one's own problems, or poor service availability (Mojtabai et al., 2012).

Technological adjuncts to therapy, such as wearable devices, are one proposed strategy for closing the treatment gap (Naslund et al., 2017). A range of wearables—devices worn as an accessory or item of clothing—have recently been developed with the goal of improving mental health (Coffey & Coffey, 2016; Hunkin, King, & Zajac, 2019; Torous & Gualtieri, 2016). Wearable devices typically operate in concert with smartphone applications ('apps') by sensing and relaying physiological signals. For instance, many of these devices work through biofeedback, monitoring bodily signals that reflect arousal state and feeding this information back to the wearer, prompting them to utilize adaptive coping skills. They include EEG headbands for aided meditation, breathing sensors, and heart rate variability monitors. Some are worn throughout the day, while others are used for regular brief sessions of self-administered training. A variety of wearable devices oriented toward mental health are now commercially available and being marketed directly to consumers, with the majority priced between $150-300 US dollars (Hunkin et al., 2019). One example is *Muse* (Interaxon, Inc.), an EEG headband designed to give auditory feedback during focused-attention meditation. While using the headband and accompanying app during meditation sessions, the wearer hears soundscapes that vary from calm to intense, according to their level of focus on the breath. By receiving feedback on what non-judgmental attention feels like, as well as tracking progress, it is theorized that the wearer can more rapidly develop proficiency as a meditator (Balconi, Fronda, Venturella, & Crivelli, 2017).

Like other e-mental health approaches such as apps, evidence-based wearable devices could potentially improve mental health outcomes due to their accessibility, flexibility, and low cost (Nicholas et al., 2017). Recent forecasts for the wearable market (Gartner, 2018) suggest that the number of devices oriented at mental health, as well as their sophistication, will continue to increase. Despite this, many questions remain regarding the use of such devices in clinical practice, such as the extent of potential risks and benefits, principles for the evaluation of devices, and the clinical circumstances in which wearables might be most effective. With the growing use of technology in clinical settings (e.g., smartphone apps, tablets, virtual reality devices), as well as ongoing developments in the consumer device market, clinicians are more likely to encounter wearable devices. However, the potential for these devices to improve therapeutic outcomes, either when used alone or as adjuncts to traditional talk therapies, will depend at least to some extent on their acceptability to clients. Research indicates that consumers' perceived benefits and limitations of e-mental health treatments differ from traditional face-to-face treatment (Musiat, Goldstone, & Tarrier, 2014), and also that individual interest in these treatments varies (Nicholas et al., 2017). Since there is a demand from clients to receive more personalized treatments (Hollis et al., 2018), and accommodating client preferences results in more positive outcomes and fewer dropouts (Swift, Callahan, Cooper, & Parkin, 2018), there is a clear need to understand which factors shape the acceptability of wearable devices in order to identify client groups for which they might be efficacious.

Research into the role of individual factors in the acceptability of wearable devices, as opposed to device factors, is limited thus far. Important individual factors are theorized to include aspects such as demographics, traits, cognitive factors, beliefs and attitudes, and disease characteristics (Ritterband, Thorndike, Cox, Kovatchev, & Gonder-Frederick, 2009). Though knowledge is limited, previous studies have evaluated some individual factors in the broader context of e-mental health treatments, such as Internet-delivered interventions. Several of these studies have focused on the *hypothetical* acceptability of such interventions, referring to the level of interest expressed in an intervention that had not yet been experienced (Berry, Lobban, Emsley, & Bucci, 2016). This type of acceptability is distinct from the acceptability of interventions which have already been experienced. It is an important target for research because if hypothetical acceptability is low, treatment uptake may be compromised, regardless of the actual quality of the treatment. Furthermore, a generally low willingness to engage with digital interventions has been cited as a major problem in digital mental health research and implementation (Mohr, Lyon, Lattie, Reddy, & Schueller, 2017). Klein and Cook (2010) examined the characteristics of 'e-preferers' (i.e. those who had a higher preference for Internet-based mental health assistance compared to face-to-face therapy) and showed they did not differ on demographic factors or previous mental health service usage, but that they had significantly higher stigma regarding mental illness. March et al. (2018) reported similar findings in regard to the absence of demographic differences, but also demonstrated that technology confidence led to a greater preference for online services relative to face-to-face services. Another recent study of university students and primary care patients found that higher help-seeking self-stigma, together with treatment expectancy, predicted a stronger preference for Internet-based approaches compared to face-to-face treatment (Wallin, Maathz, Parling, & Hursti, 2018). Taken together, these findings suggest that technological readiness, perceived effectiveness of devices, and barriers to face-to-face therapy (such as stigma) could be important predictors of interest in wearable devices relative to traditional approaches.

Given the need to effectively target wearable devices for mental health to those most likely to use them, we aimed to evaluate how the perceived acceptability of these devices was related to individual factors identified from the e-mental health literature, as well as clinical factors—psychological symptoms, prior mental health diagnoses, previous experience consulting mental health professionals, and satisfaction with previous treatment. Furthermore, because the factors motivating use of mental health wearables in self-help as opposed to clinician-facilitated approaches might differ, these options were considered separately (Arjadi, Nauta, & Bockting, 2018). Given the absence of a research evidence base addressing preference for wearables, we have adopted an exploratory approach with the aim of identifying factors that predict a desire to use wearable devices preferentially (either alone or in combination with other treatments).

Method

Participants

Eligible participants were Australian residents over the age of 18 who considered themselves as fluent in English. A total of 546 participants consented, with two ineligible, 117 partial, and 427 complete responses. Partial responses were discarded as missing items could not be reasonably imputed. Table 1 presents a summary of the characteristics of complete responders.

Measures

Demographics. Participants reported their age, gender, relationship status, household income, level of education, Australian postcode, and type of employment (according to the Australian and New Zealand Standard Classification of Occupations). The index of relative socioeconomic disadvantage (IRSD), a measure of socioeconomic status where lower values represent more disadvantageous factors, was computed based on respondent postcodes (Australian Bureau of Statistics, 2016b). Postcodes were used to determine whether respondents resided in major cities or rural/remote areas (Australian Bureau of Statistics, 2016a).

