ARTICLE IN PRESS

Archives of Physical Medicine and Rehabilitation

journal homepage: www.archives-pmr.org

Archives of Physical Medicine and Rehabilitation 2022;000: 1−8

ORIGINAL RESEARCH

Compliance With In-Home Self-Managed Rehabilitation Post-Stroke is Largely Independent of Scheduling Approach

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Abstract

Objective: To investigate how participants self-schedule their engagement with domestic rehabilitation gaming platform, and how their scheduling behavior in turn influence overall compliance.

Design: Cohort of individuals randomized to receive in-home rehabilitation gaming during a multi-site randomized controlled trial.

Setting: In-home self-managed rehabilitation.

Participants: Eighty community-dwelling participants who were >6 months post-stroke and had mild to moderate upper extremity impairment (N=80).

Interventions: Participants were prescribed 15 hours of independent in-home self-scheduled game play for upper extremity mobility over 3 weeks.

Main Outcome Measures: Total number of hours of active game play was objectively measured by the rehabilitation gaming system. Cluster analysis identified scheduling patterns from the following scheduling characteristics: total number of sessions, average session length, and consistency of play schedule.

Results: Four distinct scheduling profiles were revealed, 3 of which were associated with complete or near-complete compliance, while a fourth (inconsistent schedule of short, infrequent sessions) was associated with very poor compliance. Poor compliance could be predicted within the first 7 days of the program with 78% accuracy based on the same play pattern metrics used to identify player profiles.

Conclusions: Our findings support client autonomy in selecting the home practice schedule that works best for them, as compliance can successfully be achieved through a variety of different scheduling patterns. The objective measurements of compliance provided through rehabilitation gaming can assist therapists to identify individuals early on who exhibit scheduling behavior that is predictive of poor compliance.

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Disability increases 10-year mortality by about 50%,[1] largely due to accompanying physical inactivity.[1-3] People with post-stroke mobility limitations tend to be among the most inactive, only achieving about a quarter[4] of the recommended 5 hours of weekly exercise.[5,6] Physical inactivity after a stroke can contribute to worsening disability,[7] heightened cardiovascular risk,[7] cognitive decline,[8] and poor mental health.[8] Accordingly, the adverse health effects of disability can be largely counteracted through physical activity.[9,10] Participation in a physical rehabilitation or exercise program after a stroke is thus crucial to improving health and quality of life.[11]

Longstanding barriers such as transportation, rural dwelling, insurance caps, and cost have limited access to these programs for people with disabilities.[12] Following the outbreak of SARS-Cov-2, social distancing and safety concerns have further limited the number of individuals who can be physically present in

Presented at the UMOVE Research Symposium on February 6, 2021, to fellow researchers studying biological movement.

Dr Gauthier's contribution to this study was financially supported by The Patient-Centered Outcomes Research Institute (PCORI, AD-1409-20772).

Disclosures: Dr Gauthier is co-founder of Games That Move You, PBC, that developed the software used in this study and receives royalties. Ms Peznola is an employee of The MITRE Corporation. Ms Peznola's affiliation with The MITRE Corporation is provided for identification purposes only and is not intended to convey or imply MITRE's concurrence with, or support for, the positions, opinions, or viewpoints expressed by the author. The other authors have nothing to disclose.

0003-9993/$36 - see front matter © 2022 by the American Congress of Rehabilitation Medicine.
https://doi.org/10.1016/j.apmr.2022.10.007

rehabilitation centers and gyms.[13-15] In-home, self-led rehabilitation/exercise programs are thus becoming increasingly essential to meet the rehabilitation needs of stroke survivors.[14] Video games designed for in-home rehabilitation are accessible, engaging, objectively track progress,[16-18] and are as effective as in-clinic rehabilitation.[15,19-21]

Self-managed in-home exercise/rehabilitation programs lack the accountability and social support that comes from meeting with a therapist or trainer, however, and therefore they are often poorly adhered to.[15,16,22] Given that post-acute rehabilitation has been associated with improved motor capacity and functional independence[23]and that physical activity substantially reduces morbidity and mortality,[9,10,11] improving compliance to exercise/rehabilitation programs in the chronic phase post-stroke would convey notable effects to health and wellness.

