Exploring Predictors of Mobile Device Proficiency Among Older Adults

Kimberly Champagne and Walter R. Boot(✉)

Department of Psychology, Florida State University, Tallahassee, FL, USA
kjcl5e@my.fsu.edu, boot@psy.fsu.edu

Abstract. Technology adoption rates of older adults typically lag behind those of their younger counterparts; a digital divide. This is unfortunate because technology has many potential benefits for older people. Among older adults, attitudes and cognitive abilities predict computer and Internet adoption, use, and proficiency. However, an important trend over the past two decades has been the rise of mobile computing (specifically with respect to smartphones and tablet computers). High quality interactions with mobile technology critically depend upon individuals' technology proficiency, making it important to understand how mobile device proficiency might be anticipated. This paper explored predictors of mobile device proficiency among older adults (65+) using a dataset from a cognitive intervention study that included 60 participants. Measures of computer and mobile device proficiency were obtained. Demographic variables and assessments of reasoning ability, processing speed, and executive control were collected and explored as predictors of mobile device proficiency. Even within this older adult sample, mobile device proficiency was related to age, but contrary to predictions, cognition was not significantly related to mobile device proficiency; the strongest predictor of mobile device proficiency was computer proficiency. This implies some transfer of proficiency from one technology platform to another. These results have implications for predicting quality technology interactions given the link between interaction quality and technology proficiency.

Keywords: Technology · Older adults · Individual differences · Cognition · Digital divide

1 Introduction

Although the gap between technology adoption rates of younger and older adults has been shrinking for decades, a substantial digital divide still exits. This can clearly be observed in recent U.S. survey data from the Pew Research Center [1]. In 2016, 36% of older adults (65+) reported not using the Internet over the past year, compared to only 1% of 18–29 year-olds, and 22% of adults overall. With respect to mobile devices an even greater divide is observed. Fifty-eight percent of older adults reported not owning a smartphone in 2016, compared to only 8% of adults 18–29 years of age. This is unfortunate because the use of the Internet and mobile devices have many potential benefits to older adults [2]. For example, an older adult with limited mobility can still shop and bank online even if they have difficulty leaving their home. Smartphone

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applications (apps) can assist older adults in managing their health, and for older adults with one or more chronic diseases, apps can help them manage their schedule of medications. The Internet has a wealth of resources (global and national resources, as well as resources specific to their community) that may be beneficial to older adults, but up to 36% of older adults in the U.S. may have difficulty accessing these resources. Finally, technology can provide enrichment and social activities, such as games and video conferencing with friends and family members, which has the potential to improve well-being [3]. Older adults who are not computer proficient or do not have access to the Internet are at a disadvantage. The digital divide is even more pronounced for older, lower-income, lower-education, rural, and minority older adults. Even for older adults who are computer proficient, they may still be locked out of the benefits of being able to utilize the same resources on a mobile platform, restricting when and where they have access to important resources. Younger adults are far more likely to own a smartphone compared to a non-smartphone, while this pattern is reversed for older adults.

Why is it that older adults lag in terms of technology use? About one-third of adults who do not use the Internet in the U.S. cite usability issues as the main reason [4]. Non-users report frustration using the Internet, lack of relevant knowledge, and feelings that they are too old to learn how to use the Internet. About one-third of non-users report feelings that the Internet isn't relevant to them as the main reason for non-use. These individuals state that they don't need to use the Internet, aren't interested in using it, and feel as though Internet use is a waste of time. These responses are broadly consistent with popular models of technology acceptance and adoption in which perceived ease of use and perceived usefulness primarily dominate decisions of whether or not to adopt new technology [5, 6].

Technology design may play another important role in influencing the technology adoption rates of older adults. As we age we can expect to experience some degree of perceptual and cognitive decline. These changes are a natural consequence of the aging process. However, if the design of technology does not take these changes into account, and does not recognize the fact that older adults may not have the same mental models related to technology as younger adults, older adults may experience difficulty and frustration, discouraging their adoption and use of technology [7]. Aging specific models of technology use and adoption highlight the important role of cognition [8, 9]. This role is confirmed in studies finding that among older adults, successful use of technology across a variety of technology types appears to be related to working memory, executive control, and reasoning ability [e.g., 10, 11]. The implication is that with proper design and careful consideration, as well as a focus on training to build up relevant mental models, the quality of older adults' interactions with technology might be improved and the digital divide might be greatly reduced.

