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Associations Between Observed In-Home Behaviors and Self-Reported Low Mood in Community-Dwelling Older Adults

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Abstract

Objective—Using novel monitoring technologies, we sought to ascertain the association between self-report of low mood and unobtrusively measured behaviors (walking speed, time out of residence, frequency of room transitions, and computer use) in community-dwelling older adults.

Design—Longitudinal cohort study of older adults whose homes were outfitted with activity sensors. The participants completed internet-based weekly health questionnaires with questions about mood.

Setting—Apartments and homes of older adults living in the Portland, Oregon metropolitan area.

Participants—157 adults, average age 84, followed for an average of 3.7 years.

Measurements—Mood was assessed by self-report each week. Walking speed, time spent out of residence, and room transitions were estimated using data from sensors; computer use was measured by timing actual use. We ascertained the association between global or weekly low mood and the four behavior measures, adjusting for baseline characteristics.

Results—18,960 weekly observations of mood were analyzed; 2.6% involved low mood. Individuals who reported low mood more often showed no average differences in any behavior

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parameters compared to those who reported low mood less often. During weeks when they reported low mood, participants spent significantly less time out of residence and on the computer, but showed no change in walking speed or room transitions.

Conclusion—Low mood in these community-dwelling older adults involved going out of the house less and using the computer less, but no consistent changes in movements. Technologies to monitor in-home behavior may have potential for research and clinical care.

Keywords

Psychomotor; mood; sensors; behaviors; monitoring; technologies

INTRODUCTION

Technologies for monitoring behaviors in residential settings make it possible to reexamine assumptions about how diseases, symptoms, and syndromes are associated with patterns of behavior (1, 2). For instance, noticeable changes in activity level, described as psychomotor retardation or agitation, have long been considered a hallmark of low mood or depression (3–6). This assumption is grounded in clinical observations of significantly depressed individuals, often in inpatient psychiatry units, but has not been tested through objective monitoring of community-dwelling individuals. The few objective assessments of behavioral changes during low mood have either been in controlled experimental settings (7), or focused on specific disease states (8–12). Behavior has been measured mainly with actigraphy, which yields a global measure of gross movements rather than specific types of behavior (13). Almost all prior research has drawn from general or younger adult samples, while the phenomenology of depression may change with age (14).

We sought to determine the associations between reported low mood and objective behaviors related to activity level among community dwelling older adults. In order to track behaviors in natural home settings over an extended period of time, we utilized data from an automated, unobtrusive home assessment environment that measured walking speed, time spent out of the residence, frequency of transitions between rooms, and computer use. We hypothesized that, in a community-dwelling sample of older adults, after controlling for relevant covariates, (1) across individuals, more frequent report of low mood would be associated with slower walking speeds, less time out of residence, less frequent room transitions, and less computer use; and (2) for each individual, weeks in which there was report of low mood would be associated with the same differences in behaviors compared to weeks without report of low mood.

METHODS

Participants

We analyzed data from 157 volunteers participating in the Intelligent Systems for Assessing Aging Changes (ISAAC) study, a longitudinal cohort study of older adults in the Portland, Oregon metropolitan area (1). Participants were enrolled in a rolling process between March 2007 and September 2009, with ongoing data collection. Entry criteria for the study included (1) age 80 years or older (or 70 years or older for non-Whites), (2) living independently, (3)

Mini Mental State Examination (MMSE) score > 24 and Clinical Dementia Rating Scale (CDR) (15) score ≤ 0.5, and (4) in typical or better health for age (either no or well-controlled chronic diseases). Medical illnesses that would limit physical participation (e.g. wheelchair bound) or likely lead to untimely death (e.g., certain cancers) were exclusions. Participants lived either in retirement communities or freestanding single-family homes. Volunteers with significant medical illnesses that might dramatically affect physical participation (such as a stroke) or anticipated lifespan of less than 3 years were excluded. Full details of the sample are described elsewhere (1). All participants provided written informed consent before participating in study activities. The protocol was approved by the Oregon Health & Science University Institutional Review Board (IRB #2353).

Data Collection

Each participant either received a desktop computer and Internet connectivity, or her or his computer was adapted, in order to allow collection of self-reported data and storage of monitoring data. After training in the use of the computer interface (16), participants completed an online health questionnaire every week that assessed nine domains of health during the last week. The item related to low mood asked, “During the last week, have you felt downhearted or blue for more than three days?”, with the answers “Yes” and “No”.

