User character strengths predict engagement on a digital mental health platform for young people

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Table of Contents

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Abstract

Background: Mental ill health is a leading cause of disability worldwide, but access to evidence-based support remains limited. Digital mental health interventions offer a timely and low-cost solution. However, improvements in clinical outcomes are reliant on user engagement, which can be low for digital interventions. User characteristics, including demographics and personality traits, could be used to tailor platforms to promote longer-term engagement and improved outcomes.

Objective: This study aimed to investigate how character strengths, a set of positive personality traits, influence engagement patterns with Moderated Online Social Therapy (MOST), a national digital mental health platform offering individualised, evidence-based online mental health treatment for young people aged 12-25.

Methods: Data from 6967 young people who enrolled with MOST between August 2021 and July 2023 were analysed. Longitudinal analyses were used to investigate whether scores on three character strength dimensions (‘Social Harmony’, ‘Positive Determination’, and ‘Courage and Creativity’) were associated with (1) an accelerated or decelerated rate of dropout from the platform, and (2) patterns of engagement over the first 12 weeks following onboarding. Engagement metrics were time spent on the platform, number of sessions on the platform, use of the embedded social network, and messages with the clinical team.

Results: On average, young people used the platform for 72.64 days (SD = 106.64). The three character strengths were associated with distinct engagement patterns during this time. Individuals scoring higher on ‘Social Harmony’ demonstrated an accelerated dropout rate ($P = .008$). Interestingly, higher scores on this character strength were associated with high rates of initial engagement but a more precipitous decline in platform use over the first 12 weeks, in terms of time spent on the platform ($t = -5.05$, $P < .001$) and the number of sessions completed ($t = -2.26$, $P = .02$). In contrast, higher scores on ‘Positive Determination’ and ‘Courage and Creativity’ predicted more modest initial platform use but steadier engagement over time, in terms of time spent on the platform (Positive Determination: $t = 4.05$, $P < .001$; Courage and Creativity: $t = 2.66$, $P = .008$). Contrary to our predictions, character strengths did not predict use of the embedded social network or the number of messages sent to the clinical team.

Conclusions: Our findings illustrate how character strengths predict distinct engagement trajectories on a digital mental health platform. Specifically, individuals higher on ‘Social Harmony’ showed high initial engagement that quickly declined, while those higher on ‘Positive Determination’ and ‘Courage and Creativity’ demonstrate lower initial engagement but a steadier use of the platform over time. The findings of this study demonstrate an opportunity for digital mental health interventions to be tailored to individual characteristics in a way that would promote greater initial and ongoing engagement.

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1.0 Introduction

Youth mental health is a major global concern, with 75% of psychiatric diagnoses emerging by the age of 25 (1–3). Mental illness in adolescence can produce severe disruptions in the social and vocational transition into adulthood (4), with life-long consequences, including impaired social functioning, loneliness, poor educational attainment and unemployment. The effects of early onset mental illness are of huge consequence to young people and their families, as well as to the economy – estimated in 2021 to cost approximately US$387 billion per year (5).

Despite a significant proportion of young people living with mental health problems, access to treatment remains limited (6). Demand for youth mental health services has resulted in wait times of over 100 days (7), with many young people never attaining access to evidence-based interventions (4). Prolonged wait times are associated with symptom deterioration, maladaptive and risky coping behaviours, and diminished help-seeking (7,8). Ubiquitous mobile and internet access in recent years means that digital interventions provide an excellent opportunity to mitigate the global mental health burden by enabling timely, scalable and low-cost treatment (9–11). Early evidence shows that digital mental health technologies have similar efficacy to face-to-face treatments (12), significantly improving psychiatric symptom severity (13), social functioning (14), vocational prospects (15), and medication adherence (16), resulting in fewer hospital admissions (15) and demonstrating cost-effectiveness (11).

Digital mental health interventions offer a promising and cost-effective avenue for young people to receive mental health support. Yet while user engagement is thought to be required for users to experience the full clinical benefits, these interventions often suffer from notable rates of attrition (17). A recent study found that only 3.3% of individuals remain engaged with popular commercial mental health apps after 30 days (18). Discontinuation may be explained by positive outcomes, such as an improvement in symptoms and/or continued independent engagement in therapeutic techniques without a requirement for the platform (19). More commonly, though, attrition is due to unsatisfying user experience, technological barriers or fluctuations in motivation to conduct effortful tasks (20–23). User engagement is particularly low when there is no human support. Buelens and colleagues (24) found that subjects who enrolled in a purely self-help program showed the fastest decrease in engagement relative to guided and blended treatment paths.

With these considerations in mind, Moderated Online Social Therapy (MOST) was iteratively co-developed by a team of clinicians, young people, designers and software engineers in Australia, incorporating a decade of youth feedback and usage data (25–27). The digital intervention integrates clinical care and career support for young people aged 12-25 years old with therapeutic content and a supportive online community of other young people with similar mental health experiences. The platform recommends evidence-based content to users based on their responses to an initial assessment and provides optional tailoring from a clinician - an approach that has previously been shown to increase engagement with digital services (28). The shared, secure and private social network was designed to further address attrition rates by enhancing social support and connectedness. Indeed, the use of the social network was identified as a key driver of long-term engagement with the intervention (29). A recent national-scale evaluation of the MOST platform found that 55% of users were still engaged after 6 weeks and 40% by 12 weeks (30)— a notable improvement on other mental health apps for depression and anxiety that show a lower retention rate of 0.5% to 28.6% after 6 weeks (31). Nevertheless, ongoing research is required to determine how mental health platforms such as MOST can be tailored to enhance user experience and ensure long-term engagement.

