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ORIGINAL RESEARCH

Poststroke Fatigue and Daily Activity Patterns During Outpatient Rehabilitation: An Experience Sampling Method Study

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Abstract

Objective: To advance our understanding of poststroke fatigue by investigating its momentary and time-lagged relationship with daily activities.
Design: Longitudinal observational study using the experience sampling method (ESM).
Setting: Outpatient rehabilitation care.
Participants: Thirty individuals with stroke (N=30).
Interventions: Not applicable.
Main Outcome Measures: ESM is a structured diary method that allows assessing real-time symptoms, behavior, and environment characteristics in the flow of daily life, thereby capturing moment-to-moment variations in fatigue and related factors. Using a mobile application, individuals with stroke were followed during 6 consecutive days, and were prompted at 10 random moments daily to fill in a digital questionnaire about their momentary fatigue and current activity: type of activity, perceived effort and enjoyment, and physical activity levels.
Results: Based on all completed digital questionnaires (N=1013), multilevel regression analyses showed that fatigue was significantly associated with type of activity and that fatigue was higher when participants had engaged in physical activity. Fatigue was also higher during activities perceived as more effortful and during less enjoyable activities. Time-lagged analyses showed that fatigue was also predicted by physical activity and perceived effort earlier during the day. Importantly, the relationship between these daily activity characteristics and fatigue differed substantially across individuals.
Conclusions: This study illustrates the need for ESM to design personalized rehabilitation programs and to capture fatigue and other patient-reported outcomes in daily life.
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Stroke is the second leading cause of years lost due to poor health, disability, or early death worldwide.[1] With prevalence estimates ranging between 25% and 85%, fatigue ranks among the most common and persistent consequences of stroke.[2] Poststroke fatigue (PSF) negatively affects daily functioning and societal participation, may impede rehabilitation progress, and has been associated with poor neurologic recovery and a higher case fatality rate.[3,4]

However, the etiology of PSF remains poorly understood and effective evidence-based treatments are scarce. Individual differences in PSF cannot be explained by stroke-related characteristics alone, such as stroke type or location or neurologic deficits.[5] Indeed, PSF is a complex phenomenon determined by neurobiologic, psychological, and social factors. Although the neurobiologic mechanisms of PSF remain unclear,[6] several neurobiologic mechanisms underlying fatigue symptoms in

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neurologic and other disorders have been proposed.[7,8] For instance, pathologic fatigue has been proposed to result from the prolonged, abnormal experience of high perceived effort due to impaired sensory processing.[9] Further, premorbid factors such as demographic variables and prestroke fatigue,[10] psychological factors such as depressed mood,[11,12] and social factors such as low social support[13] have all been associated with PSF.

Detailed insight in how these variables affect the course and severity of PSF is needed to develop effective treatments. This effort is impeded by the way fatigue is commonly measured. Available evidence mainly relies on retrospective questionnaires to assess PSF, administered at one arbitrary moment in time. However, fatigue symptoms vary across months, weeks, days, and even within days where they may be associated with daily activities or mood.[14,15] Moreover, symptom questionnaires relying on memory recall are prone to recall bias and are often found to overestimate actual symptom experience (ie, the so-called memory-experience gap).[16] Cognitive impairments after stroke may further limit the reliability of retrospective questionnaires.

The experience sampling method (ESM) is a structured diary technique that allows investigating fatigue in the flow of daily life through repeated real-time ("here-and-now") assessment of symptoms, mood, current activities in natural environments.[17] The feasibility of ESM after brain injury and stroke specifically has been demonstrated in a number of studies.[14,18-23] ESM allows capturing informative variability in PSF and factors related to that variability in daily life. In addition to overcoming recall bias by measuring in real-time, a major strength of this method lies in the richness of data due to multiple observations nested within individuals, allowing reliable statistical estimation in relatively small samples.[17]

The goal of this study was to investigate the momentary and time-lagged relationship between daily activities and PSF. Previous prospective studies found that PSF predicts greater dependency in activities of daily living over a 2-year follow-up period,[4] and that the longitudinal association between fatigue and activities of daily living may be explained by motor impairments and depressive symptoms.[24] An ESM study by Jean et al[14] investigated the relationship between daily life behaviors and depressive symptoms after stroke. Thirty-six patients with stroke monitored their activities 5 times daily during a 1-week period after hospital discharge. Results showed that depressive symptoms 3 months later were predicted by fewer social interactions but also by higher levels of exercise immediately after discharge.