One potential strategy that therapists employ in attempts to improve compliance is supporting clients in scheduling their home practice.[3,24] This strategy presumes that highly structured scheduling practices that mimic in-clinic participation will lead to better compliance among patients, but evidence for this is lacking. Research in other populations provides equivocal guidance. For example, prescribing more frequent, shorter bouts of exercise to healthy women resulted in about 25 minutes more exercise per week than prescribing fewer, longer bouts of exercise.[25] Conversely, longer bouts of engagement with a web-based depression treatment program were associated with greater long-term completion.[26] Yet, to our knowledge, the research literature provides little information to inform recommendations that therapists might give to patients regarding the interplay and balance between the frequency, duration, and consistency of sessions, as well as individuality in clients' scheduling preferences.[15,16,24,27,28]

Accordingly, this paper examines how participants self-schedule their engagement with a domestic rehabilitation gaming platform, and how these scheduling behaviors in turn influence overall compliance relative to the prescribed hours of gameplay. We employed machine learning techniques on a large dataset of self-managed game play from the video game rehabilitation for outpatient stroke (ie, VIGoROUS) multi-site rehabilitation gaming trial[29] to generate profiles of scheduling behavior, which were then related to the total duration of rehabilitation game play. We hypothesized that those who employed a more consistent and scheduled routine (eg, a participant who always interacts with the gaming system on a lunch break) would better comply to the prescribed rehabilitation regimen of 15 hours of play over a 3-week period.

Methods

Participants

Ninety-eight participants completed in-home self-managed upper extremity rehabilitation through a video game during the VIGoROUS multi-site randomized controlled trial from February 2016 through May 2019. Of these, 18 had some missing kinematic (joint location) data (eg, because of technical difficulties or staff accidentally deleting these data). As kinematic data were required to remove potential artifacts from the data stream,[17] these 18 participants were excluded from analysis. The multiparadigm computational approach of Yang et al was applied to the remaining 80 participants to filter out artifacts (eg, gaming system left on when not engaged in rehabilitation, family member playing the game).[17] The proposed methodology was thus applied to these 80 participants for whom we could guarantee the accuracy of the play time data logged by the gaming system. Participants were >6 months post-stroke and had mild to moderate upper extremity hemiparesis.[29] Active range of motion criteria included >10° in at least 2 fingers, thumb, and wrist; >45° shoulder abduction and flexion; >20° elbow extension (see published protocol for detailed inclusion criteria). Informed consent was obtained from all participants prior to study participation; the Institutional Review Boards of the participating sites provided ethical oversight.[26] Participants were randomly assigned to 1 of 4 groups with varying degrees of therapist intervention and remained naive to the study hypothesis.[29]

> ***List of abbreviations:***
> **ANCOVA** **analysis of covariance**
> **VIGoROUS** **video game rehabilitation for outpatient stroke**

Game-based rehabilitation intervention

All participants were prescribed 15 hours of independent in-home game play over a 3-week period using a commercially available custom gaming system (Games That Move You, PBC). Participants installed the gaming system themselves following up to 30-minutes of in-clinic supervised instruction to teach them how to interact with the system. The gaming system used motion-capture from a Microsoft Kinect v2 camera-based sensor to deliver a high-intensity (>400 movements per hour) upper extremity rehabilitation program. The game employed in this study was designed in collaboration with stroke survivors. It involved performing various exercises (grasp-release, supination, wrist flexion/extension, elbow flexion/extension, and shoulder flexion/extension/abduction/adduction) to navigate a kayak down a river, collect objects, avoid obstacles, and solve puzzles. The game generated unlimited gaming content "on the fly," such that the order of different obstacles and scenery was never exactly the same between different sessions. While all participants received the same game and exercises, therapists could personalize the balance of different exercises to an individual's needs. The gaming system emphasized both proximal and distal movements and progressed the required range of motion as the participant improved.[17,29,30] A sample of the gaming environment is shown in figure 1.

Participants could schedule their 15 hours of independent game play at their discretion. Once a participant began a gaming session, game content was continuously generated until the participant stopped or paused the game. Periodic summary feedback (ie, score for the game segment relative to previous attempts, motor speed, range of motion) was presented every 12-16 minutes.