The Persuasive Systems Design (PSD) framework offers a set of guidelines for developers to design and tailor technology in a way that motivates and supports users with the goal of promoting positive changes in behaviour and mental state (32). The PSD framework is built around a comprehensive set of design principles and persuasive strategies categorised into four main components: (1) primary task support, focusing on how technology can help users achieve their goals on the app, (2) dialogue support, encouraging engagement through interactions that motivate and persuade users to persist in achieving their goals, (3) system credibility support, building trust and ensuring the technology is perceived as reliable and competent, and (4) social support, facilitating social influences, through social networks, to encourage sustained behaviour change. The framework considers the use of personalisation to align the technology with users' needs, interests and personalities to enhance user engagement and motivation. Recent studies have found customising different aspects of digital interventions to be advantageous, including symptom monitoring (33), digital reminders (13,34,35), therapeutic content (36,37), delivery approach (38), and interface appearance (33). As a result, there has been a growing focus on examining how individual characteristics can be used to inform the customisation of platforms to enhance their appeal and long-term use (39).

User characteristics, including symptom severity (39–42), education level (43,44), gender (45,46), and personality traits (47–49), have been shown to influence engagement with digital mental health platforms. A number of studies have reported that a user's personality can predict their willingness to engage with an online platform (47–50). For instance, those who scored higher on extraversion are shown to prefer in-person therapeutic sessions to web-based mental health services. Given that digital platforms inherently lack the interpersonal dynamics of face-to-face interactions, for these users, a social network may enhance the appeal of this type of intervention. While conceptually similar to personality traits, character strengths are a set of positive thoughts, feelings and behaviours that are assessed using the VIA Character Strengths Questionnaire upon enrolment with MOST, and results are presented to the user. Providing users with an assessment of these positive psychological attributes aims to promote self-efficacy, hope for the future, and intrinsic motivation - all of which are associated with sustained interest and improved psychological outcomes (51–53). In this study, we investigated whether a user's character strengths determined their pattern and duration of engagement with the MOST platform and, in turn, predicted their mental health outcome. Specifically, we aimed to investigate whether scores on each character strength predicted (1) the duration of engagement with MOST, (2) engagement with each component of the MOST platform, and (3) symptom outcome as a function of engagement (see https://osf.io/7thfr for full study pre-registration). Engagement in this study was quantified as time spent on the platform, number of sessions, number of reactions on the social network, and messages sent to the clinical team in the first 12 weeks following onboarding. Symptom outcome was defined as the score on the Kessler Psychological Distress scale (K10) at week 12.

2.0 Methods

2.1 MOST platform

The MOST platform integrates (1) web-based therapeutic content (journeys), (2) web-based social networking, and (3) support from the moderation team (clinicians, peer workers and career consultants) for young people aged 12-25 years old (25–27,54,55). When this manuscript was written, MOST was available in participating youth mental health services, and young people are referred by their treating clinicians across phases of care – from entry and whilst on waitlists, concurrent with face-to-face treatment, and following discharge (25,30). Young people can also be referred to MOST from a service if they are deemed unsuitable for that service (known as 'subthreshold'). Young people seeking or receiving mental health support who are referred to MOST complete an initial onboarding assessment that includes questions about their demographics, as well as an adapted 60-item version of the VIA Character Strengths Questionnaire (56). Users receive an invitation to complete optional self-report questionnaires regarding their mental health at week 0 and again at weeks 6, 12, 18, and 24. Optional self-report mental health questionnaires include the K10 (57).

After enrolment, users could opt in for a brief phone call with a mental health clinician to review their needs and tailor the therapy journey accordingly. MOST's therapeutic online guided journeys provide support for general anxiety, social anxiety, depression, insomnia, and social functioning. Each journey includes 20 to 40 interactive activities that address key drivers of symptoms, functioning, and well-being, such as mindfulness, self-compassion, cognitive restructuring, behavioural activation, and exposure.

Clinicians contact users on a weekly to fortnightly basis via a combination of direct messages, phone calls and SMS. For users who require vocational support, a career consultant provides individualised assistance, such as identifying options for tertiary study or identifying suitable job openings, supporting specific job-seeking activities, preparing for a job interview, and encouraging the use of their personal strengths. The social network is moderated and led by peer workers - young people who identify as having had lived experience of mental health problems and who are employed and trained to provide support on the MOST platform. The social network was designed for young people using the platform to communicate and facilitate social connectedness. Users can post comments, or like, react or respond to comments posted by other young people.

Data analysed in this study were from young people who enrolled in MOST between August 2021 and July 2023. Inclusion criteria were: (1) help-seeking individuals assessed by a MOST participating youth mental health service, (2) aged 12 to 25 years, and (3) individuals with the ability to provide informed consent and who have accepted the terms of service. Previous research suggests that user uptake following enrolment cannot be assumed, especially within the context of a digital intervention, and was therefore defined in this study as activity on the platform for at least one day (58). Individuals who did not meet this criterion were excluded from analyses.

