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Digital tools for executive dysfunction: Evaluating teletherapy features that improve attendance among adults with attention-deficit/hyperactivity disorder

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Abstract

Teletherapy offers new opportunities to address attendance challenges in adults with attention-deficit/hyperactivity disorder (ADHD). This quasi-experiment involved primary, prospective analyses of 15-week teletherapy attendance data from adults with ADHD, focusing on digital engagement and predictive modeling. Participants showed a female-to-male ratio of 3:1, with 12.8% identifying as trans men and 25.5% as non-binary, reflecting inclusivity of gender nonconforming, treatment-seeking clients. Average teletherapy attendance was 85.4% (standard deviation [SD] = 10.3%), significantly higher than prior in-person attendance of 72.3% (SD = 12.4%; $t[46] = 5.21$; $p<0.001$; $d = 1.15$). Attendance differed by ADHD subtype ($p=0.027$), with inattentive individuals showing the highest engagement. Attendance correlated positively with automated reminders ($\beta = 0.45$; $p<0.01$), self-scheduling ($\beta = 0.38$; $p<0.05$), and reminder acknowledgment ($r = 0.41$; $p=0.006$), and negatively with mobile-only device use ($r = -0.33$; $p=0.032$; odds ratio [OR] = 0.52, $p=0.041$). Logistic regression identified automated reminders as a strong predictor of adherence (OR = 3.4, $p=0.004$). Random forest classification achieved 87% accuracy (F1 = 0.86; area under the precision–recall curve = 0.89), with reminders, login latency, and age as top features. Interaction analyses showed subtype-specific effects: reminders benefited inattentive users ($\beta = 0.52$, $p=0.009$), and self-scheduling improved attendance among participants with combined subtypes ($\beta = 0.33$, $p=0.041$). Age modestly correlated with attendance ($r = 0.32$, $p=0.045$) but was nonsignificant in multivariate models. Sensitivity analyses confirmed robustness. Findings emphasize digital engagement and behavioral data as superior predictors of adherence compared to demographics, underscoring teletherapy's potential for neurodivergent adults across diverse gender identities.

Keywords: Attention-deficit/hyperactivity disorder; Teletherapy; Executive functioning deficits; Carepatron; Technological features; Automated reminders; Flexible scheduling; Attention-deficit/hyperactivity disorder subtypes

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1. Introduction

Attention-deficit/hyperactivity disorder (ADHD) is a lifelong neurodevelopmental disorder affecting over 60% of diagnosed individuals into adulthood, characterized by persistent symptoms of inattention, hyperactivity, and impulsivity.[1,2] Central to ADHD are significant deficits in executive functioning (EF), a set of higher-order cognitive processes that enable individuals to plan, initiate, regulate, and sustain goal-directed behavior.[3,4] These symptoms significantly impact daily functioning and quality of life.

EF theory conceptualizes these processes as essential for socio-emotional self-regulation and adaptive problem-solving.[3,4] EF includes inhibitory control, working memory, planning, and organization, which are essential for managing complex tasks and time effectively.[5,6] These EF impairments often hinder the ability to initiate, plan, and maintain engagement in structured activities such as psychotherapy, resulting in elevated dropout rates and poor clinical outcomes among adults with ADHD.[7-9] In addition, ADHD-related challenges in focus, prioritization, and translating therapeutic strategies into everyday life further diminish therapy adherence and effectiveness.[10,11]

Historically, technology has played a role in augmenting EF by providing external cognitive supports. Early devices such as clocks, watches, and personal digital assistants helped with calendar management and task reminders.[12] The rise of smartphones and digital calendars introduced more advanced tools, including programmable alarms and task management applications, significantly improving time management capabilities.[13,14]

Although EF deficits are common in ADHD, they are dynamic and can be supported through scaffolding, which involves external cognitive aids that compensate for internal regulatory challenges. Scaffolding may take social forms, such as caregiver guidance, or technological forms, like digital planners and reminders. Bal *et al.*[3] emphasize that interactive verbal scaffolding during screen use supports EF development, highlighting the importance of structured external supports. Specialized digital applications designed specifically for ADHD, including digital planners and reminder systems, have demonstrated effectiveness in improving task management and adherence.[15] More recently, innovations like virtual assistants and smart home systems have offered increasingly sophisticated means to support daily functioning for individuals with EF deficits.[16]

Teletherapy, as a mode of delivering health care, has become increasingly prevalent for neurodevelopmental and psychiatric disorders, offering critical flexibility and convenience for patients with EF challenges.[15,17] By eliminating travel requirements and facilitating flexible scheduling, teletherapy addresses key barriers to consistent therapy attendance that have been well documented in adult mental health services.[18-20] A meta-analysis confirmed teletherapy's comparable efficacy to in-person therapy across multiple disorders, including ADHD, and noted its potential to reduce dropout rates.[21] Key teletherapy platform features, such as automated appointment reminders and flexible self-scheduling, have been found to significantly enhance patient engagement and attendance by supporting behavior regulation and compensating for time management difficulties.[15,22,23]

Emerging translational models suggest that digital interfaces may function as externalized executive function scaffolds by providing just-in-time prompts and structured engagement cues, consistent with evidence from attentional cueing models in ADHD and engagement-focused behavioral health research.[14,24,25] These informatics-driven tools can offload EF burdens in ways that transcend convenience and actively mitigate core ADHD-related deficits. For adults with ADHD, these features may act not merely as convenience tools but as compensatory mechanisms that offset impairments in time-based prospective memory, attentional gating, and motivational regulation, consistent with cognitive and engagement-based models of ADHD self-management.[24-26]

While previous studies have demonstrated that teletherapy improves general attendance among ADHD populations, few empirical studies have examined the mechanisms underlying this effect, particularly the impact of specific teletherapy platform components on clinically relevant outcomes such as adherence, engagement, or EF support. This study builds directly upon prior work evaluating ADHD teletherapy attendance by focusing on a novel set of research questions:

(i). Which individual teletherapy platform features can significantly predict attendance among adults with ADHD?
(ii). Do these features function as external EF scaffolds, and how do their effects vary across ADHD subtypes?
(iii). Can platform behavioral telemetry enhance predictive modeling of adherence beyond demographic or diagnostic factors?

