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Older adults' use of self-monitoring technology within the context of their daily experiences

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Abstract

Background: Self-monitoring technologies are designed to support processes of self-monitoring, self-reflection, and action.
Objective: This study considers the daily socioemotional experiences that precede and immediately follow older adults' use of a self-monitoring application that provided visual summaries of personal data.
Methods: The 100-day Personal Understanding of Life and Social Experiences Project provided information on older adults' daily experiences and application use (n = 99, 87% female, age_{range} = 52 – 88). Every day, participants answered surveys on their experiences and interacted with a web application that offered visual summaries of their goal progress, affect, social satisfaction, and optimism. Technology use was measured as the duration of use, user engagement with the visual summaries, and the presentation of experiences as above or below the person's moving-average.
Results: Multilevel analyses showed technology use to be greater following reports of lower well-being on that day, with the exception of perceived stress, which was related to less use. Technology use was most supportive of the next day's behaviors following feedback that, for individual participants, reports of goal progress and well-being on that day were lower than the person's average.
Conclusion: Older adults' patterns of technology use suggest that self-monitoring technologies are more likely to be used in times of need. Stress was a barrier to technology use. Self-monitoring technologies and interventions should be designed with mindfulness that use follows reports of lower, rather than greater well-being. The implications for self-monitoring technology use on subsequent behavior depends on the context in which the technology was used.

Keywords: Health technology, self-monitoring technology, visual feedback, intra-individual processes, health behaviors

Introduction

Although health behaviors such as physical activity, a healthy diet, and social engagement reduce the risk of chronic disease and mortality (Rizzuto & Fratiglioni, 2014), few individuals over the age of 65 meet national guidelines for healthful behaviors (Jung et al., 2019). For people of all ages, technology has the potential to support health and well-being by reducing practical and motivational barriers to tasks in daily life (Cotten, 2017; Rogers & Fisk, 2010). These health technologies may be even more essential for supporting individuals in older adulthood who are concerned about aging well (Wang et al., 2019), but also find establishing and maintaining health behaviors more challenging (Brawley et al., 2003). Developed following the idea that insight from personal data will drive behavior change, self-monitoring technologies are integrated systems of applications and sensors that provide personalized data summaries to catalyze processes of self-reflection and action (Hermsen et al., 2016). Self-monitoring applications—both web-based and mobile—are widely available and downloaded daily (Krebs & Duncan, 2015) and older adults are the fastest growing population of users (Anderson & Perrin, 2017; Rasche et al., 2018). However, these applications are rarely used and often abandoned, especially by those who may need them the most. In order to optimize the development of self-monitoring technologies for older adults, more information is needed on the circumstances under which self-monitoring technology is most likely to be used and will be most effective. In this study we use data on older adults' daily experiences and subsequent engagement with a self-monitoring application over 100 days to examine the predictors and implications of technology use in daily life.

Benefits of self-monitoring technology use for older adults

Guided by psychological theories of self-regulation (Carver & Scheier, 1998), self-monitoring technologies are designed to support processes of self-monitoring, reflection, and action (Hermsen et al., 2016). Under normal circumstances, individuals naturally monitor goal progress by reflecting on physical and socioemotional responses to daily experiences. For example, positive and negative emotional experiences provide feedback on the importance of an event relative to one's personal goals (Lazarus, 1991). Physiological experiences and symptoms such as pain or dizziness drive processes of response and adaptation (Segerstrom et al., 2016). Research on self-regulatory processes in older adulthood has linked emotional and physical experiences (i.e., feedback) to goal striving (Hooker et al., 2013), relationship maintenance (Mejía & Hooker, 2015; Wilson et al., 2019), and perceived stress (Hooker et al., 2013). However, self-regulation requires self-relevant goals, access to feedback, and an ability to identify and pursue a successful course of action (Brandtstädter & Lerner, 1999). Although older adults are more likely than their younger counterparts to have a self-relevant health goal (Hooker, 1992), new health behaviors may be uncomfortable and their health benefit may not be immediately apparent (Brawley et al., 2003). Self-monitoring technologies address the limitations of internal self-regulatory processes by providing data summaries that are supposed to facilitate self-reflection and action (Hermsen et al., 2016). Personalized summaries of data, in visual form, may provide 'in the moment' actionable information that may not otherwise be evident to the individual.