Technology proficiency also likely plays an important role in technology adoption and the quality of a user's experience. Take, for example, an Internet-based system an older adult might use to track their health and receive information about nutrition and exercise to maintain a healthy lifestyle. If an older adult's basic computer and Internet proficiency is low, it is unlikely that they will have success using this system or that their interaction with this system will be positive. This makes understanding factors related to computer proficiency also broadly important for understanding technology adoption and user experience for a range of systems and software packages. Recently Zhang et al. [12] explored the best predictors of computer proficiency in an older adult sample (ages 60 to 95). To measure computer proficiency, the authors used a validated questionnaire specifically designed for older adults with a wide range of computer experience, the Computer Proficiency Questionnaire (CPQ) [13]. Age and education were significant predictors of proficiency. Cognition (psychomotor speed and inductive reasoning) uniquely predicted computer proficiency such that those with greater cognitive abilities tended to be more computer proficient. Socio-emotional variables were also important, with positive affect and a greater sense of control predicting some aspects of computer proficiency.

The current study aimed to explore similar questions asked by Zhang and colleagues regarding technology proficiency. Rather than explore predictors of computer proficiency, we explored predictors of mobile device proficiency (computing using a tablet or smartphone). We believe that this is important as much of the computing many individuals engage in everyday now takes place on mobile devices. Further, as mentioned previously, there is a substantial age-related digital divide for mobile devices such as smartphones and tablet computers. Understanding predictors of mobile device proficiency is also important as there are inherent advantages to mobile computing compared to desktop computing because apps and resources can be accessed from anywhere, and a lack of mobile device proficiency may "lock out" older adults from these advantages. Finally, the perceptual and cognitive demands of smaller mobile devices, and also differences in complexity between software that may be on desktop computers and mobile devices, may result in the predictors of mobile device proficiency being different compared to computer proficiency.

We explored these issues using the Mobile Device Proficiency Questionnaire (MDPQ) [14]. This measure, based on the Computer Proficiency Questionnaire, has been demonstrated to be a reliable and valid measure of smartphone and tablet computer proficiency. All analyses reported here are exploratory rather than confirmatory, as they constitute the combination and reanalysis of previously reported data [14–16]. These papers provide a full description of all measures and procedures, which will be summarized briefly here. Of primary interest are demographic and individual difference characteristics and how they relate to mobile device proficiency.

2 Methods

The current project reused data from a study in which cognitive abilities were measured before and after a tablet-based brain training intervention [15, 16]. Measures of computer and mobile device proficiency were also collected before training. Analyses are based on a dataset consisting of data from 60 participants who completed the intervention. The average age of participants included in the analyses reported here was 72 years (SD = 5.2) and the sample was 57% female. Approximately 67% of the sample had a college degree or higher.

2.1 Surveys

Computer proficiency was assessed with the short form of the Computer Proficiency Questionnaire, the CPQ-12 [13]. This measure has 12 questions, but correlates highly with the full 33-question version of the CPQ. As an example, the CPQ-12 asks participants to rate statements like the following: *I can: Use a computer to watch movies and videos*. Ratings were made on a 5-point scale (1 = Never tried, 2 = Not at all, 3 = Not very easily, 4 = Somewhat easily, 5 = Very easily). Mobile Device Proficiency was assessed using the Mobile Device Proficiency Questionnaire (MDPQ) [14]. This measure, based on the CPQ, specifically asks participants to rate their proficiency performing tasks with mobile devices such as smartphones and tablet computers (a description of these devices and photographs were provided on the first page of the questionnaire). The MDPQ consists of 46 questions, and features the following subscales: Mobile Device Basics, Communication, Data and File Storage, Internet, Calendar, Entertainment, Privacy, and Troubleshooting and Software Management. Subscale scores were calculated by averaging the response to each question in that subscale. A total mobile device proficiency score was calculated by summing all subscale scores. Participants also completed a demographics questionnaire that collected information about income, education, and age.

2.2 Cognitive Measures

Before and after the intervention, participants completed a variety of cognitive assessment measures. We used pre-intervention scores in all of the reported analyses since at least one measure suggested the intervention may have influenced outcome measure performance. Detailed descriptions of measures are previously reported [15]. Reasoning ability was measured with Form Boards [17], Letter Sets [17], Paper Folding [17], and Ravens Matrices [18]. Processing speed was measured using Pattern Comparison [19] and a Reaction Time task [20]. Memory was assessed with a version of the Corsi Block Tapping task [21]. Finally, executive control was measured using a Task-Switching task [20] and Trails B (adjusted for Trails A performance) [22].

3 Analyses

First, a principal components analysis (PCA) with varimax rotation was conducted to reduce the cognitive data. Then, bivariate correlations explored the relations among the variables of interest. Finally, linear regression analyses explored the best predictors of total mobile device proficiency, as well as proficiency related to basic, intermediate, and difficult mobile device tasks.

4 Results

Principal Components Analysis. A principal components analysis (PCA) was performed on the cognitive dataset. This analysis revealed three factors that accounted for approximately 60% of the variance in the data (Table 1).

Table 1. PCA components extracted from cognitive dataset.

