Using Large-Scale Sensor Data to Test Factors Predictive of Perseverance in Home Movement Rehabilitation: Early Exercise Frequency and Schedule Consistency

Sangjoon J. Kim, Veronica A. Swanson, George H. Collier, Amanda R. Rabinowitz, Daniel K. Zondervan, and David J. Reinkensmeyer, *Senior Member, IEEE*

***Abstract*—Home-based exercises are an important component of stroke rehabilitation but are seldom fully completed. Past studies of exercise perseverance in the general public have suggested the importance of early exercise frequency and schedule consistency (in terms of which days of the week exercises are performed) because they encourage habit formation. To test whether these observations apply after a stroke, we leveraged data from 2,583 users of a sensor-based system (FitMi) developed to motivate movement exercises at home. We grouped users based on their early exercise frequency (defined across the initial 6 weeks of use) and calculated the evolution of habit score (defined as exercise frequency multiplied by exercise duration) across 6 months. We found that habit score decayed exponentially over time but with a slower decay constant for individuals with higher early frequency. Only the group with an early exercise frequency of 4 days/week or more had non-zero habit score at six months. Within each frequency group, dividing individuals into higher and lower consistency subgroups revealed that the higher consistency subgroups had significantly higher habit scores. These results are consistent with previous studies on habit formation in exercise and may help in designing effective home rehabilitation programs after stroke.**

***Index Terms*—Home-based rehabilitation, stroke, habit formation, perseverance.**

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the UC Irvine Institutional Review Board.

Sangjoon J. Kim is with the Department of Mechanical and Aerospace Engineering, Henry Samueli School of Engineering, University of California at Irvine, Irvine, CA 92697 USA, and also with Flint Rehabilitation Devices, LLC, Irvine, CA 92614 USA (e-mail: sangjojk@uci.edu).

Veronica A. Swanson is with the Department of Mechanical and Aerospace Engineering, Henry Samueli School of Engineering, University of California at Irvine, Irvine, CA 92697 USA.

George H. Collier is with the Shepherd Center, Atlanta, GA 30309 USA.

Amanda R. Rabinowitz is with the Moss Rehabilitation Research Institute, Elkins Park, PA 19027 USA.

Daniel K. Zondervan is with Flint Rehabilitation Devices, LLC, Irvine, CA 92614 USA.

David J. Reinkensmeyer is with the Department of Mechanical and Aerospace Engineering, Henry Samueli School of Engineering, University of California at Irvine, Irvine, CA 92697 USA, and also with the Department of Anatomy and Neurobiology, UC Irvine School of Medicine, University of California, Irvine, Irvine, CA 92697 USA.

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I. Introduction

STROKE is a leading cause of serious long-term disability with approximately 86 million people per year suffering from a stroke globally [1]. Long-term motor deficits are present in the majority of patients who experience a stroke [2], and those left with severe impairment have reduced independence and quality of life [3], [4]. Fortunately, the human motor system retains substantial capacity for plasticity, and it has been shown that impairment can be reduced with intensive rehabilitation [5], [6], [7], [8], [9], [10], [11], [12]. Rehabilitation exercise for stroke patients involves targeted physical activities and movements designed to improve motor skills, strength, and flexibility. However, it is believed that most individuals do not receive enough movement practice through in-clinic therapy to recover to their full potential [7], [13].

Home exercise programs are intended to increase the dose of exercise individuals receive, but the current standard of care (i.e. providing printed sheets of exercises), is associated with poor adherence and outcomes [14], [15], [16], [17], [18]. One estimate suggested that up to 65% of patients are non-adherent or only partially adherent to their home exercise programs [19]. Adherence problems are not unique to people with stroke. In the general public, the majority of adults (95%) struggle to meet the recommended physical activity guideline [20], citing time constraints as a main barrier [21]. Understanding factors to improve long-term engagement in home-based exercise is important for maximizing recovery in individuals following stroke and may be assisted by understanding exercise adherence in the general public.

A key factor that has been shown to lead to consistent exercise behavior is forming a habit, defined as acts that have become automatic responses to cues [22], [23]. A meta-analysis of 1,979 participants (7 unique datasets) found that habits and physical activity were moderately-to-strongly correlated [22]. Habits are important for establishing regular routines that become automatic and require less conscious effort [24], [25]. This automation reduces the cognitive burden associated with initiating and maintaining physical activity, making it easier to stick to a consistent exercise regimen. A longitudinal study of habit formation emphasized the importance of behavioral repetition and demonstrated that it took on average 66 days to develop a health-related habit such as healthy eating, drinking, and exercise [26].

To determine how weekly exercise time and frequency were related to habit formation, Kaushal and Rhodes [27] studied new gym membership in the general public using self-reported surveys that quantified 1) exercise frequency and 2) exercise automaticity. They found that the initial weekly exercise frequency predicted forming a habit of regularly going to the gym, finding that exercising for at least four bouts per week during the initial 6 weeks was the minimum requirement to continue to persevere with exercise over 12 weeks (3 months) [27]. Furthermore, they analyzed four antecedents - temporal consistency, reward, environmental cues, and low behavioral complexity - that are conducive to habit formation [24]. Among the four antecedents, Kaushal and Rhodes suggested that temporal consistency was the most important predictor followed by low behavioral complexity, environment, and affect [27].

Knowing the behavioral requirements for forming a habit can provide a foundation for designing effective interventions, guiding behavior change, tailoring approaches to individual needs, and ultimately improving health outcomes for not only physical activity in the general public but also for home-based rehabilitation applications. For example, in a recent study [28], we found that individuals showed the greatest perseverance with a home-based rehabilitation system (FitMi) if they had high but not perfect success during the 1st week of completing the exercise game, highlighting the importance of reward for perseverance. In addition we showed that steady use, in contrast to decelerating or accelerating use, was associated with perseverance. In this study, we were motivated by the work of Kaushal and Rhodes [27] to examine whether weekly exercise frequency and schedule consistency predict home exercise perseverance after stroke.

