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Technology Adoption by Older Adults: Findings From the PRISM Trial

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Abstract

Background and Objectives: There is growing evidence of the benefits of computers for older adults. Yet, adoption rates are lower compared with younger adults. Extant theoretical models of technology acceptance are limited in their application to older adults—studies on which these models are based included a limited sample of older adults or none at all; none assessed use of a technology specifically designed for older adults; and most only measured intention to use a technology or short-term use, rather than longer-term use (i.e., adoption). We assessed adoption of a computer system specifically designed for older users, for a diverse sample, over an extended period of time.

Research Design and Methods: We analyzed archival data from 150 ethnically diverse older adults (65–98 years of age) who participated in the Personal Reminder Information and Social Management (PRISM) randomized controlled trial (Czaja SJ, Boot WR, Charness N, Rogers WA, Sharit J, Fisk AD,…Nair SN. The personalized reminder information and social management system (PRISM) trial: Rationale, methods and baseline characteristics. Contemp Clin Trials. 2015;40:35–46; Czaja SJ, Boot WR, Charness N, Rogers WA, Sharit J. Improving social support for older adults through technology: Findings from the PRISM randomized controlled trial. Gerontologist. 2017;58:467–477). We examined the extent to which attitudes, personal characteristics (e.g., age, gender, and personality), and cognitive abilities predicted mid-term and long-term adoption of a computer system designed for older adults.

Results: There were individual differences in PRISM use over time. Regression analyses indicated that individual differences in earlier use of the system, executive functioning, and computer efficacy predicted long-term use.

Discussion and Implications: These data provide insights for broader-based models of technology acceptance to guide design, instruction, and deployment of products for older adults. Specifically, the provision of opportunities to foster efficacy and gain positive experience with computer technologies may play a critical role in the likelihood that older adults adopt such technologies.

Trial Registration: NCT01497613.

Keywords: Technology acceptance models, Computers, Intervention

Background and Objectives

There is growing evidence of the benefits of personal computers and tablets for older adults, including improvements to their cognitive, social, and emotional well-being. The benefits include improvements in executive functioning, working memory, episodic memory, perceived quality of life, social support, and engagement (Chen & Chan, 2014; Heo, Chun, Lee, Lee, & Kim, 2015; Myhre, Mehl, & Glisky, 2017), as well as decreases in depressive states and feelings of loneliness (Cotten, Ford, Ford, & Hale, 2014; Heo et al., 2015). In a randomized controlled trial of a computer system designed specifically for older adults, participants in the intervention condition experienced less loneliness and increased perceived social support, well-being, computer self-efficacy, proficiency, and comfort with computers than those under the control condition (Czaja et al., 2015; Czaja, Boot, Charness, Rogers, & Sharit, 2017). These findings underscore the importance of understanding how computer adoption rates can be improved.

Although older adults' adoption rates of computers and the Internet have historically been low, they are steadily increasing. In 2016, 67% of older adults (65+ years of age) reported use of the Internet compared to 12% of older adults in 2000 (Anderson & Perrin, 2017). Among the younger old-age group (65–69 years of age), the rate is much higher (82% of this age group reports Internet use). Nevertheless, older adults' technology adoption rates remain significantly lower when compared with the 90% of the general adult population that regularly goes online (Anderson & Perrin, 2017). Older adults who are nonadopters of computer technologies and the Internet will not be able to benefit from its potential.

Models of technology acceptance have been developed to understand the factors contributing to technology adoption, including computer use. One of the most widely referenced is the technology acceptance model (TAM; Davis, 1989). Predictors in the most recent version of the TAM include factors such as perceived usefulness, perceived ease of use, age, education, income, race/ethnicity, gender, experience, self-efficacy, and technology characteristics (TAM 3; Venkatesh & Bala, 2008). The unified theory of acceptance and use of technology (UTAUT; Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012) was created to integrate the TAM and its variations (Davis et al., 1989; Venkatesh & Davis, 2000) with other prominent technology acceptance theories (e.g., Compeau, Higgins, & Huff, 1999; Moore & Benbasat, 1991; Taylor & Todd, 1995). The UTAUT model included higher-order determinants of technology acceptance (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions), as well as moderators of the relationship between the determinants and acceptance (i.e., gender, age, voluntariness, and experience). Additional factors that have been proposed to be predictors of technology acceptance include personality characteristics (Nov & Ye, 2008; Wixom & Todd, 2005) and cognitive abilities (Czaja et al., 2006; De Haan, 2004; Freese, Salvador, & Hargittai, 2006; Pan & Jordan-Marsh, 2010).