2.2. Platform engagement metrics

The current study captures engagement patterns during the first 12 weeks following enrolment. Engagement metrics were (1) time (minutes) on the platform, (2) sessions on the platform, (3) reactions on the MOST social network, and (4) messages with the clinical team. It is well documented that digital interventions are heavily used following onboarding, and use decreases over time (58). Hence, both time spent on the platform and the number of sessions were reported to ensure that we could distinguish users who completed infrequent but longer sessions from individuals who regularly use the platform. The time on platform metric was defined as any time spent on the MOST platform, including viewing therapeutic journeys, direct messaging with the moderation team, and activity on the social network. A session was defined as a period of activity that included more than one page visit with no more than 30 minutes of inactivity between visits. Reactions on the MOST social network were defined as any activity on the social network, including creating a post, posting a comment or liking, responding, or reacting to a comment that someone else had posted. While all participants enrolled with MOST were offered contact with clinicians, responding to messages was optional, and the degree of contact (i.e., the number of messages sent) with the clinical team was determined by each individual user. Clinical support has previously been shown to increase the duration of engagement with digital interventions (23,24) and was therefore included as an engagement metric in this study, defined as the number of messages sent to clinicians, peer workers and vocational workers.

2.3 Statistical analyses

Factor structure of character strengths

Original character strength classifications were theory-informed (56). However, factor analytical studies have converged on a three to five-factor solution to best explain the item-level responses in the VIA Character Strengths Questionnaire (59–64). Since the current study used a short-form adaptation of the questionnaire (consisting of 60 items) with a sample of adolescents experiencing mental health problems, an exploratory factor analysis was employed using Maximum Likelihood Estimation (MLE) to establish the factor structure. A Kaiser-Meyer-Olkin (KMO) test was used prior to conducting the factor analysis and confirmed factor adequacy (overall KMO = 0.95). Bartlett's Test of Sphericity was used to test the null hypothesis that the variables in the correlation matrix are unrelated and unsuitable for a factor analysis. Results from this test were statistically significant ($P < 0.001$), confirming that the correlation matrix was not an identity matrix.

A factor analysis on the 60-item questionnaire was conducted using an orthogonal rotation (equamax) due to low correlations between the factors (r<0.3 (65)). Cattell's criterion was used to determine the number of factors to extract, whereby a sharp transition or 'elbow' in the scree plot where eigenvalues begin to level out indicated that additional factors would add relatively little to the information extracted. The plot was analyzed using the Cattell-Nelson-Gorsuch (CNG) test, an objective implementation of this criterion that computes the slope and determines the point at which there is the greatest transition from horizontal to vertical. The CNG test suggested that a 3-factor structure best explained item-level responses in the dataset.

Primary analyses

Character strengths and time-to-dropout

An accelerated failure time model was used to investigate whether scores on the three character strength factors accelerated or decelerated time-to-dropout, calculated as the number of days from onboarding to the day users were last actively engaged with MOST. Data was right censored for users still engaged in MOST at the time of data extraction. Age, pronouns, treatment stage (i.e. waiting for treatment, receiving treatment, approaching discharge, subthreshold discharge, discharged, or treatment stage unknown), and K10 score at enrolment were included in the model, and numeric variables were log-transformed to ensure the comparability of resultant coefficients. Weibull, exponential, Log-Normal, and Log-Logistical distributions were compared, and the Akaike Information Criterion (AIC) for each was used to identify the best-fitting model. The Log-Normal distribution yielded the lowest AIC value and was considered the best fit for the data. Model diagnostics were performed by examining residual plots, which indicated that the Log-Normal model fit the data adequately. The accelerated failure time model was exploratory and goes beyond our pre-registration (https://osf.io/7thfr).

Character strengths and week-by-week platform engagement

Following this, we used linear mixed-effects models to further examine the relationship between character strengths and platform engagement on a week-by-week basis for the first 12 weeks following onboarding. A separate model was used to assess each of the engagement metrics independently (time spent on the platform, number of sessions, number of reactions on the social network, and messages sent to the clinical team), with week number and scores on each of the three character strength factors, as well as age, pronouns, treatment stage, and onboarding K10 score entered as predictors. Measurements of engagement metrics, age and K10 scores were log-transformed to enable comparability of resultant coefficients. All three models included a random intercept and slope to account for individual differences and the rate of change over time.

Mediation analysis

Our pre-registration stated that a path analysis would be used to investigate whether scores on the character strength factors predict mental health symptoms at 12 weeks as a function of platform engagement. However, user completion of mental health questionnaires (e.g. K10) was optional following enrolment, and the amount of missing data at the 12-week follow-up was substantial. Furthermore, missingness was not at random, which prohibited multiple imputation. Specifically, the percentage of missing values across the variables in the dataset varied between 0 and 84%. In total 6579 out of 6967 records (94%) were incomplete. Missing data was highest for K10 scores – our primary outcome - at baseline (58%), 6 weeks (80%) and 12 weeks (84%). A logistic regression model was used to investigate whether K10 scores at baseline and 6 weeks were associated with missing data at week 12 (0 for not missing, 1 for missing). The overall model was statistically significant compared to the null model ($\chi^2(1411) = 1861.5$, $P = 0.02$) and demonstrated that a 10% increase in K10 scores at 6 weeks was associated with a 2% decrease in missing data at week 12 (95% CI = [0.96, 0.99], $P = .006$) and that a 10% increase in baseline K10 score was associated with a 2% increase in missing data at week 12 (95% CI = [1.01, 1.04], $P = .01$). These results indicate the missing data was influenced by the severity of mental health symptoms. Consequently, we determined that the planned path analysis would not be appropriate. We discuss the implications of missing data in more detail in the Discussion section.