Towards this goal, we leveraged anonymous usage logs from a commercial sensorized home rehabilitation technology, called FitMi that was designed specifically for individuals with a stroke. FitMi is comprised of two puck-like sensors and software that visually guides the user through 40 therapeutic exercises for the hands, arms, legs, and torso in a game-like setting. Usage data (including the number of exercise repetitions, time spent exercising, and success rate during a session) are collected and saved to an online database. Therefore, an objective analysis of usage behavior is possible.

One thing to note is that FitMi users typically purchase the system themselves and utilize it independently, without direct supervision from a rehabilitation therapist. Thus, the study focuses on individuals who have taken proactive steps to continue their rehabilitation through the acquisition of a home rehabilitation technology. Although it is likely that FitMi users have higher levels of autonomy and self-efficacy indicated by their self-initiation of therapeutic home exercise programs, we hypothesize that there will be variations in perseverance that are predicted by early frequency and schedule consistency, even within this motivated subpopulation, based on prior habit formation research.

Fig. 1. Description of the FitMi system. A) FitMi system consists of 2 force and motion-sensing pucks, a charging station, and RehabStudio (a software application for gamified exercise). B) An example of an arm exercise (i.e., shoulder flexion exercise) that is shown in RehabStudio.

II. Methods

A. Description of FitMi

FitMi (Flint Rehab, LLC) is a commercially available FDA-listed medical device developed to help patients post-stroke perform various gamified movement exercises. The FitMi system consists of two sensorized "pucks", a charging station, and a tablet or PC running RehabStudio (software for gamified exercise) as shown in Figure 1. Each FitMi puck includes an inertia measurement unit (IMU) and a load cell used to monitor the movement and compression forces applied to the pucks. Each puck also includes a vibration motor used to provide haptic feedback when an exercise repetition is successfully completed. All sensor data is wirelessly transmitted to RehabStudio.

Forty different therapist-designed exercise games across four body regions: arms, hands, core, and legs are provided in

RehabStudio. Initially, users can interact with three baseline exercises per body region (the three easiest exercises selected by an experienced occupational therapist). For each exercise, users are asked to perform a given number of exercise repetitions within a set time. During an exercise, the allotted time to achieve the exercise is decreased or increased depending on the performance (instantaneous rate) of practice. For example, if a person stops exercising or cannot achieve a repetition for a particular exercise, time runs out more quickly. If a person succeeds in achieving repetitions, time is added to increase the remaining total time to achieve the target number of repetitions. If a user is able to achieve the target number of repetitions, the user will "level up". The difficulty increases with respect to the level requiring the user to perform more repetitions in a shorter time window. Once a user reaches a level of 10 (the maximum level) in an exercise, the user will go into "Infinite Play" mode and can no longer level up. The software unlocks additional exercises that were rated as functionally more difficult if the cumulative levels (of all currently unlocked exercises in the region) exceed a threshold (5, then 10, 15, 20, 25, 30, 40, 50). After unlocking an exercise, users can choose the exercises performed during the session. All usage data are uploaded to a secure online database managed by Flint Rehabilitation Devices after each exercise session.

The clinical efficacy of the FitMi system was recently shown in a single-blind, randomized controlled trial (N = 27) in the subacute phase of stroke [29]. Fourteen participants were assigned to use FitMi while thirteen were assigned to do conventional therapy (i.e., exercise using a paper-based exercise booklet). Participants were instructed to perform self-guided movement training at home for at least 3 hours/week for 3 consecutive weeks. Participants who used FitMi improved by an average of 8.0 $\pm$ 4.6 points on the UEFM scale compared to 3.0 $\pm$ 6.1 points for the conventional participants.

B. Data Acquisition and Cleaning

For this study, we used FitMi usage data from 2,747 individuals collected between June 20th, 2016 and December 15th, 2019. As we were interested in investigating the habit formation behavior across 24 weeks (6 months), we removed users who had the FitMi system for less than 24 weeks prior to the end of our data collection (exclusion of 493 users; 17.9%). We also removed user data who only used the FitMi system once (exclusion of 378 users; 13.8%). We found that the total number of repetitions performed by each user during their first 24 weeks had a lognormal distribution. Thus, we filtered outliers from the data using the log transform of total repetitions performed, excluding users with log-transformed data more than two standard deviations from the mean of the log-transformed data. This filter resulted in the exclusion of 103 (3.7%). A total of 1,773 users remained after filtration and outlier removal. The study was confirmed by the UC Irvine Institutional Review Board.

It is important to note that FitMi users typically buy the system out-of-pocket and use it without direct supervision from a rehabilitation therapist. Therefore, we are studying a group of users who have taken direct steps to continue their rehabilitation by acquiring a home rehabilitation technology. Furthermore, as the data is collected from commercial users, the data were anonymous without any identifying information (i.e., demographics, impairment level).

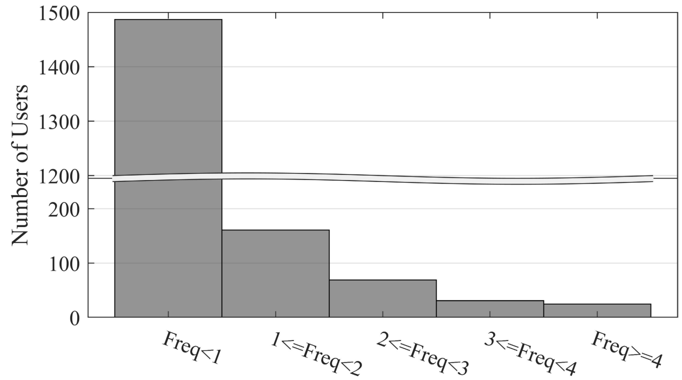

Fig. 2. Histogram of users grouped based on their initial exercise frequency (*Freq*). The majority of FitMi users (1,487 users) had an *Freq* less than 1. There were 161, 69, 31 and 25 users for the consecutive *Freq*s.

C. Data Analysis

1) Initial Exercise Frequency (Freq): We define initial exercise frequency (*Freq*) as the minimum number of days a user exercises per week during an initial 6-week window. For example, if a user has exercised 3 days/week during the first 4 weeks and exercised 5 days/week during the 5th and 6th week, the user's *Freq* is equal to 3 days/week. We first use an initial time window of 6 weeks based on the findings of Kaushal and Rhodes [27]. The histogram of the users grouped by their Freq is shown in Figure 2.