Technology acceptance is often operationally defined as the behavioral intention to use or adopt a technology. TAMs that predict behavioral intentions are limited, however, in their prediction of behavioral adoption of a technology over time. Behavioral intention may be driven by different variables than those that drive longer-stage adoption (Peek et al., 2014). Models are also limited in their application to the older adult population. Older adults have general characteristics that differ quantitatively and qualitatively from younger adults (e.g., abilities, health, attitudes about and experience with technology), yet they have within-group heterogeneity regarding the purposes for which they use technology (van Boekel, Peek, & Luijkx, 2017). The senior TAM included the characteristics of older adults (Chen & Chan, 2014); however, this model was tested for its predictive ability regarding use of a wide variety of technologies, not specifically computer use, and assessed a limited sample of older adults. Although the UTAUT model was assessed for a sample that included older adults, it was only for mobile Internet technology adoption (Venkatesh, Thong, & Xu, 2012).

In studies of older adults' computer and Internet adoption, positive perceptions of usefulness, ease of use, and efficacy predict use (Adams, Stubbs, & Woods, 2005). Computer and Internet use has also been associated with older adults who are relatively young, are more educated, have higher annual incomes, are healthier and more active, are members of community organizations, and do volunteer work (Anderson & Perrin, 2017; Berner, Rennemark, Jogréus, & Berglund, 2012; Cresci, Yarandi, & Morrell, 2010). Older adults are also more likely to use tablets if they see others using them, are advised to use them, or gifted a tablet by family members (Tsai et al., 2015). These findings are consistent with some of the predictors in the UTAUT, yet also emphasize the importance of predictors that may be more relevant to older adults than younger adults (e.g., health).

Models of technology acceptance and adoption are also limited in that they have not been empirically tested with senior-focused technologies. Chen and Chan (2014) assessed acceptance of "gerontechnology" but these were technologies designed for general use, perhaps having particular benefit for older adults. Technologies that are designed without consideration for older adults' needs and preferences can present barriers for their use. Barriers can stem from design that is incompatible with older adults' capabilities and limitations (e.g., vision, hearing, and touch), which can lead to usability issues (Fisk, Rogers, Charness, Czaja, & Sharit, 2009). Furthermore, older adults typically have less technology experience compared with younger adults and thus also have less developed mental models of how to use technologies (e.g., menu systems; Ziefle & Bay, 2004). When older adults do attempt to adopt new technologies, they may lack access to training and technology support resources (Mann, Belchior, Tomita, & Kemp, 2005; Preusse, Mitzner, Fausset & Rogers, 2017; Rosenthal, 2008). Finally, the cost to purchase and maintain new technologies may present a barrier for older adults who may have a limited income (Carpenter & Buday, 2007).

Study Overview

Personal Reminder Information and Social Management (PRISM) is a computer system specifically designed for older adults to support social connectivity, procedural and prospective memory, knowledge about topics and resources, and access to community resources (Czaja et al., 2015, 2017). PRISM was designed to be useful (content relevant to older adults) and usable (interface designed with consideration for older adults' capabilities) for older adult users. In a randomized controlled trial (ClinicalTrials.gov; Identifier: NCT01497613), we evaluated the impact of the PRISM computer system on social isolation, social support, and well-being for a large and diverse sample of older adults who live alone in the community. The PRISM trial also assessed acceptance, adoption, and usage over time.

