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Factors Predicting the Use of Technology: Findings From the Center for Research and Education on Aging and Technology Enhancement (CREATE)

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Abstract

The successful adoption of technology is becoming increasingly important to functional independence. The present article reports findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE) on the use of technology among community-dwelling adults. The sample included 1,204 individuals ranging in age from 18–91 years. All participants completed a battery that included measures of demographic characteristics, self-rated health, experience with technology, attitudes toward computers, and component cognitive abilities. Findings indicate that the older adults were less likely than younger adults to use technology in general, computers, and the World Wide Web. The results also indicate that computer anxiety, fluid intelligence, and crystallized intelligence were important predictors of the use of technology. The relationship between age and adoption of technology was mediated by cognitive abilities, computer self-efficacy, and computer anxiety. These findings are discussed in terms of training strategies to promote technology adoption.

Keywords

aging; technology adoption; cognition; attitudes

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Technology, which is broadly defined as the application of scientific knowledge (including tools, techniques, products, processes, and methods) to practical tasks (United States National Library of Medicine, 2004), is ubiquitous in most societal contexts within the United States and most other industrialized countries. Use of technology has become an integral component of work, education, communication, and entertainment. Technology is also being used increasingly within the health care arena for service delivery, in-home monitoring, interactive communication (e.g., between patient and physician), transfer of health information, and peer support.

Although older adults in the United States are increasingly using technology, data indicate that they typically have more difficulty than do younger people in learning to use and operate current technologies such as computers, the Internet, videocassette recorders, automatic teller machines, and telephone menu systems (e.g., Charness, Schumann, & Boritz, 1992; Czaja & Sharit, 1999; Czaja, Sharit, Ownby, Roth, & Nair, 2001; Rogers, Fisk, Mead, Walker, & Cabrera, 1996; Sharit, Czaja, Nair, & Lee, 2003). In 2003, only 25% of Americans over the age of 65 were "online," as compared with 56% of 30- to 49-year-olds and 36% of those in the 50- to 64-year-old age group (Pew Internet and American Life Project, 2005).

Further, seniors who use the Internet perform online activities such as e-mail and information searches at lower rates than do younger Internet users (Pew Internet and American Life Project, 2004). Results from a recent survey also suggest that computer users over the age of 65 have less confidence in their ability to use computers than do younger people and have fewer computer skills (American Association of Retired Persons [AARP], 2002).

Not being able to use technology such as computers or the Internet puts older adults at a disadvantage in terms of their ability to live and function independently and successfully perform everyday tasks. Further, older populations may not realize the full benefits of available technologies. Technology has the potential of increasing the quality of life for older people. The Internet can help mitigate problems with social isolation, foster linkages to family and friends, and facilitate the performance of essential activities such as banking and shopping. The Internet can also enhance educational opportunities for older adults and enable them to take a more active role in their own health care. However, unless researchers and clinicians have an understanding of why older adults have difficulty adopting technologies or why they choose not to adopt them, successful use of technology will continue to be a challenge for older people.

Data on the adoption and use of technology such as computers have generally shown that a number of factors, such as education, socioeconomic status, attitudes toward the technology, the perceived benefits of technology, and access to technology, influence technology adoption. For example, use of computers and the Internet is lower among older adults, minorities, disabled people, and those with less income and education (Pew Internet and American Life Project, 2004). Common reasons attributed to why older people report that they do not go online include costs, lack of skills, lack of interest, and concerns about security of information (Pew Internet and American Life Project, 2004). Several studies have also shown that attitudes toward technology is an important predictor of use (e.g., Al-Gahtani & King, 1999; Kelley, Morrell, Park, & Mayhorn, 1999); people with more positive attitudes are more likely to use technologies such as computers.

With respect to older adults, Morrell and colleagues (Morrell, Mayhorn, & Bennett, 2000) found that some of the primary reasons that older people do not use computers and the Internet are lack of access to the technology, cost, and lack of knowledge. Likewise, Rogers and colleagues (Rogers, Meyer, Walker, & Fisk, 1998) found that although older people were eager to learn how to use technologies such as fax machines, photocopiers, and computers, they also perceived that they might have difficulty learning to use these systems and that they would require more time to learn them than would younger people. Umemuro (2004) found that, among a sample of Japanese older adults, more positive attitudes toward computers were related to greater use of computers and of computerized products and services. In particular, the results indicated that comfort using computers and interest in computers were the most important predictors of use. The data also suggested that cognitive abilities (e.g., spatial abilities) were important predictors of technology use.

Other studies (e.g., Czaja & Sharit, 1998; Ellis & Allaire, 1999; Tacken, Marcellini, Mollenkopf, Ruoppila, & Szeman, 2005) have found that older adults expressed less comfort in using technology and less confidence in their ability to successfully use these systems. For example, Ellis and Allaire (1999) examined the effects of age, education, computer knowledge, and computer anxiety on computer interest among a sample of older adults ranging in age from 60 to 97 years. They found that age was negatively associated with computer knowledge and computer interest and positively associated with computer anxiety. They also found that higher levels of computer knowledge were related to less computer anxiety and higher computer interest. In addition, they found that although computer anxiety fully mediated the effects of education and computer knowledge on computer interest, not all of the age-related variance in computer interest was explained by computer anxiety or computer knowledge. They concluded that other factors, such as self-efficacy beliefs, may be important in explaining age differences in computer interest.

To date, few studies have examined the role of cognition in predicting the use of technology. Several studies (e.g., Charness, Kelley, Bosman, & Mottram, 2001; Czaja et al., 2001; Sharit et al., 2003) have shown that cognitive abilities such as memory and speed of processing are important to successful performance of technology-based tasks. However, it is not clear whether cognitive abilities are directly linked to technology adoption. Findings from the Umemuro (2004) study have suggested that cognition is an important predictor of computer use; however, the sample size was small, and the age range was restricted (60–80 years).