Hypothetical acceptability of mental health treatments. Participants were asked to report their interest in using each of four specific mental health treatments (*If you were experiencing a mental health problem (e.g. anxiety, depression), how interested would you be in [treatment type] to help your problem?*), scored on a seven-point scale (*Not at all interested – Very interested*). Treatments included (1) *using counselling or talking therapies under the guidance of a mental health professional*, (2) *using wearable devices under the guidance of a mental health professional* (i.e. blended therapy), (3) *using wearable devices <u>without</u> professional guidance*, and (4) *using other self-help options <u>without</u> professional guidance*.

Intention to use a wearable device. Participants indicated whether they would "definitely want" or "definitely not want" to use a wearable device if they were experiencing a mental health problem, or whether they would need to find out more before deciding. This categorical response was used to determine the proportion of respondents who made a relatively rapid decision based on the limited information about wearable devices that was provided to them. Those who indicated they required more information were prompted to briefly describe specific details they would need to know in order to decide. The collection of this open-ended data was intended firstly to triangulate the quantitative responses (i.e. to increase confidence in the findings through the use of multiple investigatory methods; Korstjens & Moser, 2018), and secondly to identify any aspects that had not been adequately measured by quantitative items.

Other clinical and wearable-oriented items. Items were developed to assess awareness of wearable devices for mental health (yes/no), intention to use wearables if recommended by a practitioner (yes/no), level of knowledge of wearable devices prior to commencing the survey (seven-point scale, *No knowledge – Expert knowledge*), and perceived effectiveness of wearable devices for mental health problems (seven-point scale, *Not at all effective – Extremely effective*). Use of wearable devices for mental health and well-being, or other purposes (such as fitness) was reported. Participants indicated whether they were currently consulting a mental health professional or had ever done so, as well as any prior mental health diagnosis, whether this diagnosis was still having an impact, and the duration of its impact.

Depression, Anxiety and Stress Scales (DASS-21). The DASS-21 (Lovibond and Lovibond, 1995) is an abbreviated self-report measure of the negative affective states of depression, anxiety, and stress. Items represent statements associated with depression, anxiety, or stress, rated in terms of how much they applied over the past week (0 = *Did not apply to me at all,* 1 = *Applied to me to some degree, or some of the time*, 2 = *Applied to me to a considerable degree, or a good part of time,* 3 = *Applied to me very much, or most of the time*). Item scores are summed within each of the three scales and multiplied by two, producing scale scores ranging from 0-42 where higher values represent greater symptom severity. Cronbach's alpha showed good internal consistency (depression = .93, anxiety = .84, stress = .86).

Perceived Barriers to Psychological Treatments scale (PBPT). The PBPT (Mohr et al., 2010) is a multidimensional measure of perceived barriers to face-to-face treatment, comprising nine distinct dimensions. The scale consists of 25 items relating to specific barriers rated by difficulty (1 = *Not difficult at all,* 2 = *Slightly difficult,* 3 = *Moderately difficult,* 4 = *Extremely difficult,* 5 = *Impossible*). Instructions for completion were adapted for readability and the Australian context (*Please rate how difficult these things might make it for you to see a counsellor or psychologist.*) Mean scores are calculated for each of the eight subscales so that each has a score between 1-5, where higher scores represent greater barriers to treatment. The total score is the mean of all 25 items, although notably this over-represents subscales which contain more items (particularly stigma). Internal consistency was generally good (total scale .91; subscales from .75 to .88 except 'availability of services', .59).

Technology Readiness Index 2.0 (TRI 2.0). The TRI 2.0 (Parasuraman and Colby, 2015) is a 16-item measure of attitudes toward the use of novel technologies. Four subscales encompass both motivational (optimism, innovativeness) and inhibitory (discomfort, insecurity) aspects, each containing four items which represent statements about technology. Responses indicate level of agreement with each statement (1 = *Strongly disagree,* 2 = *Somewhat disagree*, 3 = *Neutral*, 4 = *Somewhat agree*, 5 = *Strongly agree*). Subscales scores are the mean of their constituent items, ranging from 1-5. The total scale score is the mean of the subscales after reversing insecurity and discomfort subscales; higher scores thus represent more positive attitudes to novel technology. Internal consistencies were acceptable, ranging from .64 to .82 for subscales, and .85 overall.

Procedure

After obtaining human ethics approval, the online questionnaire was made active during November and December 2018. To target a broad sociodemographic range, participants were sought via Facebook advertising (n = 378) and convenience sampling (i.e. sharing of the survey through personal and professional networks; *n* = 53). In order to minimize participation bias, advertisements did not refer to wearable devices but asked potential participants to complete a short survey on "current and future approaches to treating common mental health issues like anxiety and depression", and participation was incentivized with a prize draw of three $150 (Australian dollar) vouchers. Participants were first shown an electronic information sheet describing eligibility requirements, the kind of information they would be asked to provide and how this data would be used, the estimated time to complete the survey, and the potential for experiencing discomfort from some of the questions included in the DASS-21. To continue, participants were required to indicate that they had read and understood this information, and willingly agreed to take part. Following consent, participants completed demographic questions and eligibility checks, and were asked whether they were already aware of wearable devices for mental health. Participants were shown a brief description of wearable devices for mental health, including general information about their typical size, cost, purpose, method of working, and cost (see supplementary material). After viewing this description, participants reported their interest in accessing mental health treatment through four distinct methods, as described above, before completing the remaining measures. Participants who reported 'moderate' level or higher depression, anxiety or stress symptoms according to DASS cut-off scores were shown information about some common manifestations of these problems and a range of avenues for seeking help.

Statistical Analyses

Quantitative analyses were conducted using the R statistical software, version 3.5.1 (R Core Team, 2018). Power analysis using G*Power 3.1.9.2 (Faul, Erdfelder, Buchner, & Lang, 2009) indicated that N = 395 participants were required to detect small effects (f^2 = 0.02) in linear regression models with up to 10 predictor variables, given a 5% Type I error rate and 80% power (Cohen, 1988). Categorical predictor variables were collapsed when groupings appeared to be redundant or contained only a small number of respondents. Since the effects of age on outcome variables appeared linear, age was treated as a continuous variable.