Evidence for processes of self-monitoring, reflection, and action

This assumption that individuals will be motivated to reflect on their data and act on data-driven insight has been termed the self-improvement hypothesis (Kersten-van Dijk et al., 2017). Intervention research has shown self-monitoring technologies to be moderately successful in assisting older adults in changing their health behaviors (Yerrakalva et al., 2019). However, support for the self-improvement hypothesis, which would require information on the circumstances that drive application use, the insight provided by the application, and the behaviors that follow application use, is less clear. To date, evidence on the circumstances that predict application use is rare, and support for data-driven insight is based on qualitative user reports (see Kersten-van Dijk et al., 2017 for review). In the following sections, we briefly review empirical evidence of older adults' engagement in self-monitoring, reflection, and action while using self-monitoring technologies.

To receive data-driven insight, users must actively engage with self-monitoring applications. Engagement would include allowing for data collection, opening the application, reflecting on visual summaries of data, and then acting on data-driven insights. Although processes of use and action are central to the self-improvement hypothesis, little is known about how these processes unfold in daily life among older adults. Models of technology acceptance offer some insight on facilitating conditions such as perceived ease of use and usefulness, affordability, and the technology's expected efficacy (Chen & Chan, 2011; Vaziri et al., 2019), but offer little guidance on which experiences in daily life may make technology use more or less likely in that moment. A model of mobile user engagement suggests that utility (need), social influence, and hedonic experience would drive engagement with self-monitoring applications (Kim et al., 2013).

The self-improvement hypothesis and Kim's model of mobile user engagement suggest two expectations for how older adults' daily experiences may relate to subsequent application use on that day. On the one hand, older adults may be most likely to engage with self-monitoring apps on days when a need is higher. For example, awareness of more physical symptoms than usual may inspire engaging with an app in order to reflect on whether today's symptoms are actually more severe than normal. On the other hand, if engagement is driven by hedonic motivations for a rewarding experience, older adults may be more interested in reflecting on their data following positive, rather than negative experiences.

Self-monitoring technologies are expected to change behavior by offering personalized performance feedback to its users (Hermsen et al., 2016). Designed to elicit reflection, performance feedback is most commonly provided via visual summaries of personal data that allow users to understand their current performance in reference to a performance standard (e.g., a goal) or to change over time (Le et al., 2015). Following theories on self-regulation (Carver & Scheier, 1998), this visual feedback should help users understand how far they are from their goals and then motivate appropriate action. Ideally, corrective action would be observed following feedback that performance was below a performance standard. However, although the most effective self-monitoring applications include a performance feedback feature (McDermott et al., 2016), little is actually known about the immediate relationship between self-reflection and subsequent action (Hermsen et al., 2016). There is even some evidence that feedback on performance can decrease the likelihood of behavior change. For example, a meta-analysis that compared dietary

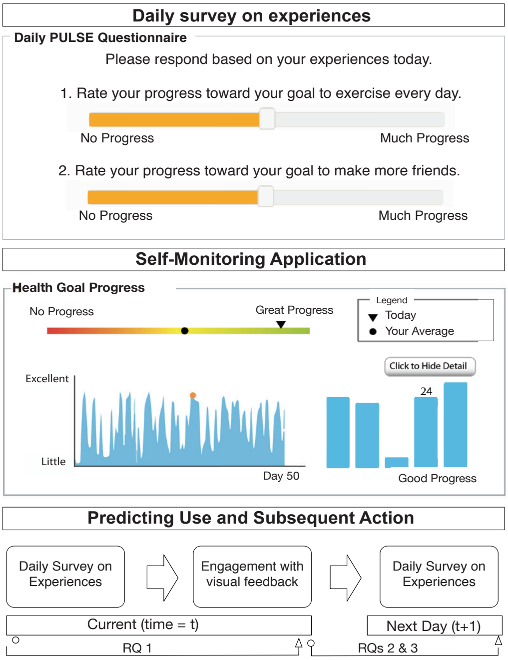

Figure 1. Conceptual figure of study design with screenshots from daily survey and self-monitoring application.

Note: Daily experiences included health and social goal progress, positive and negative affect, social satisfaction, perceived stress, optimism, and physical symptoms. Behavioral measures of engagement with visual feedback included duration of time that the visual feedback window was open, and toggling the show/hide detail button. Processes of action were operationalized as the next day's experiences and included goal progress, positive and negative affect, social satisfaction, perceived stress, and optimism.

interventions with and without feedback found behavior change to be less likely in interventions that included feedback on performance (Schoeppe et al., 2016).