The present article presents data from the Center for Research and Education on Aging and Technology Enhancement (CREATE) on use of technology, computers, and the Internet among a large, diverse sample of community-dwelling adults ranging in age from 18 to 91 years. In particular, we examined how demographic factors such as age, education, attitudinal variables, and cognitive ability variables predict general use of technology, computers, and the World Wide Web. Although there is already solid evidence that each of these factors predicts technology use, most studies examining the use of technology have focused on only a few of these factors in isolation. A unique aspect of this study is that we provide a comprehensive assessment of the relationships among these factors in a large, diverse sample of adults.

We believe that adoption of technology is a complex issue that is influenced by a number of variables, and we propose a model of technology adoption that includes social/demographic and person variables (e.g., age, education), attitudinal variables (e.g., computer anxiety), and component abilities (see Figure 1). We included age and education in the model, as the literature (e.g., Pew Internet and American Life Project, 2004) has shown that use of technology such as computers and the Internet is less frequent among those who are older and less educated. Computer attitude variables were included in the model, as several studies (e.g., Brosnan, 1999;Ellis & Allaire, 1999;Kernan & Howard, 1990) have shown that attitudinal factors such as computer anxiety are linked to computer use. We also included cognitive ability variables, as it has been shown that cognitive abilities are linked to the performance of technology-based tasks (e.g., Czaja et al., 2001;Sharit et al., 2003). In addition, adoption of new technology typically requires new learning, and learning is influenced by individual differences in cognitive abilities (e.g., Rogers, Hertzog, & Fisk, 2000;Beier & Ackerman, 2005).

Given the critical role that attitudinal variables such as computer anxiety play in computer interest and use, we hypothesized that age differences in technology adoption would be partially mediated by computer anxiety and computer self-efficacy. We also hypothesized that computer self-efficacy would have an indirect effect on technology adoption through anxiety such that people with lower self-efficacy would have higher anxiety (Bandura, 1997; Brosnan, 1999). One could claim that computer use should also influence computer self-efficacy and computer anxiety in a dynamic reciprocal fashion (Bandura, 1997). However, our focus in the present article is on predicting technology adoption; thus, our theoretical model specifies only paths from attitudinal variables to technology adoption.

In addition, distinct from attitudinal variables, we hypothesized that the relationship between age and technology adoption would be mediated by cognitive abilities, such that older people with lower cognitive abilities would have lower rates of adoption. In particular, we hypothesized that fluid intelligence declines with age and, given that use of technology requires new learning, that fluid intelligence and technology adoption would be positively related. Age was also expected to be positively related to crystallized intelligence, and in turn, crystallized intelligence was expected to be positively related to technology adoption. Given age-related increases in crystallized intelligence, one might expect that technology adoption would in fact be greater among older people. However, because adoption of technology is influenced by multiple factors such as computer anxiety and fluid abilities, the net effect of age on technology adoption should still be negative. In addition, we expected that education would also have an indirect effect on technology use through crystallized intelligence and the computer attitude variables. In particular, we expected that lower levels of education would be linked to lower levels of crystallized intelligence, higher levels of computer anxiety, and lower levels of computer self-efficacy, which in turn would be linked to lower levels of technology adoption. Our theoretical model includes direct paths between age and technology adoption and between education and technology adoption, anticipating the likelihood that the effects of age and education are not fully accounted for by attitudinal and ability factors included in our study.

Method

Sample

The sample included 1,204 community-dwelling adults (750 women and 454 men) ranging in age from 18 to 91 years ($M = 46.91$, $SD = 21.91$). Participants were recruited in three age groups: younger (18–39 years), middle aged (40–59 years) and older (60–91 years).

As shown in Table 1, the sample was fairly well educated, and there was a significant difference among the three age groups in level of education, $\chi^2(6, N = 1204) = 274.39$, $p < .001$. These differences in education were likely due to the fact that the majority of the younger participants were university students and that some college was reported as the highest level of education completed. More older and middle-aged participants had a college degree and postcollege education.

There was a significant difference among the age groups with respect to occupational status, $\chi^2(8, N = 1202) = 1311.64$, $p < .001$. As expected, most of the older participants were retired. The sample was also ethnically diverse, and ethnicity varied as a function of age, $\chi^2(6, N = 1202) = 137.75$, $p < .001$, such that a greater number of middle-aged participants were Black/ African American and a greater number of both younger and middle-aged participants were Hispanic/Latino.

Participants were asked to rate their general health and health for their age (poor to excellent) and satisfaction with health (not at all satisfied to extremely satisfied) on a 5-point Likert-type scale. They were also asked to rate the extent to which health conditions got in the way of performing routine activities. In addition, they were asked to rate the extent to which they experienced functional limitations (e.g., carrying, walking) and to indicate current chronic conditions. As shown in Table 1, there were age-related differences for general ratings of health, $\chi^2(8, N = 1204) = 72.28$, $p < .001$, ratings of health for age, $\chi^2(8, N = 1204) = 21.11$, $p < .01$, and satisfaction with health, $\chi^2(8, N = 1204) = 20.45$, $p < .01$. In general, the younger participants were more likely than the middle-aged and older participants to rate their health as very good or excellent and reported greater satisfaction with their health. There also were age differences with respect to the extent to which health problems affected performance of routine activities, $\chi^2(8, N = 1204) = 90.02$, $p < .001$, health-related functional limitations, $F(2, 1193) = 143.36$, $p < .001$, $\eta^2 = .19$, and number of chronic conditions, $F(2, 1193) = 78.57$, $p < .001$, $\eta^2 = .15$. The middle-aged and older people were more likely than the younger people to report that health problems limited routine activities and had more functional limitations and chronic conditions than did the younger people.