Therapists provided periodic face-to-face consultation throughout the 3-week intervention period at a frequency that depended on the study group that participants were randomized to a single 2-hour session prior to independent game play, the same plus 3 periodic 1-hour consultations, or the same plus 3 periodic 1-hour consultations and 6 brief consultations via teleconference. After the 15-30 minutes of initial instruction in how to operate the game during the initial therapy consultation, therapist consultations focused exclusively on behavioral intervention targeting the participation of the paretic arm in daily life. Apart from varying the frequency of therapist contact, the intervention was otherwise identical between groups.

Fig 1 Screen shots of the game play. Nine combined proximal and distal movements (eg, shoulder flexion with elbow extension and supination, targeted reach and grasp) were used to interact with game objects and score points.[28]

Measurement of compliance

Compliance with the prescription was objectively measured as the *total number of hours* of active game play logged by the gaming system. The gaming system continuously logged therapeutic movements and time-stamped Microsoft Kinect v2 motion-capture data. A multi-paradigm computational method removed artifact (eg, someone walking past the sensor but not engaging in therapeutic game play or a different individual playing, epochs of game play in which the participant was resting) from the data stream prior to calculating active play time[17].

Full compliance was achieved if the participant completed the prescribed 15 hours of game play within a 3-week period. Proportional compliance refers to the percentage of prescribed exercise completed out of the prescribed 15 hours (eg, 12 hours played is a proportional compliance of 100 [12/15]=80% or 18 hours played is a proportional compliance of 100 [18/15]=120%). Proportional compliance was used to quantify compliance in relation to the 15-hour threshold. Proportional compliance was used to describe the compliance of individual patients, while full compliance was used to characterize the overall behavior of player profiles (eg, % fully compliant), and was also used in analyzing early indicators of poor compliance. A visual representation of participant play patterns is shown in figure 2.

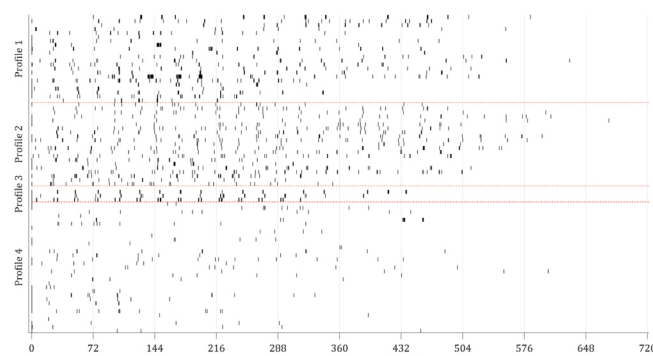

Fig 2 Participants were sorted by profile, indicated on the y-axis and separated by red dashed lines, with each row representing a different participant. The black bars reflect time spent in active game play, whereas white space reflects “downtime.” Even though patterns of active engagement and downtime exhibited by participants are highly complex and individualized, broad patterns in total number of sessions, average session length, and scheduling consistency associated with each profile can be observed.

Participants’ play pattern characteristics

A primary goal of the present study was to examine how different aspects of self-scheduled game play relate to overall compliance to the exercise prescription. We selected 3 distinct clinically applicable predictor variables that together characterize participant scheduling characteristics: total number of sessions, average session length, and consistency of play schedule. The distribution of participants in the space defined by these 3 variables is shown in figure 3: (1) Total number of sessions. A play session was defined as a time period of continuous engagement in game play in which interruptions in game play (breaks) did not exceed 5 minutes. The number of distinct play sessions was summed over the participation period; (2) Average session length (in minutes) was calculated as the mean duration across sessions; (3) Consistency in play schedule: We defined downtime durations as the time between the end of 1 session and the start of the next session where no active game play occurred. Participants who played on a consistent