We investigated PSF in relation to daily activity patterns during the long-term rehabilitation phase after stroke. More insight into daily activity patterns over time may be crucial to developing interventions that can be directly implemented in the daily lives of patients. To this end, we used ESM to measure different activity characteristics: type of activity, physical activity, and perceived effort and enjoyment of activities. Using a mobile application, we digitally obtained ESM data by prompting participants with 10 beep signals daily during 6 consecutive days. After each beep signal, a digital questionnaire about current fatigue and activities was presented. We investigated whether fatigue was predicted by type of activity and physical activity measured at the same moment and at earlier time points (ie, time-lagged analysis).[25] We also assessed whether fatigue was higher during activities experienced as more effortful or less enjoyable. Finally, we investigated the extent to which the relationship between daily activities and fatigue differed across individuals.

List of abbreviations:

ESM	**experience sampling method**
FSS	**Fatigue Severity Scale**
HADS	**Hospital Depression Anxiety Scale**
PSF	**poststroke fatigue**

Method

Participants

Thirty individuals were recruited between September 2016 and October 2017 in Zuyderland Hospital Sittard, Adelante Care Group Rehabilitation Center Hoensbroek, and University Medical Center Maastricht, the Netherlands. Inclusion criteria were as follows: (1) diagnosis of stroke confirmed by neurologist; (2) receiving outpatient rehabilitation care; (3) older than 17 years of age and legally competent; and (4) good comprehension of Dutch language. Exclusion criteria were as follows: (1) no smartphone; (2) study evaluated as too burdensome based on clinical judgment; and (3) diagnosis of chronic fatigue syndrome, fibromyalgia, or receiving cancer treatment (self-reported). The Medical ethics committee of Maastricht University Medical Center approved this study (METC16-4-101). All participants gave their written informed consent.

Measurements

A smartphone-based mHealth application called PsyMate[a] was developed by Maastricht University for moment-to-moment assessment of daily life. The application was programmed to prompt participants with 10 beep signals daily at random moments between 7:30 and 22:30, with beeps separated by at least 15 minutes and no more than 270 minutes; the average beep-interval was 90 minutes. After each beep signal, a short self-report questionnaire (approximately 2min) was presented on their smartphone about current fatigue, mood, physical well-being, location, and current activities. Participants had 15 minutes to respond after each beep before the questionnaire was skipped. Statements regarding fatigue (ie, "I feel tired"), physical activity (ie, "I have been physically active since the last beep"), enjoyment of activity (ie, "I enjoy doing this activity"), and perceived effort (ie, "this activity is effortful to me") were answered on a 7-point Likert scale. Whenever participants responded 2 points or higher to "I feel tired," they also received the statements "I feel mentally tired" and "I feel physically tired." Type of activity (ie, "what am I doing?") was presented in a multiple-choice format (ie, "nothing," "resting," "working," "household," "self-care," "relaxing," "traveling," or "other").

Questionnaires

The Fatigue Severity Scale (FSS) and Hospital Depression Anxiety Scale (HADS) were administered to describe general fatigue and depressive and anxiety symptoms of the sample. They were also collected to assess the relationship between retrospective and momentary symptom reporting, but this falls outside the scope of the current manuscript. The FSS assesses fatigue severity in daily life and consists of 9 statements (eg, “I am easily fatigued”) rated on a 7-point Likert scale.[26] The total score is calculated as the mean score per item. Scores range from 1-7, with scores of 4 or higher pointing to potentially clinically relevant fatigue. The HADS allows assessing depressive and anxiety symptoms in populations with somatic conditions[27] and has been validated in patients with stroke.[28] The depression and anxiety subscales range from 0-21, with scores of 8 or higher potentially indicating clinical depression and anxiety.