Overview of the current study

Although self-monitoring applications have the potential to support older adults in establishing and maintaining healthful behaviors, the link between need, self-monitoring, self-reflection, and action has yet to be empirically established. In this study we use data from an observational study on daily experiences and goal pursuit that also offered participants access to a web-application with personalized visual summaries of participants' goal progress, mood, stress, optimism, and social satisfaction. The design of the study provided information on days that older adults did and did not engage with the application, which allowed us to compare daily socioemotional experiences that preceded and followed technology use on that day. Therefore, our purpose in this study was to examine under what circumstances older adults were more or less likely to engage with visual feedback on their daily experiences and the implications of that engagement for the next day's behaviors. Our research was guided by the following questions:
RQ1: Are daily socioemotional experiences on a given day related to application use on that day?
RQ2: To what extent is application use associated with the next day's behaviors? RQ3: Is the effect of application use on behaviors differentiated by whether feedback is presented as positive or negative?

Method

Study design and participants

The Personal Understanding of Life and Social Experiences Project (PULSE) provided data on participants' daily experiences and application use. The PULSE project was not an intervention, but was rather designed to observe participants' naturally-occurring internal self-regulation processes. The study was administered entirely via a web application designed by the study team. Conducted during Summer/Fall of 2010, the PULSE project included an initial survey of individual characteristics and daily surveys of goal striving and socioemotional experiences over a 100-day time period. Daily surveys were followed by an application that provided visual summaries of participants' self-reported data (*Figure 1*). Participants were unfamiliar with the self-monitoring application and recruited from a human subject registry of adults age 50 and older (n = 400) that is maintained by an aging center at a large university in the United States of America. In total, 105 members responded to email invitations (M_{age} = 63.19, Range = 52 – 88; 88% female; 97% white; 73% married or partnered; 47% retired). Five participants withdrew from the study. The median completion rate for the daily questionnaires was 91%.

Self-monitoring application design

The survey and self-monitoring application were delivered by a web application. Analysis of browser data showed that the survey and self-monitoring application were accessed via a web browser for desktop computers. Screen shots from the daily survey and self-monitoring application are provided in *Figure 1*. Daily experiences were reported in the daily survey by moving a slider along a scale with descriptive anchors. The numerical scale was excluded from the participant view so that participants could not favor a specific number. The self-monitoring application that followed the daily survey was designed to engage participants in reflection. The web application provided visual summaries of participants' reported experiences of health and social goal progress, stress, positive and negative mood, optimism, and social satisfaction. Visualization elements included 2D representations of a performance bar, time series, and histogram, which were chosen for their familiarity to us-

Table 1. Descriptive statistics of Person Characteristics and Average Daily Experiences Across Lower vs Higher Visual Feedback Users.

	Infrequent Users N = 50		Frequent Users N = 49		p
	M	(SD)	M	(SD)	
Person Characteristics					
Age	62.24	(5.04)	64.36	(9.14)	
College Degree	80%		78%		
Female	84%		92%		
Retired	40%		50%		
Survey Completion Rate	.85	(.18)	.83	(.15)	
Average Daily Application Use					
Duration of Use (minutes)	0.29	(0.07)	0.97	(0.77)	< .001
Total Engagement	0.05	(0.09)	0.44	(0.92)	= .004
Average Daily Experiences					
Health Goal Progress	64.62	(18.51)	54.52	(20.55)	= .01
Social Goal Progress	65.61	(27.19)	60.00	(18.28)	
Social Satisfaction	79.21	(14.96)	70.30	(19.48)	= .01
Stress	157.31	(29.15)	142.29	(28.50)	= .01
Optimism	83.09	(14.66)	76.93	(15.08)	= .04
Positive Affect	177.75	(40.07)	165.14	(35.39)	
Negative Affect	29.76	(31.86)	31.21	(25.51)	
Total Physical Symptoms	0.99	(1.05)	1.67	(1.37)	=.007

Note. College Degree = 1 if post-secondary degree completed. The "burst" measurement group completed surveys for 7 consecutive days four times during 100-day study period. Retired = self-reported retirement status. Infrequent vs frequent application users identified via median split of application use data. P values estimated using multivariate regression.

ers (Keim, 2002). The default display included a performance bar for each of the six experiences. An inverted triangle indicated participants' responses on that day, relative to a circle that indicated participants' rolling averages. Participants could press a 'show/hide detail' button to reveal time-series and histogram summaries for each experience. The application that provided visual summaries was only accessible immediately after submitting the survey on that day.

Measures

The outcomes for this study included the extent of participants' application use and their next-day experiences following application use. Measures of use were specific to the visual feedback component of the PULSE web application. A summary of measures is displayed in *Table 1*.