By addressing these questions, this study presents a primary, prospective informatics-focused analysis that isolates cognitive and platform-based mechanisms underlying teletherapy adherence, moving beyond general attendance outcomes explored in prior clinical reports. This enables evaluation of how digital feature design supports adherence through EF compensation, particularly within neurodivergent adult populations.

2. Methodology

2.1. Study design

This study employed a quantitative, quasi-experimental design to evaluate the impact of teletherapy on attendance and engagement among adults with ADHD. Participants voluntarily enrolled in a 15-week teletherapy program delivered through the Carepatron platform, a cloud-based, Health Insurance Portability and Accountability Act (HIPAA)-compliant electronic health record (EHR) and teletherapy practice-management system featuring secure video conferencing, appointment scheduling and reminders, a patient portal, and configurable clinical note templates. While Carepatron is designed primarily for outpatient and therapist-led workflows, its default telemetry and session-log functions for detailed feature-specific adherence were analyzed. All participants had prior formal ADHD diagnoses, confirmed through collateral data from previous in-person therapy and reassessed during the teletherapy intake. This design reflects a real-world clinical setting, allowing assessment of teletherapy effectiveness without random assignment.

The investigation focused on how specific digital features influenced session adherence, leveraging naturalistic telemetry and behavioral data collected independently by the clinical practice. Carepatron's platform served as the technological infrastructure but was not directly involved in data collection, analysis, or study design. The teletherapy program was delivered in a gender-affirming, neurodiversity-focused clinical setting, which informs both the population served and the observed demographic composition.

Importantly, this analysis represents a novel, primary, prospective investigation focused specifically on informatics features, cognitive framing, and feature-specific effects on adherence using data collected with separate clinical outcome aims. While prior work reported general improvements in attendance, this study extends those findings by modeling discrete digital affordances and their interactions with EF impairments. These analytic enhancements allow this study to examine digital therapy platforms not simply as delivery mechanisms but as interactive cognitive support systems that shape user behavior. The goal is to assess how such platforms can be personalized or adapted to accommodate neurocognitive diversity, especially in populations with EF deficits.

2.2. Participants

Adults aged 18–65 with formal ADHD diagnoses confirmed through clinical interviews based on the Diagnostic and Statistical Manual of Mental Disorders-5 criteria participated in this study. Inclusion criteria required participants to have one of the following ADHD subtypes: inattentive, hyperactive-impulsive, or combined, as determined by the Adult ADHD Self-Report Scale (ASRS) version 1.1. All participants had documented histories of prior in-person ADHD therapy, verified through collateral records. Individuals with major comorbid mental health conditions (e.g., severe depression, bipolar disorder) were excluded to avoid confounding treatment engagement outcomes. In addition, basic proficiency with the Carepatron teletherapy platform was required to ensure effective participation.

The sample was recruited entirely from Colorado, a state with a predominantly White population and a sizable, diverse LGBTQIA+ community. While the clinical team consisted primarily of Black, Indigenous, and people of color practitioners, race and ethnicity data were not systematically collected; demographic data collection was limited to gender identity. The resulting sample was racially homogeneous, with all participants self-identifying as White. This reflects the natural composition of the recruited population rather than intentional exclusion.

2.3. Recruitment

Participants self-referred to a specialized outpatient teletherapy clinic focused on LGBTQIA+, neurodiversity, and suicidality counseling. Interested clients consented to study participation after confirmation of the ADHD diagnosis through collateral sources, a clinical interview, and ASRS screening for subtype classification. Screening also assessed technological competency for engaging in teletherapy.

2.4. Materials

2.4.1. Carepatron teletherapy platform

The study used the Carepatron platform, a cloud-based, HIPAA-compliant practice management and EHR system designed for outpatient behavioral health and allied health services. According to the vendor, Carepatron uses AES-256 encryption and secure cloud infrastructure to protect electronic protected health information, in accordance with HIPAA requirements.

Key features include (i) secure video conferencing for teletherapy sessions, integrated with scheduling and clinical documentation; (ii) built-in appointment scheduling and client self-booking, with automatic email and SMS reminders; (iii) a client portal accessible through desktop and mobile devices, allowing clients to view appointments, complete forms, and access session links; (iv) standardized clinical documentation templates and digital intake forms within the EHR; and (v) default usage analytics, including

session attendance timestamps, reminder interactions, and scheduling patterns, which were used as data sources in this study.

These built-in tools were examined as digital supports that may affect adherence among adults with EF impairments. Usage data were extracted from the platform's default analytics dashboards and logs.

2.4.2. ASRS 1.1

The screening tool used in this study evaluated ADHD symptom severity and classified subtypes. These subtypes include inattentive, hyperactive-impulsive, and combined presentations. Specifically, ASRS version 1.1 was used to provide data for subgroup analyses and to reconfirm diagnoses for inclusion in the study.[27]

2.4.3. Collateral data

Prior in-person therapy attendance records were obtained through the appropriate release of information from former providers to establish baseline attendance and facilitate comparative analysis.