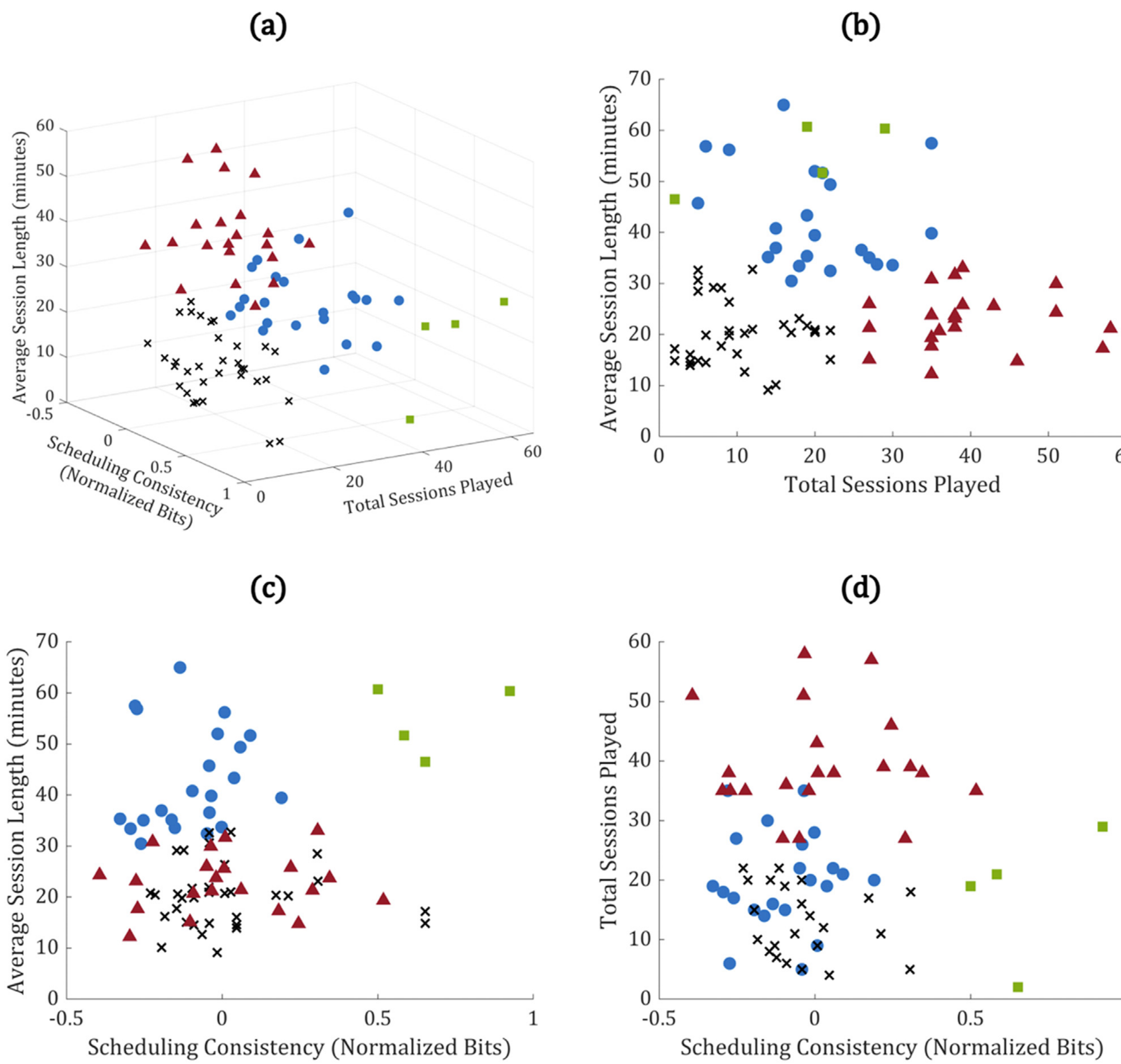

Fig 3 Data distribution and cluster assignments. (a) Scheduling profiles in the space of total number of sessions, scheduling consistency, and average session length. (b) Scheduling profiles in the space of total number of sessions and average session length. (c) Scheduling profiles in the space of scheduling consistency and average session length. (d) Scheduling profiles in the space of scheduling consistency and total number of sessions. Profiles are coded accordingly (Profile 1: blue circle, Profile 2: red triangle, Profile 3: green square, Profile 4: black X.

schedule (eg, after lunch and supper each day) would have relatively consistent intervals of time between sessions over the participation period (eg, 5- and 19-hour intervals between sessions would occur frequently). We thus defined consistency as relating to the predictability of the time between play sessions and quantified it in a single measure based on *information entropy*.[31,32] Information entropy, when applied to downtime between sessions for a particular subject, is based on the probability that observed down times will be of specific durations. Specifically, entropy for a participant is calculated as a sum over discrete duration probabilities of downtime, after multiplying by their log values. Probabilities of different downtime durations for a given subject are obtained by calculating a histogram of durations, and normalizing histogram frequency counts by the total number of downtime intervals with Laplace smoothing. Histogram bin widths are set to 5 minutes, with the total number of bins determined by the greatest downtime value of all 80 participants. Higher entropy thus indicates that play time occurred more randomly throughout the day, whereas lower entropy indicates a more structured, predictable, and consistent schedule.

