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Abstract

Background: Digital technologies can substantially improve mental health care by facilitating measurement-based care through routine outcome monitoring. However, their effectiveness is constrained by the extent to which these technologies are used by services, clinicians, and clients.

Objective: This study aims to investigate engagement with the Innowell platform, a measurement-based digital mental health technology (DMHT), to gain insights into the individual and service-level factors influencing engagement.

Methods: Participants were 2,682 help-seeking clients from 12 Australian mental health services (11 headspace centers and one private practice, Mind Plasticity) wherein the Innowell platform was implemented. Although the initial implementation was standardized, services varied in their practical and continued use of the platform, as well as in the resources allocated to foster engagement. All participants completed an initial assessment during onboarding. Engagement here was defined as their ensuing completion of the summary questionnaire, designed for routine outcome monitoring. Participants were classified as 'Initial Assessment Only', 'Single Use' (one completion of the summary questionnaire), or '2+ Uses' (two or more completions). We analyzed engagement differences across services and associations between engagement and initial assessment scores.

Results: Of the sample, 75.4% completed the initial assessment only, 11.5% had one completion of the summary questionnaire, and 13.0% had two or more completions. The service center was the strongest predictor of engagement, with Mind Plasticity participants showing over eight times higher engagement than other centers. At the individual level, higher scores in depression ($P = .002$), mania-like experiences ($P = .047$), suicide ideation ($P = .004$), hospitalization history for mental illness ($P = .013$), and physical activity ($P < .001$) were associated with increased engagement. Conversely, higher levels of anxiety symptoms ($P = .011$), substance misuse ($P < .001$), self-reported mental illness severity ($P = .024$), and social support ($P = .047$) predicted lower engagement. Age and several other clinical variables were not significant predictors when controlling for service-level factors.

Conclusions: This study reveals that both individual and service-level factors significantly influence DMHT engagement, with the service center being the strongest predictor. This highlights the importance of service-level technology integration and support roles like Digital Navigators in fostering engagement. Significant variation in engagement among user groups indicates the need for a nuanced approach to measurement-based care. While mental illness generally did not impede engagement, self-perceived severity and anxiety symptoms were barriers. These findings underscore the critical importance of systemic factors and service-level integration strategies in driving DMHT engagement. User-centered designs remain important, but effective integration of DMHTs into existing mental health services is paramount for improving engagement across diverse user groups and clinical presentations. This multi-level approach – encompassing individual, service, and system-wide considerations – is

essential for realizing DMHTs' full potential in delivering effective measurement-based care.

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Keywords: Digital mental health technology, user engagement, measurement-based care, mental health services, implementation science

Introduction

Advancements in digital technologies have transformed the way mental health care can be delivered and accessed. Innovations such as mobile applications, telemedicine platforms, and online therapy have widened the availability of mental health resources and services [1], making support more convenient and readily available to individuals – particularly for those in remote regions or those reluctant to otherwise seek care [2]. Randomized controlled trials (RCTs) have demonstrated the efficacy of digital mental health technologies [1,3,4], yet their translation into real-world settings remains problematic [5,6]. While RCTs offer valuable insights into their effectiveness under standardized and prescriptive conditions, real-world implementation is complicated by factors not fully accounted for in such studies. One of these factors is user engagement, shown to be generally lower in real-world settings compared to those in controlled studies [7–11].

Engagement with digital mental health technologies is influenced by individual-related, technology-/intervention-related, and practical factors [12–14]. However, recent reviews have focused on technologies which are largely separate from face-to-face treatment, including smartphone apps [15] or websites offering mental-health resources, activities, or support [16]. The dynamics of engagement with digital technology when used to augment conventional mental health treatment (eg, in-person therapy sessions), remains less understood. In addition to individual factors, addressing this question requires two additional factors to be considered: the systemic influences of mental health services, and the clinician's role in integrating the technology into treatment.

The Innowell platform is a measurement-based digital mental health technology (DMHT) designed to support personalized and measurement-based care (MBC) in mental health settings [17]. MBC is a practice whereby clinical decisions are informed by client data collected throughout treatment [18]. This approach supports better-informed and highly personalized clinical decisions [19], with reviews showing that continued monitoring of progress through MBC can reduce deterioration, facilitate dynamic and responsive changes to treatment plans, and enhance treatment effects [20–24]. Yet, less than 20% of mental and behavioral health providers report using MBC in their practice [25], with uptake being hindered by barriers at the level of the client, the clinician, and the organization [26,27]. Continued engagement with measurement-based DMHTs is a necessary precondition for the emergence and effectiveness of MBC in treatment and health systems. This requires clinicians and services integrating the DMHT into their care routines, and clients regularly completing their assessments. While MBC has demonstrated positive outcomes in mental health treatment, its effectiveness is constrained by the extent to which both clients and clinicians engage with MBC platforms.

Across Australia, Innowell has been implemented in 12 primary mental health care centers; with the majority of these being *headspace* centers, the nation's established youth mental health initiative [28]. These centers focus on offering early intervention for mental health problems in young people aged 12 to 25 years [25]. The Innowell platform's multidimensional framework assesses five areas: social and occupational functioning; suicidal thoughts and behaviors (STBs); substance misuse; physical health; and illness type, stage, and trajectory. This framework of routine outcome measurements facilitates the capture of a comprehensive clinical picture; aiming to support the prevention, early intervention, treatment, and continuous monitoring of mental ill health and the maintenance of wellbeing [17,19].

This study aims to enhance understanding of the factors that contribute to user engagement with the Innowell platform, exploring both the systemic and individual factors that influence engagement. Since the technology is identical across the 16 services where it is used, this investigation will discern the differences in engagement between the services and attribute these differences to system- and individual-related factors. Given that the platform is designed to be used as an adjunct to face-to-face treatment, we posit that the implementation of the platform with the service, and its integration (by the clinician) into treatment, will greatly influence participant engagement with the platform and continued routine outcome monitoring. Additionally, we seek to build upon the existing engagement literature, by examining the clinical, demographic, and behavioral characteristics of participants at their time of their onboarding, aiming to identify how these factors may affect their subsequent engagement.

Methods

Ethics

This study was approved by Northern Sydney Local Health District Human Research Ethics Committees (HREC/17/HAWKE/480), and all participants provided online informed consent (via an opt out process) [29]. Parental written informed consent was required for those aged under 14-years in accordance with Australian laws [29], and participant consent was also obtained. All data for this study was collected through a quality assurance process facilitated by the University of Sydney research team. All data is non-identifiable to protect the privacy of participants.

Participants

Participants presented for the first time to one of 12 mental health services. 11 of the 12 services were *headspace* centers, from urban and regional areas of Australia (see Table 1). The second largest participant sample from a single center was from Mind Plasticity, a private, specialist practice in Sydney, which offers multidisciplinary care to individuals of all ages who require mental health support including psychology, psychiatry, occupational therapy, neuropsychology, among other health services.