To determine whether treatment preference differed significantly by treatment, a mixed linear model specified with a random intercept for respondent was fitted and post-hoc Tukey comparisons of means were computed. Bivariate analyses were used to examine the association of individual predictors with individual treatment acceptability. Due to non-normal data, Spearman rank correlations were used for continuous predictors; *t*-tests and one-way ANOVAs were considered robust tests for categorical predictors due to the large sample size, the fact that variances were generally homogenous, and distributions did not differ substantially between groups (Fagerland, 2012; Schmider, Ziegler, Danay, Beyer, & Bühner, 2010). Given the large number of bivariate tests, Benjamini and Hochberg's (1995) false discovery rate adjustment was used to correct *p*-values. This procedure is less conservative than family-wise error rate controls such as the Bonferroni correction because it accounts for the number of actual null hypothesis rejections (Streiner, 2015).

To examine predictors of comparative acceptability, three comparisons between specific treatments (as described in the results) were computed as the *Z*-scores of the difference between interest in one treatment and another, thus representing a measure of relative preference for one treatment over the other. Multiple linear regression models were then constructed for each of the three treatment comparisons. While there are a number of limitations to automated stepwise model building approaches (Harrell, 2015), some reduction in predictors was desirable for reasons of interpretability and practicality (Houwelingen & Sauerbrei, 2013). Furthermore, redundancy analysis (Harrell, 2015) did not identify any variables that could be removed prior to modelling, and no particular variables had theoretical primacy. Predictors for each model were therefore selected using backward elimination based on optimizing the Akaike information criterion (Heinze, Wallisch, & Dunkler, 2018). Reduced models were cross-checked against the corresponding full models for each treatment comparison, to ensure that predictors with sizeable and/or statistically significant effects had been included in the reduced models, and that parameter estimates in the reduced models did not differ wildly from the full models.

For the written responses, thematic analysis from a realist perspective (i.e. assuming responses were a true articulation of participants' experience) was used to explore information respondents desired to know in order to decide whether to use wearable devices (Braun & Clarke, 2006). This process aims to find common patterns of meaning that occur across the data, and normally involves a series of steps consisting of data familiarization, generating codes for features of the data, organizing related codes into overarching themes, and iteratively reviewing and refining themes to fit the data. Data were analyzed using NVivo 12 (QSR International Pty Ltd) taking an inductive approach. The first author developed the coding frame during manual coding of responses, and together with the third author, identified themes that arose from these codes. To establish credibility (Korstjens & Moser, 2018), the second author assessed 30 randomly selected responses and identified corresponding themes. Differences in thematic associations in this subsample, as well as the categorization of codes into themes overall, were reviewed by the first and second authors in order to reach consensus ('investigator triangulation'; Korstjens & Moser, 2018). The identified themes, along with representative quotes, are presented in Table 4. To promote dependability and confirmability of the analysis, the raw data have been published separately (https://doi.org/10.25909/5d65c816af254).

Results

Table 1 presents the characteristics of study participants. A similar proportion of males and females over a broad range of ages (18-78) responded, although those over the age of 65 were less represented. Participants were predominantly either professionals (37.9%) or not formally employed (e.g. students, retired, or unpaid caregivers; 35.4%), whereas under 5% reported being sales workers, machinery operators and drivers, or laborers. Mean relative socioeconomic disadvantage was in the seventh decile, signifying somewhat fewer disadvantages than the average Australian. According to DASS cut-off scores, 47.3% of participants had at least a 'mild' level of symptoms for one or more of the depression, anxiety and stress subscales, while 12.9% reported 'moderate', 5.6% 'severe', and 2.8% 'extremely severe' symptoms (Lovibond & Lovibond, 1995). Almost a third (30.2%) of the sample reported that they were presently seeing a mental health professional, while 53.9% had done so previously but were no longer accessing treatment.

Table 2 summarizes clinical and wearable-oriented variables. Around two-fifths (40.7%) of respondents initially reported an awareness of wearable devices for mental health. However, participants later reported relatively low knowledge of the nature of these devices in the context of a description of them during the actual survey. While more than a fifth of respondents indicated that they presently used other types of wearable devices, such as fitness wearables, only eight respondents reported that they currently used a wearable device for mental health or well-being. Few respondents indicated they had no interest in using a wearable device, whereas around two-fifths indicated that they would definitely be interested in using such a device.

Acceptability of Treatments

Inspection of hypothesized predictors revealed that older participants tended to have significantly lower depression, anxiety and stress scores, perceived barriers to treatment, and technology readiness, with small-to-moderate effects (Cohen, 1992). Furthermore, greater total perceived barriers to treatment were significantly associated with lower satisfaction with previous treatment (r = -.35) and higher depression, anxiety and stress (r = .38-.39). Greater technology readiness was significantly associated with increased levels of knowledge (r = .19) and greater perceived effectiveness (r = .17) of wearables. Correlations between all study variables are shown in Table S1 (supplementary material). Analysis of variance showed that total DASS scores varied significantly according to whether respondents had ever consulted a mental health professional, $F(2, 424) = 30.89$, $p < .001$, $\eta^2 = .13$, with highest scores for those still seeing a clinician and lowest scores for those who had never visited. However, consulting a mental health professional was not significantly associated with total perceived barriers to treatment, $F(2, 424) = 2.57$, $p = .078$, $\eta^2 = .01$.

Of the four treatment options presented, respondents expressed strongest interest in using talk therapies for treatment of a mental health problem, followed closely by using wearables with the guidance of a mental health professional (i.e. blended therapy). Using wearables without assistance was the least preferred option. A mixed linear effects analysis showed a significant main effect, $F(3, 1278) = 102.24$, $p < .001$, and Tukey post-hoc testing indicated that mean preferences for all treatments were significantly different from one another. The relationships of continuous and categorical predictors with acceptability of the four treatments are provided as supplementary material (Tables S2 and S3).