2.5. Procedure

Participants provided informed consent before enrollment and were asked if they were willing to engage in online therapy using a digital platform. All participants agreed and demonstrated intuitive engagement with the Carepatron EHR system. No specific computer or platform training was provided beyond basic client portal functions and the available tutorial materials on the EHR.

Participants engaged in weekly, 50-min teletherapy sessions over 15 weeks using Carepatron's secure video platform. The sole clinician, who is also the researcher and study author, provided dialectical behavior therapy tailored specifically to the needs of adults with ADHD. The treatment program included assessment and support for workplace accommodations and was flexible, adapting to each participant's unique presentation and situation.

While the primary focus of this study is on the informatics features of the Carepatron teletherapy platform and their relationship to session adherence, *The Neurodivergent Friendly Workbook of DBT Skills* was provided as an adjunctive, self-paced resource to support participants' engagement outside of sessions.[28] This allowed for monitoring of client portal use as part of the digital interaction data collected, supporting ongoing skill development and treatment engagement. This workbook, designed to be neurodivergent-affirming and accessible, was integrated into the teletherapy program but is not the focus of the present analysis. Both the study author and the workbook's author identify as neurodivergent, informing the neurodivergent-affirming approach to treatment materials and the design of the teletherapy program.

The program addressed ADHD-specific EF challenges, leveraging the platform's scheduling, reminder, and communication features to enhance adherence. Attendance data were automatically logged through Carepatron and cross-verified by a therapist to ensure accuracy. In addition to session attendance, the platform recorded metadata related to user interaction with key digital features, including timestamped reminder acknowledgments, login latency, self-scheduling behaviors, and session initiation timing. These behavioral data were used to explore how interaction with informatics features predicted adherence across ADHD subtypes.

2.6. Data collection and management

Attendance and engagement data were collected electronically through Carepatron's platform, stored securely in encrypted databases, and accessed only by authorized personnel. Behavioral telemetry data, including feature usage patterns and interaction sequences, were extracted for exploratory modeling. Data were retained for 3-year post-study and then securely destroyed in accordance with institutional guidelines to protect participant confidentiality.

2.7. Sample size and power considerations

While the primary objective of the study was exploratory, sample size considerations were guided by recommendations for multiple regression and classification modeling in behavioral research. A minimum subject-to-predictor ratio of 10:1 was targeted to balance model stability with feasibility in a clinical setting. With a final sample of 47 participants and a regression model including up to five predictors (e.g., digital feature usage and demographic covariates), the study meets minimal thresholds for statistical power ($\beta = 0.80$) to detect medium-to-large effect sizes ($f^2 \geq 0.15$) at $\alpha = 0.05$. Nonetheless, the sample size limits the ability to detect small effects or support complex interaction modeling with high statistical precision. Power-related limitations are further addressed in the discussion of model generalizability and robustness.

2.8. Statistical analyses

To evaluate the impact of teletherapy on attendance among adults with ADHD, a multi-tiered statistical approach was employed. The analyses were designed to provide both broad and nuanced insights by examining overall trends, demographic influences, and the role of specific teletherapy features. This study expanded upon prior work by modeling informatics-related predictors and exploring EF scaffolding through user–platform

interaction patterns. Analyses included descriptive statistics to establish baseline patterns, inferential tests to assess differences and associations, and multivariable models to control for potential confounding variables. The following subsections outline the statistical procedures used to ensure methodological rigor and interpretive clarity. All analyses were conducted in R (version 4.3.2) on Windows 11. Descriptive and inferential analyses were performed using base R and standard statistical packages, and machine learning models were implemented using established R libraries for logistic regression and random forest classification. Statistical significance was assessed using a two-tailed alpha level of 0.05.

2.8.1. Descriptive statistics

Descriptive statistics were used to summarize participant demographics and attendance data across the 15-week teletherapy program. Measures included the mean (M), median, and standard deviation (SD) of session attendance to capture central tendency and variability.

(i). Age analysis. Pearson correlation coefficients were calculated to assess the relationship between participant age and attendance frequency.

(ii). Educational attainment. Frequency distributions and analysis of variance (ANOVA) were used to evaluate attendance differences across three education levels: high school diploma or equivalent, bachelor's degree, and graduate education.

(iii). Employment status. Frequency distributions and ANOVA examined variations in attendance across employment categories: full-time, part-time, unemployed, and self-employed.

(iv). ADHD subtype and attendance patterns. Frequency distributions were also used to describe the prevalence of ADHD subtypes (inattentive, hyperactive-impulsive, and combined) and examine attendance trends across these groups.

(v). Feature usage patterns. Frequencies and averages were calculated for interactions with core teletherapy features, including the number of self-scheduled sessions, the number of acknowledged reminders, and the device type used (mobile vs. desktop).

(vi). Platform behavior timing. Temporal metrics (e.g., average login time before session, cancellation lead time, weekend vs. weekday usage) were included to capture cognitive offloading behaviors.

2.8.2. Inferential statistics

(a) Comparative analysis

To assess changes in attendance between prior in-person therapy and the teletherapy program, paired *t*-tests were conducted if the data met assumptions of normality; otherwise, the Wilcoxon signed-rank test was used as a non-parametric alternative. Effect sizes were calculated to determine the magnitude of observed differences: Cohen's *d* for *t*-tests and rank-biserial correlation for Wilcoxon tests.

(b) Subgroup analysis

To analyze attendance differences across ADHD subtypes, ANOVA was used for normally distributed data with homogeneity of variances; otherwise, the Kruskal–Wallis test was used. If significant differences were found, post hoc tests were conducted: Tukey's Honestly Significant Difference for ANOVA and/or Dunn's test for Kruskal–Wallis. Chi-square tests were also conducted to examine associations between categorical variables (e.g., employment status, self-scheduling use) and attendance outcomes. In addition, a Bonferroni correction was applied to adjust for multiple comparisons and reduce the risk of Type I error.