The Innowell Platform Measures

The Innowell platform is a measurement-based digital mental health technology (DMHT) that aims to assist the assessment, management, and monitoring of mental ill-health and promote the maintenance of well-being. It was part of standard clinical care for individuals presenting to these centers to be directed to the Innowell platform. After being sent an invitation to join the platform, participants completed the initial assessment prior to their face-to-face appointment with a clinician.

The initial clinical questionnaire assesses a range of mental health concerns, as well as comorbid and associated risk factors also captures demographic information, participants' history of physical and mental health problems, and their previous treatment-seeking behaviors. These questions are from evidence-based screening and assessment tools. Further details about the included assessments can be found in previous publications [17,19,29,30]. After the initial questionnaire is completed, participants can complete a short summary questionnaire, or complete measures relevant to specific health domains. Completion of any of these measures can either be recommended by their clinician or be completed voluntarily. The summary questionnaire is a shorter assessment designed to be used repeatedly as an ongoing part of treatment and assessment plans to track key outcomes related to STBs, social and occupational functioning, mental illness severity, social support, and overall health during the treatment period.

There are also options to complete assessments relevant to specific health or mental health domains, known as health cards. These domains include substance misuse, anxiety, depressed mood, eating behaviors and body image, mania-like experiences, physical health, post-traumatic stress, psychological distress, psychosis-like experiences, overall health, self-harm, sleep-wake cycle, social and occupational function, social connectedness, and STBs. The summary and health assessments contain a mix of standardized and validated measures, or adapted versions of these measures.

Implementation of Innowell Across Centers

The implementation and use of the Innowell platform varied significantly across the different centers. This was highlighted in Mckenna et al. (2023), which investigated the implementation and use of the Innowell platform at two centers, Mind Plasticity and *headspace* Camperdown. Although a standardized phased approach to implementation was followed – comprising 1) scoping and feasibility, 2) co-design and pre-implementation, 3) implementation, and 4) sustainability and scalability [31] – the integration of the platform into standard care after initial implementation was left to the discretion of each service [32]. For instance, *headspace* Camperdown mainly utilized the platform for its initial questionnaire, using it to onboard new patients prior to their first face-to-face appointment with a clinician. In contrast, Mind Plasticity offered Innowell's initial and summary questionnaires to their existing clients of the practice, primarily for the purpose of routine outcome monitoring. Additionally, Mind Plasticity also employed a Digital Navigator as part of the EMPOWERED clinical trial [33]. The Digital Navigator was a person with lived experience who assisted the service in establishing the system processes and best practices around using Innowell, and provided ongoing support to clients, clinicians and services to enhance engagement with Innowell and improve overall service integration [34]. One major goal of the Digital Navigator was to provide support to clinical teams and clients, helping to remove barriers to engagement and support the integration of the technology into treatment by clinicians and services.

Statistical Analysis

All statistical analyses were performed using R Studio (Version 2023.6.1.524). Participants were classified into three groups based on their engagement with the summary questionnaire: (i) 'Initial Assessment Only' (those who onboarded onto Innowell but did not engage with the summary questionnaire); (ii) 'Single Use' (those who completed the summary questionnaire once); and (iii) '2+ Uses' (those who completed the summary questionnaire 2 or more times). For non-binary data, we used the Kruskal-Wallis test to compare scores on measures in the initial assessment between the groups. For binary data, chi-square tests were used for between-group comparisons. Post-hoc pairwise comparisons on significant differences between the different engagement groups were conducted using Dunn's tests and pairwise chi-square tests for binary data. The Bonferroni correction method was used to adjust for the family-wise error rate across the three comparisons conducted for each variable, setting the significance threshold at P<.017.

A multiple regression analysis was employed to control for varying demographics and center-specific effects. This analysis assessed the influence of demographic and individual factors on the number of times they completed the summary questionnaire. Due to the high proportion of zero counts in the data and potential overdispersion in regular Poisson models, a zero-inflated Poisson regression model was selected. This model accommodates the excess zeros and dispersion by combining a Poisson count model with a log link for non-zero counts and a binomial model with a logit link to model excess zeroes [35], providing a more accurate representation of the data distribution.

Results

Sample Description

The final sample included 2,682 participants who were onboarded onto the Innowell platform when they presented to one of the 12 primary mental health care centers. The mean age was 21.70 years (SD = 7.30) and 1758 (65.6%) of the sample was female. The summary questionnaire was completed on average 1.08 times by each participant (SD = 3.86), with the number of completions ranging from 0 – 53.

Across the 12 centers, *headspace* Camperdown had the greatest number of participants (n =1036), followed by Mind Plasticity (n=500). Since specific implementation efforts were made at *headspace* Camperdown [10], this center was separated from the other *headspace* centers. Differences in engagement with the summary questionnaire across the different centers are shown in Table 1. Significant differences in participant engagement were identified across Mind Plasticity, *headspace* Camperdown, and the 10 other centers using the Kruskal Wallis test, $H(2) = 385.51$, $P<.001$. Pairwise comparisons using Dunn's test indicated that Mind Plasticity had significantly higher engagement than *headspace* Camperdown (z = 15.24, $P<.001$) and the combined 10 other *headspace* centers (z = 18.24, $P<.001$). Additionally, *headspace* Camperdown showed significantly higher engagement than the combined 10 other headspace centers (z = 3.46, $P<.001$).

Table 1. Descriptive statistics for user engagement with the summary questionnaire across various services; detailing the number of completions of the summary questionnaire by users presenting to certain services.

Centre Name	Mean	Median	SD	Min	Max	Total Completions	Unique Users
Mind Plasticity	4.19	1	7.74	0	53	2,093	500
headspace Camperdown	0.48	0	1.58	0	22	493	1,036
10 other *headspace* centers	0.26	0	1.14	0	31	302	1,146

Comparisons Between Engagement Groups

The three groups classified by their engagement with the summary questionnaire (Initial Assessment Only, Single Use, and 2+ Uses) were analyzed based on their initial self-assessment. Kruskal Wallis tests and chi-square tests (for binary data) showed significant differences between these three engagement groups across several domains: age, $H(2) = 70.29$, $P<.001$; help-seeking behaviors, $\chi^2(2) = 31.12$, $P<.001$; current-treatment status, $\chi^2(2) = 135.27$, $P<.001$; diagnosed physical health history, $\chi^2(2) = 6.30$, $P=.04$; diagnosed mental illness history, $\chi^2(2) = 22.50$, $P<.001$; hospitalization history for mental health, $\chi^2(2) = 59.104$, $P<.001$; mania-like symptoms, $H(2) = 16.88$, p <.001; psychological distress, $H(2) = 19.54$, $P<.001$; psychosis-like symptoms, $H(2) = 15.52$, $P<.001$; alcohol use, $H(2) = 44.60$, $P<.001$; tobacco use, $H(2) = 10.69$, $P=.005$; cannabis use, $H(2) = 11.04$, $P=.004$; disordered eating, $H(2) = 7.46$, $P=.02$; self-harm history, $\chi^2(2) = 11.99$, $P=.002$; and daily physical activity, $H(2) = 27.80$, $P<.001$. Engagement groups did not significantly differ in their initial assessment of mental health severity, suicidal ideation, suicide intention, overall health rating, not in employment, education, or training (NEET) status, anxiety symptoms, depressive symptoms, or experience of a traumatic event.