Participants were recruited with standard methods of advertisement (e.g., newspaper and radio announcements, flyers) from three sites. Three hundred and ninety-one individuals were recruited from the greater Miami area, 325 were recruited from the greater Atlanta area, and 488 were recruited from the Tallahassee area. All participants were English speaking and required to have 20/40 near and far vision with correction. Near vision was tested with the Rosenbaum-Jaeger chart, and far vision was tested with the Snellen chart (Berson, 1993). The participants were also screened for cognitive impairment (a score ≥ 27 on the Mini-Mental State Examination; Folstein, Folstein, & McHugh, 1975), psychic distress (a score of ≤ 80 on the Brief Symptom Inventory [BSI]; Derogatis, 1994), and depression (a score < 17 on the Center for Epidemiological Studies—Depression [CES–D] Index; Radloff, 1977). Each site obtained approval from local institutional review boards for its site-specific study. Participants were paid for their participation according to the site-specific study guidelines (e.g., Sharit et al., 2003).

Materials and Equipment

A battery of measures was administered to each participant and included a demographic and health questionnaire, a self-efficacy questionnaire, a technology and computer experience questionnaire, a computer attitude questionnaire, a computer anxiety questionnaire, measures of hearing and vision, and 21 standardized measures of component cognitive abilities. The measures chosen are widely used in the literature and have demonstrated reliability and validity. The measures were chosen to assess a broad range of abilities, including verbal ability, psychomotor speed, perceptual speed, attention, long-term memory, memory span, working memory, spatial ability, reasoning, and crystallized intelligence. There were at least two markers for each of the abilities. A brief description of each test in the battery and information regarding order (group vs. individual) of administration is presented in Appendix A.

Protocol

The protocol was standardized across all three sites. A certified assessor, who received standardized training, administered the battery of measures. Participants completed a telephone prescreening to determine basic eligibility for participation in the site-specific studies. The prescreening included questions related to primary language, vision (e.g., able to read a newspaper), and hearing (e.g., able to hear conversation) abilities. As an initial screen for cognitive impairment, we also administered the Short Portable Mental Status Questionnaire (criterion: ≤ 2 errors; Pfeiffer, 1975) and the Wechsler Memory Scale (Logical Memory subscale; age-adjusted criterion; Wechsler, 1997).

Eligible participants then reported to the study site for the group-testing component of the battery. They first received an explanation of the project and read and signed the informed consent form and then completed the group testing, which included the group-administered cognitive ability tests. The CES–D and BSI were also administered during this session. The group testing lasted between 4 and 5 hr. Periodic rest periods were provided during the testing session. Participants completed the demographic and health questionnaire, the self-efficacy questionnaire, the technology and computer experience questionnaire, and the computer anxiety questionnaire in the laboratory prior to the group testing or at home.

Ability tests that required individual testing (see Appendix A) were administered on a subsequent day. Hearing and near and far vision tests were also administered on an individual basis during this time. This phase of testing lasted approximately 40–60 min.

Two thousand two hundred and eight people were prescreened for participation. Of those, 30 were disqualified during prescreening for failing to meet prescreening criteria and 548 of those who were eligible expressed disinterest in participating or failed to show for testing. Of the remaining 1,630 participants, 85 did not meet criteria for vision (n = 2), cognitive status (n = 53), or psychological distress (n = 30); 71 did not meet study-specific criteria (e.g., having telecommuting experience; Sharit et al., 2004); 146 quit or failed to show for the second day of testing; 89 did not complete the cognitive battery because of study requirements (two of the site-specific studies used a different version of the home questionnaire); and 35 had incomplete data on one component of the battery.

Results

Cognitive Ability Measures

To reduce the 21 measures of component abilities in the CREATE battery for subsequent regression analysis, seven factors were initially hypothesized: Perceptual Speed, Fluid Intelligence, Spatial Visualization, Working Memory, Episodic Memory, Crystallized Intelligence, and Psychomotor Speed. The Digit Span Test was not included in the analysis because of problems in group test administration at two of the sites. These factors are broadly consistent with taxonomies of human abilities promoted by Horn (1989) and Carroll (1993) (see McGrew, 1997).

An initial confirmatory factor analysis, with each variable loading only on its hypothesized single factor, was performed with a structural equation model, estimated with AMOS 5.0 (Arbuckle, 2003), that included the 1,110 people with complete data on the relevant cognitive measures. Because the four measures that were based on reaction times (simple reaction time, choice reaction time, Stroop Color–Word Test, and the difference between Trails B and Trails A) generally showed skewed (right-tailed) distributions, with several individuals having very long responses, we applied the natural log transformation to these variables. A freely estimated covariance between the residuals of California Verbal Learning Test–Immediate and California Verbal Learning Test–Delayed was specified because they use the same items for immediate and delayed memory tests. Likewise, a freely estimated covariance between residuals of digit symbol substitution, and digit symbol recall was specified given the likely relation between memorizing the pairings and speed of standard digit symbol substitution performance. Age was included in the model as a separate latent variable so that we could estimate correlations of age with each of the factors.

The initial model did not fit the data well, $\chi^2(N = 161) = 2160.45$, root-mean-square error of approximation (RMSEA) = .106, comparative factor index (CFI) = .866. Inspection of fit diagnostics suggested two possible sources of misfit: (a) Age had a different relationship to individual measures within a factor than was allowed by our approach, and (b) variables loaded on factors other than those specified. To address the first issue, Shipley Vocabulary, Digit Symbol Recall, Wechsler Adult Intelligence Scale–III (WAIS–III) Information, and Stroop

Color–Word were regressed on age. To accommodate possible misspecification, Reading Comprehension was allowed to load on Memory, and Inferences was allowed to load on Crystallized Intelligence. The latter two relationships are consistent with what is known about these specific constructs and how they are measured. Reading Comprehension is tested with memory for text passages, which is known to be more broadly related to episodic memory (e.g., Hultsch, Hertzog, Dixon, & Small, 1998). The inferences test requires that inferences be made regarding propositions about the world and is probably, for that reason, influenced both by reasoning abilities (a primary marker for fluid intelligence) and by world knowledge (a primary marker for crystallized intelligence; see Horn, 1989, for further discussion of why reasoning tests may load on knowledge factors).