Multivariable Linear Models of Comparative Treatment Preferences

Multivariable linear models comparing preference for wearable devices relative to other treatment preferences are presented in Table 3. In the model comparing wearables (blended) with talk therapies, six predictors explained 17% of variance in treatment preference. Greater perceived efficacy of wearables, current use of other wearable devices, and negative evaluations of therapy predicted significantly greater interest in accessing treatment using wearable devices in a blended format rather than talk therapies alone. On the other hand, previous or ongoing consultation with a mental health professional predicted a significantly greater preference for talk therapies, as did greater prior knowledge of wearable devices. A second model considering wearables (self-help) vs other self-help incorporated eight predictors and explained 14% of variance in preferred treatment. Greater perceived efficacy of wearables and negative evaluation of therapy predicted a significantly stronger preference for using wearable devices rather than other types of self-help. However, previous or current experience consulting a mental health professional, stigma, and discomfort with technology predicted a significantly greater preference for other self-help options. The last model considered wearables (blended) vs wearables (self-help) and incorporated seven predictors explaining 15% of variance in preferred treatment. Older age and rural/remote location predicted significantly greater preference for using wearables in a blended format rather than for self-help. Furthermore, relative to those in the top two household income quintiles (>$105,000), being in the second quintile (~$35,000-65,000) predicted a significantly greater preference for using wearables in the blended format, as did the presence of participation restrictions and previous or ongoing consultation with a mental health professional. On the other hand, negative evaluation of therapy was associated with a preference for using wearable devices without clinician assistance. Satisfaction with prior treatment was not included in these models because of incomplete responding. However, bivariate analyses (Table S1) indicated that prior treatment satisfaction was associated with a reduced preference for wearables (blended) relative to talk therapies ($r = -.19$, $p < .001$) and a greater preference for wearables in a blended format relative to self-help format ($r = .15$, $p < .05$).

Written Responses

Around half of study participants (58.3%, $n = 249$) reported an interest in wearables for mental health but indicated that they required further information before deciding whether to use them. Of these, 97.9% ($n = 244$) provided written responses indicating what information they desired in order to inform whether or not to use such devices. Thematic analysis of these responses suggested thirteen distinct themes, which are presented along with representative quotes in Table 4. Around half of the responses were considered to appeal to evidence and efficacy, as well as knowing how devices worked. Privacy was also an important theme for many respondents, particularly in relation to data storage and access control. Further themes concerned discretion, practicality, risks and negative outcomes, positive outcomes, cost, time and effort needed, matching devices to the problem or situation, knowing how devices are used, and the availability of professional support.

Discussion

This study evaluated predictors of the acceptability of wearable devices for mental health concerns, relative to conventional mental health treatment options. The results indicate that overall, interest in using wearable devices with clinician support was almost as strong as interest in using talk therapies alone. However, use of mental health wearables appeared to be dependent upon the perceived effectiveness of these devices and knowledge regarding “how they work”.

Importantly, the use of wearable devices appeared to reduce some barriers to accessing treatment, particularly negative evaluations of therapy, but was contraindicated by higher stigma. Furthermore, prior experience accessing mental health services was associated with a greater preference for treatments involving a higher level of clinician involvement (i.e. talk therapies, followed by wearables in blended format). These findings have several implications for clinical practice and further research with this emerging technology.

The perceived effectiveness of wearable devices was consistently one of the strongest predictors of interest in using wearables over other treatment options. While this is congruent with research into e-mental health treatments more broadly (Gun, Titov, & Andrews, 2011; Musiat et al., 2014), generating robust evidence for wearable devices is troublesome because devices and apps tend to be updated on short, commercially-oriented timescales, whereas controlled trials are costly and results may become quickly outdated (Kumar et al., 2013). Alternative approaches to evaluation have been proposed (e.g. continuous evaluation systems or rapid research designs; Mohr, Cheung, Schueller, Hendricks Brown, & Duan, 2013; Riley, Glasgow, Etheredge, & Abernethy, 2013), but these new methods have not been widely adopted, and neither is there a consensus view that they supersede existing methods (Torous et al., 2019). Similarly to mental health apps, the current state of evidence for wearables means they may best serve as adjuncts to extend existing evidence-based treatments (e.g. devices such as assisted meditation headbands), while exercising caution (Lui, Marcus, & Barry, 2017). Brief clinical evaluation frameworks such as the App Evaluation Model (American Psychiatric Association, 2017) can be easily adapted for use with wearable devices (Hunkin et al., 2019), and may provide a pragmatic way to systematically assess the suitability and safety of a given wearable device used adjunctively in a specific clinical situation.

The results of this study provide some insight into factors associated with a desire for clinician guidance when using wearable devices. Respondents' preference for clinician involvement with wearables is consistent with previous work demonstrating that e-mental health interventions are more acceptable and/or helpful when coupled with therapeutic support (Berry et al., 2016; Casey, Joy, & Clough, 2013; Klein & Cook, 2010). Research suggests that guided use of e-mental health interventions results in fewer drop-outs (Anton & Jones, 2017) and superior clinical outcomes (Mehrotra et al., 2017) relative to unguided use. Equally, the use of e-mental health interventions as adjuncts to face-to-face interventions may improve compliance with the primary treatment (Lui et al., 2017). However, interrelated factors including negative evaluation of therapy, having no experience consulting mental health professionals, or being less satisfied with prior experiences (and to a lesser extent, younger age) were associated with an increased desire to use wearable devices without clinician support. This is consistent with existing research linking these factors with lower rates of treatment-seeking and treatment continuance, often connected to a desire for managing one's own problems (Mojtabai et al., 2012; Montague, Varcin, Simmons, & Parker, 2015; Rickwood, 2015).

Self-help interventions have been viewed as a conduit to accessing higher intensity face-to-face services by increasing mental health literacy and emotional competence (Christensen & Hickie, 2010; Rickwood, Deane, & Wilson, 2007). However, without clinician guidance as to the suitability of wearable devices, there is a risk that they could be unhelpful, or even iatrogenic (Hunkin et al., 2019). Several strategies can be used by practitioners to overcome these emotional and attitudinal barriers in hesitant clients, including working through harmful effects of self-stigma (Corrigan & Rao, 2012), challenging extreme attitudes about self-reliance (Labouliere, Kleinman, & Gould, 2015), and increasing insight into the severity of one's condition (Mojtabai et al., 2012). Notably, the present results show that negative evaluation of therapy predicted increased interest in using wearables blended with face-to-face therapy compared with accessing talk therapy alone. This is consistent with evidence that increasing client control over an intervention can reduce resistant behavior linked to emotional barriers (Beutler, Harwood, Michelson, Song, & Holman, 2011).