Pairwise Comparisons

Following significant tests, pairwise comparisons between the three engagement groups (see Table 2) were conducted using either Dunn's test or chi-square tests (for binary data). A critical *P* value of .017 was obtained using the Bonferroni method. Dunn's tests revealed that the 'Initial Assessment Only' group was significantly younger than both the 'Single Use' (Z = 3.75, $P<.001$) and the '2 + Use' group (Z = 7.94, $P<.001$).

Comparing clinical characteristics at their initial assessment, the 'Initial Assessment Only' group reported higher mania-like experiences than both the 'Single Use' (Z = 3.35, $P=.001$) and '2+ Uses' groups (Z = 2.83, $P=.007$), and higher in psychosis-like experience compared to the 'Single Use' group (Z =3.52, $P<.001$). Compared to the 'Initial Assessment Only' group, the '2+ Uses' group had higher rates of self-harm history (χ^2 = 24.43, $P<.001$), but reported lower psychological distress (Z = 3.78, $P<.001$).

Across the alcohol and substance misuse domain, the '2+ Uses' group reported lower alcohol use (Z = 5.00, $P<.001$), tobacco use (Z = 3.27, $P=.002$), and cannabis use (Z = 3.24, $P=.002$) than the 'Initial Assessment Only' group. Further, the 'Single Use' group also reported less alcohol use than the 'Initial Assessment Only' group (Z = 5.08, $P<.001$).

The 'Single Use' group reported lower activity levels (daily metabolic equivalent of task [MET] minutes) than both the 'Initial Assessment Only' (Z = 5.26, $P<.001$) and the '2+ Uses' (Z = 3.84, $P<.001$) groups.

There were significant differences across the health history domain. Those in the '2+ Use ' had higher rates of previously seeking mental health treatment than the 'Initial Assessment Only' (χ^2 = 347.07, $P<.001$) and 'Single Use' (χ^2 = 47.44, $P<.001$) groups, more likely to be currently receiving mental health treatment than the 'Initial Assessment Only' (χ^2 = 290.68, $P<.001$) and the 'Single Use' groups (χ^2 = 15.79, $P<.001$), had higher rates of previous mental illness diagnosis than the 'Initial Assessment Only' (χ^2 =319.1, $P<.001$) and the 'Single Use' groups (χ^2 = 56.25, $P<.001$), had higher rates of hospitalization history for a mental illness than the 'Initial Assessment Only' (χ^2 = 901.67, P<.001) and the 'Single Use' groups (χ^2 = 111.37, P<.001), and had higher rates of previous physical illness diagnosis than the 'Initial Assessment Only' (χ^2 =191.01, P<.001) and the 'Single Use' groups (χ^2 = 16.86, P<.001).

Table 2. Initial assessment scores, group comparisons, and pairwise comparisons between engagement groups.[1]

Measure	Initial Assessment Only	Single Use	2 + Uses	Between-group comparison	No vs Single Use	Single vs 2+ Uses	No vs 2+ Uses
Participants, n (% of total sample)	2023 (75.4%)	310 (11.5%)	349 (13.0%)				
Female, n (% of group)	1326 (65.6%)	196 (63.2%)	236 (67.6%)				
Age (years), mean (SD)	20.88 (6.17)	22.72 (7.76)	25.59 (10.80)	*H*(2)=70.29 (*P*<.001)	Z=8.03 (*P*<.001)	Z=-3.50 (*P*<.001)	Z=3.02 (*P*=0.001)
Clinical Characteristics							
Mania-like-experiences (ASRM-5), mean (SD)	2.99 (2.94)	2.47 (2.89)	2.63 (2.97)	*H*(2)=16.88 (*P*<.001)	Z=-2.72 (*P*=0.003)	Z=3.37 (*P*<.001)	Z=0.76 (*P*=0.22)
Anxiety (OASIS), mean (SD)	9.24 (4.25)	8.60 (5.15)	8.63 (4.80)	*H*(2)=4.43 (*P*=.11)			
Depressive symptoms (QIDS), mean (SD)	13.67 (4.96)	12.47 (6.47)	12.74 (6.10)	*H*(2)=1.37 (*P*=.50)			
Disordered eating (EDE), mean (SD)	4.73 (2.93)	4.23 (3.25)	4.47 (3.22)	*H*(2)=7.46 (*P*=.023)	Z=-1.51 (*P*=0.07)	Z=2.22 (*P*=0.01)	Z=0.70 (*P*=0.24)
Self-harm history (B-NSSI-AT)†, n (% of group)	936 (56.0%)	106 (52.5%)	186 (66.2%)	χ^2(2)=11.99 (*P*=.002)	χ^2=.79 (*P*=.37)	χ^2=.50 (*P*=.48)	χ^2=.24.43 (*P*<.001)
Psychological distress (K10), mean (SD)	31.35 (8.00)	27.88 (12.34)	28.44 (10.68)	*H*(2)=19.54 (*P*<.001)	Z=-3.90 (*P*<.001)	Z=2.89 (*P*=0.002)	Z=-0.51 (*P*=0.30)
Psychosis-like experiences, mean (SD)	5.09 (3.84)	4.31 (4.01)	4.66 (3.98)	*H*(2)=5.78 (*P*=.056)	Z=8.03 (*P*<.001)	Z=-3.50 (*P*<.001)	Z=3.02 (*P*=0.001)
Experienced traumatic event (PC-PTSD), n (% of group)	447 (57.6%)	54 (51.4%)	79 (57.2%)	χ^2(2)=1.82 (*P*=.40)			
Suicide ideation (SIDAS), mean (SD)	8.95 (11.31)	8.21 (10.50)	9.37 (12.13)	*H*(2)=.403 (*P*=.818)			
Suicide intention (CSSRS)†, n (% of group)	204 (18.8%)	27 (17.3%)	34 (18.0%)	χ^2(2)=.23 (*P*=.89)			
Severity of mental illness (CGI), mean (SD)	3.52 (1.42)	3.46 (1.44)	3.48 (1.41)	*H*(2)=.787 (*P*=.675)			
Overall health rating (EQ-5DY), mean (SD)	60.14 (24.13)	59.74 (22.93)	57.95 (25.23)	*H*(2)=1.35 (*P*=.510)			
Functioning							
Work and social functioning, mean (SD)	18.09 (8.57)	17.24 (9.93)	17.37 (9.67)	*H*(2)=.951 (*P*=.62)			
NEET Status, n (% of group NEET)	216 (11.1%)	25 (9.8%)	24 (8.0%)	χ^2(2)=2.83 (*P*=.24)			
Social support (SSSS), mean (SD)	7.14 (3.47)	7.34 (3.56)	7.28 (3.23)	*H*(2)=1.75 (*P*=.416)			
Social and occupational functioning (SOFAS), mean (SD)	3.39 (1.43)	3.49 (1.48)	3.40 (1.43)	*H*(2)=1.97 (*P*=.37)			
Activity level (MET-minutes), mean (SD)	166.47 (174.83)	120.53 (159.14)	164.58 (177.69)	*H*(2)=27.80 (*P*<.001)	Z=-0.49 (*P*=0.31)	Z=5.33 (*P*<.001)	Z=3.81 (*P*<.001)
Health History							
Previously sought mental health treatment, n (% of	1261 (72.3%)	166 (72.8%)	247 (87.9%)	χ^2(2)=31.12 (*P*<.001)	χ^2=.01 (*P*=.94)	χ^2=47.44 (*P*<.001)	χ^2=347.07 (*P*<.001)