(c) Correlation analysis

To examine how specific teletherapy features impact attendance, Pearson or Spearman correlation coefficients were used, depending on data assumptions. Features analyzed included automated reminders, self-scheduling tools, and multi-device access. Pearson was used for normally distributed linear relationships, while Spearman was used for monotonic relationships in non-normally distributed data. Additional correlations included telemetry variables such as average login time before session, cancellation latency, and frequency of mobile vs. desktop access.

(d) Regression analysis

A multiple regression model was employed to predict attendance rates based on teletherapy platform features, while controlling for ADHD subtype, age, education, and employment status. This allowed the study to isolate the influence of technological features and demographic factors on attendance.

(e) Exploratory predictive modeling

As an extension, exploratory models using logistic regression and random forest classifiers were trained to predict high vs. low adherence based on combined demographic, diagnostic, and behavioral telemetry features. Adherence was dichotomized at 85% attendance (≥85% vs. <85%). Given the potential for class imbalance, the distribution of participants across adherence categories was explicitly examined. To address imbalance concerns, model performance was evaluated using multiple metrics, including accuracy, area under the receiver operating characteristic (ROC) curve (area under the curve [AUC]), F1-score, and precision-recall AUC, which provide a more

nuanced assessment of classification quality in the presence of imbalanced classes. Feature importance scores were also reported to identify key predictors.

(f) Feature selection and overfitting control

To mitigate overfitting and reduce model complexity, a limited set of input features was used based on theoretical relevance and exploratory bivariate correlations. No automated dimensionality reduction techniques (e.g., principal component analysis) were applied due to sample size constraints and the need for interpretability. In the logistic regression model, multicollinearity was assessed using variance inflation factors, and none exceeded the recommended threshold. For the random forest model, internal feature selection was handled through embedded permutation-based importance measures, which naturally down-weight redundant or uninformative predictors. No additional feature selection algorithm (e.g., recursive elimination, least absolute shrinkage and selection operator) was used.

(g) Model calibration assessment

In addition to standard performance metrics, the logistic regression model's calibration was evaluated using the Brier score, which measures the mean squared difference between predicted probabilities and actual binary outcomes. Lower Brier scores indicate better calibration and reliability of probabilistic predictions. Due to sample size constraints and the exploratory nature of the study, visual calibration plots (e.g., calibration curves) were not generated.

(h) Sensitivity analysis

Sensitivity analyses were conducted to assess the robustness of the findings across varying assumptions, including alternative model specifications, missing data strategies, and distributional assumptions. These tests helped ensure that observed effects were not artifacts of specific analytic choices. In addition, sensitivity checks tested whether predictive feature importance held across subgroups (e.g., low-income participants, older adults, or mobile-only users).

3. Results

3.1. Participant characteristics and dataset overview

The dataset included 47 adult participants diagnosed with ADHD who completed a 15-week teletherapy protocol. Participant ages ranged from 22 to 55 years (M = 34.5, SD = 9.2). Gender identity was distributed as female (46.8%), male (14.9%), trans men (12.8%), and non-binary (25.5%). Race data were not formally collected; all participants self-identified as White. Educational attainment was distributed as high school diploma or equivalent (21.3%), bachelor's degree (38.3%), and graduate degree (40.4%). Employment status included full-time (46.8%), part-time (21.3%), unemployed (17.0%), and self-employed (14.9%). ADHD subtype classification was inattentive (31.9%), hyperactive-impulsive (25.5%), and combined (42.6%).

3.2. Attendance metrics and telehealth engagement

Overall mean session attendance was 85.4% (SD = 10.3%). Attendance rates by ADHD subtype were inattentive (M = 87.2%, SD = 9.8%), hyperactive-impulsive (M = 82.1%, SD = 11.2%), and combined (M = 86.5%, SD = 9.1%). These figures represent engagement metrics at the participant level, used to inform both adherence modeling and interaction effects with digital health features.

3.3. Sample size and power analysis

Before conducting inferential and predictive analyses, an a priori power analysis was used to assess sample adequacy for multivariate modeling. With $N = 47$ and up to five predictors in the linear and logistic regression models, the study met the minimum subject-to-predictor ratio of 10:1, providing 80% power ($\beta = 0.80$) to detect medium-to-large effect sizes ($f^2 \geq 0.15$) at $\alpha = 0.05$. Although this sample limits the detection of small effects or complex interaction terms, it supports a valid estimation of primary main effects. Tables 1 and 2 summarize the inferential tests and multivariate models evaluating digital feature engagement and adherence outcomes across ADHD subtypes.

3.4. Summary of statistical analyses

Table 1 summarizes the key inferential statistics used to evaluate subgroup differences, the effects of digital features, and predictive modeling results.

Table 2 delineates the outcomes of multivariate modeling procedures employed to isolate the predictive utility of digital health platform affordances, specifically user-initiated interactions and temporal telemetry metrics on behavioral adherence within a clinically confirmed ADHD sample.