Procedure

A treating therapist screened patients on inclusion and exclusion criteria and gave information letters to eligible participants. After obtaining informed consent, a 45-minute briefing session was planned. The PsyMate app was also installed on participants' smartphones during this session. Participants were guided through the application and were able to practice with the questionnaire. Subsequently, they were requested to collect ESM data for 6 consecutive days. Importantly, they were instructed to continue their habitual sleep-wake rhythm and to avoid adjusting their daily routines to the study. After the PsyMate period, a 1-hour debriefing session was planned during which participants completed the FSS and the HADS based on their experience in the past week. The researcher provided graphical ESM-derived feedback to each participant.

Statistical analysis

STATA software version 13[b] was used. ESM data have multilevel structures, with beeps or observations (level 1) nested within individuals (level 2). Therefore, multilevel regression analyses were conducted to investigate the momentary and time-lagged relationship between daily activities and fatigue. For all regression models, Likert scale data (range, 1-7) were transformed to a range of 0-6 in order to have meaningful intercepts. The categorical variable “type of activity” was recoded into dummy variables. Because this variable had 8 values (ie, “nothing,” “resting,” “working,” “household,” “self-care,” “relaxing,” “traveling,” or “other”), 7 dummy variables were created with “doing nothing” as reference category. Separate analyses were run to test whether type of activity, self-reported physical activity, perceived effort, and enjoyment of activities predicted fatigue at the same point in time.

To investigate the time-lagged relationship between daily activity and fatigue, new variables were created by generating a time lag of each predictor. These new variables represent the values of the first (t-1), second (t-2), or third (t-3) preceding time point for each activity variable. Thus, for these regression analyses, activity predictors at t-1, t-2, or t-3 were entered as predictors, whereas fatigue at t0 was used as the dependent variable. For these analyses, we also included a time-lagged variable of fatigue (t-1, t-2, or t-3) as a predictor to assess whether activity at t-1, t-2, or t-3 significantly predicted fatigue at t0 while controlling for fatigue at t-1, t-2, or t-3. All analyses were run in a random intercepts and random slopes model, except for the analyses with type of activity as predictor, which employed a random intercepts model. In these multilevel models, the fixed effects reflect the overall association between a predictor (eg, physical activity) and fatigue, whereas the random effects reflect individual differences in this association.

Results

Sample characteristics

Four participants were excluded from the analyses. Two withdrew from the study within 2 days, and 2 others completed less than 30% of all beeps and were excluded based on ESM guidelines. The remaining 26 participants (13 female) had a mean age (y) ± SD of 55.3±7.6. Participants completed 1013 ESM questionnaires, averaging to 39 out of 60 questionnaires per participant (65% completion rate). HADS data from 1 participant were missing. Average score ± SD on the FSS was 5.22±1.04 (range, 2.67-7.00). Twenty-three (88%) individuals scored 4 or higher on the FSS which may be indicative of clinically significant fatigue. Average score on the depression subscale of the HADS ± SD was 7.80±4.36 (range, 1-15). For the anxiety subscale, this was 8.32±3.98 (range, 1-15). Thirteen individuals (52%) scored 8 or higher on the depression subscale, and 15 (60%) on the anxiety subscale, pointing to the possible presence of a depressive or anxiety disorder. Five (19%) participants were using antidepressant or mood-altering medication at the time of the study. All subjects participated within the first 12 months after stroke and were past the acute stage (ie, receiving outpatient rehabilitation care).

Momentary fatigue

At the level of the ESM questionnaires, average momentary fatigue ± SD was 3.83±1.78 (range, 1.00-7.00). Person-level averages can be found in supplemental table S1 (available online only at http://www.archives-pmr.org/). Participants responded 2 or higher to the general statement “I feel tired” in 860 completed ESM questionnaires, which means that participants indicated that they experienced at least some fatigue in 85% of all momentary observations. A score of 4 or higher was given 618 times, pointing to the presence of more severe fatigue in 61% of all observations. Average mental fatigue ± SD was 4.08±1.59 (range, 1.00-7.00), and average physical fatigue was 3.70±1.59 (range, 1.00-7.00).

Daily activity patterns

With respect to type of activity, participants most frequently indicated to be relaxing (23.8%) or doing nothing (13.0%), followed by “household” activities (12.4%), resting (12.1%), working (6.4%), self-care (5.9%), or using transport (3.9%). In 22.3% of recorded questionnaires, participants indicated to be doing something else. On a scale ranging from 1-7, participants rated their activities as moderately effortful (3.04±1.66; range, 1-7) and as rather enjoyable (5.01±1.19; range, 1-7). Self-reported physical activity (since the last beep) was rated on average 2.91±1.81 (range, 1-7).