	Component		
	1	2	3
Ravens	**.510**	**.516**	.036
Letter Sets	.376	**.786**	.086
Form Board	**.513**	.025	.044
Paper Folding	−.154	**.817**	.032
Task-Switch	−.188	.280	**.719**
Corsi Block	**.732**	−.018	−.107
Reaction Time	−.197	.117	**−.785**
Pattern Comparison	**.701**	.000	.385
Trails B (Minus A)	**−.711**	−.331	.070

A diverse set of tasks loaded onto the first component, though in general these tasks all had relatively high visuospatial demands (spatial reasoning, spatial memory, visuospatial judgments). Although this first component appears to be more complex than that, for the sake of simplicity we refer to it as the *Visuospatial* factor. Reasoning and problem-solving tasks most highly loaded onto the second component. We refer to this as the *Reasoning* factor. Finally, the two tasks that required quick responses loaded most highly onto the third component, which we interpret as a *Processing Speed* factor. Note that Reaction Time, Task Switch, and Trails B are all measures for which better performance is associated with lower scores, explaining negative factor loadings.

Bivariate Correlations. Next we explored potential correlations between the variables of primary interest. These variables included age, education, technology proficiency, and cognition (Table 2). Contrary to predictions, neither computer nor mobile device proficiency were predicted by cognitive abilities. However, higher levels of education were associated with greater mobile device proficiency, and higher levels of computer proficiency were associated with higher levels of mobile device proficiency. Education also predicted cognitive performance with respect to the *Reasoning* factor.

Predictors of Mobile Device Proficiency. Finally, we explored the question of primary interest: Which factors best predict mobile device proficiency? A linear regression analysis was conducted with Mobile Device Proficiency (Total Score) as the criterion variable and age, education, computer proficiency (CPQ-12), and the three cognitive factors as predictor variables. This model accounted for 49% of the variance in proficiency ($F(6, 46) = 7.44$, $p < .001$). The strongest predictor was computer proficiency, followed by age (Table 3). As computer proficiency increased, so did mobile device proficiency. As age increased, mobile device proficiency decreased. Contrary to predictions, cognitive abilities did not significantly predict mobile device proficiency (all p values > .40).

It's possible that important predictors might vary for different domains of mobile device proficiency. We explored predictors of subscale scores of the MDPQ that reflected proficiency with respect to basic, intermediate, and difficult mobile device tasks. The Basics subscale of the MDPQ assessed proficiency with simple tasks such as

Table 2. Correlations among technology proficiency, demographic, and cognitive measures. Note that Ns varies due to missing or incomplete data for some tests.

		Age	Education	CPQ	MDPQ	Visuospatial	Reasoning	Processing speed
Age	Pearson corr.	1	.021	−.120	−.241	−.168	−.159	−.074
	N	60	60	58	59	56	56	56
Education	Pearson corr.	.021	1	.255	**.266***	.154	**.298***	−.141
	N	60	60	58	59	56	56	56
CPQ	Pearson Corr.	−.120	.255	1	**.683****	.119	−.063	.102
	N	58	58	58	57	54	54	54
MDPQ	Pearson corr.	−.241	**.266***	**.683****	1	.077	−.050	.111
	N	59	59	57	59	55	55	55
Visuospatial	Pearson corr.	−.168	.154	.119	.077	1	.000	.000
	N	56	56	54	55	56	56	56
Reasoning	Pearson corr.	−.159	**.298***	−.063	−.050	.000	1	.000
	N	56	56	54	55	56	56	56
Processing speed	Pearson corr.	−.074	−.141	.102	.111	.000	.000	1
	N	56	56	54	55	56	56	56

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

Table 3. Linear regression analysis predicting Mobile Device Proficiency (Total) from age, education, computer proficiency, and cognition.

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. error	Beta		
(Constant)	14.162	15.410		.919	.363
Age	**−.400**	**.198**	**−.224**	**−2.027**	**.048**
Education	1.115	.923	.145	1.207	.233
CPQ	**1.135**	**.215**	**.594**	**5.285**	**<.001**
Visuospatial	−.009	.994	−.001	−.009	.993
Reasoning	−.882	1.037	−.098	−.851	.399
Processing speed	.122	.990	.013	.124	.902

turning the device on and typing using a touchscreen (Table 4). The same predictors were entered into the linear regression analysis. This model accounted for 35% of the variance in the Basics subscale score ($F(6, 46) = 4.05$, $p < .01$). The strongest predictor was computer proficiency. However, in this analysis age was not a significant predictor, nor were any of the cognitive ability measures (all p values > .51).