Results from this model showed extremely high factor correlations, leading us to an alternative model in which we reduced the number of factors. In particular, the Working Memory and Spatial Visualization factors were absorbed into the Fluid Intelligence factor. To preserve fit to the correlations of variables that measured the narrower abilities of working memory and spatial visualization, we modelled the Computation Span/Alphabet Span and the Cube Comparison/Paper Folding relations as residual covariances. In addition, because the associations of age with Paper Folding (main indicator for Spatial Ability) and Letter Sets (main indicator for Fluid Intelligence) differed, we included a regression of Paper Folding on age. This five-factor model fit the data well, $\chi^2(N = 163) = 714.124$, RMSEA = .055, CFI = .963. Figure 2 reports the standardized factor loadings and factor correlations for the final model. Although age was included in the model, it is not depicted in Figure 2 for purposes of clarity. The correlations of age with the five factors were −.12 with crystallized intelligence, −.06 with fluid intelligence, −.54 with memory, −.48 with psychomotor speed, and −.71 with perceptual speed.

We computed composite ability variables on the basis of the factor analysis results, with unit weighting of standardized variables that loaded uniquely on each factor. For instance, the crystallized intelligence composite was formed by summing *z* scores for Shipley Vocabulary, Multidimensional Aptitude Battery (MAB) Information, and WAIS–III Information. Reading Comprehension was excluded from the composite because of its loading on perceptual speed. Because Inferences loaded somewhat weakly on both crystallized intelligence and fluid intelligence, it was not included in either of those composite variables.

One-way analyses of variance (ANOVAs) were used to examine age differences on these composite variables. Post hoc comparisons were performed with Scheffé's test ($\alpha = .05$). Age-group differences were found for crystallized intelligence, $F(2, 1132) = 19.42$, $p < .001$, $\eta^2 = .03$; fluid intelligence, $F(2, 1132) = 301.68$, $p < .001$, $\eta^2 = .35$; memory, $F(2, 1132) = 203.23$, $p < .001$, $\eta^2 = .27$; psychomotor speed, $F(2, 1132) = 131.22$, $p < .001$, $\eta^2 = .19$; and perceptual speed, $F(2, 1132) = 317.46$, $p < .001$, $\eta^2 = .36$. The younger adults performed better than did the middle-aged adults, who performed better than did the older adults, on the perceptual speed, memory, fluid intelligence, and psychomotor speed factors. For the crystallized intelligence factor, older adults outperformed both younger adults and middle-aged adults, who did not differ from each other (see Table 2). (The means and standard deviations on the individual ability tests as a function of age are presented in Appendix B.)

Attitudes Toward Computers

All participants completed the Attitudes Toward Computers Questionnaire (ATCQ; Jay & Willis, 1992), a 35-item multidimensional scale assessing seven dimensions of attitudes toward computers: comfort (feelings of comfort with computers and their use), efficacy (feelings of competence with computers), gender equality (the belief that computers are important to both men and women), control (the belief that people control computers), interest (the extent to which one is interested in learning about and using computers), dehumanization (the belief that computers are dehumanizing), and utility (the belief that computers are useful). Each dimension is assessed with five or six items and scored on a 5-point Likert-type scale with anchors of *strongly agree* to *strongly disagree*. After inspection of the items, we decided to drop the gender/equality scale from further analysis because of the possible dated item content. Participants also completed a 10-item Computer Anxiety Scale (Loyd & Gressard, 1984) that assessed feelings of comfort/ease with computers. Participants were required to indicate the degree to which they agreed with the 10 statements (e.g., “Computers make me feel uncomfortable”) on a 4-point Likert-type scale with anchors of *strongly agree* to *strongly disagree*.

Given that there was content overlap between the ATCQ scales and the Computer Anxiety Scale, we computed correlations among the six remaining ATCQ scales and the Computer Anxiety Scale. Correlations were in the expected direction and were generally moderate to large in magnitude. Hence, we conducted an exploratory factor analysis on the seven scales to determine whether composite scales should be constructed. An unweighted least squares factor analysis revealed two initial factors with eigenvalues greater than 1.0, accounting for 66% of the variance of the data. After promax rotation, the correlation between the two factors was .57. The first factor consisted of the comfort, anxiety, and self-efficacy scales, with factor pattern weights of .92, −.87, and .64, respectively. Clearly, the factor was primarily marked by the two affect-related scales, but the association of self-efficacy and anxiety constructs was also expected from the self-efficacy literature (Bandura, 1997). The second factor was defined by dehumanization, utility, and control, with loadings of −.62, .90, and .41, respectively. The interest scale was split approximately evenly between the two factors. On the basis of these outcomes, we then rescaled the seven scales to standard scores ($M = 0$, $SD = 1$) with the means and standard deviations of the total sample. We then formed a composite variable of general computer attitudes as the average of the (reversed-scored) dehumanization, utility, and control scales. The comfort and anxiety scales were also averaged (after reverse scoring of the comfort scale) to define an anxiety scale. We used a unit-weighted method to form these composites, as generally, these methods are less affected by differences in sample size and are preferred for oblique factors (Grice, 2001). Given the importance of computer self-efficacy as a construct and the conceptual distinction of anxiety as a derivative of self-efficacy, we opted to leave the self-efficacy scale as a separate variable. Likewise, interest was left as a separate variable.

Age-group and gender differences in computer attitudes, computer anxiety, computer self-efficacy, interest, and general attitudes were examined with univariate 2 (gender) × 3 (age group) ANOVAs. Interactions were tested with contrasts through the general linear model procedure. The results of these analyses are presented in Table 3.

Significant Age × Gender interactions were found for the anxiety scale, $F(2, 1183) = 3.05$, $p < .05$, $\eta^2 = .01$, and the general attitude scale, $F(2, 1183) = 3.67$, $p < .05$, $\eta^2 = .01$. The older women reported more anxiety and less positive general attitudes about computers relative to older men. Neither the difference between the middle-aged women and the middle-aged men nor the difference between the younger women and the younger men was significant for these variables. In general, the older adults (both men and women) indicated more computer anxiety and lower computer self-efficacy than did younger and middle-aged adults. The middle-aged adults were also significantly different on these constructs than were the younger adults. The older adults also reported less interest in computers than did the younger and middle-aged adults. Women, overall, also reported higher computer anxiety, lower computer self-efficacy, lower general computer attitudes, and less interest in computers than did men.