group)							
Currently receiving mental health treatment[†], n (% of group)	516 (29.6%)	84 (36.8%)	183 (65.1%)	$\chi^2(2)=135.27$ (*P*<.001)	$\chi^2=4.68$ (*P*=.03)	$\chi^2=15.79$ (*P*<.001)	290.68 (*P*<.001)
Diagnosed mental illness history, n (% of group)	1245 (71.4%)	74.9%	85%	$\chi^2(2)=22.50$ (*P*<.001)	$\chi^2=1.05$ (*P*=.31)	$\chi^2=56.25$ (*P*<.001)	$\chi^2=319.10$ (*P*<.001)
Diagnosed physical illness history, n (% of group)	33.3%	36.4%	40.9%	$\chi^2(2)=6.30$ (*P*=.04)	$\chi^2=.66$ (*P*=.42)	$\chi^2=16.86$ (*P*<.001)	$\chi^2=191.91$ (*P*<.001)
Hospitalization history, n (% of group)	14.0%%	15.0%	32.2%%	$\chi^2(2)=59.10$ (*P*<.001)	$\chi^2=.08$ (*P*=.78)	$\chi^2=113.37$ (*P*<.001)	$\chi^2=901.67$ (*P*<.001)
Alcohol and Substance Misuse							
Alcohol use (AUDIT-C), mean (SD)	4.48 (4.03)	3.31 (3.87)	3.27 (3.52)	*H*(2)=44.60 (*P*<.001)	Z=-4.96 (*P*<.001)	Z=5.08 (*P*<.001)	Z=0.52 (*P*=0.30)
Cannabis use (ASSIST), mean (SD)	1.69 (2.99)	1.47 (2.76)	1.13 (2.42)	*H*(2)=11.04 (*P*=.004)	Z=-3.41 (*P*<.001)	Z=1.27 (*P*=0.10)	Z=-1.42 (*P*=0.08)
Tobacco use (ASSIST), mean (SD)	1.54 (2.24)	1.51 (2.26)	1.05 (1.93)	*H*(2)=10.68 (*P*=.005)	Z=-3.38 (*P*<.001)	Z=0.46 (*P*=0.32)	Z=-2.04 (*P*=0.02)

* p < 0.017, ** < .001. Abbreviations: cm, centimeters; kg, kilograms; ASRM, Altman self-rating mania scale; ASSIST, Alcohol smoking, and substance involvement screening; AUDIT-C, alcohol use disorders identification test; B-NSSI-AT, brief non-suicidal self-injury assessment tool; CGI, Clinical Global Impressions (self-report); SIDAS, Suicidal Ideation Attributes Scale; C-SSRS, Columbia-Suicide Severity Rating Scale; EDE, Eating Disorder Examination (modified), EQ-5D-Y, EuroQol 5-Dimension Youth; IPAQ, International Physical Activity Questionnaire; SSSS, Schuster's Social Support Scale (higher scores indicate lower social support); SOFAS, Social and Occupational Functioning Assessment (higher scores indicate higher impairment); MET, Metabolic Equivalent of Task; WSAS, Work and Social Functioning (higher scores indicate higher impairment; OASIS, Overall Anxiety Severity and Impairment Scale; PC-PTSD-5, The Primary Care Posttraumatic Stress Disorder Screen for DSM-5; QIDS, Quick Inventory of Depressive Symptomology; NEET, not in employment, education, or training.

[†] Indicates that the assessment is a binary single-item measure, where 1 = yes, and 0 = no, so scores represent the proportion of the group that responded 'yes'. For these binary measures, chi-square tests were used to conduct group and pairwise comparisons.

[1] Unless otherwise stated, higher scores indicate higher levels of the measured construct.

Multiple Regression

While using the engagement groups to analyze the differences in scores at the time of initial assessment revealed some trends, these differences could be influenced by varying demographics across the 12 centers. To control for this potential confound, a multiple regression analysis was performed, including Mind Plasticity, *headspace* Camperdown, and the combined group of the other *headspace* centers into the model. The dependent variable was the number of times the summary questionnaire was completed. A zero-inflated model was chosen due to the substantial proportion of zero counts observed in the dataset, with 75.4% of the sample reporting no completions of the summary questionnaire [35]. This model comprises two components: a count model (see Table 3) predicting the count for non-zero observations using a Poisson distribution with log link, and a zero-inflation model predicting excess zeros using a binomial distribution with logit link (see

Table 4). The model's appropriateness was supported by multiple fit indices. The zero-inflated Poisson model demonstrated a significantly lower Akaike Information Criterion value (2935.80) compared to the regular Poisson model (4228), indicating a better fit to the data. To address potential multicollinearity and maintain model parsimony, the initial set of assessment variables was reduced to 14 based on conceptual overlap and correlation analysis. The highest correlation among the retained variables was r = 0.66.

In the count model (see Table 3), several variables were significant predictors of engagement with the summary questionnaire. Participants presenting to Mind Plasticity showed the strongest positive association (β = 1.19, *P*<.001), followed by *headspace* Camperdown (β = 1.12, *P*<.001, while 'Other *headspace* centers' was negatively associated (β = -0.56, *P*<.001). Other significant positive predictors included suicide ideation (β = 0.01, *P*=.004), depressive symptoms (β = 0.03, *P*=.002), mania-like experiences (β = 0.02, *P*=.047), hospitalization history (β = 0.17, *P*=.013) and physical activity (β = 0.0007, *P*<.001). Significant negative predictors included alcohol use (β = -0.05, *P*<.001), mental illness severity (β = -0.06, *P*=.024), social and occupational functioning (β = -0.06, *P*=.012), and anxiety symptoms (β = -0.02, *P*=.011). Notably, because the social support measure is reverse-scored–with higher scores indicating poorer social support–the positive association (β = 0.02, *P*=.047) indicates that participants with lower level of social support showed increased engagement.