2) Weekly Habit Score: We adopted the definition of habit strength (time $\times$ frequency) presented in [27]. We calculate the weekly habit score (H) using:

$$H(\mathrm{w}) = T(\mathrm{w}) \times F(\mathrm{w}), \quad \mathrm{w} = 1, 2 \ldots 24 \tag{1}$$

where T is the weekly exercise duration (the total amount of time spent exercising in a given week) in hours for week w, and F is the weekly exercise frequency for week w. This definition of habit score favors higher weekly exercise frequency. For example, although the total time a user exercises was identical, a user who did a single 2-hour session during a week has a habit score of 2, while a user who did two 1-hour sessions during a week has a habit score of 4 (i.e., 2 hours x 2 sessions = 4 habit score).

We then fit a first-order exponential function to the 24-week time series habit score data for users grouped by their *Freq* using,

$$\tilde{H}(\mathrm{w}) = A_0 + A_1 \times e^{-A_2 \mathrm{w}}, \quad \mathrm{w} = 1, 2 \ldots 24 \tag{2}$$

where $\tilde{H}$ is the group median habit score for week w. Here A_0, A_1, and A_2 are constants. Using the following equation has the advantage that the constants A, A_1, and A_2 provide intuitive and psychologically meaningful results [26]. A_0 represents the asymptote of the exponential curve where the habit score reaches a steady state, such that larger values of A_0 indicate stronger lasting habits. A_1 is the difference between the asymptote and the modeled initial value of $\tilde{H}$ when w = 0, and A_2 is the decay constant at which the asymptote (plateau) is reached.

3) Schedule Consistency: To investigate the effects of schedule consistency on habit formation, we quantified how consistently individuals exercise the same days of the week across multiple weeks by calculating the coefficient of variation (C) between the matrix consisting of weekly binary arrays of active days. For example, if a user exercised every day except the last day of a week, the user's weekly binary array will be [1 1 1 1 1 1 0]. Here, an active day is defined as a day a user opened the FitMi software (RehabStudio) and performed at least one exercise repetition. C is calculated using the following equation:

$$C = \frac{\bar{\sigma}}{\bar{\mu}}, \tag{3}$$

where,

$$X_{ij} = \begin{pmatrix} x_{1,1} & \dots & x_{1,7} \\ \vdots & \dots & \vdots \\ x_{N,1} & \dots & x_{N,7} \end{pmatrix} \tag{3a}$$

$$\sigma = \sqrt{\frac{\sum (X - \bar{X}_{col})^2}{N-1}}, \tag{3b}$$

$$\bar{\sigma} = \frac{\sum \sigma}{7}, \tag{3c}$$

$$\bar{\mu} = \frac{1}{N} \sum \mu = \frac{\sum X_{ij}}{7N} \tag{3d}$$

Here X is the matrix consisting of the array of active days during a given week, $\bar{X}$ is the mean of the binary arrays across N weeks, σ is a vector with the standard deviations of active days for each day of a week (i.e., standard deviation of each column in X_{ij}), $\bar{\sigma}$ is the mean of σ, μ is a vector with the mean active days for each day of the week (i.e., mean of each column in X_{ij}), and $\bar{\mu}$ is the mean μ. C is calculated starting from week 2 and a smaller C value denotes higher consistency. Examples of users with different weekly behavioral patterns are given in Table I and the corresponding average coefficient of variation is shown in Figure 3. It is important to note that a higher number of weekly active days or total active days does not guarantee a lower coefficient of variation (i.e., higher consistency).

TABLE I
EXAMPLE OF USERS WITH DIFFERENT ACTIVE DAYS DURING 4 WEEKS. AN ACTIVE DAY IS REPRESENTED WITH A"1" AND A NON-ACTIVE DAY WITH A"0" IN THE BINARY ARRAY FOR EACH WEEK

	Wk 1	Wk 2	Wk 3	Wk 4	# of active days [days]
E1	[1111111]	[1111100]	[0000000]	[0000000]	12
E2	[1000000]	[1000000]	[1000000]	[1000000]	4
E3	[1000000]	[0100000]	[1000000]	[1000000]	4
E4	[1110000]	[1110000]	[1000011]	[1000011]	12
E5	[1110000]	[1001100]	[1001011]	[0000111]	12
E6	[1111110]	[1111101]	[1111011]	[1110111]	24

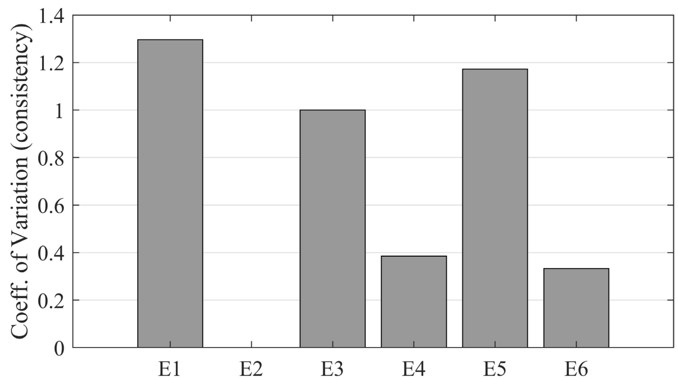

Fig. 3. Example of users with different weekly exercise consistencies. Smaller values of the consistency metric indicate more consistent weekly exercise patterns. The weekly active days for each user are summarized in Table I. A greater total number of active days does not guarantee higher weekly consistency.

D. Statistical Methods

We tested three main factors on long-term habit score in this study: the effect of initial exercise frequency (*Freq*), the window size of *Freq*, and schedule consistency (C). To test these factors, we investigated the following analyses: (1) the effect of different *Freq*s on the 24-week time series data of habit score, (2) the effect of the initial window size of *Freq* on the 24-week time series data of habit score, (II-C.3) the percentage of users from each *Freq* group who exercise more than 150 minutes per week (i.e., a dose that has been found previously to be sufficient to induce significant improvements in motor function after stroke [30]; this translates to at least a habit score of 2.5) across 24 weeks, (4) the effect of scheduled consistency within *Freq* groups, and (5) the number of total exercise repetitions performed after forming a habit (exercise repetitions performed between week 7 and week 24) for each *Freq* group.