Measures of application use

Measures of use were automatically logged by the application. *Duration of use* was measured in seconds from the time that the web-application of visual summaries appeared until the time that the browser window was closed (iM = .63 min, SD = 0.65, range = 0.06 – 5.62). Extreme values suggested that browsers were left open and unattended. Thus, durations greater than 15 minutes were tagged as invalid and imputed with participants' rolling averages. Alternative treatments of improbable values (unadjusted and set to missing) were also tested. *User Engagement* was a binary variable that indicated whether or not the participant had toggled the show/hide detail button for a given visual summary of an experience on that day. *Total user engagement* was the sum of total engagement across visual summaries of experiences on that day (iM = 0.25 toggles/day, SD = .70, range = 0 – 5). *Visual presentation* (presentation) was a binary variable assigned to each visual summary that indicated whether the experience presented as above or below the participants' average on that day.

Measures of daily experiences

The variables used to describe daily experiences preceding and following application use were collected from the daily surveys. Items in scales were reverse coded as necessary and summed to measure each construct. Where applicable, internal consistency (Cronbach's alpha) was calculated for each day, and is reported as the mean and range across the study period. *Health and Social Goal Progress* were reported on a scale from 'no progress' (0) to 'much progress' (100). Goals were set during the initial survey and did not change during the study period. *Perceived Stress* was the sum of two negative and two positive items from the perceived stress scale (Cohen et al., 1983; Hooker et al., 2013). Responses ranged from 'strongly disagree' (0) to 'strongly agree' (49) (iM = 149.89, SD = 29.66, αM = .83, αrange = .65 - .93). *Positive* and *Negative Affect* were the sum of five positive and five negative adjectives from the 10-item affect scale (Kleban et al., 1992) that were rated from 'not at all' (0) to 'extremely' (49); iM_{PA} = 171.52, SD = 38.16, α_M = .92, α_{range} = .83 - .96; iM_{NA} = 30.45, SD = 28.75, αM, = .90, αrange = .82-.96. *Optimism* was the sum of two items from the Life Orientation Test (Scheier et al., 1994), which were rated from 'strongly disagree' (0) to 'strongly agree' (49); iM = 80.04, SD = 15.11, $\alpha_{M'}$ = .73, α_{range} = .41-.88. *Social Satisfaction* was measured from participants' ratings of interactions with their five closest social partners (identified during the initial survey) on that day. Interactions were rated from 'unsatisfied' (0) to 'satisfied' (100)). *Satisfaction* was summed and then divided by the number interactions on that day; iM = 74.80, SD = 17.82. *Physical Symptoms* were the sum of 13 items from the Self-Rated Health, Pain, and Symptoms Checklist (Winter et al., 2007); iM = 1.69, SD = 1.58. All analyses controlled for participants' age, gender, and retirement statuses. Time to complete the

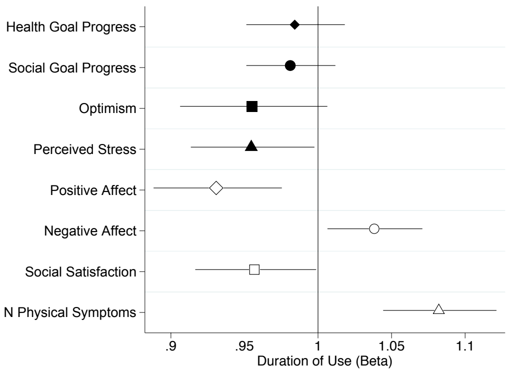

Figure 2. Estimated effects of daily experiences on duration of visual feedback use.

Note: Beta coefficients are exponentiated and can be interpreted as the expected percent change in duration of visual feedback use with each standard deviation change in the independent variable. All models are adjusted for age, gender, measurement group, retirement status, elapsed time (days), and elapsed time during that day's survey. Independent variables are presented in the order in which their respective dimension was subsequently presented in the visual feedback.

daily questionnaire was included as a proxy for day-to-day variability in availability.

Analysis overview

Data were analyzed using multilevel models, which nest observations within persons and simultaneously estimate intraindividual processes at level 1 (daily experiences) and individual differences at level 2 (e.g., age and retirement status). Time-varying covariates were decomposed into intraindividual (person-centered) and interindividual (person-mean) components that addressed variation at levels 1 and 2, respectively.