Use of Technology and Experience With Computers and the World Wide Web

General use of technology was measured by having the participants indicate on a 17-item list whether they had used common, everyday technology (e.g., cellular phone, automated teller machine, fax machine, microwave oven, videocassette recorder). The list did not include computer equipment. A composite score was obtained by summing the responses (0–17). Participants were also asked whether they had experience with computers. Those who reported having experience with computers then responded to six questions that assessed frequency of use and breadth of computer experience and knowledge. A breadth-of-computer-use variable was computed by summing responses to questions regarding experience with input devices (e.g., keyboard, mouse [0–7]); proficiency with basic computer operations (e.g., insert a disk, save a file [0–6]); and proficiency with computer applications (e.g., computer graphics, e-mail, spreadsheets [0–12]). Given that the number of items for each of the breadth questions varied, *z* scores were computed for each question and averaged to generate a composite score.

Participants who reported computer experience were asked to respond to five questions regarding their experience with the World Wide Web. The questions pertained to frequency of Web use, training, and activities performed on the Web (e.g., e-mail, games, news information, shopping). A breadth-of-Web-experience variable was computed by summing the number of activities for which participants reported experience (0–33). The activities were also grouped into the following categories: communication, news and weather, information gathering (legal information), community resources, health, travel, leisure/entertainment, and shopping.

The data indicated a significant Age Group × Gender interaction for use of technology, $F(2, 1197) = 6.70$, $p < .001$, $\eta^2 = .01$. As shown in Figure 3, older women reported using fewer types of technology than did older men. Gender differences for the younger and middle-aged groups were not significant. There were also significant differences in use of technology as a function of age, $F(2, 1197) = 206.96$, $p < .001$, $\eta^2 = .26$. In general, older people reported less use of technology than did middle-aged people, and older people and middle-aged people reported less use of technology than did younger people.

The age groups also differed in terms of having computer experience, $\chi^2(2, N = 1204) = 77.50$, $p < .001$. As expected 99% of the younger participants reported experience with computers, as compared with 90% of the middle-aged participants and 84% of the older participants. Overall, there was no difference in experience with computers between men (91%) and women (92%). However, when examining age differences within each gender, younger men (99%) were more likely than middle-aged (84%) and older (86%) men to report having had experience with computers, $\chi^2(2, N = 454) = 26.58$, $p < .001$. With respect to women, both younger women (100%) and middle-aged women (94%) were more likely than older women (82%) to have experience with computers, $\chi^2(2, N = 750) = 61.87$, $p < .001$.

There was a significant Age Group × Gender interaction for breadth of computer experience, $F(2, 1087) = 6.63$, $p < .001$, $\eta^2 = .01$. For younger and older adults, breadth of computer experience was lower among women as compared with men. There was no difference in breadth of computer experience between middle-aged men and women. In general, younger people reported more breadth of computer experience than did middle-aged people, and middle-aged people reported more experience than did older adults, $F(2, 1087) = 350.92$, $p < .001$, $\eta^2 = .39$. Overall, women reported less breadth of computer experience than did men, $F(2, 1087) = 55.60$, $p < .001$, $\eta^2 = .05$.

There was also a significant age-group difference in experience with the Web, $\chi^2(2, N = 1203) = 182.68$, $p < .001$. As expected, experience with the Web was greater among the younger participants (97%) as compared with the middle-aged (75%) and older (61%) participants. The difference in Web experience between the middle-aged and older adults was also significant. These age differences in Web experience were found for both men, $\chi^2(2, N = 454) = 159.03$, $p < .001$, and women, $\chi^2(2, N = 749) = 133.89$, $p < .001$. Younger men (93%) were more likely than middle-aged men (69%) and older men (69%) to report having experience with the Web; however, there was no difference in Web experience between older and middle-aged men. With respect to women, younger women (97%) were more likely than middle-aged (79%) and older women (56%) to have Web experience. The difference in Web experience between middle-aged and older women was also significant. There was no overall difference in Web experience between men (80%) and women (77%).

Similar to the findings regarding breadth of computer experience, there was also a significant difference among the age groups in breadth of Web use, $F(2, 938) = 125.78$, $p < .001$, $\eta^2 = .21$. The younger participants ($M = 21.90$, $SD = 7.47$) reported that they used the Web for more activities than the did participants in the middle-aged ($M = 16.88$, $SD = 8.61$) and older age ($M = 13.63$, $SD = 7.70$) groups, and the middle-aged participants reported that they used the Web for more activities than did the older participants. There was also a difference among men and women in use of the Web, $F(2, 938) = 22.32$, $p < .001$, $\eta^2 = .02$. Women ($M = 16.00$, $SD = 8.42$) reported less breadth of experience with the Web than did men ($M = 18.16$, $SD = 8.60$).

As shown in Figure 4, there were also differences among the age groups in Web activities. The two most frequent Web activities for the younger and middle-aged participants were communicating and searching for information. For the older people, the two top activities were communication and entertainment, followed by searching for information and travel-related activities. The older people used the Web much less for shopping and finding information about community resources than did younger and middle-aged people.

Participants were asked to indicate how they learned to use the Web. Overall, the most common methods were learning by trial and error (self-taught; 75%), following directions on the Web (25%), attending a class (19%), and reading books (14%). (Note that the question asked participants to indicate all the methods that they used.) It is interesting that 87% of the younger participants indicated that they learned by trial and error, as compared with 70% of the middle-aged participants and 61% of the older participants, $\chi^2(2, N = 717) = 67.62$, $p < .001$. A greater number of the older adults (27%), as compared with the younger adults(4%), indicated that they learned by reading books, $\chi^2(2, N = 717) = 80.93$, $p < .001$, and attending classes (25% vs. 14%), $\chi^2(2, N = 717) = 18.11$, $p < .01$.