To test whether there were significant differences between groups with different *Freq*s in analysis (1), (2), and (II-C.3), we used a non-parametric Kruskal-Wallis test on the 24-week median distribution to examine the statistical significance across *Freq* groups. Then we carried out post hoc pairwise comparisons between the median distributions using Tukey's Honest Significant Difference (HSD) test among *Freq* groups. For (4), we divided users within each *Freq* group into a high- and low-consistency subgroup using the median value of the coefficient of variation as the threshold for each *Freq* group. Then we compared the average habit score of the subgroups using a two-sampled t-test between groups. Finally, for (5), to compare the total exercise repetitions between groups with different *Freq*s, we used non-parametric Kruskal-Wallis and Tukey's HSD test. All analyses were conducted in Matlab 2021b [31].

III. RESULTS

A. Initial Exercise Frequency Predicts the Steadiness of Habit Score

We first analyzed how the 24-week group habit scores trajectories (defined as weekly exercise duration × frequency)

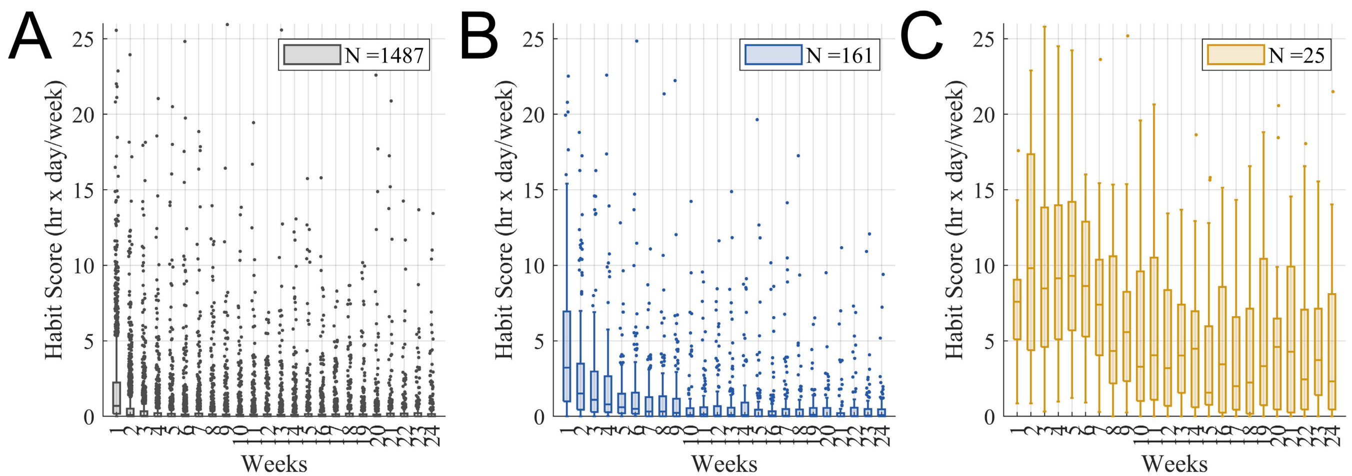

Fig. 4. Twenty-four week (i.e., 6 months) habit score of A) users with an *Freq* < 1 day/week (N = 1,487), B) users who with a 1 ≤ *Freq* < 2 days/week (N = 161), and C) users who had an *Freq* ≥ 4 days/week (N = 25). Boxplots include the group median, the 25th percentile, 75th percentile, and outliers. In this figure, trends of groups with Freq < 1 days/week, 1 ≤ Freq < 2 days/week, and Freq ≥ 4 days/week are only shown as they are the most representative groups with distinct characteristics. Groups with 2 ≤ Freq < 3 days/week and 3 ≤ Freq < 4 days/week showed similar characteristics with group 1 ≤ Freq < 2 days/week but had a slower exponential decay rate (Supplementary Material).

varied for users with different initial frequencies (i.e., *Freq*) (Figure 4). The median habit score of the group with *Freq* < 1 days/week converged to zero starting from week 4, while the group with 1 ≤ *Freq* < 2 days/week converged to approximately zero starting from week 10. Similarly, the group with 2 ≤ *Freq* < 3 days/week and 3 ≤ *Freq* < 4 days/week also converged to zero starting from week 11 and week 15, respectively. The twenty-four-week habit score for all frequency groups including the group with 2 ≤ *Freq* < 3 days/week and 3 ≤ *Freq* < 4 are shown in the Supplementary Material, Figure S1. The median habit score of the group with *Freq* ≥ 4 days/week did not converge to 0 during the 24-week period (6 months). Exponential curves well fit the 24-week median habit scores for all *Freq* groups (Figure 5, R^2 > 0.95 for all groups except the group with *Freq* ≥ 4 days/week which had R^2 = 0.75)

The decay constant (i.e., A_2 from equation 2) which relates to the inverse of time the time it takes to reach the steady state was smaller for groups with higher *Freq*s (Table II). For instance, the decay constant was 4.1 times larger for the group with 1 ≤ *Freq* < 2 days/week compared to the group with *Freq* ≥ 4 days/week, indicating that low *Freq* decay was 4.1 times faster than high *Freq* decay. The decay constant was also 80 % larger when compared between the group with *Freq* ≥ 4 and 3 ≤ *Freq* < 4. Also, the asymptotes (i.e., A_0 from equation 2) of all groups except the group with *Freq* ≥ 4 days/week were approximately 0 (Table II). The Kruskal-Wallis test yielded statistical significance ($p < 0.001$) indicating overall group difference between habit score trends. Subsequent, pairwise comparison indicated that the habit scores between all groups were statistically highly different (Tukey's HSD, $p < 0.001$) except between the group with *Freq* < 1 days/week and the group with 1 ≤ *Freq* < 2 days/week (Tukey's HSD, $p = 0.0265$) and between the group with 3 ≤ *Freq* < 4 days/week and *Freq* < 4 (Tukey's HSD, $p = 0.0423$). There were no statistical differences between groups with 1 ≤ *Freq* < 2 days/week and the group with 2 ≤ *Freq* < 3 days/week (Tukey's HSD, $p = 0.9273$) and between 2 ≤ *Freq* < 3 days/week and the group with 3 ≤ *Freq* < 4 days/week (Tukey's HSD, $p = 0.1681$).