The purpose of this analysis was to understand predictors of older adults' use of the PRISM computer system over time (i.e., technology adoption). Given that the PRISM system is designed to be usable by and useful for older adults, we had the opportunity to evaluate adoption of a computer system with fewer barriers for older adults compared with traditional computer interfaces. Specifically, the following characteristics of the PRISM system and trial were intended to facilitate adoption: improved usability with research-based design choices (e.g., font size, simpler and more consistent design), decreased financial burden by provision of computer system and Internet service for free during the trial, and provision of training and education (nonelectronic user manual, access to a helpline). The training protocol was also designed specifically for older adults.

Predictor variables included in the analyses were selected based on technology and computer acceptance literature: demographics (age, education, race/ethnicity, gender, income), personal characteristics (mental and physical health, personality), technology experience, computer attitudes (efficacy, comfort, interest), technology acceptance (perceived ease of use and usefulness), cognitive abilities (fluid and crystallized), and quality of life. To understand computer adoption over time (i.e., following initial introduction and training on the system), we examined mid-term and long-term use of the PRISM system as outcome variables.

Materials and Methods

Data and Study Sample

Here, we present a brief summary of the PRISM trial; the methods and main outcomes of the trial have been previously reported in depth (Czaja et al., 2015, 2017). Recruitment targeted older adults who were at risk for social isolation, which was operationalized as living alone, not spending more than 10 hr each week at a Senior Center, not working or volunteering for more than 5 hr per week, and having minimal computer and Internet experience in the past 3 months. To be eligible for the study, individuals had to be 65 years of age or older, English speaking, and able to read at the sixth grade level. Participants were recruited through advertisement and outreach methods (e.g., churches and community organizations) from the Atlanta (GA), Miami (FL), and Tallahassee (FL) regions of the United States (see Czaja et al., 2015 for details about recruitment methods).

Participants were randomly assigned to either the intervention condition (PRISM) or a control condition. The intervention group received the PRISM computer system in their home for a period of 12 months. The control group received a binder containing content parallel to the PRISM system in a paper form (e.g., resource guides, calendar, and games).

For this analysis, only participants from the PRISM condition were included (N = 150). Participants were 65–98 years of age (M = 77, SD = 7.30), primarily of lower socioeconomic status, with some college or less education (78%) and ethnically diverse (operationalized as self-identifying to the following categories: Caucasian, n = 90; African American, n = 51; Other, n = 9). Most participants self-identified as female (n = 119; male n = 31) and reported themselves to be in good general health (M = 3.0, SD = 0.85 on a scale from 1 to 5, where 3 = "good").

Materials

The PRISM computer system comprised a 19-in. LCD monitor, keyboard, mouse (or trackball if the participant experienced difficulty using the mouse), and desktop PC with a Microsoft Windows operating system (all off the shelf). The PRISM software included seven system features (E-mail, Internet, Classroom, Calendar, Photos, Games, and Community) as well as a help section. Participants received one-on-one training, were given a hard copy user manual, and had access to a helpline they could call if they encountered technical issues with the system. The PRISM system and the corresponding training were developed with a user-centered design approach, involving multiple iterations of testing with older adults. Internet service was provided for 1 year.

Procedures

Following randomization, participants completed a baseline assessment. The PRISM system was then installed in participants' homes by study personnel. Participants received three individualized sessions of PRISM training. Whenever participants used a PRISM feature, a message was sent to a central server in Miami. PRISM system use was measured over the course of the 12-month trial. The institutional review boards at all research sites approved the study, and all participants provided informed written consent.

Measures

Predictor variables

A battery of assessments was administered at baseline, 6 months, and 12 months. For a comprehensive list, see Czaja and colleagues (2015). The present analyses focused on the relationship between baseline measures and mid-term and long-term adoption variables. Predictor variables were selected based on their predictive ability reported in the literature (i.e., theoretically driven) and if they were significantly correlated ($r > .10$) with outcome variables (e.g., PRISM use). Baseline measures included in this analysis are presented in Table 1. We also controlled for *early-term use of PRISM* defined as the average number of days that any feature of PRISM was used during weeks 1–3, given that training and early learning of PRISM was occurring during this period.