Table 3: Zero-Inflated Poisson Regression Results: Count Model

	Estimate	Standard Error	z Value	*P*
(Intercept) (*headspace* Camperdown)	1.12	0.20	5.59	< .001
Mind Plasticity	1.19	0.10	11.77	< .001
Other *headspace* centers	-0.56	0.15	-3.86	< .001
age	-.01	0.00	-1.54	.17
Depressive symptoms	0.03	0.01	2.91	.002
Anxiety symptoms	-0.02	0.01	-2.82	.011
Mania-like experiences	0.02	0.01	1.98	.047
Psychosis-like experiences	-0.02	0.01	-1.78	.172
Disordered eating	-0.01	0.01	-1.32	.216
Suicidal ideation	0.01	0.00	2.97	.004
Suicide intention	0.18	0.10	1.91	.057
Mental illness severity	-0.06	0.03	-2.25	.024
Receiving current treatment	0.16	.099	1.68	.106
Hospitalization history	0.17	.067	2.49	.013

Social and occupational functioning	-0.06	0.03	-2.52	.012
Daily physical activity	.0007	0.00	4.68	< .001
Overall health rating	0.00	0.00	-0.52	.602
Alcohol Use	-0.05	0.01	-6.00	< .001
Social support	0.02	0.01	1.99	.047

Note. N=2682.

In the zero-inflated Poisson model (see Table 4), fewer variables were significant. Mind Plasticity was strongly negatively associated with excess zeros (β = -1.29, *P*<.001), while 'Other *headspace'* was positively associated (β = 0.57, *P*=.008). Better social support was also associated with excess zeros (β = -0.06, *P*=.034), again reflecting the inverse scoring of this measure. Several variables, including age, suicide intention, psychosis-like experiences, disordered eating, and overall health, were neither significant predictors in the count nor zero-inflation models.

Table 4: Zero-Inflated Poisson Regression Results: Zero-Inflation Model

	Estimate	Standard Error	z value	*P*
(Intercept) (*headspace* Camperdown)	1.15	0.62	1.84	.066
Mind Plasticity	-1.29	0.27	-4.77	<. 001***
Other *headspace* centers	0.57	0.21	2.67	.008
age	0.00	0.01	0.22	.823
Depressive symptoms	0.02	0.03	0.54	.590
Anxiety symptoms	-0.03	0.03	-1.22	.224
Mania-like experiences	0.05	0.03	1.45	.146
Psychosis-like experiences	-0.05	0.03	-0.18	.861
Disordered eating	-0.03	0.03	-1.02	.305
Suicide intention	-0.12	0.26	-0.44	.658
Suicidal ideation	0.08	0.01	0.73	.464
Mental illness severity	0.04	0.08	0.48	.630
Receiving current treatment	-0.09	0.02	-0.44	.661
Hospitalization history	-0.16	0.215	-0.75	.455
Social and occupational functioning	0.01	0.07	0.15	.880
Daily physical activity	0.001	0.00	0.30	.766
Overall health rating	0.00	0.00	0.02	.989
Alcohol Use	0.04	0.03	1.73	.084
Social support	-0.06	0.03	-2.13	.034*

Note. N=2682.
**P*<.05. ***P*<.01. ****P*<.001.

Discussion

This study provides valuable insights into key characteristics of users who engage with a digital technology in mental health services. Specifically, this work shows that there are clear individual differences that separate those who are using the Innowell platform most and least regularly. Importantly, this work underscores the substantial influence of broader structural or systematic factors on the utilization of digital mental health technologies (DMHTs), with the participants' treatment center emerging as the strongest predictor of engagement. By providing a detailed and nuanced understanding of DMHT technology engagement in mental health services, this work has important implications for guiding clinical practice and informing policy decisions aimed at enhancing user engagement.

The Innowell platform is designed to guide and support treatment by a clinician or a service provider; and is not intended to be used as a stand-alone tool for medical or health advice, diagnosis, or treatment. As such, the utility of the platform for the client is largely dependent on its active integration into treatment by the clinician [34,36]. Like the systematic barriers to MBC uptake that Van Sonsbeek and colleagues [26] describe, this suggests that there exist some obvious service-level factors that influence individual engagement with measurement-based DMHTs. So, independent of the technology itself, the extent to which the platform is integrated into the service and treatment will affect individual engagement in routine outcome monitoring behaviors.

We found that the largest influence of engagement was the service from which participants received treatment. Participants from Mind Plasticity had, on average, over eight times the engagement with the summary questionnaire (M = 4.19) compared to the next highest-engaging center (M = 0.48). While the implementation of the Innowell platform across all centers was guided by a strategy for implementation science [31], there were some substantive differences in how different centers embedded the platform as part of standard care [10]. The primary contributing factor is likely that Mind Plasticity used the platform as a means of routine outcome monitoring, whereas other centers primarily used the tool as an initial assessment for patient onboarding. This approach to routine outcome monitoring was enhanced by Mind Plasticity's implementation of a Digital Navigator [34], a unique feature among the centers studied.

Digital Navigators provide valuable support to clinical teams and clients, helping to remove potential barriers to client engagement and support the integration of DMHTs into treatment by clinicians and services.

While traditionally used to support self-guided online therapy modules, the increased engagement observed in Mind Plasticity suggests that Digital Navigators can also be effective in supporting the integration of measurement-based DMHTs into traditional therapies provided by health professionals. The role included providing non-clinical technical support, interpreting data with clients before clinical sessions, and building therapeutic alliances with clients and clinicians around DMHT use [34,37,38]. Crucially, previous findings from Mind Plasticity suggest that the engagement benefits from the Digital Navigator extend beyond mere client support. Prior research has shown that clinicians who integrated the Digital Navigator as part of their care team and maintained frequent contact with them saw higher engagement among their clients. Specifically, following Digital Navigator contact, clients were more likely to engage with the platform if their health professional had strongly promoted DMHT use and had high engagement with the Digital Navigator themselves [34]. This underscores the importance of clinician adoption and integration of DMHTs, facilitated by Digital Navigators, in driving client engagement with DMHTs within traditional therapeutic contexts.

While our findings show that service-level factors have the largest influence on engagement, there also exists individual-level factors which also play a significant role. The relationship between clinical presentation at initial assessment and subsequent engagement with the Innowell platform revealed complex patterns. Higher scores in depression, mania, suicidal ideation, and hospitalization history were associated with increased engagement, partially aligning with Borghouts and colleagues' [12] finding that more severe mental health symptoms generally increase interest in DMHTs. However, our results diverge from their conclusion that depressive symptoms hinder engagement. Interestingly, we found anxiety and self-assessed mental illness severity to be negatively associated with future engagement. This nuanced relationship suggests that DMHT engagement is not simply a function of overall symptom severity but may depend on specific symptom profiles. Factors such as the perceived value of symptom monitoring, potential avoidance behavior, or varying levels of clinician encouragement could also contribute to these complex associations. These findings underscore the need for tailored approaches in implementing DMHTs, considering the intricate interplay between clinical presentation and engagement patterns. Importantly, these results demonstrate that, generally, the presence of mental illness is not a barrier to engagement – and can in fact be associated with higher engagement. This insight could inform strategies to optimize DMHT use across diverse clinical groups.