In order to assess physical motion, the participants’ living spaces were fitted with infrared motion sensors (MS16A, from X10.com). These were placed in rooms and spaces where participants most frequently visited (bedroom, bathroom, kitchen, living room(s), and hallway or entry areas). Sensors on the ceiling in areas in or through which participants walked (such as the entry way or hallway) were modified to have a narrow field of view and to fire only when someone passed directly in their path, to allow accurate location for measuring walking velocity. Time-stamped walking event data from these walking line sensors were wirelessly sent to a research laptop computer located in the home, different than the participant’s computer, and the data was uploaded automatically (1, 17–19). For each day of observation, walking speed was computed from the firing times of the walking line sensors, and for each one-week period a mean walking speed was recorded.

Time out of residence was computed by an algorithm that evaluated the ordering of an exterior door sensor firing followed by absence of motion sensor firing, followed later by the firing of the exterior door sensor and then measured movement in the home. It was measured as the average number of hours per day during the previous week. Room transitions were estimated by calculating the total number of times that there was firing of sensors in different rooms (including the hallway), and summed as the average number of transitions per hour while the participant was at home during the previous week. Movement through rooms would count as multiple transitions, for instance bedroom to hallway to living room to kitchen, and then back again, would be six transitions. Computer use was calculated by an algorithm that tracked input (mouse clicks and keyboard presses), measured as the average number of hours of computer use per day during the prior week.

Data Cleaning and Preparation

Self-report data was examined every week. Research assistants contacted participants who failed to complete their online health questionnaire on time. Since the mood question related to the last week, the behavior measures that overlapped with four or more of the preceding seven days were used. Weeks with two or fewer days of behavioral observations were excluded. Only single-person homes were included in this analysis. Weeks with overnight visitors recorded or travel away from home were excluded in order to ensure that the participant's average behavior measures were simultaneous with self-report.

Analysis

We first described the sample with mean values for sociodemographic characteristics, covariates, and outcomes, with separate groups for those who never reported low mood, and those who reported low mood at least once. We described and adjusted for three covariates that might confound the association of behavior parameters and mood: age, sex, and chronic disease burden obtained at baseline. Chronic disease was assessed by the modified Cumulative Illness Rating Scale (mCIRS), a measure of 13 organ systems, each scored from 0 to 4 according to severity; 0 represents no disease and 4 a risk of death, with a maximum of 52 (20). We chose not to control for baseline depressive symptoms, measured by the Geriatric Depression Scale (GDS (21)) because these symptoms might have changed during the several years observation time, and we were interested in the proximal associations of self-reported mood and behavior parameters.

Global average measures were constructed for each participant based on all of her or his observations. We calculated the mean walking speed, mean time spent out of residence, room transitions, and mean computer use for the entire observation period. We calculated the percent of time during which the participant reported low mood by dividing the number of "yes" answers to the mood questions by the number total observations. Using chi-squared or t-tests, we compared the difference between individuals who never reported low mood with those who reported low mood at least once. We constructed regression models, adjusting for age, sex and mCIRS, with percent of time blue as the predictor, and the four behavior variables as outcomes. This provided a measure of the association between the frequency of low mood reporting and the individual's average behavior parameters.

Next we created generalized estimating equations, which account for correlations among multiple observations on the same individual, with weekly report of low mood as the predictor, and each of the four behavior parameters as the outcome. In order to accommodate differences in scale and nonlinear effects, we used log-transformed values of each outcome, and then exponentiated the coefficient to estimate the percentage change. To give context to the results, we computed an estimate of the absolute difference in each variable in weeks with and without low mood. These latter models were adjusted for age, sex, chronic disease score, and the global mean of the individual's behavior parameter (e.g. the average walking speed for the individual during the whole observation period). Adjusting for this mean value was necessary because the mean values between individuals differed considerably. Analyses were conducted using Stata 11.2 (Statacorp, College Station, TX).

RESULTS

Sample Characteristics

157 participants had self-reported mood data. Table 1 shows the characteristics of the entire sample, and separated by whether or not the participants reported having low mood at least once during the observation period (59% of cohort). There were no significant differences between the groups based on these characteristics, other than the GDS and the mCIRS which were higher (worse) in those who reported low mood. The mean MMSE score was 28.6 ± 1.6 out of 30.