Outcome variables

PRISM system adoption was operationally defined as use, measured at two different time points over the 12-month trial (midterm and long term). *Long-term use of PRISM* was defined as the period toward the latter end of the trial (i.e., 41–43 weeks). We did not choose the final 5 weeks for long-term use because we were concerned about end of the study effects, such as participants transitioning to other software systems in anticipation of PRISM support ending (i.e., a month before the study close reminding them that the study would no longer be paying for their Internet service). *Mid-term use of PRISM* was defined as 21–23 weeks; that is, the period approximately midway between early-term use (1–3 weeks) and long-term use (41–43 weeks). We did not include early-term use as an outcome variable because training and early learning was occurring during this period, and the focus of this analysis was on extended system use. For each term of use, we calculated the mean number of days that any feature of the PRISM system was used during the 3-week period.

Analytical Plan

The goal of this analysis was to understand the extent to which a set of theoretically defined factors predicted mid-term and long-term use in the PRISM study (see Czaja et al. 2017 for additional analyses). A random effects model (*xtreg* in STATA) followed by *contrast* across levels was estimated to assess for differences in usage across the three terms. Descriptive statistics and correlations for all study variables were computed. Variables that had correlations greater than .10 with either outcome variable (i.e., mid-term or long-term use) were included in the remainder of the analyses. We also retained some variables that were theoretically meaningful as predictors in the analyses. To test the main aim of the study, two simultaneous ordinary least squares regression models, analogous to path analyses (*Pathreg* in STATA), were estimated to evaluate how the addition of each component of the conceptual model contributed to the explained variance in the outcome. All analyses were performed in STATA, v. 14, using an intention-to-treat protocol (Gupta, 2011). In this context, that means that even if participants did not end use the PRISM system at all during the trial, they were included in the analysis. Nonuse for the mid-term time period was 17% ($n = 25$); for the long-term time period nonuse was 22% ($n = 33$).

First, baseline predictors were entered in the model to estimate their association with PRISM use at the midterm of the trial. These included variables listed in Table 1 and early-term use of PRISM. Second, all of the baseline predictors along with early-term and mid-term use of PRISM were included in the model to predict long-term use of PRISM. Age and gender were included as control variables for both outcomes. Unstandardized and standardized direct effects and indirect effects are reported.

Results

Table 2 and Figure 1 provide descriptive statistics for the sample. Change in mean number of days/week of PRISM

Table 1. Predictor Variables

Variables	
General technology experience	Modified from Czaja and colleagues (2006)
Computer proficiency	Computer Proficiency Questionnaire; Boot et al. (2015)
Center for Epidemiologic Studies Depression Scale (CES-D)	Center for Epidemiological Depression Scale (Irwin, Artin, & Oxman, 1999; Radloff, 1977)
General health	Czaja and colleagues (2006)
Ten-Item Personality Inventory (TIPI)	TIPI (Gosling, Rentfrow, & Swann, 2003)
Quality of life	Logsdon, Gibbons, McCurry, and Teri (2002)
Computer attitudes	Czaja and colleagues (2006)
Technology acceptance	Modified from Davis (1989)
Fluid abilities	Trails B-A (Reitan, 1958); Letter sets (Ekstrom et al., 1976); Stroop span (McCabe, Robertson, & Smith, 2005); Animal fluency (Rosen, 1980); Fuld object-memory evaluation (Fuld, 1980)
Crystallized abilities	Shipley vocabulary (Shipley, 1940; Zachary, 1986); Wide Range Achievement Test (WRAT T-3) (Wilkinson, 1993)