All analyses were performed in RStudio using psych (version 2.3.12), lme4 (version 1.1-34) and survival (version 3.5-7). Code is available at https://osf.io/suhgf/.

3.0 Results

3.1 Demographics and descriptive statistics

The data presented in this paper is from the 6967 young people who enrolled with MOST between August 2021 and July 2023 and provided consent for their data to be used for research purposes. The demographic characteristics of this sample are presented in **Table 1**.

	Total (N=6967)
Age (years)	
Mean (SD)	17 (± 3.3)
Pronouns, number (%)	
She/Her	4591 (66 %)
He/Him	1445 (21 %)
They/Them	746 (11 %)
Else	185 (3 %)
Indigenous status, number (%)	
Non-Indigenous	2248 (32 %)
Aboriginal	144 (2 %)
Unknown	4560 (65 %)
Torres Strait Islander	8 (0 %)
Aboriginal and Torres Strait Islander	7 (0 %)
Treatment stage, number (%)	
Waiting	3439 (49 %)
Receiving	1504 (22 %)
Unknown	1090 (16 %)
Approaching Discharge	626 (9 %)
Subthreshold Discharge	299 (4 %)
Discharged	9 (0 %)

Table 1. Sample demographics.

Mean K10 score was 34.47 ± 8.28 (N=2958) at enrolment, 32.19 ± 8.24 (N=1879) at week 6, and 31.70 ± 9.33 (N=1454) at week 12 **(Supplementary Figure S1).** A repeated measures ANOVA was performed to examine K10 scores over the 12-week period. Results revealed a significant effect of time on K10 score, $F(2, 1745) = 56.58$, $P < .001$. Tukey post-hoc comparisons further explored pairwise differences in K10 scores between time points. K10 scores significantly decreased between onboarding and week 6 ($P < .001$), onboarding and week 12 ($P < .001$), and week 6 and week 12 ($P < .001$). Mean scores on all additional mental health questionnaires are presented in **Supplementary Table S1**.

On average, users remained engaged with the platform for 72.64 days (SD = 106.64), with 14.22 (SD = 32.09) of those days spent actively using the platform. **Figure 1** illustrates user engagement with the MOST platform in terms of the amount of time users spent on the platform, number of sessions on the platform, reactions on the social network, and interactions with the clinical team, measured on a week-by-week basis for the first 12 weeks following enrolment. Users spent an average of 126.23 (SD = 500.04) minutes on the platform, logged in for 17.72 (SD = 39.34) sessions, reacted 11.54 (SD = 39.58) times on the social network, and contacted the clinical team 11.79 (SD = 27.66) times in the first 12 weeks.