An important consideration in this study is the potential overestimation of non-engagement with the DMHT. According to the 2022 evaluation of the national *headspace* program [44], a substantial proportion of young people (36%) accessed a *headspace* service only one time. Given that measurement-based care assumes multiple visits to monitor progress over time, these attendees with only a single occasion of service may not have the opportunity or necessity to re-engage with the DMHT. Consequently, the observed 75.4% rate that had no further engagement beyond the initial assessment could be inflated due to the inclusion of participants who did not continue with the service beyond their initial visit.

The observed patterns in help-seeking behaviors, physical activity, and substance misuse across engagement groups, and their associations with engagement, could be explained by 'health consciousness' – the self-awareness of one's health and the propensity to pursue health-promoting behaviors [39]. Although not directly measured, engaging with mental health tracking tools, such as the Innowell platform, is a 'healthy' behavior and could have contributed to this effect. Help-seeking behaviors and physical activity levels were associated with higher engagement, and substance misuse was associated with lower engagement. Since this pattern aligns with typical 'healthy' and 'unhealthy' behaviors, it is possible that the construct 'health consciousness' could underlie this pattern of differences. Previous literature has shown that comorbid substance misuse is one of the strongest factors associated with non-initiation and non-engagement in mental health treatment [40], and may also act as a barrier to engagement and adherence to treatment [41]. These findings, interpreted alongside the other variables, supports the idea that individual-level health consciousness may influence levels of engagement.

The mean participant age varied significantly between engagement groups; however, these results should be interpreted with caution. The *headspace* centers serve individuals aged 12-25, whereas Mind Plasticity accommodates all ages, resulting in a higher average age (29.84 years) compared to other centers (21.83 years). This discrepancy, combined with the higher engagement levels from participants from Mind Plasticity, confounds the apparent age-engagement relationship. When age was entered into the regression model, controlling for the presenting center, there was no effect on engagement. Surprisingly, social support was found to be negatively associated with engagement. Previous findings have shown that access to social support via social networks and forums can enhance engagement to standalone website- or app-based digital mental health interventions [14,42]. However, in our context, individuals with higher levels of social support may also have more diverse coping strategies and resources available to them, potentially reducing their reliance on digital tools for mental health monitoring. While social support interventions specifically targeted at treatment can be helpful for engagement, already established social support networks may reduce engagement to measurement-based DMHTs. Further research is needed to understand the precise mechanisms underlying this association.

Limitations

There are several limitations to be considered. Firstly, the disparity in engagement levels across centers, and significantly higher engagement in participants from Mind Plasticity may have introduced some biases. Though this difference in engagement can be explained by the center's emphasis on routine outcome monitoring and their adoption of the platform into its clinical practice, the center's location in inner-city Sydney represents a demographic that differs from more regional Australian centers. Though this was controlled for in the multiple regression, previous research has shown that those presenting to urban services were more likely to have previously sought help, and have more problems with alcohol use compared to regional service youth [30]. Future efforts should be made to encourage the adoption of the Innowell platform for routine outcome monitoring purposes across diverse centers to facilitate a broader and more representative analysis of routine outcome monitoring and engagement patterns.

Another limitation of the study arises from the absence of data linking participants to specific clinicians, making us unable to differentiate whether engagement is primarily driven by the individual, the service, or the clinician. Understanding this could foster the development of more targeted approaches to increase engagement. Recent qualitative research has demonstrated the importance of the role of the clinician on engagement with the Innowell platform [34]. While maintaining patient and clinician confidentiality, future studies should also track clinician-participant pairings to better understand the clinician's role in patient engagement.

Finally, engagement is operationalized as completion of the Innowell summary questionnaire, which covers domains of physical health, mental illness severity, functioning, suicidal thoughts and behaviors, and social connectedness [19]. However, its relevance may vary among individuals. While it broadly assesses mental health and functioning, some participants may have preferred completing repeat measures of specific symptoms or conditions, such as anxiety or depression. Thus, there could be further engagement with the platform not captured by solely looking at the summary questionnaire. Further, this definition of engagement is specific to the context of the Innowell platform. Although there have been calls to adopt a standardized definition of engagement, emphasizing the incorporation of multidimensional indices [43], the summary questionnaire–designed to track outcomes during treatment–serves as a useful measure of engagement in this context. Still, future research is needed to define dynamic thresholds for optimal level engagement.

Conclusion

These findings provide insight into the demographic and clinical factors of users who are more or less likely to interact with DMHTs. Importantly, we also show that the most prominent predictor of participant engagement is the center that they present to. This highlights the role of broader systemic factors in influencing engagement with DMHT. Further, the severity of mental illness at time of initial assessment does not necessarily impede subsequent engagement with the DMHT. We show that the Innowell Platform can be an effective tool for the delivery of measurement-based care. However, the observed variability in engagement across centers suggests effective integration is largely dependent on integration with mental health services, rather than solely on individual user characteristics. Further, our results indicate that low engagement may be partly attributable to a broader systemic issue: the high prevalence of single-occasion visits to mental health services. This highlights a critical challenge in continuity of care that extends beyond DMHT use. These findings underscore the need for a multi-faceted approach: developing nuanced, user-centered DMHT designs, promoting comprehensive service-level integration to foster routine outcome monitoring, and addressing systemic issues that lead to discontinuous care. By addressing technological, systemic, and continuity-of-care aspects, DMHTs can become more effective, accessible, and personalized tools to deliver measurement-based care, helping to meet the needs of both users and healthcare providers while promoting sustained engagement in treatment.

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LJB wrote the manuscript. LJB conducted the formal data analysis with MV’s consultation. LJB, SM, and FI contributed to the conceptualization, design, interpretation of results, and writing of the manuscript. All authors (LJB, SM, FI, IBH, AT, CG, HLM, MKC, MV, WC, GD, RB, BW, BH, EMS) substantively edited and revised the manuscript, approved the final version of the manuscript, and agree both to be personally accountable for the author's own contributions and ensure that questions related to the accuracy or integrity of any part of the work, even ones in which the author was not personally involved, are appropriately investigated, resolved, and the resolution documented in the literature.

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Conflicts of Interest

IBH is the Co-Director, Health and Policy at the Brain and Mind Centre (BMC) University of Sydney. The BMC operates an early-intervention youth services at Camperdown under contract to headspace. He is the Chief Scientific Advisor to, and a 3.2% equity shareholder in, InnoWell Pty Ltd which aims to transform mental health services through the use of innovative technologies. He is funded by an NHMRC Senior Principal Research Fellowship.

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Darlinghurst until January 2021. She has received honoraria for educational seminars related to the clinical management of depressive disorders supported by Servier, Janssen and Eli-Lilly pharmaceuticals. She has participated in a national advisory board for the antidepressant compound Pristiq, manufactured by Pfizer. She was the National Coordinator of an antidepressant trial sponsored by Servier.