Table 2. Participant Characteristics

Variables	*N*	%	*M*	*SD*	Range
Demographics					
Age			76.97	7.30	65–98
Annual income					
<$30,000	116	84.67	—	—	—
$30,000–$59,999	18	13.14	—	—	—
>$60,000	3	2.19	—	—	—
Race/ethnicity					
White/Caucasian	86	59.72	—	—	—
Black/African American	49	34.03	—	—	—
Asian	1	0.69	—	—	—
Native Hawaiian/Pacific Islander	1	0.69	—	—	—
Multiracial	4	2.78	—	—	—
Other	3	2.08	—	—	—
Hispanic					
Yes	12	8.33	—	—	—
No	132	91.67	—	—	—
Personal characteristics					
Center for Epidemiologic Studies Depression Scale (CES-D)			9.69	4.05	6–24.16
General health			3.03	.85	1–5
Ten-Item Personality Inventory (TIPI)					
Extroversion			8.74	2.73	2–14
Agreeableness			12.3	1.91	5–14
Conscientiousness			12.28	2.27	2–14
Emotional stability			11.33	2.74	4–14
Openness to experience			11.03	2.55	3–14
Quality of life			39.02	5.56	24–51
Technology experience					
General technology experience			11.28	3.98	4–23
Computer proficiency			9.86	4.05	6–24.16
Computer attitudes					
Computer self-efficacy			20.3	2.9	12–25
Computer comfort			16.74	4.21	7–25
Computer interest			20.46	3.40	11–25
Technology acceptance					
Perceived ease of use			34.63	6.40	7–42
Perceived usefulness			34.70	7.43	6–42
Fluid abilities					
Trails B-A (log)			4.47	0.79	2.07–6.07
Letter sets			8.70	5.19	0–23
Stroop span			55.77	9.92	14–63
Animal fluency			16.38	4.59	5–33
Fuld object-memory evaluation			22.83	2.91	12–30
Crystallized abilities					
Shipley vocabulary			29.33	6.72	10–39
Wide Range Achievement Test (WRAT T-3)			47.99	5.56	19–57
PRISM use (in days/week)					
Early term			4.08	2.21	0–7
Mid term			3.49	2.55	0–7
Long term			3.11	2.65	0.7

use during the early ($M = 4.08$, $SD = 2.21$), mid ($M = 3.49$, $SD = 2.55$) and long ($M = 3.11$, $SD = 2.65$) term was evaluated and significant differences ($p < .01$) in use were found between the three terms.

Table 3 provides the correlations of predictor variables with mid-term and long-term use variables. Note that early-term use was not significantly correlated with any of the predictor variables, hence we have only included its correlation with mid-term and long-term use in Table 3. Several personal factors were significantly associated with mid-term and long-term PRISM use ($p < .05$). Depression was negatively associated with mid-term and long-term use

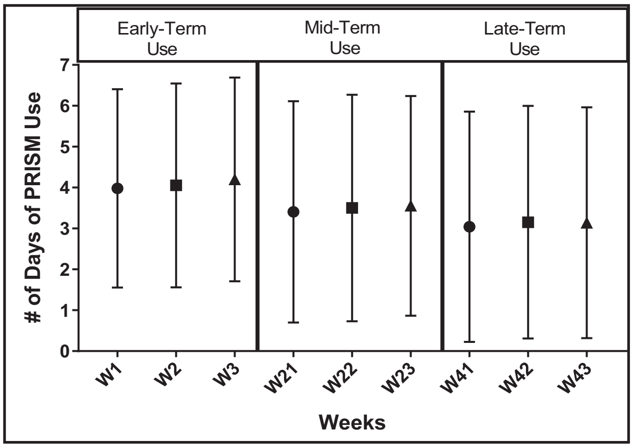

Figure 1. Means (and standard deviations) for number of days of early-term use (weeks 1–3), mid-term use (weeks 21–23), and long-term use (weeks 41–43) of the PRISM system.

of PRISM during the trial. Computer proficiency was also negatively associated with mid-term and long-term use. Emotional stability was positively associated with mid-term PRISM use. Higher computer interest and perceived ease of use were all associated with greater PRISM use in the mid term. Computer self-efficacy was positively correlated with mid-term and long-term PRISM use. Finally, the Trail Making test, a neuropsychological test of visual attention and executive function, was negatively associated with mid-term and long-term PRISM use. Note that the Trail Making test is timed, hence a lower score is associated with better executive control.

Predictors of Mid-Term and Long-Term PRISM Use

Table 4 shows that early use of PRISM strongly predicted mid-term use of PRISM ($B = 0.66$, $\beta = .57$, $p < .01$). Higher executive functioning, measured by the Trail Making test, also strongly predicted PRISM use during the mid term of the PRISM trial ($B = -0.48$, $\beta = -.15$, $p < .05$). There was a trend found for gender, wherein women were found to be more likely to use PRISM during the midterm of the trial ($B = 0.78$, $\beta = .13$, $p = .06$).