Values of information entropy calculated using the histogram method are expected to display negative bias for small sample sizes (ie, people who played fewer sessions would show greater consistency). Indeed, the total number of sessions was found to have a strong negative exponential[33] relation with inconsistency in play schedule across participants. To negate this confounding effect, the residual values for entropy were computed from this negative exponential best fit model. As such, the entropy above/below what would be predicted based on the number of sessions served as our metric of consistency for all further calculations. As higher entropy values indicate more random session occurrence, we multiplied these values by -1 to reflect *consistency* of scheduling, rather than inconsistency, for ease of interpretation.

Thus, the consistency variable used here is an unbiased numerical value centered on 0 with units of normalized bits. The value itself represents the average amount of uncertainty associated with predicting downtime between sessions. Higher entropy thus indicates that play time occurred more randomly throughout the day, whereas lower entropy indicates a more structured, predictable, and consistent schedule.

Statistical approach to creating scheduling profiles

Cluster analysis is a collection of methods for grouping data points on the basis of their similarity, in other words for identifying groups of clusters of participants with similar scheduling profiles. We used k-means cluster analysis to group participants into clusters on the basis of the 3 predictor variables: scheduling consistency, average session length, and total number of sessions. K-means is a nonparametric method that is widely used for cluster analysis. Moreover, Bicalho et al have previously shown that k-means clustering is useful for the formation of behavioral scheduling profiles in single player games.[34] Clusters, once determined, can be considered distinct scheduling profiles that can be further characterized by examining the mean variable values of participants assigned to each cluster (ie, the k-means).

K-means relies on knowing the number of clusters to be found (ie, the value of k). The value of k was selected objectively using the silhouette method for evaluating the overall quality of clustering for a range of k values.[35] In the present analysis, values of k ranging from 2 through 5 were considered, as 6 or more scheduling profiles were assumed to be too many to reasonably track in a clinical context. Values of the 3 predictor variables were standardized prior to application of k-means so all variables were on a scale with a mean of 0 and a standard deviation of 1.

Statistical analysis of the effect of scheduling profiles on compliance

Differences in compliance (ie, total hours played) between scheduling profiles were analyzed using analysis of covariance (ANCOVA), followed by Kolmogorov-Smirnov significant difference test for post hoc pairwise comparison of profile differences. Given that the VIGoROUS study randomly assigned participants to different treatment groups that received different frequencies of physical therapist intervention, and that frequency of therapist contact could potentially influence compliance, treatment group was included as a covariate in the model. The effect of various demographic variables (age, chronicity, sex, and race) on player profile formation were also analyzed using 1-way analysis of variance,

Bootstrap approach to analysis of covariance

Prior to conducting the ANCOVA, conformity with normality assumptions were assessed using a bootstrap analysis on residual estimates of the mean. A Kolmogorov-Smirnov test on the subsample means led to the conclusion that the normality assumptions of ANCOVA were in violation based on a P value $<<0.01$. Critically, the addition of this bootstrap analysis allows us to assess the significance of the ANCOVA results irrespective of any data nonnormality.

To mitigate concerns over non-normality within our data, a bootstrap resampling methodology was implemented to empirically derive unbiased probability values via resampling our dataset to generate a null distribution. Scheduling profile assignments were resampled without replacement for 5000 iterations within the same ANCOVA model used for primary analysis. The rank of the P value from the actual analysis, relative to the distribution of P values derived from the resampled data, dictated the P value (ie, P = rank of P value from actual analysis/5000 iterations). A P value would have to fall within the lowest 5%, or the first 250 P values of the empirically derived null distribution, to be deemed statistically significant at $\alpha<0.05$.

Post hoc multiple comparison of means

Following the determination of a significant P value from the ANCOVA, post hoc multiple comparison tests were conducted via Kolmogorov-Smirnov significant difference test, α=0.05, to identify which scheduling profiles significantly differed from one another.