Daily activity patterns and fatigue

Momentary relation between daily activity and fatigue

Table 1 provides the output of 4 regression models where the relationship between activity predictors and fatigue was assessed at the same point in time. The model with type of activity as predictor showed that fatigue was highest when participants were “doing nothing” (reference category; ß=3.154; SE=0.301; $P<.001$; indicating significant difference from zero), or

Table 1 Overview of the fixed parameters of the 4 final models with each of the activity characteristics as predictors of fatigue

Model	Predictor	SCC (ß)	SE	95% CI	*P* Value
Type of activity	Doing nothing	3.154	0.301	2.574-3.734	<.001
	Resting	0.146	0.134	-0.117 to 0.409	.275
	Working	-0.490	0.168	-0.819 to -0.162	.003
	Household	-0.352	0.134	-0.614 to -0.090	.008
	Self-care	-0.475	0.166	-0.801 to -0.148	.004
	Relaxing	-0.418	0.116	-0.647 to -0.190	<.001
	Traveling	-0.480	0.190	-0.853 to -0.106	.012
	Other	-0.375	0.117	-0.605 to -0.145	.001
Perceived effort	Intercept	2.512	0.272	1.953-3.070	<.001
	Effort	0.166	0.037	0.091-0.243	<.001
Enjoyment of activity	Intercept	3.950	0.258	3.424-4.474	<.001
	Enjoyment	-0.257	0.052	-0.363 to -0.151	<.001
Physical activity	Intercept	2.699	0.277	2.129-3.269	<.001
	Activity	0.087	0.031	0.023-0.151	.010

NOTE. All Likert scale data (range, 1-7) were transformed to range from 0-6 in order to obtain meaningful intercepts.
Abbreviation: CI, confidence interval; SCC, standardized correlation coefficient.

"resting," as fatigue during this activity did not differ significantly from the reference category. During all other activities, fatigue was significantly lower, although differences were relatively small. This is shown graphically in figure 1A, depicting average levels of fatigue during all activities. However, the significant variance of the random intercept in table 2 indicates that this average relationship varied significantly across participants.