Table 2 summarizes the results of several predictive models assessing the relationship between digital feature use and session adherence. In the multiple linear regression model, both reminder use ($\beta = 0.45$, $p<0.01$) and self-scheduling ($\beta = 0.38$, $p<0.05$) were significant predictors of attendance, while ADHD subtype did not reach significance. The logistic regression model confirmed these effects; reminder use increased the odds of high adherence (odds ratio = 3.4, $p=0.004$), and mobile-only access decreased it (odds ratio = 0.52, $p=0.041$). The model achieved high discrimination (AUC = 0.84) and accuracy (81%). Random forest classification identified

Table 1. Inferential and exploratory analyses of ADHD subtypes, demographics, and digital feature effects on teletherapy attendance

Variable/subgroup	Feature(s)tested	Analysis type	Statistics/outcome
ADHD subtype	Reminders	Regression interaction	β = 0.52, p=0.009 (Reminder×Inattentive)
	Self-scheduling	Regression interaction	β = 0.33, p=0.041 (Self-scheduling×Combined)
Age (continuous)	Attendance	Pearson correlation	r=0.32, p=0.045
	Age as covariate	Regression	No significant feature×age interaction
Employment status	Self-scheduling	Chi-square	χ^2 (3) = 6.13, p=0.047 (Unemployed used self-scheduling more)
	Rescheduling frequency	Frequency comparison	Full-time participants rescheduled more sessions
Education level	Attendance	One-way ANOVA	F (2, 44) = 2.85, p=0.068 (trend-level difference)
Device type (Mobile vs. desktop)	Platform usage type	Correlation/logistic regression	r = –0.33, p=0.032; OR=0.52, p=0.041 (mobile use associated with lower adherence)
Login latency	Minutes before the session	Pearson correlation	r = –0.29, p=0.048 (longer latency associated with lower attendance)
Reminder acknowledgment	Count	Pearson correlation	r=0.41, p=0.006
Rescheduling frequency	Sessions rescheduled	Pearson correlation	r = –0.25, p=0.071 (trend-level negative association)
ADHD subtype (Main effect)	Attendance	ANOVA+Tukey's Honestly Significant Difference	Inattentive > Hyperactive-impulsive (p=0.027)
Attendance mode (Teletherapy vs. in-person)	Attendance rates (EHR vs. digital)	Paired-samples t-test	t (46) = 5.21, p<0.001; Cohen's d=1.15 (large effect)
Digital feature exposure	Reminder usage (binary)	Pearson correlation	r=0.62, p<0.001
	Self-scheduling tool (binary)	Pearson correlation	r=0.55, p<0.001

Note: Table 1 includes all exploratory, descriptive, and inferential statistics used to examine individual differences and feature-level associations before predictive modeling.
Abbreviations: ADHD: Attention-deficit/hyperactivity disorder; ANOVA: Analysis of variance; EHR: Electronic health record; OR: Odds ratio.

Table 2. Multivariate predictive modeling of digital health engagement and behavioral adherence in adults with ADHD

Model type	Predictors included	Key results	Performance/fit metrics	Interpretive notes
Multiple linear regression	Reminders, Self-scheduling, ADHD subtype	β (reminders) = 0.45 (p<0.01); β (self-scheduling) = 0.38 (p<0.05); ADHD subtype=not significant	R^2=0.46 (adjusted); F (3, 43) = 12.1, p<0.001	Digital features significantly predicted attendance beyond clinical subtype
Logistic regression	Reminders, mobile device use, subtype, age, education, employment	OR (reminders) = 3.4 (p=0.004); OR (mobile-only) = 0.52 (p=0.041)	AUC=0.84; Brier score=0.118; accuracy=81%	Reminders increase the odds of high adherence; mobile-only access reduces the odds
Random forest classifier	All digital features and demographics	Top features: Reminders, login latency, age, ADHD subtype	Accuracy=87%; F1=0.86; PR AUC=0.89	Model robust to feature noise; supports the importance of temporal behaviors
Permutation feature importance	All digital features and demographics	Reminders, login latency, age, subtype	Not available	Informatics metrics prioritized over demographic or diagnostic variables
Calibration assessment	Logistic regression probabilities	Brier score=0.118	Indicates good calibration (lower=better)	Model probability estimates aligned with observed adherence outcomes
Sensitivity analyses	Alternate specifications, missing data, interaction terms	No material change to the significance or rank order of key predictors	Results are stable across models	Increases confidence in generalizability given a small sample

Note: Table 2, a companion to Table 1, presents predictive modeling results, emphasizing the predictive value of digital feature interactions and telemetry metrics within a behavioral informatic framework.
Abbreviations: ADHD: Attention-deficit/hyperactivity disorder; ANOVA: Analysis of variance; AUC: Area under the curve; EHR: Electronic health record; OR: Odds ratio; PR: Precision–Recall.

reminders, login latency, age, and ADHD subtype as the most important predictors, with high overall performance (accuracy = 87%, F1 = 0.86). Permutation feature importance analyses ranked reminders and login latency as more influential than demographic variables. Calibration and sensitivity tests indicated the models were stable and well-fitted, with consistent predictor rankings and acceptable Brier scores.

4. Discussion

4.1. Principal findings and informatics interpretation

This study demonstrates that technology-enabled therapy substantially improves session adherence among adults with ADHD, with engagement metrics surpassing those of prior in-person care. The significant increase in teletherapy attendance rates, with a large effect size compared to historical in-person sessions, suggests that asynchronous scheduling and platform-enabled nudges effectively overcome traditional barriers such as scheduling conflicts, transportation, and stigma, which have consistently been identified as contributors to non-attendance in mental health services.[18-20]

These findings align with Liman *et al.*,[29] who analyzed EHR from adults with ADHD and psychiatric comorbidities, demonstrating that treatment response and changes are significantly influenced by patient engagement and demographic factors, supporting the critical role of patient engagement and personalization in shaping treatment response and real-world outcomes in digital mental health interventions.[25,29] In addition, Bryant *et al.*[30] conducted a meta-analysis on gamified digital mental health interventions, finding significant efficacy in improving ADHD symptom severity, further validating the benefits of incorporating interactive and engaging digital tools to enhance therapy adherence.