18,960 weekly self-reports of mood were recorded; 489 (2.6%) reported low mood. On average, individual participants reported low mood 4% of the time (SD: 9%, Range: 0% – 67%). Of these, 13,008 had a measure of walking speed within the four previous days prior to the day of self-report (n=134 participants); 11,873 had a matching measure of time out of house (n=136); 14,524 had a matching measure of computer use (n=112); and 7978 had a matching measure of room transitions (n=123). Those who reported low mood at least once had a significantly higher GDS score and higher mCIRS score, but no difference in the other parameters.

Regression of Global Means

Table 2 shows the coefficients from linear regressions with percentage of weeks with low mood (on a 0–100 scale) as the predictor and the mean of each of the four behavior parameters variables as the outcomes. There was no significant association between percentage of reports with low mood and any of the behavior parameters.

Regression of Weekly Measures

Table 3 shows the coefficients from generalized estimating equation models, with weekly report of low mood as the predictor and the measured behavior parameters as the outcome. After adjusting for baseline covariates and the mean values of the variable for each individual, we found that during weeks with low mood reported compared to weeks without low mood reported, individuals spent 9% (24 minutes) less time out of house (p=0.007), and 13% (10 minutes) less time on the computer (p=0.004). These differences remained significant when adjusted for multiple comparisons (four outcomes, p=0.0125). There were no significant differences in walking speed (1% or 0.6cm/s slower, p = 0.347) or room transitions (3% or 0.3 fewer transitions per hour, p = 0.306).

DISCUSSION

Monitoring technologies can assess real-world behaviors in ways that were previously impossible, yet they almost never applied in clinical settings, and are only infrequently used as outcomes in research studies. Beyond solving technical issues, research must ascertain how behaviors are related to outcomes of interest. If reproducible behavioral metrics can be reliably associated with relevant outcomes, these could be used to clarify diagnosis, track symptoms, or assess treatment response. Real-time monitoring might thus promote “aging-in-place” by providing surveillance for concerning behavioral or symptomatic changes, or

identifying individuals at risk for worsening symptoms or functional decline. Such findings can also deepen the understanding of diseases, symptoms, and syndromes by associating them with objective behavioral changes. Despite the promise of these technologies, an important clinical issue that has not been widely addressed is the receptiveness of older adults to being monitored, since they may have privacy or other concerns.(22)

Based on our approach, we found two variables (time out of residence and computer use) that seem to be markers for low mood. There may be other behavior parameters, such as frequency of task completion, use of other communication devices, or engagement in hobby or social pursuits, that have even stronger association with mood. Our work suggests a different association between depressive symptoms and behavior than generally assumed. We found, in this population of community-dwelling older adults, that there was no association between frequency of reporting low mood and any of the behavior parameters. Those who had low mood more often were not more sluggish than others.

Instead of a significant association of low mood with changes in movement, we found that during periods of low mood older adults spent less time getting out of the house and less time on the computer. Because much of social connection is outside the house, and much of computer use is around connecting with others, it seems reasonable to speculate that the primary change in low mood in older adults may thus be one of *engagement* rather than one of physical slowing. This concept is captured in several items from the Geriatric Depression Scale (23), “Have you dropped many of your activities and interests?” and “Do you prefer to stay at home, rather than going out and doing new things?” These items do not have a parallel in other depression instruments, and our research argues for more attention to monitoring these parameters. Moreover, some treatments for depression are focused on activation and social participation (24), and could have particular utility in sustaining behavioral changes. More refined monitoring technologies might identify individuals at risk for depression or functional decline, or quantify response to depression or other treatments.

This work is preliminary. First, the sample was somewhat skewed: predominantly female and highly educated, mainly over age 80, living independently, and without significant depression at baseline. Following larger samples over longer periods of time is needed to understand more fully how mood and behavior are related. Second, the report of low mood was quite uncommon in this sample, about 2% of all observations, and two-fifths of participants never reported low mood. Third, the means of assessing mood was rough and entirely subjective, and not tantamount to the clinical syndrome of depression. Fourth, the simultaneous occurrence of low mood with behavioral changes should not imply that mood drives behavior, since behavioral changes could influence mood. Further research in other samples will be needed to advance the understanding of how mood, depression, and behaviors are related.