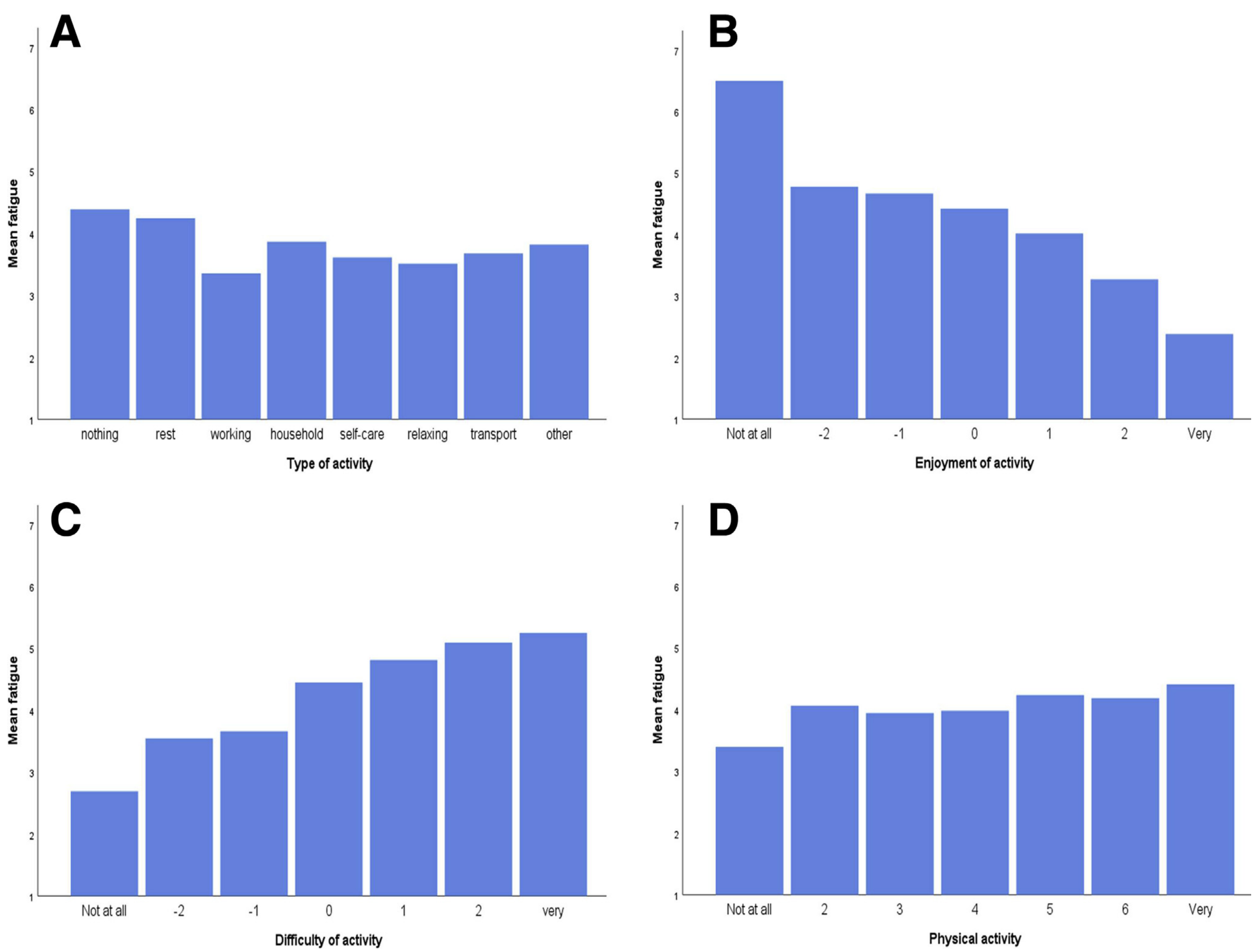

Fig 1 Average fatigue as a function of (A) type of activity; (B) enjoyment of activity; (C) perceived effort during activities; and (D) physical activity.

Table 2 Overview of the random parameters of the 4 final models with fatigue as dependent variable

Model	Predictor	Estimate	SE	95% CI	*P* Value
Type of activity	Intercept	2.054	0.578	1.183-3.564	<.001
Perceived effort	Intercept	1.809	0.527	1.022-3.204	.001
	Effort	0.020	0.009	0.008-0.050	.036
Enjoyment of activity	Intercept	1.240	0.424	0.635-2.422	.003
	Enjoyment	0.040	0.017	0.018-0.090	.017
Physical activity	Intercept	1.917	0.548	1.094-3.357	.001
	Activity	0.012	0.006	0.004-0.033	.053

Abbreviation: CI, confidence interval.

With respect to subjective evaluation of daily activities, higher perceived effort (ß=0.166; SE=0.037; $P<.001$) and lower enjoyment (ß=-0.257; SE=0.052; $P<.001$) were significantly associated with higher levels of fatigue. Figure 1 shows the average change in fatigue as enjoyment (fig 1B) or perceived effort (fig 1C) increase. Again, as indicated by the random effects in table 2, these relationships differed significantly between individuals. First, the significant variance of the random intercepts indicates that fatigue differed between individuals when activities were experienced as requiring little effort or as not at all enjoyable (intercept). In addition, the significant variance of the random slopes indicates that the change in fatigue as activities become more effortful or more enjoyable also differs between individuals (slope). Supplemental figure S1 (available online only at http://www.archives-pmr.org/) depicts the level of fatigue as a function of perceived effort for each participant separately.

Finally, with respect to physical activity (fig 1D), results showed that higher levels of activity are associated with higher levels of fatigue. However, this relationship is less strong relative to the previously discussed predictors, with fatigue being already rather high when no physical activity is reported, and only a slight increase in fatigue with increasing levels of activity. The random intercept presented in table 2 indicates that there is substantial variance in fatigue between individuals in the absence of physical activity. The variance of the random slope, however, indicates that the change in fatigue with increasing levels of physical activity does not differ greatly between individuals. This is illustrated in figure 2, which depicts the level of fatigue as a function of physical activity for each participant separately.