4.2. Gender distribution of treatment-seeking clients

The gender distribution observed in this study diverges significantly from typical male-to-female ratios reported in adult ADHD research, which commonly range from 2:1 to 3:1, favoring males.[31] In this sample, however, the ratio is reversed: approximately 14.9% of clients identified as male and 46.8% as female, with an additional 12.8% identifying as trans men and 25.5% as non-binary. This contrasts sharply with earlier studies that primarily classified participants within binary gender categories.

This atypical distribution likely reflects the clinical context: a gender-affirming teletherapy practice specifically designed to serve LGBTQIA+ and neurodivergent adults. Such settings may reduce barriers to care for individuals who have historically been marginalized or misrepresented in traditional clinical environments.[32,33] In addition, the broader gender spectrum observed may be influenced by the inclusivity and accessibility of technology-enabled teletherapy platforms, which can more effectively engage individuals who identify outside binary gender norms.[34]

These findings underscore the potential of technology-enabled mental health services to reach a more diverse adult ADHD population. Supporting this, a recent study reported a notable increase in ADHD diagnoses among females under the age of 35 in a post-COVID urban clinic, suggesting broader shifts in recognition and treatment-seeking patterns.[35] This aligns with the elevated representation of female and gender-diverse clients in the present sample, emphasizing the role of teletherapy in enhancing access and engagement for historically underserved gender groups.

4.3. Clinical informatics evaluation

User-facing functionalities embedded within clinical platforms act as digital adherence mediators by externalizing executive function demands such as memory, task initiation, and planning, consistent with evidence that reminder-based and text-based interventions improve engagement across health behaviors.[14,25] These platform features externalize EF demands, such as memory and task initiation, aligning with cognitive load-informed models of behavior change, which suggest that reducing internal cognitive burden can enhance sustained engagement, particularly for individuals with attentional dysregulation.[14,24] The positive correlation between age and attendance likely reflects the accumulation of compensatory organizational strategies and greater self-regulatory capacity over time, consistent with age-related findings in ADHD treatment and symptom management literature.[26,36] Behavioral telemetry measures, including login latency, reminder acknowledgment, and device switching, provide granular, real-time insights into engagement patterns and EF scaffolding, functioning as dynamic proxies for moment-to-moment fluctuations in attention and motivation that static clinical variables cannot capture.

Further emphasizing the expanding role of telehealth in ADHD treatment, Staley *et al.*[37] found that nearly half of United States adults with ADHD had engaged with telehealth services by late 2023; this reflects a marked shift in treatment-seeking behavior toward digitally mediated care. Such widespread adoption not only underscores the growing feasibility of remote interventions but also illustrates a shifting patient preference for flexible, stigma-reducing platforms, consistent with broader trends in

telehealth normalization and adoption among adults with ADHD.[18,37] When these modalities are integrated with informatics-driven personalization, they may mitigate executive dysfunction more effectively than static, in-person approaches; ultimately, they serve not merely as delivery mechanisms but as cognitive scaffolds that enhance adherence through dynamic, context-sensitive support.

4.4. User profiles: Understanding behavioral engagement through informatics

The findings of this study reveal distinct patterns of user engagement with a digital teletherapy platform among adults with ADHD. By interpreting behavioral telemetry and clinical data, we can characterize representative user profiles that reflect the heterogeneous ways in which individuals interact with digital health tools. These profiles provide actionable insights for tailoring platform features and informatics-driven personalization strategies that address the diverse needs of neurodivergent populations. The following user profiles synthesize the principal findings and elucidate the behavioral and clinical nuances underlying differential engagement trajectories.

4.4.1. Inattentive engager: Organized but forgetful

Individuals with the inattentive ADHD subtype demonstrated the highest levels of session adherence, strongly benefiting from automated reminders and self-scheduling functionalities. These users rely on digital nudges as external cognitive scaffolds that compensate for memory and task initiation deficits intrinsic to their condition. Their behavioral telemetry, characterized by low login latency and consistent acknowledgment of reminders, indicates effective integration of platform cues into daily routines. This profile underscores the critical role of thoughtfully timed, modality-optimized prompts in sustaining engagement among users with EF challenges.

4.4.2. Combined subtype autonomist: Flexible and feature-oriented

Users exhibiting combined ADHD subtype traits displayed a pronounced preference for autonomy in managing their therapy schedules. Self-scheduling tools were particularly salient for this group, enabling them to navigate fluctuating attention and impulsivity by exerting control over session timing. While automated reminders supported engagement, their effect was comparatively moderated. These individuals benefited from platform flexibility, including multi-device access and rescheduling options, highlighting the importance of adaptable digital architectures that can accommodate dynamic symptom profiles and lifestyle variability.

4.4.3. Hyperactive-impulsive user: Requirement for real-time engagement

Predominantly hyperactive-impulsive users were characterized by lower overall adherence and less consistent interaction with platform reminders. Their engagement patterns suggest that asynchronous features may not fully address their needs, given challenges with sustained attention and susceptibility to feature fatigue. The negative association with mobile-only use further implicates environmental distractions in reducing adherence. This profile suggests the necessity for real-time, interactive engagement mechanisms, such as gamification, immediate feedback loops, and dynamic prompts, to enhance motivation and counteract attentional lapses.

4.4.4. Mature digital adapter: Older adult with compensatory skills

Older adults in the sample exhibited higher attendance rates despite potential assumptions about lower digital fluency. Their success likely reflects accumulated organizational maturity and compensatory cognitive strategies developed over time. Telemetry data indicating shorter login latency and consistent acknowledgment of reminders further reinforces their disciplined engagement. This profile highlights the synergy between life experience and cognitive load-aware platform design, suggesting that digital health systems must accommodate not only usability but also nuanced cognitive scaffolding to maximize adherence across age groups.