Mid-term PRISM use was strongly associated with long-term PRISM use ($B = 0.78$, $\beta = .75$, $p < .1$), whereas computer efficacy showed a slight trend in predicting long-term PRISM use ($B = 0.11$, $\beta = .12$, $p = .08$). Executive functioning no longer had a direct effect but continued to have an indirect effect on long-term PRISM use ($B = -0.37$, $\beta = -.11$, $p < .05$).

In sum, individuals who used PRISM more at the beginning of the trial, those with higher executive functioning, and women were more likely to use PRISM at the midterm of the trial, whereas those who used PRISM system more during the midterm of the trial and those with higher computer efficacy were more likely to adopt and use PRISM in the long term. Executive functioning continued to play an important role in PRISM use, and women were more likely than men to continue using PRISM. The final model is presented in Figure 2.

Discussion and Implications

Given the growing research on the benefits of computer use for older adults, it is critical that we understand the factors that influence adoption. The current body of technology acceptance literature is limited in that few studies have examined adoption of computer applications designed with consideration for older adults' needs and preferences. The PRISM computer system was designed to reduce many of the barriers that older adults encounter with traditional computer systems, which enabled us to examine the impact of other factors. Moreover, the PRISM sample was larger relative to other studies that examined older adults' use of technology (e.g., Shapira, Barak, & Gal, 2007; White et al., 2010).

Predictor variables were selected based on their predictive ability reported in the technology acceptance literature (theoretically driven) and/or if they were significantly correlated with outcome variables (data driven). Mid-term adoption was predicted by early use, executive function, and gender (women). Those who used PRISM more at the beginning of the trial, those with higher executive functioning, and women were more likely to adopt and use PRISM at the mid term of the trial. Long-term adoption was predicted by mid-term PRISM use and computer efficacy. That is, those who used PRISM more at the mid term and those with higher confidence in their ability to use computers were more likely to adopt and use PRISM over the long term.

Most of the prior research in the technology acceptance literature has focused on older adults' acceptance, such as initial perceptions of ease of use and usefulness (e.g., Mitzner et al., 2016) and behavioral intentions (e.g., Davis, 1989, 2004). Technology acceptance and behavioral intention to adopt are important factors in and of themselves and are correlated with behavioral adoption. However, use over time is necessary to reap the benefits of using a technology. Examining behavioral intention alone does not allow for the disambiguation of those who start using a technology initially and then abandon it or intend to use it but never do. Our results show that for a technology that was designed to be usable to and useful for older adults, the provision of initial independent experience with that technology was a strong facilitator to both mid-term and long-term adoption.

The finding that early use of technology predicts later use of a technology is consistent with previous research (Czaja et al., 2006; Forquer, Christensen, & Tan, 2014; Kim & Malhotra, 2005). Note that the earlier use predictors (early use as a predictor of mid-term use and mid-term use as a predictor of long-term use) were the strongest predictors of PRISM use. Early-term use was independent use after the training period. The provision of training and the usability of the system likely facilitated early-term use

Table 3. Correlations of Mid-Term Use and Long-Term Use with Individual Characteristics