CONCLUSIONS

Data from in-home sensors allowed quantifying the association between self-reported mood states and objective behaviors in older adults. The picture of behavior in low mood that we found was not that of sluggishness typically associated with low mood, but rather more time

spent in the home, and interruption of at least some activities. These results are a first step in using objective measures of behavior to understand mood changes in older adults, and to develop methods for identifying early or subclinical changes. Unobtrusive in-home monitoring systems may have the potential to identify people who are suffering or unwell, but better metrics, algorithms, and measures of association are needed for them to have broader use. It will also be necessary to ascertain older adults' receptiveness to monitoring technologies.

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Table 1

Characteristics of the Sample and Subsets Reporting or Never Reporting Low Mood

Characteristics	Total	Reported Low Mood Once or More	Never Reported Low Mood	p-value of difference
N	157	92	65	
Age (yrs)	84.2 ± 5.2	84.5 ± 4.8	83.7 ± 5.8	0.45
Gender (% Women)	83%	84%	82%	0.72
Education (yrs)	15.2 ± 2.5	15.1 ± 2.4	15.3 ± 2.7	0.41
Race (% Non-White)	17%	15%	20%	0.43
Duration of follow-up (yrs)	3.7 ± 1.2	3.8 ± 1.1	3.5 ± 1.3	0.20
MMSE	28.6 ± 1.6	28.6 ± 1.7	28.6 ± 1.5	0.72
GDS	0.8 ± 1.4	1.1 ± 1.6	0.5 ± 0.8	<0.01
Cumulative Illness Rating Scale (mCIRS)	21.2 ± 3.2	21.8 ± 3.8	20.3 ± 2.1	0.02
Group mean of walking speed (cm/s) [SD]	61 ± 16	58 ± 14	64 ± 18	0.08
Group mean of time out of residence (hours/day) [SD]	3.9 ± 1.5	3.8 ± 1.5	4.1 ± 1.4	0.23
Group mean of room transitions (#/hour) [SD]	10.8 ± 5.6	10.6 ± 5.7	11.0 ± 5.5	0.68
Group mean of computer use (mins/day) [SD]	78 ± 48	72 ± 48	84 ± 54	0.38

MMSE: Mini Mental Status Exam; GDS: Geriatric Depression Scale.

Table 2

Association Between Global Average Behavior Measures and Global Relative Frequency of Low Mood Reporting, Using a Linear Regression Model.

	Coefficients			
Parameter	**Walking speed (cm/s)**	**Time out of residence (minutes/day)**	**Room transitions (#/hour)**	**Computer use (minutes/day)**
# of participants in analysis	134	136	123	112
# of measures in analysis	13008	11873	7978	14524
Low Mood Frequency (unadjusted)	−0.27	−1.2	−0.96	1.1
Low Mood Frequency (adjusted for covariates)	−0.20	−0.6	−0.46	0.98

The model adjusted for sex, age, and chronic disease score at baseline.

Coefficients represent the change in the behavior parameter based on the relative frequency of low mood reporting for each participant. For instance, a 10% difference in low mood frequency would correspond to a difference in the outcome variable of 0.1 times the coefficient.

No p-values less than 0.05 for any of the coefficients.

Table 3

Coefficients from Generalized Estimating Equation Models for Within-Subject Differences in Behavior Parameters for Weeks with Low Mood Compared to Weeks without Low Mood.

	Participants/observations in model	% Difference [95%CI] during low mood week	Estimated difference in parameter	p
Walking speed (cm/s)	83/8027	−1% [−3%, 1%]	−0.6 cm/s	0.347
Time out of residence (hours/day)	84/8427	−9% [−15%, −3%]	−24 minutes/day	0.007
Room transitions (#/hour)	54/3977	−3% [−7%, 2%]	−0.3 per hour	0.306
Computer use (mins/day)	67/8640	−13% [−20%, −4%]	−10 mins/day	0.004

The models adjusted for sex, age, chronic disease score at baseline, and the individual's mean value of the behavior parameter during the observation period.

The coefficients represent the percentage difference in the parameter during weeks when low mood was reported compared to weeks when low mood. The estimated difference in the parameter represents the absolute numerical difference in each of the outcomes during weeks when low mood was reported compared to weeks when low mood was not reported.