Predictors of application use (RQ1) were modeled using linear, logistic, and negative binomial multilevel models that tested the association between daily experiences and duration of use, user engagement, and total engagement on that day. Daily experiences were standardized to allow for comparison and tested separately (due to multicollinearity). Duration of use was logged to correct for skewed Level 1 residuals. The negative binomial models were adjusted for exposure (duration of use) to the visual feedback.

The implications of application use for the next day's experiences (RQ2) were examined using linear multilevel models where the next day's experiences were individually regressed on duration of use and user engagement. The effect of viewing experience as above or below average (RQ3) was explored via a usage×presentation interaction. Person-centered daily experiences at time (t) were included as covariates to differentiate the effect of the presentation of experience as above or below average from the autocorrelation of yesterday's experiences.

Individual differences in effect magnitude—random effects—were tested for all time-varying covariates using the log-likelihood test. To meet the stationarity assumption (that residual variance is invariant and independent across time) of longitudinal analysis, models were adjusted for linear time and weekend effects. Visual inspection of the autocorrelation function showed a first-order autoregression process to render residual sequences statistically independent. Data were analyzed using Stata 15.

Results

Characteristics of our healthy older adult sample are presented in *Table 1*. We begin by describing general patterns of and individual differences in application use. On the whole, with a median survey completion rate of .91, study participation was high. However, engagement with the visual feedback application in this unfamiliar sample was low. The average intraindividual mean in the duration of use was 38 seconds (range = 4.2 sec to 5 min 37 sec). Median split in the duration of use was used to differentiate frequent with infrequent users (*Table 1*). Compared to infrequent users, frequent users tended to have higher needs. They reported lower health goal progress, social satisfaction, and optimism, as well as more physical symptoms.

In addition to individual differences, both daily experiences and application use varied considerably from day-to-day. The inversed intraclass correlation (1-ICC) showed 85% of the variation in the duration of use to be within-persons. As a result, for this sample of older adults, indicators of daily experiences, rather than characteristics of the person, were necessary to explain the daily use of self-monitoring technologies.

Daily experiences and technology use

To identify predictors of daily self-monitoring technology use, we examined the association between daily experiences and subsequent application use on that day (*Figure 2*). The general patterns of application use and daily experiences were two-fold. First, the duration of use was longer than usual following reports of lower well-being than usual for that person. For example, duration of use was longer following reports of higher negative affect, lower positive affect, lower social satisfaction, and more physical symptoms (all ps $< .05$). Perceived stress was a notable exception to this pattern, where reports of higher than normal stress were followed by a shorter duration of application use on that day ($p < .04$). Sensitivity analysis showed the above associations to be robust to alternative treatments of the improbable duration of use values. The second general pat-

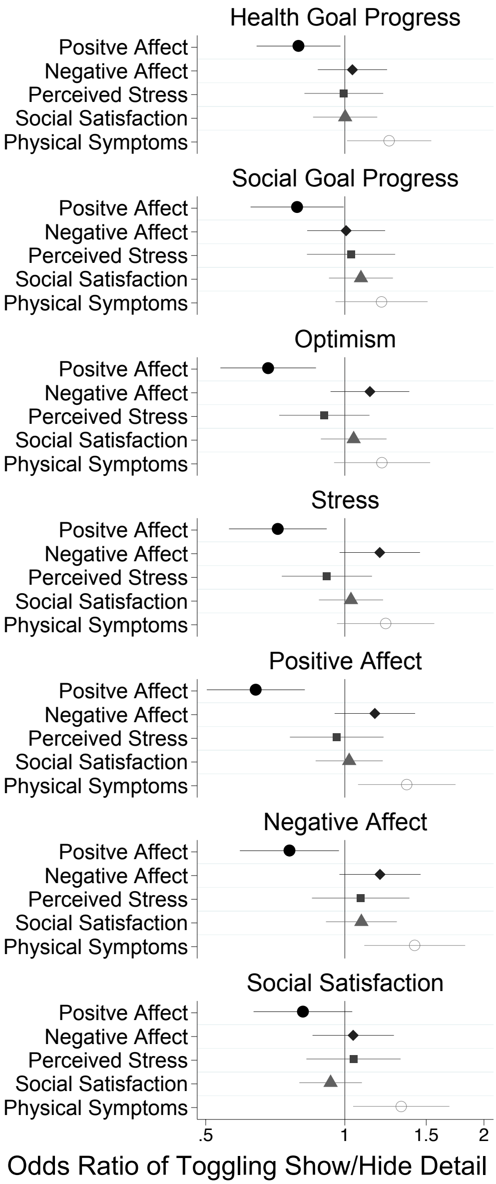

Figure 3. Effects of daily experiences on subsequent interactions with visual feedback.

tern was that the strength of these associations varied significantly across individuals. Adding a random coefficient significantly improved model fit for positive affect ($\chi^2(3) = 18.66$, $p < .001$), social satisfaction ($\chi^2(3) = 27.49$, $p < .001$), and perceived stress ($\chi^2(3) = 26.72$, $p < .001$).