Results

Overall compliance

Of the 80 program participants, 22 (28%) fully complied by playing a minimum of 15 hours over a 3-week period, while 58 (72%) did not reach this benchmark. The mean compliance was 10.06 hours (67% of the prescribed 15 hours).

K-means clustering formed distinct scheduling profiles

K-means clustering was performed to group participants into distinct scheduling profiles on the basis of scheduling consistency, average session length, and total number of sessions (see figure 3). The mean Silhouette scores indicated that 4 or 5 clusters best categorized the data (mean Silhouette scores =0.52). Further examination revealed that the fifth cluster resulted from subdivision of 1 of the 4 clusters into 2 smaller groups and also rendered the data more challenging to interpret clinically. The more parsimonious 4 cluster grouping was thus chosen for further analysis. Table 1 summarizes each of the 4 clusters' play time characteristics. Table 2 demographically describes the subjects in each of the 4 clusters.

Pairwise comparisons of compliance between the profiles

ANCOVA revealed a significant effect of scheduling profile (P<.001). Post hoc multiple-comparison tests revealed that Profile 4 differed significantly from Profiles 1, 2, and 3, whereas the other 3 profiles did not differ significantly from one another. Sex, race, chronicity, and age were also found to not have significantly affected player profiles.

Follow-up analysis to determine early indicators of poor compliance

Given the large difference in compliance between Profile 4 and the other 3 scheduling profiles, we conducted a follow-up analysis to

Table 1 Descriptive characteristics of each scheduling profile and their relation to adherence

	Profile 1 *(n=22)*		Profile 2 *(n=21)*		Profile 3 *(n=4)*		Profile 4 *(n=33)*	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Average session length (min.)	42.75	9.96	22.83	5.67	54.81	6.94	20.24	6.17
Number of sessions	19.96	8.07	39.43	8.83	17.75	11.35	10.82	6.21
Scheduling consistency	-0.10	0.142	0.19	0.24	0.67	0.183	0.01	0.211
Total hours played	13.40	5.95	15.27	5.01	16.75	11.77	3.70	2.36
% Fully adherent	41%		48%		75%		0%	
Proportional adherence	89%		102%		117%		25%	
Qualitative description	Inconsistent schedule of long, moderately frequent sessions		Consistent schedule of short, frequent sessions		Very consistent schedule of long, moderately frequent sessions		Inconsistent schedule of short, infrequent sessions	

NOTE. A qualitative description of each pattern is provided on the last row of the table to ease interpretation.

determine if a pattern of short play times spaced inconsistently (scheduling Profile 4) could be detected early on in treatment. Early detection of a scheduling pattern predictive of subsequent lack of compliance could facilitate timely intervention by clinicians (eg, behavioral interventions to support compliance), potentially improving outcomes. To assess the feasibility of early prediction of lack of compliance, we built and tested a classifier model that attempted to predict whether or not a patient in our data set was associated with profile 4 on the basis of their play patterns during the first week. Specifically, we calculated the features for each subject using only their first 7 days of data. We then used those features to perform a Linear Discriminant Analysis with Mahalanobis distance to predict whether or not patients were labeled as being in profile 4 during the cluster analysis already described. It was demonstrated that the classifier model was able to predict with 78% accuracy, which is substantially higher than the baseline (ie, random guessing whether a given participant was a member of profile 4) accuracy of 59%.

Table 2 Demographic characteristics of each scheduling profile

	Age			
	Profile 1	Profile 2	Profile 3	Profile 4
Mean	59.74	57.64	62.88	63.04
	Chronicity			
	Profile 1	Profile 2	Profile 3	Profile 4
Mean	3.29	4.47	9.07	5.72
	Sex (%)			
	Profile 1	Profile 2	Profile 3	Profile 4
Men	68.18	61.90	25.00	60.61
Women	31.82	38.10	75.00	39.39
	Race (%)			
	Profile 1	Profile 2	Profile 3	Profile 4
White	40.91	100	75.00	54.55
African American	40.91	0	0	30.30
Asian	9.09	0	25.00	9.09
Hispanic	0.00	0	0	0
Pacific Islander	0	0	0	0
American Indian	0	0	0	0
Undisclosed	4.55	0	0	6.06
Other	4.55	0	0	0

NOTE. For each profile, the average age and chronicity (time since stroke occurrence) are presented along with the percentage breakdowns of age and race.