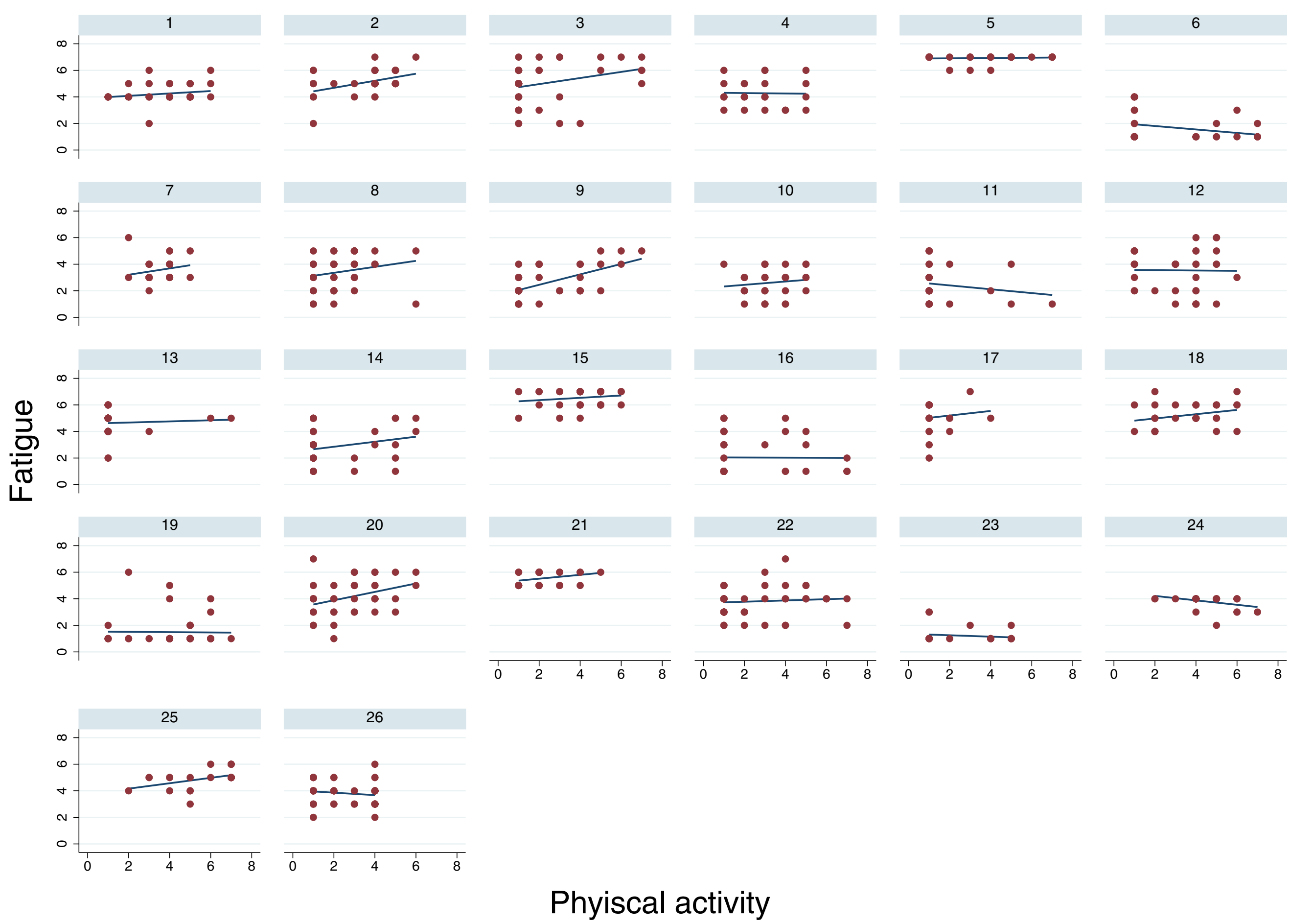

Fig 2 Fatigue as a function of physical activity, presented for each participant separately.