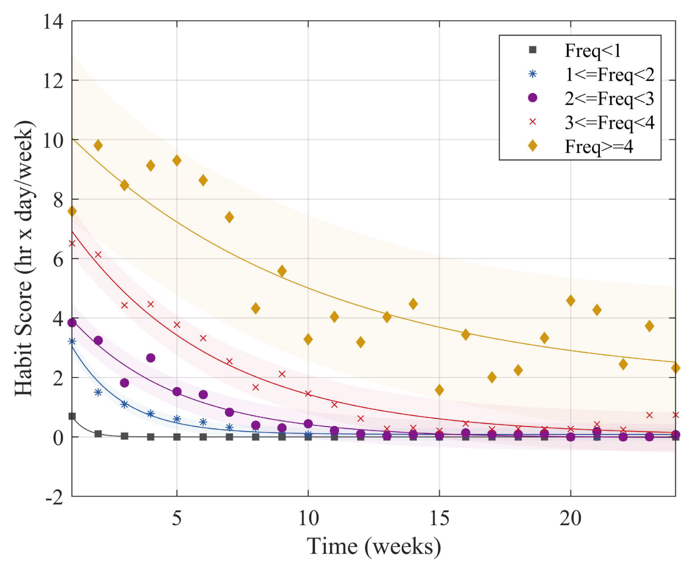

Fig. 5. The 24-week median habit score of groups with different *Freq*s and the first order exponential fitting function (shaded areas represent the 95 **%** confidence interval of the fit).

B. The Window Size of the Initial Exercise Frequency Matters

Based on the study of [27], we initially used a window size of 6 weeks as our estimate of time required to form a habit. To investigate the impact of the window size, we compare the 24-week habit score for users with an *Freq* ≥ 4 days/week for different window sizes. We varied the window size from 2 weeks through 8 weeks (Figure 6). For example, the '2wk' group includes users who had an *Freq* ≥ 4 days/week for only the initial 2 weeks while the '3wk' group includes users who had an *Freq* ≥ 4 days/week for the initial 3 weeks. Results showed that the habit score of users with a window size of

TABLE II
FIRST-ORDER EXPONENTIAL FITTING PARAMETERS FOR THE HABIT SCORE OF GROUPS WITH DIFFERENT *Freq*. 95% CONFIDENCE INTERVALS ARE SHOWN IN BRACKETS

Freq [day/week]	Decay constant (A_2) [week^{-1}]	Asymptote (A_0) [hr × day/week]	R-square
Freq < 1	1.87 (1.80, 1.94)	0.00 (0.00, 0.00)	0.99
$1 \leq$ *Freq* < 2	0.51 (0.43 0.59)	0.09 (0.02, 0.15)	0.97
$2 \leq$ *Freq* < 3	0.24 (0.19, 0.30)	-0.03 (-0.21, 0.15)	0.95
$3 \leq$ *Freq* < 4	0.18 (0.14, 0.21)	0.03 (-0.33, 0.4)	0.97
Freq ≥ 4	0.10 (0.01, 0.20)	1.76 (-1.14 4.66)	0.75

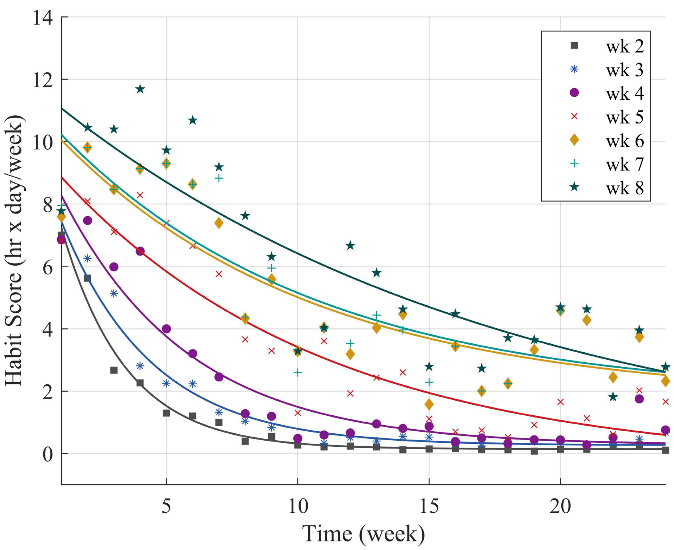

Fig. 6. Habit score of users with an *Freq* $\geq$ 4 for different window sizes.

TABLE III
PAIRWISE TUKEY'S HONEST SIGNIFICANT DIFFERENCE (HSD) TEST BETWEEN DIFFERENT WINDOW SIZES OF *Freq*

	2wk	3wk	4wk	5wk	6wk	7wk	8wk
2wk		0.188	0.0214	<0.001	<0.001	<0.001	<0.001
3wk			0.325	0.0113	<0.001	<0.001	<0.001
4wk				0.121	<0.001	<0.001	<0.001
5wk					0.0765	0.0667	0.0128
6wk						0.950	0.474
7wk							0.513
8wk							

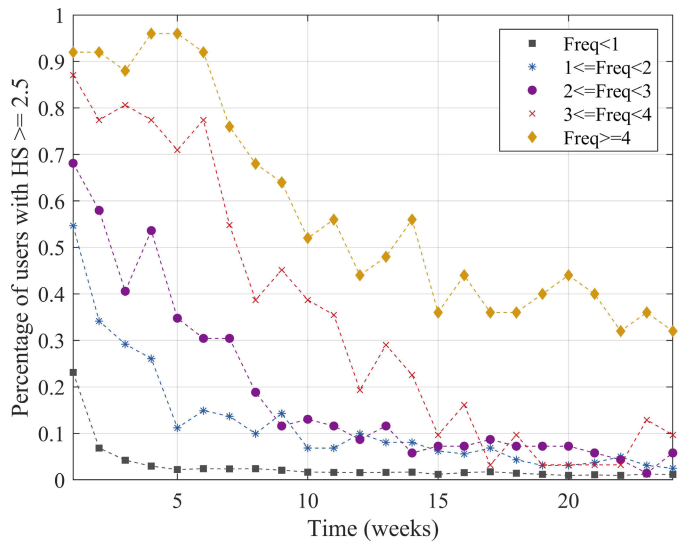

Fig. 7. Percentage of users who had a habit score larger or equal to 2.5 for each *Freq* group.