Predictors of Use of Technology, Computers, and the World Wide Web

One of the primary goals of this study was to determine whether and how individual differences in demographic characteristics, attitudes, and abilities predict technology and computer use patterns. The first question we addressed was whether these variables predicted general technology use and experience with computers. The next set of analyses focused only on those participants who reported experience with computers. People may use computers minimally or for a wide range of tasks. Our goal was to determine whether breadth of computer experience was predicted by demographic variables, attitudinal variables, and abilities. Finally, we examined factors that predicted having experience with the World Wide Web. Again, the analysis of breadth of Web use was restricted to those with Web experience.

Multiple regression analyses were performed to examine these relationships. Given the high correlations among all of the ability factors (see Figure 2), the two most broadly defined ability factors, fluid and crystallized intelligence, were chosen as ability predictors for these analyses. Also, given the high correlation among all the health variables, we used functional health as the health predictor, given our interest in functional impact and the fact that this measure had the highest correlation with the technology use variables. For these analyses, we restricted the ethnic group variable to include participants from three ethnic groups: White/European Americans, Black/African Americans, and Hispanic/Latino Americans. These ethnic groups represented 91% of the sample, and the remaining 9% consisted mostly of Asian students (41%) and a few individuals from other ethnic groups such as Native Americans (*n* = 8) and multiracial (*n* = 23).

For both gender and ethnicity, we used weighted effects coding. For the ethnicity variable, the reference group was White/European Americans. We chose effects coding because we wanted to interpret the first-order effects of gender and ethnicity as average effects; we used weighted coding because the sample sizes were unequal for the levels of the variables (Cohen, Cohen, West, & Aiken, 2003).

For each of the outcomes measures, we conducted an initial hierarchical regression analysis. We entered all of the main effects in the first step, all of the two-way interactions in the second step, and the three-way interactions in the third step (Cohen et al., 2003). The following variables were entered into the model in the first step: functional health, gender, education, ethnicity, fluid and crystallized intelligence, the four computer attitude measures, and age. The following two-way interactions were entered in the second step: Age × Education, Age × Crystallized Intelligence, Age × Fluid Intelligence, Age × Computer Anxiety, Age × Computer Efficacy, Ethnicity × Education, Ethnicity × Computer Anxiety, Ethnicity × Computer Efficacy, and the interactions among each of the ability measures and computer anxiety and computer efficacy. The three-way interactions among age, each of the ability measures, and computer anxiety and computer efficacy were entered in the third step. Interaction terms were retained in the model on the basis of the significance of the F statistic for increments to R^2. Nonsignificant predictor variables entered in Step 1 were trimmed from the model if there were no significant interaction terms associated with that variable. Separate equations were computed for each of the significant interaction terms, and tests of simple slopes were performed at $\alpha = .05$ (Aiken & West, 1991). Given that experience with computers and the World Wide Web were dichotomous variables, logistic regression was used for those variables.

We then used the trimmed models to conduct hierarchical multiple regressions for each of the dependent measures. We were interested in determining (a) excluding age, how much variance could be explained by the remaining exogenous sociodemographic variables (gender, education, ethnicity) and then by basic cognitive abilities (crystallized and fluid intelligence) and attitudinal measures (computer self-efficacy and computer anxiety); (b) how much age-related variance remains after the other independent variables have been entered; and (c) how much variance was explained by the remaining two-way and three-way interactions. Given the large sample size, we considered only interaction effects that accounted for at least 1% of the variance as being meaningful for interpretation.

General use of technology—Results of the hierarchical regression analysis for general use of technology are summarized in Table 4. After accounting for the exogenous social/ demographic variables, the cognitive variables resulted in a significant increment in R^2 of .29. Adding age to the model after accounting for the exogenous social/demographic variables, cognitive ability variables, and computer anxiety and self-efficacy variables resulted in a significant increment in R^2 of .06. The interaction terms also resulted in significant changes in R^2.

As shown in Table 5, general use of technology was predicted by education, age, ethnicity, fluid and crystallized intelligence, computer anxiety, and computer self-efficacy. In general, people who were better educated, were younger, had higher levels of crystallized and fluid intelligence and computer self-efficacy, and had lower levels of computer anxiety used more types of technology. Black/African Americans used less types of technology than did White/ European Americans and Hispanic/Latino Americans.

The two-way interactions accounted for 2% of the variance. As shown in Table 5, this was the combined effect of six different interaction terms. The squared semipartial correlations for these terms were examined, and the only interaction that satisfied our criterion of 1% was the interaction between fluid intelligence and computer efficacy. In general, for people with lower fluid intelligence, $t1081 = 5.91$, $p < .01$, greater computer self-efficacy was associated with more use of technology. This relationship was not found for people with high fluid intelligence, $t1081 = -.88$, $p < .05$ (see Figure 5).

Computer use—With respect to experience with computers, as shown in Table 6, having experience with computers was predicted by age, fluid intelligence, ethnicity, computer anxiety, and education. In general, people who were younger, had higher levels of fluid intelligence and education, and had lower levels of anxiety about computers were more likely to have experience with computers. Black/African Americans and Hispanic/Latinos were also less likely than White/European Americans to have experience with computers. This set of predictors accounted for about 34% of the null deviance (Cohen et al., 2003). The data also indicated that ethnicity, cognitive abilities, and computer anxiety had the strongest effect on experience with computers (see Table 6). After accounting for gender and education, ethnicity resulted in an increment in Nagelkerke R^2 of .03, and after accounting for the exogenous social/demographic variables, the cognitive ability variables resulted in a significant increment in Nagelkerke R^2 of .19. Finally, adding the computer anxiety variables to the model, after accounting for the exogenous social/demographic variables and the cognitive ability variables, resulted in a significant increment in Nagelkerke R^2 of .07.