Similar to duration of use, user engagement with the visual summaries was also more likely following reports that well-being was lower than usual for that person on that day. Daily experiences that were significantly linked to the duration of use were also tested as predictors of user engagement. As shown in *Figure 3*, reports of lower positive affect were associated with a higher likelihood of subsequent engagement with visual summaries of goal progress, optimism, stress, and affect (all ps < .05). Lower positive affect on a given day was also related to engaging with a higher number of visual summaries than usual for that person on that day ($\beta = -0.17$, SE = 0.08, $p = .03$). Reports of more physical symptoms were associated with a higher likelihood of engagement with visual summaries of health goal progress, affect, and social satisfaction (all ps < .05). The results were consistent when analysis excluded those who never pressed the show/hide detail button.

Technology use and the next day's experiences

We concluded our analysis by testing the implications of application use for the next day's behaviors (*Figure 4*). First, we report how day-to-day variation in the duration of use was related to subsequent behaviors. Duration of use was significantly linked to only health and social goal progress on the following day. Surprisingly, social goal progress was lower than usual following days that participants' duration of use was longer than usual (use = -.02, SE = 0.01, $p = .03$). As shown in Figure 4, the effect of duration of use on health goal progress was fully conditioned by the presentation of progress as above or below the person's average. On days that health goal progress was presented as lower than average, longer duration of use was followed by higher health goal progress on the next day. However, on days that health goal progress was presented as lower than the person's average, longer duration of use was followed by lower health goal progress on the following day; (use = 0.01, SE = .01, $p = .13$; use×presentation = 0.03, SE = 0.01, $p = .02$). This means that self-monitoring application use was helpful following reports of lower goal progress, but detrimental following higher reports of goal progress. Sensitivity analysis found the effects of duration of use on health and social goal progress to be nonsignificant when the improbable duration of use-values remained unadjusted.

Engaging with the visual feedback application was related to the next day's social satisfaction and perceived stress (*Figure 5*). Similar to the effects of duration of use on the next day's health goal progress, engagement with feedback that presented social satisfaction as lower than average was associated with higher social satisfaction the following day (engagement = 0.20, SE = 0.09, $p = .04$; engagement×presentation = -0.45, SE = 0.11, $p < .001$). A similar effect was found for total engagement, where only on days that satisfaction was presented as lower than average, was engaging with more visual summaries than usual related to higher social satisfaction the next day; total engagement = 0.05, SE = 0.02, p =

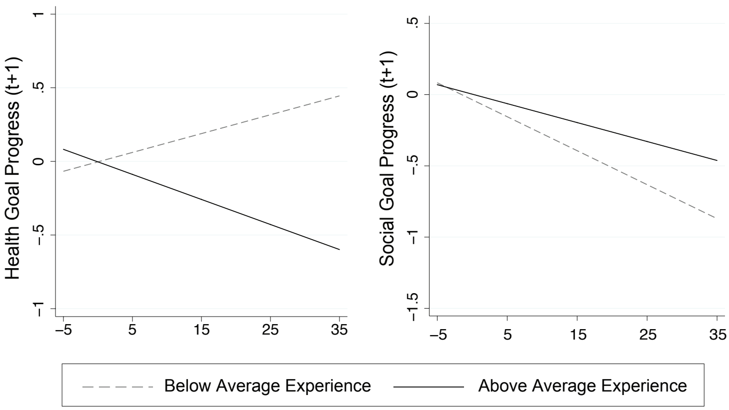

Figure 4. Effects of duration of use on the next day's experiences.
Note: Measures of daily experience are standardized. All models are adjusted for study covariates, weekend effects, duration of current survey, and current experiences.

.007; total engagement×presentation = -.09, SE = 0.02, p < .001. Although application use was less likely on days with higher stress, engaging with the visual summary of today's stress and engaging with more visual summaries than usual was related to lower stress on the follow day (engagement = -0.17, SE = 0.07, p = .02; total engagement = -0.03, SE = 0.01, p = .03). The effects of engagement remained significant when participants who never pressed the show/hide detail button were excluded from the analysis.