Variables	Mid-term use Spearman Rho/Point Biserial	*N*	Long-term use Spearman Rho/Point Biserial	*N*
Demographics				
Education	.01	150	.00	150
Gender	.13	150	.07	150
	Pearson *r*	*N*	Pearson *r*	*N*
Age	−.08	150	−.13	150
Income	.02	137	.1	137
Personal characteristics				
Center for Epidemiologic Studies Depression Scale (CES-D)	−.19*	150	−.17*	150
General health	.03	149	.00	149
Ten-Item Personality Inventory (TIPI)				
Extroversion	.02	149	.02	149
Agreeableness	−.03	149	−.07	149
Conscientiousness	.10	149	.14	149
Emotional stability	.16*	148	.10	148
Openness to experience	.11	149	.03	149
Quality of life	.15	150	.07	150
Technology experience				
General technology experience	−.06	149	−.08	149
Computer proficiency	−.17*	147	−.18*	147
Computer attitudes				
Computer self-efficacy	.19*	149	.19*	149
Computer comfort	.09	149	.01	149
Computer interest	.19*	149	.16	149
Technology acceptance				
Perceived ease of use	.17*	149	.09	149
Perceived usefulness	.10	149	.08	149
Fluid abilities				
Trails B-A (log)	−.22*	148	−.19*	148
Letter sets	.10	137	.15	137
Stroop span	.05	142	.12	142
Animal fluency	.12	149	.15	149
Fuld object-memory evaluation	.06	160	.11	150
Crystallized abilities				
Shipley vocabulary	.11	150	.06	150
Wide Range Achievement Test (WRAT T-3)	.02	150	−.00	150
Early-term use of PRISM	.64	150	.57	150

as well as computer efficacy. The early-term use may have allowed participants to see and experience the benefits and usefulness gained from using the system.

The present findings are also consistent with previous literature in identifying the influence of cognitive abilities (executive functioning; Czaja et al., 2006; Pan & Jordan-Marsh, 2010). Although all participants were given the same system and provision of training, those with lower executive functioning were less likely to be using the system at the mid term of the trial. System design and training may not have ameliorated all barriers to use for those with lower executive functioning skills. Future research is needed to understand what additional supports could facilitate computer use to a greater extent for this population. Additional supports that should be explored include a less deep menu structure, additional training, and more training materials.

Previous research has shown the importance of computer self-efficacy (Czaja et al., 2006) on older adults' technology adoption; our findings also showed the positive impact of self-efficacy for long-term adoption of the PRISM system. These results reflect the need for individuals to be confident in their ability to use a technology for long-term adoption. Just as additional supports may be necessary to facilitate computer use for those with low executive functioning, additional supports may also be needed for those with low computer self-efficacy. Individuals with low computer self-efficacy may need more one-on-one training than those with higher computer self-efficacy. It may be

Table 4. Simultaneous Ordinary Least Squares Regressions Predicting Mid-Term and Long-Term Usage of PRISM

	Mid-term use of PRISM		Long-term use of PRISM			
	Direct effects		Direct effects		Indirect effects	
	B (SE)	β	*B (SE)*	β	*B (SE)*	β
Early-term use of PRISM	0.66 (0.08)**	.57	0.10 (0.08)	.08	0.52 (0.07)**	.43
Mid-term use of PRISM	—		0.78 (0.07)**	.75	—	—
Computer attitudes						
Computer interest	0.08 (0.08)	.11	−0.03 (0.06)	−.04	0.06 (0.06)	.08
Computer efficacy	0.04 (0.07)	.05	0.11 (0.06)†	.12	0.03 (0.06)	.04
Technology acceptance						
Perceived ease of use	0.00 (0.04)	.00	−0.05 (0.03)	−.12	0.00 (0.03)	.00
Perceived usefulness	−0.01 (0.04)	−.02	0.03 (0.03)	.09	0.00 (0.03)	−.01
Technology experience						
General technology experience	−0.03 (0.04)	−.05	−0.04 (0.04)	−.06	−0.03 (0.03)	−.04
Fluid abilities						
Trails B-A (executive function)	−0.48 (0.22)*	−.15	0.03 (0.19)	.01	−0.37 (0.17)*	−.11
Personal characteristics						
Center for Epidemiologic Studies Depression Scale (CES-D)	−0.02 (0.02)	−.06	−0.02 (0.02)	−.05	−0.02 (0.02)	−.05
Emotional stability	0.06 (0.07)	.07	−0.06 (0.06)	−.06	0.05 (0.05)	.05
Demographics						
Gender	0.78 (0.40)†	.13	−0.39 (0.34)	−.06	0.61 (0.31)*	.09
Age	0.01 (0.02)	.03	−0.03 (0.02)	−.08	0.01 (0.02)	.02
Intercept	−1.01 (2.49)		2.56 (2.08)			
Error, *sqrt* $(1–R^2)$	0.73		.58			
R^2	0.46		.66			

Note: †$p < .1$; *$p < .05$; **$p < .01$.