Breadth of computer use—The results of the hierarchical regression analysis (Table 7) indicate that, after accounting for the exogenous demographic/social variables, cognitive abilities resulted in a significant increment in R^2 of .27. The addition of the computer attitude variables to the model accounted for a significant increment in R^2 of .144, and the addition of age to the model accounted for a significant increment in R^2 of .13.

Breadth of computer use was predicted by gender, education, fluid and crystallized intelligence, computer anxiety, and age (see Table 8). Ethnicity was not a reliable predictor of breadth of computer use. In general, people who were less educated, were older, and had lower fluid and crystallized intelligence had less breadth of computer experience. Women also had less breadth of computer experience than did men. Breadth of computer use was also lower among people with high computer anxiety as compared with those with low computer anxiety. Although there were also significant interactions for this outcome variable, none met the criterion of accounting for at least 1% of the variance.

Use of the World Wide Web—Having experience with the World Wide Web was predicted by education, ethnicity, fluid and crystallized intelligence, computer anxiety, and age (see Table 9). People who were less educated, were older, had lower fluid and crystallized intelligence, and had more anxiety about using computers were less likely to have experience with the World Wide Web. Black/African Americans were also less likely than White/European Americans to have experience with the Web. As shown in Table 9, the strongest predictors of having experience with the Web were ethnicity, fluid intelligence, and computer anxiety. After accounting for gender, education, and ethnicity, cognitive abilities resulted in an increment in Nagelkerke R^2 of .31, and after controlling for the exogenous social/demographic variables, cognitive ability variables, and computer anxiety and self-efficacy variables, age resulted in a significant increment in Nagelkerke of R^2 of .07. The Age × Fluid Intelligence interaction, although significant, resulted in an increment in Nagelkerke R^2 of only .01; thus, we constrained the model to include only main effects, given the tradeoff between the improved goodness of fit and the complexity of interpreting interactions in logistic regression. As the inclusion of the interaction resulted in only a small improvement in the model, we determined that the increased complexity associated with interpretation of the interaction was not warranted (Glantz & Slinker, 1990).

Breadth of World Wide Web experience—The results of the hierarchical regression analysis (Table 10) indicate that cognitive abilities resulted in a significant increment in R^2 of .17. The addition of the computer attitude variables to the model accounted for a significant increment in R^2 of .11, and the addition of age to the model accounted for a significant increment in R^2 of .10.

Breadth of Web experience was predicted by age, crystallized intelligence, computer anxiety, and computer self-efficacy (Table 11). In general, people who were older, had lower crystallized intelligence, had lower computer anxiety, and had higher computer self-efficacy had more breadth of web experience. Gender and ethnicity were not reliable predictors of breadth of Web experience. The two-way interactions, although significant, accounted for less than 1% of the variance. It is interesting that there was a significant three-way interaction between age, fluid intelligence, and computer anxiety. As shown in Figure 6, computer anxiety had a more debilitating effect for older adults with high fluid intelligence than for older adults with low fluid intelligence. Computer anxiety had less impact on younger adults.

Structural Regression Models

To test our hypothesized model and to determine the extent to which computer attitude variables and cognitive abilities mediate the effects of age and education on breadth of computer experience and breadth of web experience, we used structural equation modeling with AMOS 5.0 (Arbuckle, 2003). We restricted our analysis to these variables because having experience with computers and having experience with the World Wide Web were categorical variables with two response categories (Byrne, 1998). General use of technology was included as a potential mediator that, in principle, indirectly reflected prior domain-specific knowledge and experience with technology that is relevant as a predictor of computer use (e.g., Beier & Ackerman, 2005). Although our previous multiple regression analyses revealed some significant interaction effects, we did not attempt to include interaction effects in the model; instead, we chose to evaluate mediated paths averaged over interaction effects. Bootstrapping techniques were used to test for indirect effects.

We used single indicators in the structural models with the procedure recommended by Liang, Lawrence, Bennett, and Whitelaw (1990). This procedure allowed us to use the same composites that were used in the regression analysis and still disattenuate regression coefficients for measurement error. Cronbach's alpha reliability estimates were calculated for each indicator variable. The factor loadings for each indicator variable were fixed at $\sqrt{\alpha}(\sigma)$, and their error variances were fixed at $(1 - \alpha)\sigma^2$, where α is the estimated reliability and σ^2 is the variance of the indicator. This correction was not applied to the use of technology variable because coefficient alpha would not have been an appropriate estimate of reliability for that index. This procedure was used because we did not have multiple scales measuring both computer self-efficacy and computer anxiety and because we wanted to maintain similar correction procedures for both ability and attitude predictors. We checked the results by using multiple indicator models for abilities and found good agreement in estimated structural regression coefficients, justifying the present approach.

Separate structural equation models evaluated the two target criteria of breadth of computer use and breadth of Web use. The initial model was the hypothesized model in which the effects of age and education were mediated by the computer attitude variables and cognitive abilities (see Figure 1). We added general use of technology as a mediator to examine whether experience with technology predicted computer use independently of attitude and ability variables. We specified use of technology as an influence on computer self-efficacy and computer anxiety and evaluated whether it had a direct effect on breadth of computer use and breadth of Web use independent of these attitude variables. Our models also specified a specific order of flow of influence for the attitude and ability variables. We specified that computer efficacy influenced computer anxiety and that fluid intelligence influenced crystallized intelligence. The latter direction of influence is justified by Cattell's investment theory (see Beier & Ackerman, 2005); the former is justified by Bandura's (1997) theoretical claim that anxiety is typically an outcome of low self-efficacy.

We adjusted models in two ways. First, we trimmed nonsignificant regression coefficients ($p > .01$), unless retaining the coefficient was needed to ensure statistical control on other predictors. Second, we used modification indices to assess whether additional parameters would improve the fit of the model to the data.