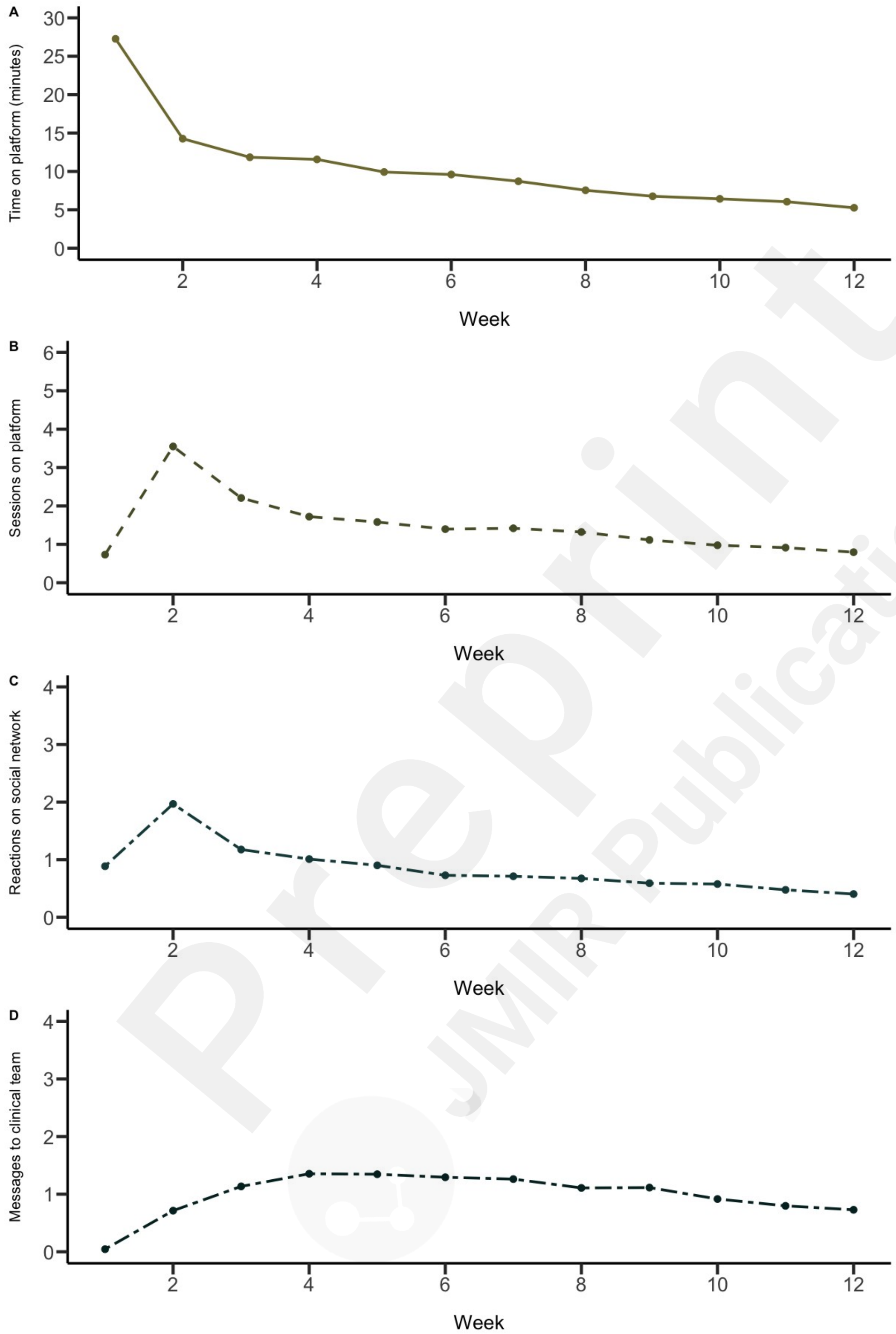


Figure 1. MOST 12-week engagement patterns. (A) Mean time on platform, **(B)** sessions on platform, **(C)** reactions of the social network, and **(D)** messages sent to the clinical team, measured week-by-week for the first 12 weeks from enrolment.

3.2 Factor structure of character strengths

Responses to the 60 VIA Character Strength Questionnaire items were entered into a factor analysis. Both a scree-plot and CNG test indicated that a 3-factor solution best explained the variance in the item-level responses in this dataset (**Supplementary Figure S2**). Factors were labelled 'Social Harmony', 'Positive Determination' and 'Courage and Creativity' based on the strongest individual item loadings (**Table 2**). These factors were comparable with other three-factor models produced in the personality literature, which typically report a social factor, a personal agency factor, and a conscientiousness factor, with similar component loadings, respectively (66).

Subscale	Factor 1	Factor 2	Factor 3
Kindness	**0.58**	0.09	0.21
Teamwork	**0.60**	0.12	0.07
Creativity	0.06	**0.32**	**0.54**
Discretion	**0.51**	0.15	0.18
Humour	0.13	0.12	**0.49**
Forgiveness	0.16	**0.34**	0.06
Honesty	**0.46**	0.08	0.25
Love of Learning	-0.00	0.28	**0.35**
Inspiration	**0.40**	0.21	0.26
Leadership	0.28	0.23	**0.37**
Perspective	**0.46**	0.11	**0.34**
Gratitude	**0.49**	**0.35**	0.08
Courage	0.13	0.17	**0.56**
Curiosity	0.25	**0.42**	0.23
Social Intelligence	0.12	**0.37**	**0.36**
Fairness	**0.62**	0.01	0.12
Hope	0.16	**0.63**	0.16
Enthusiasm	-0.01	**0.62**	0.19
Love	**0.37**	**0.37**	0.08
Perseverance	0.07	**0.51**	0.21

Table 2. Factor loadings. Loadings from a factor analysis on the VIA Character Strengths Questionnaire. Each column corresponds to a factor. Loadings indicate the strength and direction of the relationship between the character strength subscale and the respective factor. Higher loadings suggest a stronger association. Loadings greater than 0.3 are in bold to highlight the dominant subscales, aiding in the interpretation of the underlying latent factors. Based on these loadings, factors were labelled 1) 'Social Harmony', 2) 'Positive Determination' and 3) 'Courage and Creativity'.

Primary analysis

3.3. Character strengths and time-to-dropout

An accelerated failure time model was used to investigate whether higher scores on each of the character strength factors accelerate or decelerate time-to-drop out, defined as the number of days from enrolment to the day users last actively engaged with MOST. Scores on the Social Harmony, Positive Determination and Courage and Creativity factors were entered into a single model, as well as age, treatment stage, pronouns and baseline K10 score. Age and K10 scores were log-transformed to aid interpretation of the results.

A higher score on the Social Harmony Factor was associated with an accelerated drop-out rate (coefficient = -0.15, 95% CI: -0.26 to -0.04, *P* = .008), indicating that individuals who scored higher on Social Harmony character strengths disengaged with the digital platform more rapidly. Scores on the Positive Determination Factor and Courage and Creativity Factor did not show significant effects on drop-out rate (Positive Determination Factor: coefficient = 0.09, 95% CI: -0.01 to 0.19, *P* = .09; Courage and Creativity Factor: coefficient = -0.02, 95% CI: -0.11 to 0.07, *P* = .66).