less than 4 weeks converged to 0 and users with a window size of 5 weeks converged to 0.59 at week 24. On the other hand, users with a window size of 6, 7, and 8 converged to approximately 2.3. The Kruskal-Wallis test yielded statistical significance ($p < 0.001$) indicating overall group difference between habit score trends. Subsequent, pairwise comparisons are shown in (Table III). Having an initial window size of 5 weeks was marginally significant compared to a window size of 6 and 7 ($p = 0.0765$ and $p = 0.0667$, respectively). Having a window size of 6, 7, and 8 were not significantly different. We only tested the effect of window size for the group with *Freq* $\geq$ 4 as it is the only group that was able to form a long-term habit across 24 weeks. Note that we only included the group with Freq $\geq$ 4 days/week as this was the only group that was able to achieve long-term perseverance across the 24 week window of observation. The same analysis for other Freq groups are shown in the Supplementary Material, Figure S2.

C. Percentage of Users Who Did More Than the Recommended Exercise Standard

The percentage of users in each *Freq* group who did more than 150 minutes/week of exercise (i.e., a dose that has been found previously to be sufficient to induce significant improvements in motor function after stroke [30]; this translates to at least a habit score of 2.5) is shown in Figure 7. All groups except the users with an *Freq* $\geq$ 4 days/week converged to less than or equal to 10% at week 15. Approximately 37% of the users who had an *Freq* $\geq$ 4 days/week maintained a weekly dose that has been found previously to be sufficient to induce significant improvements in motor function [30] during 22 weeks. The Kruskal-Wallis test yielded statistical significance ($p < 0.001$) between the survival graphs for groups with different *Freq*. Subsequent, pairwise comparison indicated that all groups were statistically highly different (Tukey's HSD, $p < 0.001$) except between the group with $1 \leq$ *Freq* < 2 days/week and $2 \leq$ *Freq* < 3 days/week (Tukey's HSD, $p = 0.840$), between the group with $1 \leq$ *Freq* $<$ 2 days/week and $3 \leq$ *Freq* < 4 days/week (Tukey's HSD, $p = 0.1242$), between the group with $2 \leq$ *Freq* < 3 days/week and $3 \leq$ *Freq* < 4 days/week (Tukey's HSD, $p = 0.670$) and between the group with $3 \leq$ *Freq* < 4 days/week and *Freq* < 4 days/week (Tukey's HSD, $p = 0.093$).

D. Higher Scheduled Consistency Predicts Higher Habit Score

Average scheduled consistency and habit score over the lifetime of FitMi usage were moderate to strongly correlated (Pearson correlation, $r = 0.67$, p-value < 0.001). We compared the average habit scores of users within *Freq* groups in order to see the effect of consistency (Figure 8). Each *Freq* group was divided into a "low-consistency subgroup" and a "high-consistency subgroup" using the median value of the coefficient of variation as the threshold. The "high-consistency

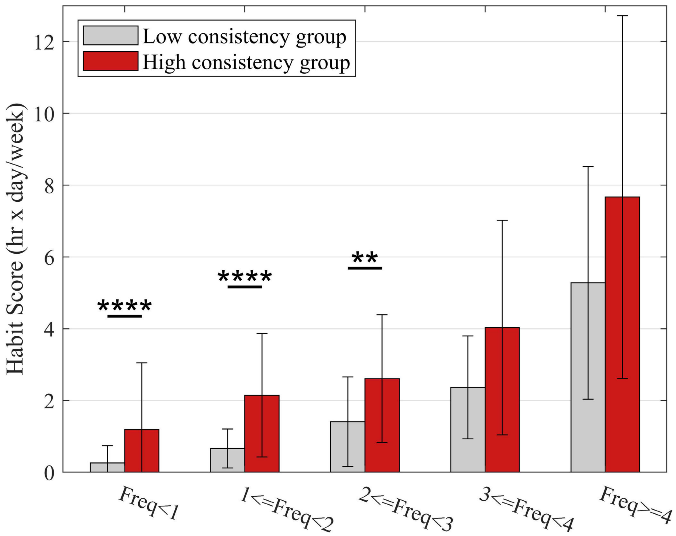

Fig. 8. Average habit score of users with low- and high-consistency within *Freq* groups. A two-sampled t-test showed significance between low- and high-consistency groups for users with an *Freq* less than 3. (∗∗∗∗) represents a p-value ≤ 0.0001 and (∗∗) represents a p-value ≤ 0.01.

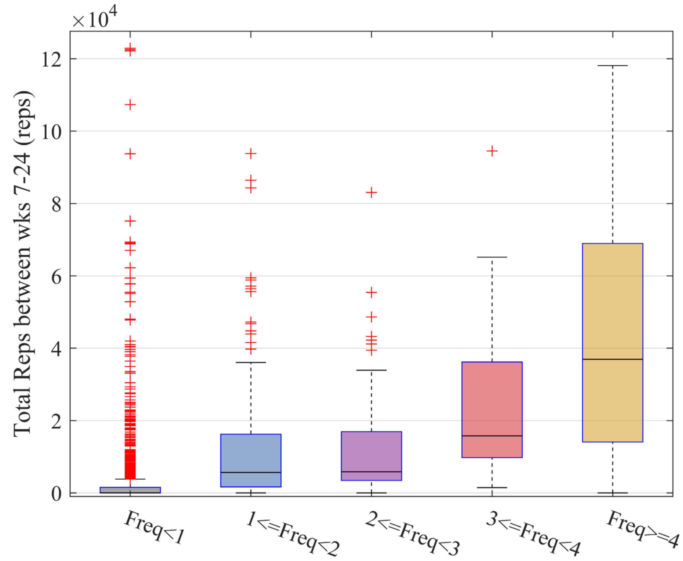

Fig. 9. Comparing the number of total exercise repetitions performed after forming a habit (i.e., between week 7 and week 24) for groups with different *Freq*s. The boxplots include the group median, the 25th percentile and the 75th percentile.

subgroup" showed higher average habit scores across all *Freq* groups (Figure 8). The high-consistency subgroup had a significantly larger habit score (t-test, p-value < 0.01) for the three groups with an *Freq* < 3 days/week. There was no significant difference in the habit score for users with $3 \leq$ *Freq* < 4 (t-test, p-value $= 0.06$) and for the *Freq* ≤ 4 group (t-test, p-value $= 0.17$).