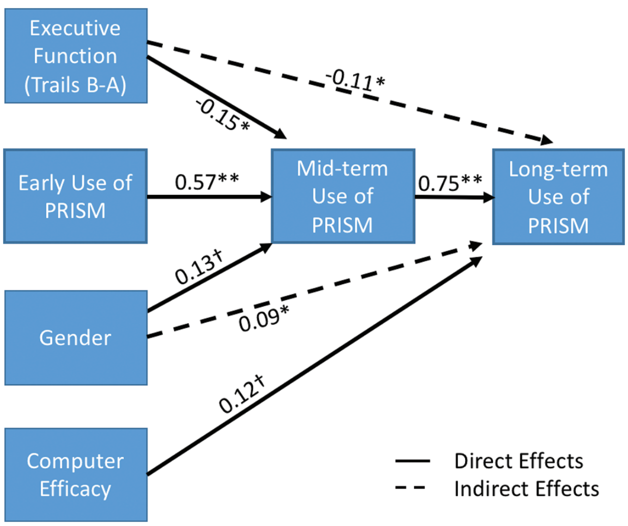

Figure 2. Predictors of mid-term and long-term PRISM use (β values shown). Note: **<.01; *<.05; †<.10.

advantageous to assess self-efficacy at the end of a computer training course to ascertain whether some participants would benefit from additional training sessions.

Models of technology acceptance typically find perceived ease of use and usefulness to be significant predictors of adoption (e.g., Venkatesh & Bala, 2008). However, Chen and Chan (2014) examined "gerontechnology" and did not find perceived ease of use and usefulness to be significant predictors of use. The gerontechnologies Chen and Chan (2014) assessed were electronic or digital products and services that could increase independent living and social participation for older adults. They were everyday technologies, not specifically designed for older adults. Chen and Chan (2014) measured usage as self-report. Our findings extend theirs in that we also did not find initial ease of use and usefulness to be significant predictors but with an objective measure of usage. Given that PRISM was designed to be useful and easy to use for older adults, typical barriers to adoption were likely reduced, such as perceptions about ease of use and usefulness, usability, and financial burden.

Technologies, such as PRISM, have the potential to increase well-being by various mechanisms, including supporting communication with friends and family and by facilitating access to resources for mental health. We found depression to be significantly negatively correlated with mid-term and long-term PRISM use. Albeit, depression was not a significant predictor of adoption in our final model. Given the potential benefits, more research is needed to understand how to facilitate adoption for people who show depressive symptoms.

One limitation of this study is that participants were largely of lower socioeconomic status, and study inclusion was restricted to individuals who lived alone in the community. Our sample also primarily identified as female, which limits interpretation of our finding of gender predicting mid-term PRISM use. Broader samples will determine if the findings generalize to other subpopulations of older adults. The findings are also partly technology dependent; they may generalize to other senior-focused technologies or other technologies that are useful and easy to use for older adults, but the same pattern of findings would not be expected to generalize to technologies that pose traditional barriers for older users. In addition, this study used a global measure of *any* use of the PRISM system. A deeper understanding of technology adoption could be gained by looking specifically at specific features of the system, and the amount of time spent on each feature. Despite these limitations, the present findings add to the growing body of literature on older adults' technology adoption.

Our findings provide insights for models of technology acceptance to guide design, instruction, and deployment of products for older adults. Understanding the factors that influence older adults' computer adoption is critical given documentation of the benefits of computers and tablets, ranging from memory improvements (Chan et al., 2014; Myhre et al., 2017) to decreased prevalence of depressive states (Cotten et al., 2014), and higher levels of social support, lower feelings of loneliness, and a better perceived quality of life (Heo et al., 2015). The PRISM computer system was designed to be more useful and easier to use for older adults compared with traditional computer systems, and experience using the system was critical for enabling longer-term adoption and use. Beyond designing technologies with consideration for older adults' needs and preferences, providing access and support for using a technology in the early weeks of its deployment may be one of the single most important steps that can be taken to facilitate adoption.

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Conflict of Interest

None to declare.

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