Abbreviations

ASRM: Altman Self-Rating Mania Scale

ASSIST: Alcohol, Smoking and Substance Involvement Screening Test

AUDIT-C: Alcohol Use Disorders Identification Test-Concise

B-NSSI-AT: Brief Non-Suicidal Self-Injury Assessment Tool

CGI: Clinical Global Impressions

C-SSRS: Columbia-Suicide Severity Rating Scale

DMHT: Digital mental health technology

EDE: Eating Disorder Examination

EQ-5D-Y: EuroQol 5-Dimension Youth

IPAQ: International Physical Activity Questionnaire

K10: Kessler Psychological Distress Scale

MBC: Measurement-based care

MET: Metabolic Equivalent of Task

NEET: Not in Employment, Education, or Training

OASIS: Overall Anxiety Severity and Impairment Scale

PC-PTSD-5: The Primary Care Posttraumatic Stress Disorder Screen for DSM-5

QIDS: Quick Inventory of Depressive Symptomatology

RCT: Randomized controlled trial

SIDAS: Suicidal Ideation Attributes Scale

SOFAS: Social and Occupational Functioning Assessment Scale

SSSS: Schuster's Social Support Scale

WSAS: Work and Social Adjustment Scale

References

1. Torous J, Bucci S, Bell IH, Kessing LV, Faurholt-Jepsen M, Whelan P, Carvalho AF, Keshavan M, Linardon J, Firth J. The growing field of digital psychiatry: current evidence and the future of apps, social media, chatbots, and virtual reality. World Psychiatry Off J World Psychiatr Assoc WPA 2021 Oct;20(3):318–335. PMID:34505369

2. Titov N, Hadjistavropoulos HD, Nielssen O, Mohr DC, Andersson G, Dear BF. From Research to Practice: Ten Lessons in Delivering Digital Mental Health Services. J Clin Med Multidisciplinary Digital Publishing Institute; 2019 Aug;8(8):1239. PMID: 31426460

3. Gan DZQ, McGillivray L, Han J, Christensen H, Torok M. Effect of Engagement With Digital Interventions on Mental Health Outcomes: A Systematic Review and Meta-Analysis. Front Digit Health Frontiers; 2021 Nov 4;3. PMID: 34806079

4. Firth J, Torous J, Nicholas J, Carney R, Pratap A, Rosenbaum S, Sarris J. The efficacy of smartphone-based mental health interventions for depressive symptoms: a meta-analysis of randomized controlled trials. World Psychiatry 2017;16(3):287–298. PMID: 28941113

5. Bond RR, Mulvenna MD, Potts C, O'Neill S, Ennis E, Torous J. Digital transformation of mental health services. Npj Ment Health Res Nature Publishing Group; 2023 Aug 22;2(1):1–9. doi:10.1038/s44184-023-00033-y

6. Eysenbach G. The Law of Attrition. J Med Internet Res 2005 Mar 31;7(1):e402. doi: 10.2196/jmir.7.1.e11

7. Rodriguez-Villa E, Rauseo-Ricupero N, Camacho E, Wisniewski H, Keshavan M, Torous J. The digital clinic: Implementing technology and augmenting care for mental health. Gen Hosp Psychiatry 2020 Sep 1;66:59–66. doi: 10.1016/j.genhosppsych.2020.06.009

8. Lewis CC, Boyd MR, Walsh-Bailey C, Lyon AR, Beidas R, Mittman B, Aarons GA, Weiner BJ, Chambers DA. A systematic review of empirical studies examining mechanisms of implementation in health. Implement Sci IS 2020 Apr 16;15(1):21. PMID:32299461

9. Koh J, Tng GYQ, Hartanto A. Potential and Pitfalls of Mobile Mental Health Apps in Traditional Treatment: An Umbrella Review. J Pers Med 2022 Aug 25;12(9):1376. PMID:36143161

10. McKenna S, Piper S, Capon W, Crowley A, Lira L, LaMonica HM, Chong MK, Scott E, Hickie I, Iorfino F. The Polarization of Clinician and Service Staff Perspectives After the Use of Health Information Technology in Youth Mental Health Services: Implementation and Evaluation Study. JMIR Hum Factors 2023 Jul 25;10(1):e42993. doi:10.2196/42993

11. Lipschitz JM, Pike CK, Hogan TP, Murphy SA, Burdick KE. The Engagement Problem: a Review of Engagement with Digital Mental Health Interventions and Recommendations for a Path Forward. Curr Treat Options Psychiatry 2023 Aug 25; doi: 10.1007/s40501-023-00297-3

12. Borghouts J, Eikey E, Mark G, De Leon C, Schueller SM, Schneider M, Stadnick N, Zheng K, Mukamel D, Sorkin DH. Barriers to and Facilitators of User Engagement With Digital Mental Health Interventions: Systematic Review. J Med Internet Res 2021 Mar 24;23(3):e24387. PMID:33759801

13. Ho TQA, Le LK-D, Engel L, Le N, Melvin G, Le HND, Mihalopoulos C. Barriers to and facilitators of user engagement with web-based mental health interventions in young people: a systematic review. Eur Child Adolesc Psychiatry 2024 Feb 14; doi:10.1007/s00787-024-02386-x

14. Saleem M, Kühne L, Santis KKD, Christianson L, Brand T, Busse H. Understanding Engagement Strategies in Digital Interventions for Mental Health Promotion: Scoping Review. JMIR Ment Health 2021 Dec 20;8(12):e30000. doi:10.2196/30000

15. Baumel A, Muench F, Edan S, Kane JM. Objective User Engagement With Mental Health Apps: Systematic Search and Panel-Based Usage Analysis. J Med Internet Res 2019 Sep 25;21(9):e14567. PMID:31573916

16. Gunn J, Cameron J, Densley K, Davidson S, Fletcher S, Palmer V, Chondros P, Dowrick C, Pirkis J. Uptake of mental health websites in primary care: Insights from an Australian longitudinal cohort study of depression. Patient Educ Couns 2018 Jan 1;101(1):105–112. doi: 10.1016/j.pec.2017.07.008

17. Iorfino F, Cross SP, Davenport T, Carpenter JS, Scott E, Shiran S, Hickie IB. A Digital Platform Designed for Youth Mental Health Services to Deliver Personalized and Measurement-Based Care. Front Psychiatry 2019;10. PMID:31507465

18. Scott K, Lewis CC. Using Measurement-Based Care to Enhance Any Treatment. Cogn Behav Pract 2015 Feb 1;22(1):49–59. doi:10.1016/j.cbpra.2014.01.010

19. Hickie IB, Scott EM, Cross SP, Iorfino F, Davenport TA, Guastella AJ, Naismith SL, Carpenter JS, Rohleder C, Crouse JJ, Hermens DF, Koethe D, Markus Leweke F, Tickell AM, Sawrikar V, Scott J. Right care, first time: a highly personalised and measurement-based care model to manage youth mental health. Med J Aust 2019 Nov;211 Suppl 9:S3–S46. PMID:31679171