E. Higher Habit Scores Predict Higher Total Exercise Repetitions

The number of total exercise repetitions a user performed after the putative habit formation window (i.e., between week 7 and week 24) was moderately correlated with habit score (Pearson correlation, $r = 0.53$, p-value < 0.001) across users with *Freq* ≥ 1 day/week. The total number of exercise repetitions performed after the putative habit formation window was greater for groups with higher initial exercise frequencies (Figure 9). The group with *Freq* < 1 day/week had a median of zero where there were 233 outliers, which means that the majority of users within this *Freq* group did not exercise with the FitMi system between week 7 and week 24. The median repetitions (25th and 75th percentile) were 5,663 (1,666, 16,236), 5,854 (3,470, 16,954), 15,768 (9,754, 36,189), and 36,941 (14,089, 68,944) repetitions with respect to the groups with *Freq* between 1 and 2, 2 and 3, 3 and 4, and greater than 4 days/week (Figure 9). The total number of exercise repetitions that the group with *Freq* < 1 day/week performed was significantly less than that performed by all other groups (Tukey's HSD, $p < 0.001$). There was no significant difference between the total exercise repetitions for groups with $1 \leq$ *Freq* < 2 and $2 \leq$ *Freq* < 3. Groups with an *Freq* ≥ 3 did significantly more exercise repetitions compared to those with *Freq* ≤ 3 (Tukey's HSD, $p = 0.029$). There was no significant difference between the total repetitions performed for groups $3 \leq$ *Freq* < 4 and *Freq* ≥ 4.

IV. Discussion

Weekly exercise frequency and scheduled consistency during an initial period of exercise predicted exercise perseverance with a home-based rehabilitation system after stroke. Users with high initial exercise frequency measured during the initial 6 weeks of use (i.e., the variable we named"*Freq*") showed steadier habit score profiles across 6 months. The rate at which habit score decayed toward a steady state decreased with higher *Freq*, meaning these users persevered longer with the system. Only the frequent user group that had a *Freq* ≥ 4 days/week had a non-zero habit score asymptote, setting to a median habit score of 2.3 hours × days/week at 6 months (which corresponds to approximately a single 138-minute exercise per week or two 35-minute exercise sessions per week). This is important as it has been previously found that doing at least 150 minutes of exercise per week was sufficient to induce significant improvements in motor function after stroke [30]. As a result of having steadier habit scores, users with higher *Freq* did significantly more exercise repetitions after the putative habit formation window (i.e., during week 7 through 24). Within groups with different *Freq*, dividing individuals into higher and lower consistency subgroups revealed that the higher consistency subgroup had significantly higher habit score. We discuss these results in light of prior habit formation literature, as well as limitations and directions of future research.

A. Perseverance With Home Rehabilitation After Stroke and Habit Formation

We were motivated by the work of Kaushal and Rhodes [27] on factors associated with habit formation to try to understand predictors of perseverance with home rehabilitation after stroke. Consistent with their study, we found that exercising at least 4 days/week during the initial 6 weeks appears to be a minimum requirement to establish long-term perseverance with exercise [27]. Kaushal and Rhodes attributed a portion of this perseverance to the mechanism of habit formation (i.e., an act that has become an automatic response to a stimulus), based on modeling of the time-history of survey responses to the Self-Reported Behavior Automaticity Index (SRBAI) [32]. Although we did not quantify automaticity with the SRBAI in our population, the features and time of exercise perseverance were similar. For example, we found a non-zero habit score at 6 months only for the group with the highest *Freq* (i.e., $\geq$ 4 days/week), which was also the minimum *Freq* identified by Kaushal and Rhodes. The results in the present study also depended on the initial window that we used to calculate *Freq*, with a 6-week window being required to predict a habit score that did not decay to zero at six months. Although having a 5-week window was not significantly different from having a 6-week initial window size ($p = 0.0765$), a 5-week window converged to 0.59 at week 24 while users with a window size of 6, 7, and 8 converged to approximately 2.3. This again is consistent with the observations by Kaushal and Rhodes that a minimum duration of 6 weeks is needed for habit formation.

Finally, exercise consistency also predicted higher habit scores, again consistent with Kaushal and Rhodes observation that consistency was a key antecedent of habit formation. The average habit scores of the high-consistency subgroup were higher in all *Freq* groups and the effect was larger in groups with lower *Freq* (i.e., $Freq < 3$), resulting in approximately double the average habit score for the high consistency subgroup. Thus, overall, these results are consistent with the habit literature for physical activity in the general public [26], [27] and suggest that habit formation may play a key role in home exercise following stroke, an interesting possibility that should be explored in future work.

B. Limitations

The present study has limitations that are important to consider. The findings are consistent with the idea that initial exercise frequency and consistency causally contribute to perseverance via a mechanism of habit formation, but do not prove a causal link or that the perseverance mechanism is habit formation alone. Dual Process theory suggests that both conscious intention and unconscious habit formation processes operate in parallel to determine exercise behavior [33]. Randomizing FitMi users to different target exercise frequency and consistency groups could help establish causality. Obtaining measures of automaticity from FitMi users, such as by using the SRBAI survey, could help confirm the habit mechanism. Further, despite the use of a large dataset ($N = 2{,}581$), the majority of the users (84%) had a $Freq \leq 1$ day/week while the groups with $3 \leq Freq < 4$ days/week and $Freq \geq 4$ days/week were only 1.7% users and 1.4% of users, respectively (corresponding to 10.8 % and 9.1% of the users who were apparently able to form a habit excluding those with $Freq < 1$). The results should therefore be understood as applying to a select group of people and should be confirmed with an even larger sample of users. Further, we were unable to investigate users with *Freq* greater than 4 days/week because there were too few of them (9 individuals had a $5 \leq Freq < 6$ and there were no individuals with $Freq \geq 6$ for the initial 6 weeks).