Table 3 Overview of the fixed parameters of the 4 final time-lagged models

Model	Predictor	SCC (ß)	SE	95% CI	*P* Value
Type of activity (t-1)	Doing nothing	2.103	0.246	1.604-2.602	<.001
	Resting	-0.233	0.133	-0.493 to 0.027	.079
	Working	0.235	0.168	-0.941 to 0.564	.161
	Household	0.018	0.132	-0.242 to 0.277	.892
	Self-care	-0.150	0.166	-0.476 to 0.175	.365
	Relaxing	-0.006	0.117	-0.236 to 0.225	.963
	Traveling	0.208	0.192	-0.169 to 0.586	.279
	Other	0.014	0.117	-0.216 to 0.243	.908
	Fatigue (t-1)	0.263	0.041	0.178-0.348	<.001
Perceived effort	Intercept (t-1)	2.063	0.229	1.614-2.512	<.001
	Effort (t-1)	0.052	0.024	0.006-0.100	.029
	Fatigue (t-1)	0.237	0.040	0.158-0.317	<.001
Enjoyment of activity	Intercept (t-1)	2.376	0.277	1.822-2.931	<.001
	Enjoyment (t-1)	-0.531	0.035	-0.123 to 0.017	.135
	Fatigue (t-1)	0.238	0.041	0.154-0.322	<.001
Physical activity	Intercept (t-1)	2.045	0.234	1.565-2.525	<.001
	Activity (t-1)	0.067	0.021	0.022-0.111	.006
	Fatigue (t-1)	0.237	0.041	0.152, 0.322	<.001

NOTE. All Likert scale data (range, 1-7) were transformed to range from 0-6 in order to obtain meaningful intercepts. The first preceding time point for each activity variable is represented by t-1.
Abbreviations: CI, confidence interval; SCC, standardized correlation coefficient.

With mental fatigue as the dependent variable, the relationship with physical activity remained similar, with an average of 2.72 when no physical activity was reported (intercept) and a slope of ß=0.081, SE=0.025, and $P=.001$. For physical fatigue, this relationship became much stronger, with a slope of ß=0.174, SE=0.034, and $P<.001$ (intercept: 2.220).

Time-lagged relation between daily activity and fatigue

To investigate whether current fatigue was also predicted by earlier activities, time-lagged analyses were carried out with activity characteristics at previous time points as predictors (t-1, t-2, t-3) while also controlling for fatigue at those previous time point. The average observed interval between time points (min) ± SD was 120±80 (median, 102min). Results of the t-1 multilevel regression analyses are presented in table 3 (fixed effects) and table 4 (random effects). After controlling for fatigue at the previous time point, fatigue was only significantly predicted by perceived effort (ß=0.052; SE=0.024; $P=.029$) and physical activity (ß=0.067; SE=0.021; $P=.006$) earlier in time; indicating that current fatigue was higher when earlier activities required more physical activity or were perceived as more effortful. Type of activity and the perceived enjoyment of activities measured at t-1 did not significantly predict current fatigue. With activity predictors at t-2 or 2 time points earlier (ie, on average 240min or 4h earlier), perceived effort (ß=0.070; SE=0.029; $P=.015$) and physical activity (ß=0.072; SE=0.026; $P=.006$) remained (the only) significant predictors. At t-3, no more activity predictors significantly predicted current fatigue.

Discussion

The goal of this study was to investigate relationship between daily activities and PSF using ESM. We found that fatigue in daily life differed significantly between different types of activity, with the highest levels of fatigue when participants reported to be

Table 4 Overview of the random parameters of the 4 final time-lagged models

Model	Predictor	Estimate	SE	95% CI	*P* Level
Type of activity (t-1)	Intercept	1.056	0.356	0.545-2.047	.003
	Fatigue (t-1)	0.017	0.011	0.005-0.060	.125
Perceived effort	Intercept (t-1)	1.063	0.355	0.555-2.046	.003
	Effort (t-1)*	0.000	0.000	0.000-0.000	-
	Fatigue (t-1)	0.015	0.010	0.004-0.058	.155
Enjoyment of activity	Intercept (t-1)	1.066	0.369	0.542-2.096	.004
	Enjoyment (t-1)	0.001	0.005	0.000-6.460	.819
	Fatigue (t-1)	0.015	0.010	0.004-0.058	.179
Physical activity	Intercept (t-1)	1.115	0.374	0.578-2.152	.003
	Activity (t-1)	0.000	0.003	0.000-2263	.900
	Fatigue (t-1)	0.017	0.011	0.005-0.060	.118