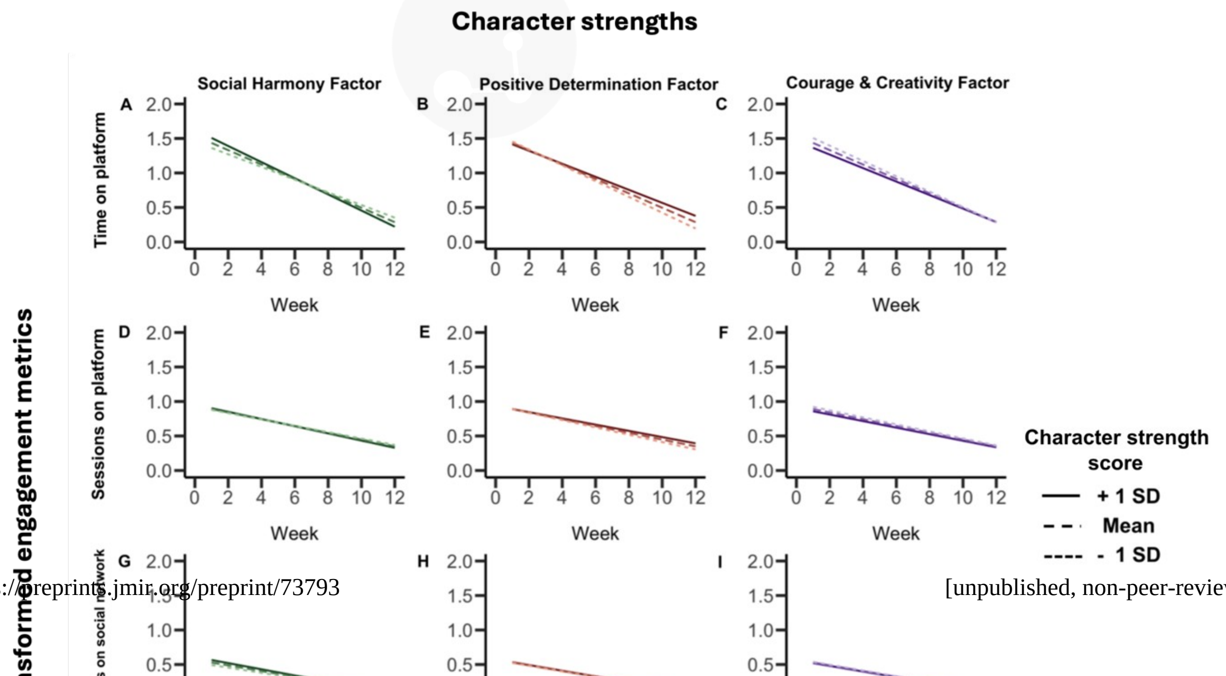
Treatment stage was also predictive of time to drop out, with individuals who were receiving face-to-face treatment, and whose treatment stage was unknown demonstrating an accelerated drop-out rate (Face-to-face treatment: coefficient = -0.60, 95% CI: -1.01 to -0.19, *P* = .004; Unknown treatment stage: coefficient = -1.46, 95% CI: -1.87 to -1.05, *P* < .01). Age, pronouns and K10 score at enrolment were not related to time-to-drop out.

3.4. Character strengths and week-by-week platform engagement

Linear mixed-effects models were next used to investigate whether character strength factors were associated with changes in each engagement metric (time on platform, number of sessions, reactions on the social network, and interactions with the clinical team) week-by-week over 12 weeks. To aid the interpretation of the time-by-character strength interaction, mean-centred continuous character strength variables were plotted (**Figures 2-4**). Plots of mean ± 1SD depict the model-implied relationship for each character strength.

Time spent on platform

There was a significant interaction effect between scores on Social Harmony and week number, indicating that the effect of character strength on time spent on the platform changed over the 12-week period (**Figure 2A**; *B* = -.01, *SE* = 0.00, *t*(2748) = -5.05, *P* < .001). Specifically, for individuals scoring higher on this factor, while time spent on the platform was initially greater, the rate of decline in platform usage over the 12 weeks was more pronounced. The opposite was true for the Positive Determination factor, whereby individuals scoring higher on this character strengths factor initially spent less time on the platform but demonstrated a slower decline in platform use over the 12 weeks (**Figure 2B**; *B* = .01, *SE* = 0.00, *t*(2748) = 4.05, *P* < .001). For Courage and Creativity character strengths, a significant interaction effect with week number suggested that individuals scoring higher on this character strength factor spent less time on the platform, and the rate of decline in time spent on the platform over the 12 weeks was less pronounced (**Figure 2C**; *B* = .01, *SE* = 0.00, *t*(2748) = 2.66, *P* = .008). Age (*t* = 1.39, *P* = .16), pronouns (all *P* > 0.05), and K10 score at enrolment (*t* = -1.47, *P* = .14) were not related to time spent on the platform. However, individuals whose treatment stage was unknown spent a greater amount of time on the platform over the 12-week period (*B* = .36, *SE* = 0.08, *t*(2737) = 4.68, *P* < 0.001).