Proficiency with respect to mobile device tasks of intermediate difficulty was explored using the Internet subscale of the MDPQ (Table 5). This subscale measures proficiency with tasks such as using search engines and shopping online. The same predictors were entered into a linear regression analysis. The model accounted for 44% of the variance in Internet subscale scores ($F(6, 46) = 6.05$, $p < .001$). Again, computer proficiency was the strongest predictor, followed by age. Unexpectedly, reasoning ability *negatively* predicted Internet proficiency using mobile devices.

Table 4. Linear regression analysis predicting Mobile Device Basics subscale scores of the MDPQ from age, education, computer proficiency, and cognition.

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. error	Beta		
(Constant)	−.354	2.774		−.128	.899
Age	−.014	.036	−.049	−.388	.699
Education	.077	.166	.063	.463	.646
CPQ	**.167**	**.039**	**.553**	**4.331**	**<.001**
Visuospatial	.040	.179	.027	.222	.826
Reasoning	−.124	.187	−.087	−.663	.511
Processing speed	−.112	.178	−.077	−.628	.533

Table 5. Linear regression analysis predicting Internet subscale scores of the MDPQ from age, education, computer proficiency, and cognition.

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. error	Beta		
(Constant)	3.707	2.867		1.293	.203
Age	**−.082**	**.037**	**−.258**	**−2.224**	**.031**
Education	.176	.172	.129	1.024	.311
CPQ	**.165**	**.040**	**.486**	**4.125**	**<.001**
Visuospatial	.106	.185	.065	.573	.569
Reasoning	**−.461**	**.193**	**−.289**	**−2.390**	**.021**
Processing speed	−.041	.184	−.025	−.220	.827

Table 6. Linear regression predicting Troubleshooting and Software Management subscale scores of the MDPQ from age, education, computer proficiency, and cognition.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	2.287	2.526		.905	.370
Age	−.064	.032	−.222	−1.970	.055
Education	.082	.151	.066	.541	.591
CPQ	**.177**	**.035**	**.578**	**5.030**	**<.001**
Visuospatial	.047	.163	.032	.287	.776
Reasoning	−.188	.170	−.130	−1.104	.276
Processing speed	.121	.162	.082	.745	.460

Finally, we examined the Troubleshooting and Software Management subscale as a measure of proficiency with respect to difficult mobile device tasks. This subscale focuses on updating device and application software, recovering from a crash of the device, and deleting unwanted applications. Entering the same predictors into a regression analysis, this model accounted for 47% of the variance in the Trouble Shooting subscale ($F(6, 46) = 6.80$, $p < .001$). Computer proficiency was a strong predictor, though age was a marginally significant predictor as well (Table 6). Cognitive abilities did not predict proficiency with these more challenging mobile device tasks (all p values > .27).

5 Discussion

There exists a striking age-related digital divide with respect to mobile device ownership, and many older adults do not have the proficiency to perform tasks using smartphones and tablet computers [14]. This puts them at a disadvantage with respect to benefiting from mobile devices and applications, and inexperience and low levels of proficiency can result in lower quality technology interactions. The purpose of this exploratory set of analyses was to better understand factors that relate to mobile device proficiency.

Interestingly, even within this older adult sample (65+), greater age was associated with less mobile device proficiency. This is likely due to less mobile device experience being associated with increasing age within the older adult cohort. This speaks to the diversity of the older adult cohort; not all individuals over the age of 65 are alike. However, in addition to experience, this may also be partly due to sensory and physical changes that make mobile device use more challenging. Surprisingly, we found little evidence that cognitive abilities were related to mobile device proficiency or even computer proficiency (Table 2). This is in contrast to a recent study using similar measures [12]. Why did we find that cognition did not predict proficiency while this previous study did? Statistical power may be one explanation, with this previous investigation assessing 97 participants, and our dataset containing data from only 60 participants (with even fewer entering analyses due to missing data). Second, at this point, many older adults have some experience using computers. Because many older adults have some computer experience, proficiency may be driven primarily by cognitive factors rather than experience factors. However, since many older adults do not have experience with mobile devices, in this case, differences in proficiency may be largely experience based. Finally, it should be noted that like many laboratory studies, our participants were screened for cognitive impairment. This means the range in cognitive abilities observed was lower compared to the general population, and it is not appropriate to anticipate a lack of a relationship between cognition and mobile device or computer proficiency in the general population.

The most consistent predictor of mobile device proficiency was computer proficiency. This implies some transfer of either knowledge or attitudes toward technology from one form of technology to another, which may be important in encouraging the adoption of technology useful to older adults. Providing experience with an easy-to-use system, or appropriate technology training, may facilitate technology use more broadly through this mechanism. Previous findings suggest that technology use can increase self-efficacy and reduce technology anxiety, which may partly explain the positive relationship between mobile device and computer proficiency. While exploratory, these results provide insight into mobile device proficiency and factors that may shape technology adoption.

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