While the standardized effect sizes for some individual predictors of acceptability were substantial, the variance explained by the predictive models in Table 3 was less than 20% in all cases. This large proportion of unexplained variance suggests the existence of various unmeasured factors that modulate interest in wearable devices. One widely cited model of technology acceptance (Venkatesh, Thong, & Xu, 2012) implicates a broad range of possible factors, such as attitudes, perceived behavioral control, compatibility (i.e. consistency with needs and values), subjective norm, image (i.e. perceived status enhancement), complexity, perceived ease of use, hedonic motivation, and price value. Participants' written responses, while supporting quantitative findings, also provided insight into some of these other factors. Responses highlighted the importance of perceived efficacy and a desire for clinician support, while a lack of responses concerning issues such as technology readiness or symptom severity was also consistent with quantitative data. Responses also suggested that time and cost, common barriers to more traditional therapy, may remain as substantial barriers to accessing wearable devices. Further themes indicated the presence of other barriers more specific to wearables, such as privacy, discretion, and practicality. These barriers highlight the importance of matching individual needs to devices with specific features (e.g., robust data protection, or a discreet form factor). Lastly, the theme of matching devices to the mental health problems being experienced indicated a desire for devices that can be tailored to meet individual requirements.

The present study has several limitations. These findings may not be generalizable across sociocultural boundaries, since attitudes, barriers, and decision-making processes regarding mental health technology uptake may differ substantially (Bagozzi, 2007; Clough et al., 2017; Rojas-Méndez, Parasuraman, & Papadopoulos, 2015). Responses were not entirely representative of the broader Australian population in regard to variables such as education level and type of employment. The use of an online survey could also be expected to cause bias toward respondents who are more comfortable with technology. Although these kinds of biases can be expected given the sampling approach used, recruitment via Facebook does compare favorably with traditional methods as far as representativeness (Thornton et al., 2016). Furthermore, the sample did contain sufficient variability to model the impact of various inter-individual differences on treatment preference—including a wide range of scores on technology readiness. Lastly, heterogeneity in devices, individual needs, and mental health conditions means that more specifically targeted wearable interventions may garner stronger interest, as suggested by written responses.

The high proportion of respondents who had experienced mental health conditions and accessed clinical treatments was a strength of this research. Furthermore, we were able to provide some support for the notion that e-mental health may help to improve access to treatment—and perhaps also retention—which has been identified as a priority area for research (Hollis et al., 2018). Given our findings, one direction for future study is to evaluate the factors that influence the perceived effectiveness of wearable devices. Secondly, while hypothetical acceptability should be a good predictor of willingness to engage in specific treatments, future work could determine how this relates to measures of actual acceptability (e.g. ease of use, perceived helpfulness, and satisfaction ratings; Berry et al., 2016), which is likely to moderate the sustained use of wearable devices.

Conclusion

Wearable devices, among other e-mental health approaches, may play a major role in future psychological interventions. Respondents' strong interest in wearables and their general preference for professional guidance highlights the need for clinicians to provide opportunities for integrated approaches for some clients. Furthermore, since augmenting traditional approaches with wearable devices appeared more acceptable for those with negative perceptions of therapy, these adjuncts could be a novel approach to tackling treatment resistance. Although devices need to be seen as effective in order for clients to want to use them, clinicians must also take care to ensure that they adequately inform clients about the evidence base for wearable devices, which is currently limited. These issues notwithstanding, the broad cross-demographic acceptability of wearable devices in the present data suggest strong potential for incorporating these devices into clinical care, providing that risks and benefits are evaluated for each client and treatment scenario.

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Tables

Table 1

Sociodemographic characteristics of participants (N = 427)

	M ± *SD* or *n* (%)
Age	44.63 ± 15.25
18-34	144 (33.7%)
35-54	150 (35.1%)
55+	133 (31.1%)
Gender Male	184 (43.1%)
Education	
Diploma or below	177 (41.5%)
Bachelor degree	178 (41.7%)
Postgraduate degree	72 (16.9%)
Relationship status	
Single/divorced/separated	156 (36.5%)
Married/committed relationship	271 (63.5%)
Household income	
< $35,000	112 (26.2%)
$35,000-$65,000	92 (21.5%)
$65,000-$105,000	103 (24.1%)
> $105,000	120 (28.1%)
Socioeconomic disadvantage	1019.11 ± 56.40
Rural/remote	124 (29.0%)

Table 2
Clinical and wearable-oriented variables

	M ± *SD* or *n* (%)
Pre-existing awareness of wearables for mental health	174 (40.7%)
Previous knowledge	1.75 ± 1.26
Interest in using a wearable device	
Definitely yes	162 (37.9%)
Need to know more	249 (58.3%)
Definitely no	16 (3.7%)
Would use wearable device if recommended by clinician	411 (96.3%)
Wearable devices currently used for mental health/wellbeing[a]	
1 device	7 (1.6%)
2 devices	1 (0.2%)
Use of wearable devices for other reasons	92 (21.5%)
Perceived effectiveness	4.02 ± 1.21
Interest in treatments	
Talk therapies	5.61 ± 1.66
Wearables (blended)	5.28 ± 1.62
Wearables (self-help)	4.01 ± 1.95
Other self-help	4.50 ± 1.74
DASS[b]	
Depression	14.39 ± 11.20
Anxiety	8.78 ± 8.12
Stress	15.37 ± 9.23
Ever consulted a mental health professional	
Yes, and still seeing	129 (30.2%)
Yes, but no longer seeing	230 (53.9%)
No	68 (15.9%)
Ever been diagnosed with a mental health problem	
Yes, and still impacting	239 (56.0%)
Yes, but no longer impacting	70 (16.4%)
No	118 (27.6%)
Satisfaction with prior treatment[c]	4.70 ± 1.70
Years affected by condition[d]	18.57 ± 14.13
Barriers to treatment	1.98 ± 0.60
Stigma	1.85 ± 0.79
Lack of motivation	2.21 ± 1.04
Emotional concerns	1.89 ± 0.90
Negative evaluation of therapy	2.05 ± 0.91
Misfit of therapy to needs	1.84 ± 0.78
Time constraints	2.11 ± 0.96
Participation restrictions	1.59 ± 0.75
Availability of services	2.40 ± 0.95
Cost	3.02 ± 1.13
Technology readiness	3.24 ± 0.63
Optimism	3.65 ± 0.76

	$M \pm SD$ or n (%)
Innovation	3.20 ± 0.96
Discomfort	2.68 ± 0.79
Insecurity	3.19 ± 0.88

Note: [a]Devices reported include FitBit 'Relax' app (n = 5), Interaxon Muse headband (n = 2), Sentio Feel wristband (n = 1), and Spire Stone respiration monitor (n = 1).
[b]Adjusted for DASS-42 equivalence.
[c]For respondents who had previously consulted a mental health professional (n = 359).
[d]For those who reported a diagnosed condition and reported duration (n = 234).