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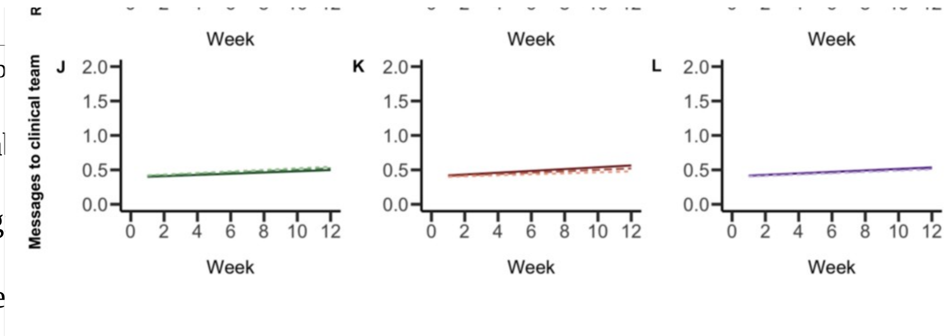

Figure 2. Character strengths and week-by-week engagement. Interaction effects derived from linear mixed effects models investigating the relationship between character strength factors and week-by-week platform engagement for the first 12 weeks since onboarding. The x-axis represents the week number and the y-axis represents the log-transformed engagement metric (**A-C**: time on platform; **D-F**: sessions on platform; **G-I**: reactions on the social network; **J-L**: messages to clinical team). Measurements of engagement metrics were log-transformed to allow comparability of the resultant coefficients. The solid lines represent the mean score on the character strengths factor, while the dashed lines represent one standard deviation (+/- SD) from the mean. The interaction effect is visualized by the divergence or convergence of the mean and the dashed lines over time.

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the 12 weeks (**Figure 2E;** *B* = .00, *SE* = 0.00, *t*(2837) = 3.02, *P* = .003). While scores on Courage and Creativity were unrelated to the rate of change in the number of sessions on the platform over the 12 weeks (**Figure 2F;** *B* = -.00, *SE* = 0.00, *t*(2837) = -1.26, *P* = .21), a significant main effect of Courage and Creativity scores on the number of sessions spent on the platform indicated that higher scores on this character strength were associated with fewer overall sessions on the platform (*B* = -.03, *SE* = 0.01, *t*(2863) = -2.64, *P* = .008).

Age (*t* = -0.06, *P* = .95), pronouns (all *P* > .05), and K10 score at enrolment (*t* = -1.02, *P* = .31) were not related to the number of sessions on the platform. Individuals whose treatment stage was unknown were more engaged with the platform, demonstrated by a greater number of sessions over the 12-week period (*B* = .13, *SE* = 0.05, *t*(2826) = 2.87, *P* = .004).

Use of the social network

We did not find evidence for interaction effects between week number and scores on Social Harmony (**Figure 2G;** *B* = -.00, *SE* = 0.00, *t*(1092) = -1.80, *P* = .07), Positive Determination (**Figure 2H;** *B* = -.00, *SE* = 0.00, *t*(1092) = -0.01, *P* = .99), or Courage and Creativity (**Figure 2I;** *B* = .00, *SE* = 0.00, *t*(1092) = 0.26, *P* = .80), suggesting that scores on these factors were not predictive of the rate of decline in use of the social network. In addition, we did not find evidence for a main effect of scores on Social Harmony (B = .04, SE = 0.02, $t(1252)$ = 1.89, P = .06), Positive Determination (B = .00, SE = 0.02, $t(1179)$ = 0.23, P = .82), or Courage and Creativity (B = -.01, SE = 0.02, $t(1113)$ = -0.47, P = .64) on the number of reactions posted on the social network. Nevertheless, a significant main effect of week number indicated an overall decrease in the use of the social network reactions over 12 weeks across individuals (B = -.04, SE = 0.00, $t(1092)$ = -20.84, $P < .001$). Treatment stage (all $P > .05$), age (t = -1.99, P = .05), pronouns (all $P > .05$), and K10 score at enrolment (t = -1.48, P = .14) were not related to the use of the social network over the 12-week period.

Messages with the clinical team

We did not find evidence for interaction effects between week number and scores on Social Harmony (**Figure 2J;** B = -.00, SE = 0.00, $t(1429)$ = -0.79, P = .43), Positive Determination (**Figure 2K;** B = .00, SE = 0.00, $t(1429)$ = 1.94, P = .05), or Courage and Creativity (**Figure 2L;** B = .00, SE = 0.00, $t(1429)$ = 0.43, P = .67), suggesting that scores on these factors were not predictive of a change in the number of messages sent to the clinicians. In addition, we did not find evidence for a main effect of scores on Social Harmony (B = -.01, SE = 0.01, $t(1596)$ = -0.65, P = .52), Positive Determination (B = .01, SE = 0.01, $t(1518)$ = 0.54, P = .59), or Courage and Creativity (B = .01, SE = 0.01, $t(1440)$ = 0.50, P = .61) on the overall number of messages sent to the clinical team. In contrast to the other platform engagement metrics, a significant main effect of week number indicated an overall increase in the number of messages sent over the 12 weeks (B = .01, SE = 0.00, $t(1429)$ = 6.55, $P < .001$). Furthermore, a significant main effect of age (B = .28, SE = 0.07, $t(1419)$ = 3.82, $P < .001$) suggested that older individuals had a greater number of interactions with the clinical team over the 12 weeks. Treatment stage (all $P > .05$), pronouns (all $P > .05$), and K10 score at enrolment (t = 1.87, P = .06) were not related to the number of interactions with the clinical team.