NOTE. The first preceding time point for each activity variable is represented by t-1.
Abbreviation: CI, confidence interval.
* Indicates the test parameter was redundant in the model.

resting or doing nothing. This finding has not been reported previously, but also leaves open to question whether resting or doing nothing contributes to fatigue or instead should be considered as behavioral responses to fatigue. Time-lagged analysis revealed that resting and doing nothing did not predict significantly higher fatigue at a later point in time relative to other activities. This may suggest that doing nothing and resting should be considered as responses to fatigue rather than behaviors contributing to fatigue. However, it cannot be excluded that excessive resting behavior may contribute to a pattern of chronic fatigue and physical deconditioning over longer time periods.[29]

Second, fatigue was higher during more effortful and less enjoyable activities. Time-lagged analyses revealed higher perceived effort also predicted fatigue later in time, suggesting that high perceived effort may have a lingering effect on fatigue hours later. This finding is in line with theoretical accounts of fatigue symptoms arising from high perceived effort.[9] Finally, results showed that higher levels of self-reported physical activity predicted fatigue measured at the same point in time as well as at a later time point. For mental and physical fatigue, results showed that both significantly increased with higher levels of physical activity. However, physical activity had a greater effect on physical fatigue than on mental fatigue. This may be intuitively plausible but also demonstrates the validity of ESM data and indicates that physical and mental fatigue are experientially discernible experiences affected differentially by different factors.

An important overarching finding is the high degree of individual differences in the described relationships as indicated by the random effects. That is, the average fixed effects at the group level were subject to substantial variability at the level of the individual. This is illustrated in figure 2 and is perhaps the most informative finding when considering clinical implications. Indeed, because these relationships differ between individuals, potential effectiveness of a one-size-fits-all intervention for PSF seems a priori limited. ESM allows detailed and ecologically valid insight in the relationship between fatigue and daily activities for each individual, paving the way toward more personalized treatment. For instance, figure 2 shows more fatigue after physical activity for some individuals, but no association or even less fatigue for others. These individuals may require different approaches in treatment. Gaining such detailed insight in differences between and within individuals is not possible when relying on retrospective questionnaires alone.

Study limitations

First, our sampling period was restricted to 6 days. Future studies could assess the relationship between daily activities and PSF over longer time periods using less intensive ESM protocols to prevent drop-out (eg, fewer beeps per day). Such studies would allow assessing long-term effects of daily activities on PSF. Further, participants categorized their activity as “other” in 22% of all observations, indicating that our multiple-choice list may not have sufficiently captured the range of daily activities. It is also possible that participants completed fewer questionnaires when engaging in, for instance, physical activity or work relative to resting, resulting in an underestimation of participants’ activity levels. In spite of problems inherent to the use of retrospective questionnaires discussed earlier, one could argue that our sample consisted mainly of individuals high in “trait fatigue” based on the distribution of FSS-scores. Future studies could investigate the relationship between daily activities and momentary fatigue in individuals low in trait fatigue as well. Likewise, we deliberately chose not to exclude participants based on the presence of depressive symptoms, thereby allowing better generalization of our findings to stroke populations. However, given the close interrelationship between fatigue and depressive symptoms, future studies controlling for (or excluding participants based on) depressive symptoms would allow identifying variance in daily activity patterns uniquely related to fatigue. Finally, the inclusion of individuals who sustained a stroke longer than 12 months ago would allow assessing the long-term PSF complaints using ESM.

Conclusions

These results demonstrate the complexity of PSF in daily life. The current study represents one of the first steps incorporating this complexity in research designs by the use of ESM. In our view, an important next step is to use ESM as a potential new therapeutic tool. Therapeutic application of ESM is illustrated by Kramer et al,[30] who showed that 6 weeks of ESM combined with personalized face-to-face feedback was effective in improving symptoms in individuals with depression. Future studies should investigate the effectiveness of personalized ESM interventions for PSF.

Suppliers

a. PsyMate application; Maastricht University.
b. STATA software version 13; StataCorp.

Keywords

Ecological momentary assessment; Fatigue; Rehabilitation; Stroke

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