Table 3

Linear regression models predicting relative interest in wearable treatments compared with three other specified interventions

Model/predictor	$B \pm SE$	β [95% CI]	p
1. Wearables (blended) vs talk therapies			
Intercept	-1.82 ± 0.41		<.001
Current wearable usage: Yes[a]	0.43 ± 0.18		.016
Ever consulted: Yes (no longer seeing)[a]	-0.51 ± 0.21		.017
Ever consulted: Yes (still seeing)[a]	-1.27 ± 0.23		<.001
Perceived effectiveness	0.39 ± 0.06	0.28 [0.19, 0.37]	<.001
Barrier: Negative evaluation of therapy	0.21 ± 0.08	0.11 [0.02, 0.20]	.014
Barrier: Time	0.14 ± 0.08	0.08 [-0.01,0.17]	.067
Previous knowledge about wearables	-0.13 ± 0.06	-0.10 [-0.18, -0.01]	.033
2. Wearables (self-help) vs other self-help			
Intercept	-1.19 ± 0.55		.030
Current wearable usage: Yes[a]	0.32 ± 0.21		.132
Ever consulted: Yes (no longer seeing)[a]	-0.62 ± 0.25		.014
Ever consulted: Yes (still seeing)[a]	-0.65 ± 0.28		.021
Perceived effectiveness	0.47 ± 0.07	0.30 [0.21, 0.39]	<.001
Barrier: Stigma	-0.52 ± 0.15	-0.22 [-0.34, -0.09]	<.001
Barrier: Negative evaluation of therapy	0.48 ± 0.14	0.22 [0.10, 0.35]	<.001
Barrier: Time	0.14 ± 0.10	0.07 [-0.02, 0.17]	.138
Barrier: Participation restrictions	-0.22 ± 0.13	-0.09 [-0.19, 0.02]	.103
Technology readiness: Discomfort	-0.07 ± 0.03	-0.11 [-0.20, -0.02]	.018
3. Wearables (blended) vs wearables (self-help)			
Intercept	0.56 ± 0.42		.193
Remoteness: Rural/remote[b]	0.43 ± 0.19		.021
Household income: <$35,000[c]	0.03 ± 0.24		.896
Household income: $35,000-65,000[c]	0.56 ± 0.24		.022
Household income: $65,000-105,000[c]	-0.04 ± 0.23		.851
Ever consulted: Yes (no longer seeing)[a]	0.50 ± 0.24		.037
Ever consulted: Yes (still seeing)[a]	1.03 ± 0.26		<.001
Age	0.02 ± 0.01	0.14 [0.05, 0.23]	.018
Barrier: Negative evaluation of therapy	-0.53 ± 0.10	-0.26 [-0.36, -0.16]	<.001
Barrier: Participation restrictions	0.27 ± 0.13	0.11 [0.00, 0.21]	.043
Previous knowledge about wearables	-0.11 ± 0.07	-0.08 [-0.17, 0.01]	.089

Note: Dependent variables in each model are the standardized differences between one treatment and another; positive estimates predict a higher preference for the first treatment described in each model, and vice versa. Predictors were selected using backward elimination to optimize the Akaike information criteria. All three models were significant: (1) Adjusted $R^2 = .17$, $F(7, 419) = 13.82$, $p < .001$; (2) Adjusted $R^2 = .14$, $F(9, 417) = 8.89$, $p < .001$; (3) Adjusted $R^2 = .15$, $F(10, 416) = 8.34$, $p < .001$. Comparison conditions: [a]No, [b]Major cities, [c]>$105,000.

Table 4

Themes relating to important factors in decision-making about wearable device use

Theme	Description	Excerpts from written responses
Knowing how devices work (n = 112)	How devices work; what devices are measuring; what devices do; how devices help or the theory behind them	*"More detail about how the devices might assist"* (#38) *"What data the device collects, how it would help me in managing my mental health"* (#446)
Evidence and efficacy (n = 100)	Whether devices were efficacious; what evidence or research there was for devices; success rates; reliability	*"Whether it is effective, helpful or a time waster"* (#33) *"A lot of background research and/or reasons for believing they might help."* (#81)
Privacy (n = 45)	Access to data; storage of data; use of data by others (e.g. for monitoring, treatment enforcement, withholding benefits or insurance claims)	*"How the data associated with my use of the wearable device would be gathered, stored and shared; and the particulars of exactly what data would be gathered."* (#127) *"What data was being tracked, if that information was secure, and I'd need to be 100% certain the data could NOT be shared without my consent - and specifically never to insurance or other financial services companies"* (#509)
Discretion (n = 36)	Discreetness, visibility, or obtrusiveness of devices; stigma	*"Having it visible to others would cause me much more anxiety."* (#63) *"…whether I can have it disguised as something else to not single me out as struggling, say a watch or Fitbit for example."* (#493)
Positive outcomes (n = 36)	Potential benefits and advantages; expected effects; helpfulness; positive impact	*"The outcomes that may be expected from the devices."* (#69) *"…how it would benefit in during anxiety and or depressive episodes."* (#357)
Risks and negative outcomes (n = 36)	Side-effects, unexpected effects or potential harm; safety; disadvantages; working counter to therapeutic aims; risks of use without professional support	*"Does it harm the body, any side effects."* (#361) *"I would need reliable evidence regarding the possibility of negative outcomes."* (#342)