Another limitation of this study is that the demographics or clinical characteristics of the FitMi users were not collected and considered in the analysis. Although we assume most users are individuals recovering from a stroke as FitMi is marketed for stroke rehabilitation, other types of users could have used the system which may have introduced variability. There may be high variability in the users' motor impairment levels not captured in the dataset, and their exercise behavior is likely strongly related to their motor impairment levels. Indeed, in a previous study, we observed that there was a downward trend in the probability of achieving more total repetitions, minutes of use, and active days of exercise with higher impairment levels [28]. Therefore, it will be important to further investigate impairment level may affect the behavioral requirements in forming a habit. To address this limitation, Flint Rehabilitation is planning to add a survey to collect basic demographic and clinical information when a user initiates the first FitMi session.

As the importance of high-volume movement practice has been widely emphasized in motor recovery [7], [8], [9], [10], [34], we expected users with higher habit scores to perform more exercise repetitions after forming a habit. Indeed, the number of total exercise repetitions a user performed after forming a habit (i.e., between week 7 and week 24) was moderately correlated with the average habit score ($r = 0.53$). However, the total exercise repetitions between weeks 7 and 24 for users with $3 \leq Freq < 4$ days/week and $Freq \geq 4$ were not significantly different due to the high variability in the results. This high variability may have been driven by different motor impairment levels between groups or due to the smaller group size for groups with higher *Freq*s. We believe this will become clearer by collecting more users in higher *Freq* groups.

Finally, it is important to understand to what extent will the results generalize to other home exercise technologies. We note that the motivation for the analysis presented here came from a study of gym-based exercise from the general population [27]. The results of the current study were strikingly similar to Kaushal and Rhodes [27] - both found a distinct increase in perseverance when individuals exercised for at least four days/week for the first four weeks. This is despite differing exercise contexts (gym vs. home) and differing populations (unimpaired versus impaired, and, likely, younger versus older). This suggests that there may be a general psychological principle of habit formation at work, which may apply to other home exercise technologies as well. However, the current results should ultimately be compared to analyses performed with other home exercise technologies used by adults recovering from stroke, to determine the extent to which the results generalize, and the factors that may limit generalization.

C. Future Work

For this study, we focused on the ability of initial exercise frequency and scheduled consistency to predict long-term perseverance with a home-based rehabilitation system. It has been shown in the literature that there are also other antecedents such as behavioral complexity and reward that play an important role in habit formation [24], [35]. Behaviors that are perceived as more complex or have not been sufficiently practiced likely require conscious processes which would consequently prevent automaticity [24], [27], [36]. In a previous study that also studied usage patterns of FitMi [28], we found that users who experienced lower levels of success in the 1st week of FitMi use exhibited decreased probabilities of achieving long-term perseverance during an 8-week window, as did people who experienced 100% success. Here, "success" was defined as leveling up on each exercise game. Therefore, there seems to be an optimal range of success (which is presumably associated with reward) associated with long-term perseverance, and the behavioral complexity of the presented task relative to the user's impairment presumably affects the range of success. Examining interactions between initial exercise frequency, consistency, and success in habit formation is an important direction for future research. Additionally, RehabStudio was designed to unlock exercises in a sequence of increasing difficulty for each body region. Initially, the three simplest exercises for each body region were accessible. Upon completion of all levels of these three exercises, the next exercise in the sequence is unlocked (The percentage distribution of all exercises performed is illustrated in Supplementary Material, Figure S3). We hypothesize that the variety of exercises may influence long-term adherence. Therefore, we plan to investigate the correlation between exercise types and changes in habit scores.

When forming an exercise habit, it has been suggested that environmental cues play a critical role that can prompt automatic behavior [35], [37], [38]. We believe conversational agents (i.e., chatbots) have potential to provide cues to the user to promote exercise habit formation at home. Recently, chatbots have become increasingly common in healthcare to support users in developing healthy behavior habits, thanks to their ability to provide personalized and interactive content [39]. Studies have shown the positive effects of conversational agents in multiple healthcare domains such as physical activity [40], [41], [42], [43], [44], weight loss [45], [46], and management of mental health conditions [47], [48]. These chatbots frequently offer cues and reminders to users that can help promote habit formation. While conversational agents have been developed and tested for a wide variety of medical applications [49], little work has been done for people with stroke in the context of home exercise [50], [51]. Further research is needed to fully evaluate the efficacy and feasibility, but, based on the present results, we hypothesize that a chatbot that is designed to encourage high initial exercise frequency and schedule consistency could promote habit formation for home-based stroke rehabilitation.

V. Conclusion

Understanding factors that contribute to the persistence of home-based exercise is vital for optimizing the recovery process of stroke survivors. This study found that individuals who engaged in exercise at least four times per week during the initial six weeks were more likely to persevere with exercise over a 24-week period. Additionally, when comparing users in the same *Freq* group, those who displayed greater consistency showed higher levels of habit score. These findings align with previous research on the formation of exercise habits among the general population. While further investigation is necessary, the behavioral insights gained from this study can serve as a basis for designing effective interventions, guiding behavior change, and ultimately enhancing health outcomes in the context of home-based rehabilitation programs.

VI. Conflict of Interest

The author(s) declared the following potential conflicts of interest with respect to the research, authorship, and/or publication of this article: David J. Reinkensmeyer has a financial interest in Hocoma A. G. and Flint Rehabilitation Devices LLC, companies that develop and sell rehabilitation devices. Flint Rehabilitation Devices produces the FitMi sensor used in this study. The terms of these arrangements have been reviewed and approved by the University of California at Irvine, in accordance with its conflict-of-interest policies. Daniel K. Zondervan has a financial interest in Flint Rehabilitation Devices, LLC. All other authors declare that they have no competing interests.

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