The effect of application use on the remaining experiences of positive affect, negative affect, and optimism at t+1 was also tested. All estimated effects were found to be non-significant (all ps > .16).

Discussion

Although self-monitoring technologies have the potential to support older adults' health and independence by helping individuals set, monitor, work toward, and accomplish goals, little is known about how these processes unfold in daily life. Our purpose in this study was to examine the predictors and implications of self-monitoring application use in daily life. We found that: (1) with the exception of stress, application use was greater following reports of lower well-being on that day; (2) user engagement with a visual feedback domain was associated with the next day's experiences in that domain; and (3) the presentation of experiences as better than or worse than average mattered.

User engagement with visual feedback was most supportive on days that current experiences were presented as below average for the person. Extant models of technology use allude to the importance of need through the concept of perceived usefulness and outcome expectancies (Chen & Chan, 2011; Mitzner et al., 2019). Compared to infrequent users, frequent users in this study reported more physical symptoms and less satisfaction in their social interactions, goal progress, and optimism. Although in this study we did not ask directly about need, we believe that need was expressed through lower daily reports of goal progress and well-being.

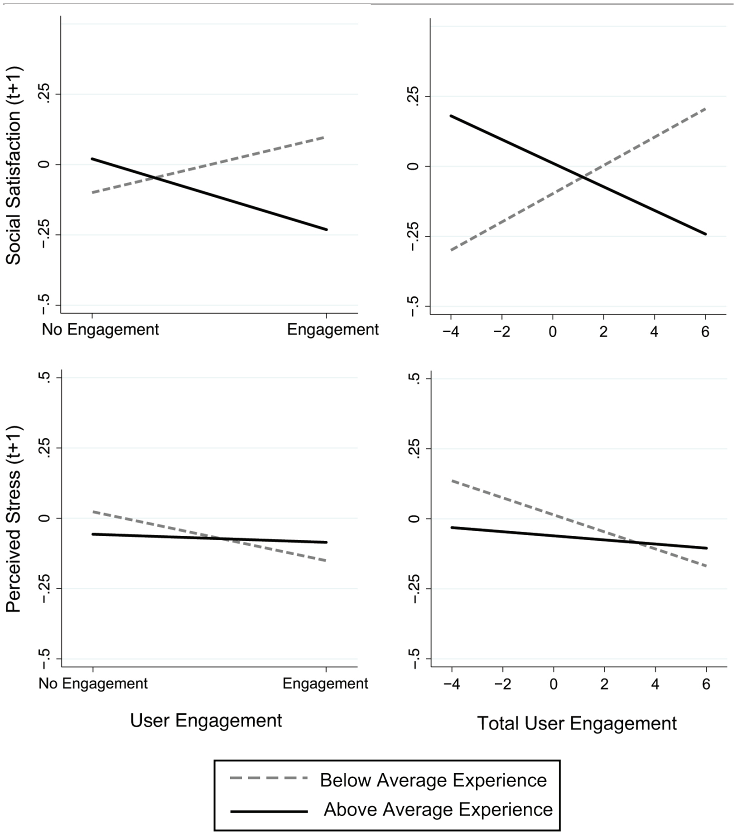

Figure 5. Effects of user engagement on the next day's experiences.
Note: Measures of daily experience are standardized. All models are adjusted for study covariates, weekend effects, duration of current survey, and current experiences.

Therefore, with respect to individual differences, consistent with models of technology acceptance, we found that technology use was the most frequent among those with the greatest need.

However, in this study, we also found that technology use varied more from day-to-day than it did from person-to-person. Therefore, the findings from this study emphasize the importance of daily experiences as facilitators and barriers to older adults' daily engagement with self-monitoring applications. Our findings suggest that need can also be characterized as a momentary state that fluctuates from day-to-day and potentially motivates technology use. Ours is the first study, to our knowledge, to examine how daily socioemotional experiences predict and immediately follow technology use. In their model of user engagement with mobile devices, Kim and colleagues (2013) suggest the importance of both utility and hedonic experience. Improvement mandates reflection on performance. Consistent with Kim's model and the self-improvement hypothesis, we found individuals to be more likely to use and engage with the visual feedback application on days that their needs-characterized by lower positive affect, higher negative affect, and more physical symptoms-were higher than normal for the individual. That the likelihood of engagement increased, rather than decreased, in times of need suggests a potential for self-monitoring apps to be a tool that older adults reach for as they strive to age well.