Theme	Description	Excerpts from written responses
Cost (n = 31)	Financial cost of purchase and use	*"Is it affordable?"* (#526)
Time and effort needed (n = 29)	Length of treatment; time consumed/required frequency of using; effort involved; ease of use; convenience; time cost vs benefit	*"How long per day and overall duration"* (#50) *"…whether the effort of collecting the data would be worth it."* (#519)
Physical form (n = 25)	Size; type of device/what it is; appearance; design/materials	*"Size/inconvenience."* (#515) *"If it were a watch or similar, I'd wear it. I'd probably not wear a head band or ear clips"* (#356)
Matching devices to problem or situation (n = 21)	Match to problem/situation; whether it is customized for the individual or generic; contraindications	*"I'd want to know if the person or computer knew what my condition was and not just put me in a basket with all other patients."* (#370) *"Would it be specifically tuned for me or offer a generic instruction like go for a walk or have a nap"* (#442)
Practicality (n = 20)	Comfort; durability; intrusiveness/obstructiveness	*"How limiting to normal function it may be."* (#484) *"…practicality when wearing the device, maintenance…"* (#483)
Knowing how devices are used (n = 18)	How to use the devices; how feedback is received, or how to interpret/respond to feedback	*"How to interpret the symptoms that the device is monitoring"* (#230) *"Details of how the sessions proceed"* (#282)
Availability of professional support (n = 15)	Whether support is available; whether devices are recommended by a professional; whether professionals are aware of devices	*"Detailed professional advice from consulting psychologist or psychiatrist well acquainted with my condition to date"* (#113) *"I'd also want to talk to my doctor/psych to gauge how effective they think they are, whether their other patients liked it/had success, that kind of thing."* (#229)

Note: Data based on a subsample of n = 244 responses where respondents indicated they required more information in decision-making about wearable device use.

Supplementary Material

Description of wearable devices shown to participants

Wearable devices for mental health:

- are small devices like headbands, clips which attach to the ear or finger, or wristbands/watches
- might be used to improve general wellbeing or to treat mental health problems
- detect body signals like breathing, heart rate, skin dryness or level of brain activity
- generally work through relaxation training and give the user feedback about signals of relaxation or stress in the body
- may be worn either all day or for brief periods of time
- are low cost - around the same as one session with a psychologist, or less

Table S1

Spearman correlations between all study variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Age	—	-.11[c]	-.13[c]	-.04	.10	-.20[a]	-.26[a]	-.24[a]	-.27[a]	-.19[a]	.10[d]	.07	-.14[b]	-.10[d]	-.01	-.08	.18[a]
2. Socioeconomic disadvantage	-.11[c]	—	.03	-.03	.09	-.10[d]	-.05	-.04	-.01	.02	-.03	-.08	-.01	-.03	-.03	.02	-.04
3. Previous knowledge	-.13[b]	.03	—	.16[b]	.00	-.02	.04	.00	.00	.19[a]	.05	.05	.12[c]	.07	.00	.04	-.08
4. Perceived effectiveness	-.04	-.03	.16[a]	—	.15[c]	.02	.13[c]	.13[c]	-.01	.17[b]	.23[a]	.51[a]	.46[a]	.20[a]	.24[a]	.26[a]	-.04
5. Satisfaction with prior treatment[e]	.10[d]	.09[d]	.00	.15[b]	—	-.20[a]	-.12[d]	-.11[d]	-.35[a]	.12[d]	.30[a]	.09	-.06	.01	-.19[a]	-.08	.15[c]
6. Depression	-.20[a]	-.10[c]	-.02	.02	-.20[a]	—	.60[a]	.61[a]	.39[a]	-.01	.06	.02	.02	.12[c]	-.04	-.05	-.02
7. Anxiety	-.26[a]	-.05	.04	.13[b]	-.12[c]	.60[a]	—	.71[a]	.39[a]	-.04	.13[c]	.10[d]	.10[d]	.15[b]	-.04	.00	-.04
8. Stress	-.24[a]	-.04	.00	.13[b]	-.11[c]	.61[a]	.71[a]	—	.38[a]	-.02	.14[c]	.14[b]	.12[c]	.16[b]	-.01	-.01	-.04
9. Barriers to treatment (total)	-.27[a]	-.01	.00	-.01	-.35[a]	.39[a]	.39[a]	.38[a]	—	-.13[c]	-.21[a]	-.08	.10[d]	.17[b]	.10[d]	-.01	-.18[a]
10. Technological readiness	-.19[a]	.02	.19[a]	.17[a]	.12[c]	-.01	-.04	-.02	-.13[b]	—	.06	.10[d]	.11[d]	-.07	.04	.15[b]	.01
11. TT	.10[c]	-.03	.05	.23[a]	.30[a]	.06	.13[b]	.14[b]	-.21[a]	.06	—	.44[a]	.01	.04	-.54[a]	-.06	.34[a]
12. WB	.07	-.08[d]	.05	.51[a]	.09[d]	.02	.10[c]	.14[b]	-.08[d]	.10[c]	.44[a]	—	.47[a]	.19[a]	.45[a]	.29[a]	.29[a]
13. WS	-.14[b]	-.01	.12[c]	.46[a]	-.06	.02	.10[c]	.12[c]	.10[c]	.11[c]	.01	.47[a]	—	.46[a]	.43[a]	.59[a]	-.65[a]
14. OS	-.10[c]	-.03	.07	.20[a]	.01	.12[c]	.15[b]	.16[b]	.17[a]	-.07	.04	.19[a]	.46[a]	—	.12[c]	-.39[a]	-.36[a]
15. WB v TT	-.01	-.03	.00	.24[a]	-.19[a]	-.04	-.04	-.01	.10[c]	.04	-.54[a]	.45[a]	.43[a]	.12[c]	—	.34[a]	-.09
16. WS v OS	-.08	.02	.04	.26[a]	-.08	-.05	.00	-.01	-.01	.15[b]	-.06	.29[a]	.59[a]	-.39[a]	.34[a]	—	-.35[a]
17. WB v WS	.18[a]	-.04	-.08[d]	-.04	.15[b]	-.02	-.04	-.04	-.18[a]	.01	.34[a]	.29[a]	-.65[a]	-.36[a]	-.09[d]	-.35[a]	—

Note: N = 427. Significance values shown in the upper right triangle are adjusted using the false discovery rate method. TT = talk therapies, WB = wearables (blended), WS = wearables (self-help), OS = other self-help. Treatment comparison variables (15-17) are the standardised differences between one treatment and another; positive estimates predict a higher preference for the first treatment described, and vice versa.