4.4.5. Mobile-only user: Convenience with cognitive load trade-offs

Users who exclusively accessed the platform on mobile devices showed lower adherence, potentially due to increased distractibility and the higher cognitive demands of managing therapy on smaller screens. The lack of device-switching opportunities may reduce their capacity to engage flexibly with platform features. This profile points to a critical need for mobile interface optimization, focusing on reducing cognitive load and distractions by simplifying navigation and enabling focused interaction modes to support sustained attention in mobile contexts.

Table 3 summarizes user profiles derived from key behavioral engagement patterns, highlighting distinct characteristics and interactions with digital health platforms among adults with ADHD.

4.5. Predictive modeling and clinical phenotype

Predictive models confirmed that telemetry-based indicators demonstrated greater predictive utility than static demographic or clinical labels, aligning with

Table 3. Behavioral user profiles informing personalized teletherapy for adults with attention-deficit/hyperactivity disorder

User profile	Key behavioral features	Engagement pattern	Informatics implications
Inattentive engager	High reminder use, self-scheduling reliance	Highest adherence	External cognitive scaffolding is critical
Combined subtype autonomist	Prefers autonomy, flexible scheduling	Moderate to high adherence	Need adaptable, modular platform design
Hyperactive-impulsive user	Lower adherence, less consistent reminders	Lowest adherence	Requires real-time engagement, gamification
Mature digital adapter	Experienced, consistent reminder use	Reliable, sustained	Cognitive load-aware design benefits older adults
Mobile-only user	Mobile-exclusive, susceptible to distractions	Low adherence	Optimize the mobile user interface for reduced cognitive load

prior evidence that client-level engagement behaviors are stronger predictors of treatment adherence and outcomes than demographic characteristics alone.[19,25] Notably, the ADHD subtype lost statistical significance in multivariate models once platform feature use was accounted for, implying that behavioral engagement with digital affordances drives adherence more than underlying clinical phenotype. This suggests that digital platforms have the potential to "level the playing field" by compensating for symptom-driven barriers, highlighting the value of feature-driven personalization over categorical clinical subgroup targeting. The robustness of these models across statistical and machine learning approaches (logistic regression, random forests) underscores their promise for integration into digital health personalization engines and clinical decision support systems.

4.6. Teletherapy affordances by ADHD subtype

While all ADHD subtypes benefited from the digital intervention, attendance differed significantly by subtype, with inattentive individuals showing the highest engagement. This insight indicates opportunities for adaptive platform development through subtype-sensitive nudging or interface personalization. Hyperactive-impulsive users exhibited lower overall attendance, suggesting a need for alternative engagement strategies, such as real-time feedback loops or gamification, to counter potential feature fatigue. The differential interaction effects, in which reminders particularly benefited inattentive users and self-scheduling was most effective for combined subtype users, reinforce the importance of mapping digital interventions closely to subtype-specific executive dysfunction profiles, enabling more nuanced, clinically informed personalization.

4.7. Digital feature impact: Designing for executive function deficits

The strongest predictors of attendance were platform-level features explicitly designed to support EF. Automated reminders functioned as exogenous cognitive prompts, effectively reducing reliance on impaired memory and task management systems. Their large effect sizes suggest that timely, appropriately formatted digital nudging may function as effective therapeutic adjuncts, consistent with prior evidence demonstrating the efficacy of reminder-based interventions in improving adherence and engagement across clinical contexts.[14,19] Self-scheduling tools enhanced autonomy and minimized friction in aligning therapy with real-world demands, endorsing modular, asynchronous scheduling interfaces as critical components for populations experiencing fluctuating energy, mood, or focus. Features such as multi-device access and rescheduling flexibility also uniquely contributed to adherence; the lower engagement among mobile-only users may reflect limitations in cognitive load management or increased susceptibility to distractions on mobile devices, indicating a need for optimized mobile interface design tailored to sustained focus demands. In addition, session rescheduling frequency, though not statistically significant, trended toward instability in routines and may warrant exploration in adaptive scheduling interventions.

4.8. Informatics insight: Age, tech proficiency, and cognitive load

Contrary to the assumption that younger age and greater technological proficiency would enhance engagement, older adults exhibited higher attendance rates. This suggests that digital fluency alone is insufficient to drive adherence in neurodivergent populations. Instead, older users may bring greater organizational maturity, self-regulation experience, and motivation, which, combined with digital platforms that reduce cognitive load, results in improved adherence. This underscores the importance of cognitive load-aware system design that moves beyond usability to incorporate cognitive scaffolding for sustained behavior change, especially among users with fluctuating attention and impulse control. Behavioral telemetry can serve as a proxy for these latent compensation strategies; for example, older users may display shorter login latencies and more consistent reminder acknowledgments, providing actionable signals for platform adaptation.

4.9. Broader contextualization in clinical informatics

These findings contribute to the clinical informatics literature by evaluating real-world impacts of digital features on patient engagement, expanding the focus to neurobehavioral framing, and explaining differential outcomes by ADHD subtype and age. The study empirically supports data-driven personalization strategies in teletherapy, illustrating that modest digital interventions can yield disproportionately large adherence benefits when aligned with cognitive-behavioral profiles. By integrating traditional statistical and machine learning approaches, this work bridges clinical informatics with real-time decision support, positioning digital health systems to evolve toward precision behavioral modeling for complex, fluctuating conditions like ADHD. Moreover, the identified predictive features and telemetry could be leveraged in clinical decision support systems to dynamically tailor treatment pathways and allocate resources.

4.10. Design and implementation implications

For health informatics practitioners and digital therapy developers, three key takeaways emerge:

(i). Behavioral predictive modeling: ADHD subtype is not a significant predictor in multivariate models when platform feature use is accounted for, suggesting that behavioral telemetry logs are more powerful predictors of adherence than static clinical labels.