20. Bickman L, Kelley SD, Breda C, de Andrade AR, Riemer M. Effects of routine feedback to clinicians on mental health outcomes of youths: results of a randomized trial. Psychiatr Serv Wash DC 2011 Dec;62(12):1423–1429. PMID:22193788

21. Gondek D, Edbrooke-Childs J, Fink E, Deighton J, Wolpert M. Feedback from Outcome Measures and Treatment Effectiveness, Treatment Efficiency, and Collaborative Practice: A Systematic Review. Adm Policy Ment Health Ment Health Serv Res 2016 May 1;43(3):325–343. doi:10.1007/s10488-015-0710-5

22. Lambert MJ, Whipple JL, Kleinstäuber M. Collecting and delivering progress feedback: A meta-analysis of routine outcome monitoring. Psychotherapy 2018 Dec;55(4):520–537. doi:10.1037/pst0000167

23. Shimokawa K, Lambert MJ, Smart DW. Enhancing treatment outcome of patients at risk of treatment failure: Meta-analytic and mega-analytic review of a psychotherapy quality assurance system. J Consult Clin Psychol 2010;78(3):298–311. doi:10.1037/a0019247

24. Tam HE, Ronan K. The application of a feedback-informed approach in psychological service with youth: Systematic review and meta-analysis. Clin Psychol Rev 2017 Jul 1;55:41–55. doi:10.1016/j.cpr.2017.04.005

25. McGorry PD, Purcell R, Hickie IB, Jorm AF. Investing in youth mental health is a best buy. Med J Aust 2007 Oct 1;187(7). doi:10.5694/j.1326-5377.2007.tb01326.x

26. van Sonsbeek MAMS, Hutschemaekers GJM, Veerman JW, Vermulst A, Tiemens BG. The results of clinician-focused implementation strategies on uptake and outcomes of Measurement-Based Care (MBC) in general mental health care. BMC Health Serv Res 2023 Apr 1;23(1):326. doi:10.1186/s12913-023-09343-5

27. Black WE, Nagarkatti-Gude DR, Jetmalani A, Keepers G. Harnessing Technology to Implement Measurement-Based Care. Acad Psychiatry 2018 Oct 1;42(5):711–716. doi:10.1007/s40596-018-0929-z

28. Rickwood DJ, Telford NR, Parker AG, Tanti CJ, McGorry PD. headspace - Australia's innovation in

youth mental health: who are the clients and why are they presenting? Med J Aust 2014 Feb 3;200(2):108–111. PMID:24484115

29. Davenport TA, LaMonica HM, Whittle L, English A, Iorfino F, Cross S, Hickie IB. Validation of the InnoWell Platform: Protocol for a Clinical Trial. JMIR Res Protoc 2019 May 31;8(5):e13955. PMID:31152524

30. Capon W, Hickie IB, McKenna S, Varidel M, Richards M, LaMonica HM, Rock D, Scott EM, Iorfino F. Characterising variability in youth mental health service populations: A detailed and scalable approach using digital technology. Australas Psychiatry 2023 Jun;31(3):295–301. PMID:37035873

31. LaMonica HM, Davenport TA, Braunstein K, Ottavio A, Piper S, Martin C, Hickie IB, Cross S. Technology-Enabled Person-Centered Mental Health Services Reform: Strategy for Implementation Science. JMIR Ment Health 2019 Sep 19;6(9):e14719. doi:10.2196/14719

32. LaMonica HM, Davenport TA, Ottavio A, Rowe SC, Cross SP, Iorfino F, Jackson TA, Easton MA, Melsness J, Hickie IB. Optimising the integration of technology-enabled solutions to enhance primary mental health care: a service mapping study. BMC Health Serv Res 2021 Jan 15;21(1):68. doi:10.1186/s12913-021-06069-0

33. Hickie IB, Iorfino F, Rohleder C, Song YJC, Nichles A, Zmicerevska N, Capon W, Guastella AJ, Leweke FM, Scott J, McGorry P, Mihalopoulos C, Killackey E, Chong MK, McKenna S, Aji M, Gorban C, Crouse JJ, Koethe D, Battisti R, Hamilton B, Lo A, Hackett ML, Hermens DF, Consortia MP, Consortia headspace C, Scott EM. EMPOWERED trial: protocol for a randomised control trial of digitally supported, highly personalised and measurement-based care to improve functional outcomes in young people with mood disorders. BMJ Open British Medical Journal Publishing Group; 2023 Oct 1;13(10):e072082. PMID:37821139

34. Gorban CS, McKenna S, Chong MK, Capon W, Battisti R, Crowley A, et al. Building mutually beneficial collaborations between Digital Navigators, mental health professionals and clients: Naturalistic observational case study. JMIR Prepr. 2024 Mar. doi:10.2196/preprints.58068

35. Gelman A, Hill J. Data Analysis Using Regression and Multilevel/Hierarchical Models. High Educ Camb Univ Press. Cambridge University Press; 2006. doi:10.1017/CBO9780511790942

36. Chong MK, Hickie IB, Ekambareshwar M, Poulsen A, McKenna S, Hutcheon A, et al. Personalized and collaborative care are crucial elements for sustained engagement with digital measurement-based care tools: A mixed-methods study. 2024. Doi:10.21203/rs.3.rs-4362142/v1

37. Ben-Zeev D, Drake R, Marsch L. Clinical technology specialists. BMJ. 2015;350:h945. doi:10.1136/bmj.h945

38. Noel VA, Carpenter-Song E, Acquilano SC, Torous J, Drake RE. The technology specialist: a 21st century support role in clinical care. NPJ Digit Med 2019;2:61. PMID:31388565

39. Espinosa A, Kadić-Maglajlić S. The Mediating Role of Health Consciousness in the Relation Between Emotional Intelligence and Health Behaviors. Front Psychol 2018 Nov 8;9:2161. PMID:30467488

40. Dixon LB, Holoshitz Y, Nossel I. Treatment engagement of individuals experiencing mental illness: review and update. World Psychiatry 2016 Feb;15(1):13–20. PMID:26833597

41. Patel MX, David AS. Medication adherence: predictive factors and enhancement strategies. Psychiatry 2007 Sep 1;6(9):357–361. doi:10.1016/j.mppsy.2007.06.003

42. O'Sullivan S, van Berkel N, Kostakos V, Schmaal L, D'Alfonso S, Valentine L, Bendall S, Nelson B,

Gleeson JF, Alvarez-Jimenez M. Understanding What Drives Long-term Engagement in Digital Mental Health Interventions: Secondary Causal Analysis of the Relationship Between Social Networking and Therapy Engagement. JMIR Ment Health 2023 May 22;10:e44812. PMID:37213197

43. Boucher EM, Raiker JS. Engagement and retention in digital mental health interventions: a narrative review. BMC Digit Health 2024 Aug 8;2(1):52. doi: 10.1186/s44247-024-00105-9

44. KPMG Consulting. (2022). Evaluation of the national headspace program. Final Report to Department of Health. Sydney, NSW, Australia: KPMG, 2022.