[a]$p < .001$, [b]$p < .01$, [c]$p < .05$, [d]$p < .10$

[e]For respondents who had previously consulted a mental health professional (n = 359).

Table S2

Spearman correlations of continuous predictors with hypothetical acceptability of four mental health treatments

	TT	WB	WS	OS
Age	.10^	.07	-.14**	-.10^
Socioeconomic disadvantage	-.03	-.08	-.01	-.03
Previous knowledge	.05	.05	.12*	.07
Perceived effectiveness	.23***	.51***	.46***	.20***
Satisfaction with prior treatment[a]	.30***	.09	-.06	.01
Years affected by condition[b]	-.03	.01	-.12	-.14^
DASS				
Depression	.06	.02	.02	.12*
Anxiety	.13*	.10^	.10^	.15**
Stress	.14*	.14**	.12*	.16**
Barriers to treatment (total score)	-.21***	-.08	.10^	.17**
Stigma	-.24***	-.12*	.11^	.22***
Lack of motivation	.00	.07	.09	.13*
Emotional concerns	-.18***	-.06	.11*	.18***
Neg. evaluation of therapy	-.29***	-.18***	.05	.05
Misfit of therapy to needs	-.33***	-.17**	.08	.13*
Time constraints	-.11*	.02	.19***	.11*
Participation restriction	.06	.00	.01	.04
Availability of services	-.04	.04	.08	.09
Cost	.05	.02	-.02	.08
Technology readiness (total score)	.06	.10^	.11^	-.07
Optimism	.13*	.20***	.13*	-.01
Innovativeness	.02	.04	.10^	.00
Discomfort	-.03	-.02	-.04	.13*
Insecurity	-.01	-.04	-.02	.12*

Note: TT = talk therapies, WB = wearables (blended), WS = wearables (self-help), OS = other self-help.

[a]For respondents who had previously consulted a mental health professional (n = 359).

[b]For those who reported a diagnosed condition and reported duration (n = 234).

^ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$ (adjusted using the false discovery rate method).

Table S3

Categorical predictors of hypothetical acceptability of four mental health treatments (M ± SD)

	TT	WB	WS	OS
Gender				
Female	5.71 ± 1.61	5.37 ± 1.53	4.00 ± 2.01	4.56 ± 1.72
Male	5.47 ± 1.71	5.17 ± 1.74	4.01 ± 1.88	4.41 ± 1.77
d	.14	.12	.00	.08
p_{FDR}	.322	.483	.971	.632
Relationship status				
Single/divorced/separated	5.65 ± 1.61	5.14 ± 1.75	3.90 ± 1.97	4.40 ± 1.85
Married/committed relationship	5.58 ± 1.68	5.37 ± 1.54	4.07 ± 1.94	4.55 ± 1.67
d	.04	-.13	-.08	-.08
p_{FDR}	.829	.392	.632	.632
Remoteness				
Major cities	5.64 ± 1.61	5.28 ± 1.57	4.19 ± 1.97	4.58 ± 1.75
Rural/remote	5.53 ± 1.76	5.30 ± 1.76	3.56 ± 1.82	4.29 ± 1.72
d	.06	-.01	.34	.17
p_{FDR}	.742	.947	.011	.278
Current wearable usage				
No	5.58 ± 1.69	5.14 ± 1.70	3.84 ± 1.91	4.46 ± 1.75
Yes	5.71 ± 1.53	5.78 ± 1.20	4.58 ± 1.98	4.62 ± 1.70
d	-.07	-.49	-.41	-.13
p_{FDR}	.742	<.001	.005	.519
Education				
Diploma or below	5.44 ± 1.76	5.22 ± 1.71	3.91 ± 2.01	4.47 ± 1.86
Bachelor degree	5.66 ± 1.66	5.25 ± 1.61	4.07 ± 1.95	4.48 ± 1.72
Postgraduate degree	5.92 ± 1.32	5.51 ± 1.43	4.08 ± 1.81	4.60 ± 1.48
η^2	.01	.00	.00	.00
p_{FDR}	.252[a]	.632	.823	.941
Household income				
< $35,000	5.56 ± 1.70	5.25 ± 1.75	4.00 ± 2.02	4.56 ± 1.88
$35,000-$65,000	5.64 ± 1.63	5.22 ± 1.73	3.43 ± 1.93	4.04 ± 1.83
$65,000-$105,000	5.54 ± 1.66	5.15 ± 1.56	4.10 ± 1.88	4.51 ± 1.57
> $105,000	5.68 ± 1.66	5.48 ± 1.47	4.38 ± 1.87	4.77 ± 1.62
η^2	.00	.01	.03	.02
p_{FDR}	.950	.632	.026	.079
Consulted a professional				
No	4.79 ± 1.75	5.26 ± 1.62	4.65 ± 1.76	4.50 ± 1.82
Yes (no longer seeing)	5.42 ± 1.72	5.20 ± 1.68	3.96 ± 1.91	4.55 ± 1.63
Yes (still seeing)	6.37 ± 1.12	5.45 ± 1.52	3.75 ± 2.05	4.40 ± 1.90
η^2	.11	.00	.02	.00
p_{FDR}	<.001[a]	.632	.033	.871
Mental health diagnosis				
No	5.08 ± 1.70	5.18 ± 1.71	4.26 ± 1.86	4.58 ± 1.71
Yes (no longer impacting)	5.51 ± 1.89	5.16 ± 1.66	3.69 ± 1.86	4.14 ± 1.67

	TT	WB	WS	OS
Yes (still impacting)	5.90 ± 1.50	5.37 ± 1.57	3.97 ± 2.00	4.56 ± 1.77
η^2	.05	.00	.01	.01
p_{FDR}	<.001	.632	.312	.380

Note: TT = talk therapies, WB = wearables (blended), WS = wearables (self-help), OS = other self-help. *t*-tests used to infer significance of two-group variables and ANOVA for more than two groups. *p*-values adjusted using the false discovery rate method.

[a]Levene's test indicates non-homogenous variance; interpret *p*-values with caution..