(ii). Personalization frameworks: Systems should advance toward real-time tailoring, where usage data inform adaptive workflows, nudging, and interface customization to maintain engagement.

(iii). Human–computer interaction considerations: The pronounced efficacy of reminders underscores the importance of attention-sensitive human–computer interaction principles, including optimized interface cues, modality selection (e.g., SMS vs. push), timing, and redundancy to address attentional dysregulation. In addition, device-specific engagement differences point to cognitive effort thresholds and situational constraints, advocating for differentiated interface designs for mobile versus desktop environments.

4.11. Limitations

From a data science perspective, several methodological limitations should be acknowledged. The modest, racially homogenous sample (N = 47, all White) with uneven gender distribution limits generalizability and precludes meaningful assessment of predictive model fairness or subgroup disparities across race, sex, and gender. Findings are further constrained by the single-platform context, being limited to Carepatron's feature set, which may not generalize to other teletherapy systems with differing functionality or user experience.

The retrospective, non-randomized comparison between in-person and digital attendance introduces possible confounds such as therapy setting preferences and COVID-19-related disruptions, limiting causal inference. In addition, this study did not capture granular usage metrics such as total time-on-platform or detailed clickstream data, restricting insight into deeper engagement patterns. The scope of passive telemetry was selective, focusing on behavioral features like reminders and login latency but excluding richer data such as screen time or interaction complexity.

Model calibration assessment was limited to the Brier score without visual calibration plots, due to sample size constraints. In addition, due to the modest sample size (N = 47), cross-validation and bootstrap validation were not employed to assess model stability. Instead, overfitting was controlled through theory-driven feature selection, variance inflation factor checks, and embedded permutation-based importance measures in the random forest models. This limitation may affect the confidence in the stability of the predictive models.

The absence of direct qualitative user feedback, interpretations regarding cognitive compensation mechanisms, and interface friction remains inferential. Future mixed-methods research is needed to validate these interpretations and explore user experience dimensions more rigorously. Despite promising initial findings, further studies with larger and more diverse samples are needed to validate these informatics-driven engagement strategies, as supported by Liman *et al.*,[29] Bryant *et al.*,[30] Amin *et al.*,[35] and Staley *et al.*,[37] who collectively stress the importance of ongoing real-world evidence to refine and optimize teletherapy interventions for ADHD across demographic and clinical subgroups.[29,30,35,37] Together, the limited sample size and single-platform context constrain the generalizability of these findings and warrant cautious interpretation when applying results beyond similar digital settings or populations. Reliance on a single teletherapy system also raises concerns regarding interoperability with other platforms and the potential for feature obsolescence, which may limit the long-term applicability of the informatics insights presented here.

4.12. Future directions

Building on these findings, several promising research trajectories emerge for clinical informatics and digital mental health innovation. Behavioral segmentation using machine learning could cluster users by real-world usage patterns rather than traditional diagnostic categories,

enabling adaptive, personalized care plans. Integration of behavioral telemetry into clinician dashboards may support real-time decision-making and intervention tailoring. Development of artificial intelligence-augmented adherence tools, such as natural language processing-driven recommendation systems, could automate personalized nudging strategies tailored to user preferences and engagement history. Predictive modeling can identify drop-off risk early, facilitating timely retention interventions. Future work should incorporate multimodal data sources, including wearables and biometric signals such as heart rate variability and sleep patterns, to explore physiological correlates of adherence and dropout risk. In addition, randomized controlled trials testing gamification strategies based on cognitive-behavioral game mechanics may provide novel engagement enhancements. Crucially, expanding research to racially and socioeconomically diverse populations is essential to ensure equitable benefit and prevent exacerbation of health disparities.

5. Conclusion

This study affirms the role of targeted informatics interventions in improving therapy adherence among adults with ADHD. By demonstrating that specific platform features, namely automated reminders and flexible scheduling, predict engagement more strongly than demographic or diagnostic variables, it highlights the importance of designing digital systems that align with neurocognitive profiles. New analyses involving behavioral telemetry and predictive modeling further show that interaction-level data (such as login latency, device switching, and reminder responsiveness) can outperform static clinical labels in forecasting session attendance. These findings emphasize the value of embedding real-time analytics and cognitive scaffolding into teletherapy platforms, moving beyond convenience to directly mitigate executive dysfunction. As teletherapy continues to develop, integrating granular usage data, adaptive interface behaviors, and artificial intelligence-driven personalization will be a key to building equitable, effective, and scalable mental health systems for neurodivergent populations.

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Conflict of interest

The author is the founding CEO and clinical director of Easy Does It Counseling and is under salary. The author declares no financial or commercial conflicts of interest related to this research. Carepatron, the teletherapy platform used, had no involvement in the study design, data collection, analysis, or manuscript preparation and provided no financial support. The authors' lived experience with neurodiversity informed the study design and interpretation but did not influence the outcomes.

Author contributions

This is a single-authored article.

Ethics approval and consent to participate

This study was conducted in accordance with ethical standards outlined in the Declaration of Helsinki. All participants provided informed consent before participation. The research procedures were reviewed by the author for ethical compliance and aligned with best practices for teletherapy and human subject research.

Consent for publication

Participants provided informed consent for the anonymized use of their data in research publications. No identifying information is included in the manuscript.

Availability of data

Due to the sensitive nature of participant information and ethical considerations related to confidentiality, full datasets cannot be publicly shared. However, de-identified, aggregate data and analysis code are available from the corresponding author upon reasonable request, subject to the author's approval, and compliance with ethical guidelines.

Further disclosure

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