4.0 Discussion

In recent years, digital mental health interventions have generated significant public interest as an accessible and cost-effective treatment avenue for mental health problems. However, engagement remains an area of concern for these interventions. Indeed, a recent study found that only 3% of users still opened mental health applications one month after download (18). Adjusting digital platforms according to user needs is a key approach to ensuring user engagement and effectiveness. In this study, we examined whether users' scores on three character strength dimensions–'Social Harmony', 'Positive Determination', and 'Courage and Creativity'–were related to patterns of engagement on the MOST digital mental health platform. Our findings revealed that distinct character strengths were associated with dissociable patterns of user engagement. Specifically, individuals higher on Social Harmony, defined by traits such as kindness, teamwork, gratitude, and fairness, demonstrated high initial engagement that rapidly reduced over time. In contrast, both those scoring higher on Positive Determination (defined by traits of hope, enthusiasm, and perseverance) and Courage and Creativity (comprising creativity, humour, and courage) demonstrated modest initial engagement but steadier usage than those scoring lower on these character strengths.

Results from the longitudinal analysis reported in this study demonstrate how one's character strengths determine engagement patterns over time. These findings can be used to decide the timing at which platform features that enhance user engagement should be integrated. For instance, while individuals higher on Social Harmony may drop out at an accelerated rate due to symptom improvement, their propensity to drop out may also be attributed to reduced motivation. As such, they may benefit from early long-term goal setting, followed by regular automated reminders that encourage continued platform engagement, and personalised feedback on progress (19,67). Conversely, those scoring higher on Positive Determination and Courage and Creativity, who demonstrate more modest initial engagement, may benefit from supplementary human support during the first few weeks following enrolment. Interestingly, findings from the accelerated failure time model reported in this paper indicated that individuals receiving face-to-face treatment drop out at a faster rate. This result is consistent with the idea that engagement with a digital mental health intervention is influenced by the level of clinical contact that a user is receiving, such that individuals receiving face-to-face treatment may not have required additional intervention. Although therapist guidance is resource-intensive and may not be feasible for many low-cost digital mental health interventions, several recent studies have demonstrated that peer support can enhance feelings of social connectedness in a manner that also mitigates stigma and shame (68,69). Human support can also be replicated using AI chatbots—a feature that was recently shown to double engagement and enhance the effectiveness of a smoking cessation app (70).

Engagement with digital interventions is also thought to be determined by user experience, including the ease of use, gamification, layout, and visual appearance of a platform (71–74). Seeking feedback from individuals with lived experience who demonstrate lower initial engagement could improve the uptake and use of digital mental health interventions. For instance, individuals high in creativity who demonstrate low initial engagement may respond better to a platform that offers flexibility, self-expression, and features that align with their personal goals or creative preferences. Indeed, previous studies have provided evidence that personalising platforms to take into account factors such as one's personal capacity, level of motivation and illness severity can enhance engagement, reduce the requirement for clinical contact and lead to more positive attitudes towards the use of digital mental health interventions (67,75,76). Concerns around the security of personal information may be an additional determinant of early disengagement and dropout (77). Ensuring that users are informed about privacy and data security policies at the enrolment stage may help to address this issue.

While the results of this study offer valuable insights into the relationship between character strengths and engagement with digital mental health interventions, the substantial amount of missing data at the 12-week follow-up precluded our planned analysis of the relationship between engagement patterns and mental health outcomes. Missing data at follow-up time points is a common issue in digital health research and one that prohibits the robust investigation into the effectiveness of digital interventions (78). Without this data, it is not possible to investigate whether patterns of platform engagement directly translate into meaningful mental health improvements or sustained behavioural change. Previous studies that have investigated the degree of platform engagement that is required for significant decreases in clinical measures have yielded mixed results. The mixed findings might reflect the active versus passive engagement styles of different users (79–82). A study by Hoffman et al. (83) identified 3 clusters of engagement types, differing in terms of behaviour, cognitive and affective engagement, as well as the timing of engagement. 'Efficient engagers', who were highest on affective and cognitive engagement, demonstrated the greatest decline in depressive symptoms and stress. This data highlights the importance of measuring active user attendance (e.g., clicks on a page, entries into text boxes, etc.) rather than passive use of digital platforms. This leads us to another important limitation of the study. The engagement metrics reported here may not equally reflect user attendance on the different elements of the platform. Specifically, social network use and messages with the clinical team may reflect more active platform use. Indeed, a recent study demonstrated that use of the MOST social network in addition to engagement with therapy components was necessary for users to experience symptom improvements (84). On the other hand, time on the platform and the number of sessions on the platform may not adequately quantify the active time spent on the therapeutic journeys if users were not engaged with the material. Future studies should consider quantifying engagement as the number of clicks on a page, modules completed, entries into text boxes, or use eye-tracking metrics to determine where the user's attention is being directed.

The findings of this study suggest that different character strengths predict distinct patterns of engagement over time, with some individuals showing greater initial engagement but an accelerated dropout rate, while others demonstrate more modest initial engagement but a steadier decline in engagement over time. Our results demonstrate the importance of employing multi-component digital mental health interventions with flexible features that can meet the needs of a diverse range of individuals. The substantial decline in user engagement over 12 weeks also highlights the challenges of long-term engagement in digital health interventions and points to the need for more innovative approaches to retention in future research.

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Conflicts of Interest

The authors declare no competing interests.

Data availability

The data and code used to run the analyses and create the plots in this paper are shared openly on OSF (https://osf.io/suhgf/), and the pre-registration can be found at https://osf.io/7thfr.

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Supplementary Files

Multimedia Appendixes

Supplementary materials.
URL: http://asset.jmir.pub/assets/616c441ed6d68bdf6cea8e653b6ee727.docx