Discussion

A majority of program participants (72%) did not fully comply with the prescribed rehabilitation regimen. Using cluster analysis, we were able to identify 4 distinct and easily interpretable scheduling profiles. The relatively small differences in overall compliance between 3 of these profiles (less than 20% on average, not significantly different in pairwise analyses) suggests that clients may achieve compliance through a variety of different strategies. The fourth profile was significantly different in terms of compliance, with a much lower number of average hours played (25%). The therapist may therefore support and encourage a client's chosen approach. Clients can in fact successfully comply whether or not they strictly schedule their exercise, and regardless of whether they choose to exercise for long vs short bouts. This is consistent with a strong patient preference for flexible scheduling.[13]

While a variety of scheduling profiles were associated with greater compliance, noncompliant individuals tended to exhibit inconsistently scheduled, shorter sessions that occurred infrequently. This profile was present in 41% of participants, suggesting that a sizeable proportion of the stroke population requires extensive support to increase both the frequency and duration of their exercise participation. This profile differed most substantially from the other "short bout" profile in terms of session frequency. Those who ultimately meet the exercise prescription through the "short bout" strategy typically exercise at least daily or multiple times on a given day. This profile also exhibited a meaningful decrease in consistency of scheduling compared to the other "short bout" profile (Cohen's d=0.81). Clients who initially exhibit short sessions spaced days apart, and who perform these sessions at inconsistent intervals, may struggle with intrinsic barriers to exercise that required further intervention.[2]

Technologies that objectively track client behavior, such as rehabilitation gaming systems, can assist therapist in accurately identifying clients who require additional behavioral supports early on in their treatment program.[36] Given that therapist treatment is costly and time-limited, future work should employ n-of-1 methods to establish how modifying scheduling strategies can positively affect home exercise compliance among individuals with a suboptimal scheduling profile. Meanwhile, therapists may incrementally explore prescribing greater exercise frequency,[25] encouraging these individuals to engage in longer duration bouts of exercise, or more tightly scheduling their home exercise (eg, by having it follow other routine activities) to determine which, if any, of these approaches may improve compliance for these individuals. Of note, prescribing a greater frequency of exercise may be the most promising approach given its past success in enhancing exercise adherence and participant preference for shorter-duration exercise.[28,37,38] Long-duration continuous exercise may not be feasible for all individuals with neurologic disability given that only about one-third of participants in this study favored long-duration exercise. When scheduling manipulations are insufficient to promote compliance, the literature suggests that behavioral counseling that provides both accountability and support (eg, problem-solving through barriers to compliance with a therapist[39,40]) is a promising approach for increasing exercise behavior for noncompliant individuals, whereas approaches that rely on technology rather than human interaction are typically less successful.[41,42]

We presented here a novel methodology to quantify how individual variations in scheduling behavior ultimately relate to successful compliance to exercise/physical rehabilitation. This paper may therefore represent a first step toward developing targeted interventions aimed toward the subpopulation of individuals who demonstrate early indications of poor compliance to self-management. While the present findings are specific to neurorehabilitation post-stroke, the approach used here can be broadly applied to identify behavioral patterns associated with compliance across settings and populations. The continued growth of gamified rehabilitation as an effective,[43,44] accessible adjuvant to traditional therapy[20,21,45] renders this type of investigation essential for moving the field toward more efficient and personalized models of care.

Study limitations

Limitations of this study include an inability to establish causal relations between scheduling profiles and compliance given the observational study design. Possible limitations also stem from the choice of k-means clustering to infer scheduling profiles, which does not capture complex non-linear relations between the variables that may better categorize the data. Finally, we note that additional measures of play pattern characteristics may be possible to define, in addition to the 3 predictor variables chosen.

Conclusion

Our findings support client autonomy in selecting the home practice schedule that works best for them, as compliance can successfully be achieved through a variety of different scheduling patterns. The objective measurements of compliance provided through rehabilitation gaming can assist therapists to identify individuals early on who exhibit scheduling behavior that is indicative of poor compliance, such as short sessions scheduled infrequently, and at inconsistent intervals.

Keywords

Cluster analysis; Compliance; Game-based rehabilitation; Play profiles; Rehabilitation; Scheduling consistency; Stroke

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