Although the findings from this study highlight how technology use is linked to technologies on that day, the magnitude of these effects varied considerably across persons. In other words, the reasons for technology use are personal. Future research should examine individual differences in the extent to which daily experiences related to technology use on that day. Individual differences in cognition, perceived mastery, adaptivity, and cognitive ability (Chopik et al., 2017; Kamin et al., 2017; Kamin & Lang, 2016; Mitzner et al., 2019), as well as factors such as education, economic resources, and health (Robbins et al., 2017) have been linked to general patterns of technology use. These factors may explain why daily socioemotional experiences are stronger predictors of technology use for some more than for others.

In this study, we also explored the implications for technology use on the next day's behaviors and experiences. Consistent with the self-improvement hypothesis, we found that application use was most supportive of the next day's experiences and behaviors when current experiences were presented as lower than average for that person. This pattern was most evident for health goal progress. Application use supported progress following a bad day but hindered progress following a good day. On the one hand, this illustrates how visual summaries of health data may be the most effective in contexts when they are most needed, as has been shown in experimental research (Oscar et al., 2017). However, our findings also raise questions about the potential negative effects of application use for behavior. Our findings warrant further research on the intraindividual dynamics of self-monitoring applications use older adults' well-being. To our knowledge, our study is the first to link technology use to subsequent behaviors among older adults. We acknowledge that the effects of technology use on behavior observed in this study, while statistically significant, were relatively small. The PULSE project was not a digital behavior change intervention. Instead, it was designed to observe older adults' internal self-monitoring processes—that is, how daily social experiences relate to progress towards health and social goals. For this reason, the visual feedback offered in the self-monitoring app evaluated in this study was not designed to change behavior per se, but rather to provide opportunities for reflection. Similarly, participants were not encouraged by the web platform to engage with the visual feedback following the completion of their daily surveys. Thus, our study offers a unique insight into the effects of spontaneous self-monitoring technology use outside of an intervention context.

Perceived stress offered an important exception to the pattern of socioemotional experiences that precede and immediately follow self-monitoring technology use described above. In contrast to negative affect, which catalyzed technology use, higher perceived stress on a given day was a barrier to technology use on that day. This finding aligns with known properties of the stress response system-where stress reflects appraisals that demands exceed available resources (Lazarus, 1991) and hinders self-monitoring and action processes (Hooker et al., 2013). Noting that health technology use is less common in vulnerable populations, who are also more likely to endure chronic stressors (Krebs & Duncan, 2015; Robbins et al., 2017), the results from our study suggest that stress may be a barrier to technology use. That technology use was related to lower the stress the following day, however, suggests promise for aiding stress management.

The findings presented here must be interpreted within the context of the study's limitations. The generalizability of our findings is limited based on our sample of well-educated older adults with access to email from home and enough technological fluency to sign up for and complete a study that was conducted entirely via the internet. We also acknowledge that although adherence to the study protocol was high, the frequency of interaction with the visual feedback was low. This limitation results from our decision that visual feedback use should be voluntary rather than compulsory-a design decision that allowed us to examine the qualities of day that would be most predictive of application use. However, the frequency of engagement observed in this study aligns with estimates of technology use among naïve users (Rapp & Cena, 2016). Additionally, technological advances have been made since this study was conducted in 2010. Most notably, smartphone use has increased, and mHealth applications have become more ubiquitous. Although today's seniors are likely more tech-savvy than in 2010, the level of application use and user engagement documented in this study aligns with contemporary estimates (Patel et al., 2017). Additionally, the key outcome of this study was application use and engagement. Therefore, although modern applications integrate data from sensors and require less data-entry from participants than described in this study, the need for the participant to engage with application in order for the technology to affect behavior change remains (Yardley et al., 2016). We, therefore, expect that the predictors and implications of application use identified in this study to be relevant today. Finally, although our study was longitudinal, a thorough examination of the reciprocal processes of monitoring, reflection, and action was beyond the scope of this study. Our findings justify experimental work to further disentangle the dynamics of these processes.

Conclusion

Although self-monitoring technologies are intended to support internal self-monitoring and action processes, technology use in itself is a behavior that individuals would engage or disengage in based on the context of their day. We found individuals to engage with visual feedback on their experiences on days that their need was higher. Technology use was related to the next day's behaviors, and the effect of technology use was most supportive when feedback presented experiences as below average. Our research takes a first step toward understanding the intraindividual processes that link technology use to behavior change and suggests the potential for self-monitoring technologies to support older adults in maintaining healthful behaviors within the context of daily life.

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