With respect to breadth of computer use, the final model fit was excellent, $\chi^2(N = 11) = 20.44$, RMSEA = .028, CFI = .997. The standardized effects for the final models are presented in Table 12. The model accounted for 64% of the variance in breadth of computer use, with direct paths from age, computer anxiety, crystallized intelligence, and general use of technology (see Figure 7). In addition, age was indirectly linked to breadth of computer use through fluid intelligence, crystallized intelligence, computer efficacy, and computer anxiety ($p < .01$). An important feature of the model is that the direct effect of age was larger than the indirect effects of age, suggesting that our study variables did not account for all the pathways by which age differences in computer use are realized. Only 37% of the total effects of age on breadth of computer use were indirect; the rest were direct. On the other hand, it should be noted that the final model contained no direct effects of education on breadth of computer use. We trimmed a small path from education to breadth of computer use that was reliable at the .05 level (but not the .01 level), but the standardized effect of education was only .04. Also, there was no direct effect of fluid intelligence on breadth of computer use. Instead, effects of fluid intelligence were fully mediated by use of technology and crystallized intelligence.

We evaluated a few alternative models to test the robustness of our solution and the theories that generated it. Some alternatives matter conceptually but are not empirically testable. For example, our assumption that computer efficacy influences computer anxiety, versus the alternative assumption that anxiety influences efficacy, is not empirically testable. The alternative assumptions generate equivalent models fits and hence cannot be evaluated on the basis of differential empirical fit of the models to the data (MacCallum, Wegener, Uchino, & Fabrigar, 1993). However, we identified two alternative specifications that are not empirically equivalent and hence represent meaningful alternatives to the assumptions specified in our accepted model. In one model, we allowed computer self-efficacy to directly influence breadth of computer use, eliminating the effect of computer anxiety. This model stipulates that self-efficacy is the primary influence on computer use, with anxiety being an inert derivative of self-efficacy. Despite the strong relationship of self-efficacy to anxiety, the locus of the effect was not interchangeable. This model fit the data considerably worse than did our preferred model, even though the overall level of fit was good, $\chi^2(N = 11) = 89.80$, RMSEA = .081, CFI = .977. Thus, it seemed more plausible to model the effect of computer efficacy on breadth of computer use as being fully mediated by computer anxiety. In the second model, we attempted a model in which use of technology had no direct effect on breadth of PC use, instead being mediated through computer efficacy and computer anxiety. This model also specified a direct effect of fluid intelligence on breadth of computer use (in the accepted model, this had been modeled as an indirect effect of fluid intelligence mediated through use of technology). This alternative model also fit more poorly than did our accepted model, $\chi^2(N = 11) = 147.20$, RMSEA = .107, CFI = .961. Further, the direct effect of fluid intelligence on breadth of computer use was not reliable ($p > .01$). Thus, we concluded that prior use of technology was an important, independent influence on breadth of computer use.

A similar pattern of results was also found for the breadth of Web use variable (see Figure 8). The regression model fit extremely well, $\chi^2(N = 11) = 12.80$, RMSEA = .013, CFI = .999. The final model accounted for 46% of the variance in breadth of Web use, and 29% of the age effect was mediated by the attitudinal and ability variables (see Table 12). Given that the pattern of indirect and direct effects was similar to the breadth of computer use variable, we do not elaborate further on these outcomes.

We did test the same two alternative models considered earlier for breadth of computer use. Forcing computer efficacy, instead of computer anxiety, to predict breadth of Web use degraded the fit of the model, $\chi^2(N = 11) = 38.84$, RMSEA = .052, CFI = .989. Removing the direct effect of use of technology on breadth of Web use likewise resulted in poorer fit, $\chi^2(N = 11) = 82.66$, RMSEA = .083, CFI = .971. We concluded that neither alternative model was preferable to our accepted model.

Discussion

Technology has become an important part of everyday life and an integral component of most activities. The present article presents data from a large, diverse sample of community-dwelling adults regarding use of technology, computers, and the World Wide Web. The study is unique from others addressing this issue (e.g., Ellis & Allaire, 1999; Umemuro, 2004) in that (a) we included a broader range of outcome measures that encompasses general use of technology, experience with computers and breadth of computer use, and experience with the World Wide Web and breadth of Web experience; (b) our measures of these variables are more extensive than are those used by others (e.g., Ellis & Allaire, 1999); (c) we examined the impact of social/demographic variables, attitudinal variables, and cognitive abilities on technology adoption; and (d) we examined the issue of technology adoption across a large and diverse sample spanning a wide age range.

Overall, our findings parallel those of other reports (e.g., Pew Internet and American Life Project, 2004), indicating that a digital divide still exists for certain segments of the population, such as those who are minorities, those who are older, and those who are less educated. Although technology is being rapidly produced and deployed in most settings, the older adults in our sample reported less use of technology in general and less experience with computers and the World Wide Web. They also reported that they had less breadth of computer experience and used the Web for fewer activities. We also found that people from minority populations reported differences in patterns of technology adoption. In particular, Black/African Americans reported less use of technology in general and of the World Wide Web than did Hispanic/Latino and White/European Americans, and both Black/African American and Hispanic/Latino Americans reported having less experience with computers than did White/European Americans. This is an important finding given the projected increases in older adults from minority populations. People in our sample who were less educated also reported less use of technology in general and less experience using computers and the World Wide Web. Of note is that the percentage of older people who used computers and the Web in our sample is higher than that reported in recent surveys. This is probably due to the fact that our sample of older adults was healthy and fairly well educated. However, despite the fact that our older participants were well educated, significant age differences in computer and Web use were still evident. Thus, our findings may underestimate the influence of age on technology use.

Findings indicating less use of technology and computers among older adults have clear social ramifications. As technology becomes more integrated into everyday life, people with less use of technology are more likely to become more disenfranchised and disadvantaged. This is especially true in the workplace, where some form of technology is an integral component of most jobs, and in the health care arena, where technology is increasingly being used for the delivery of health care services. For example, many older adults have some type of chronic condition (Federal Interagency Agency Forum on Aging Statistics, 2001) and use home medical devices such as a blood pressure monitor, a blood glucose meter, or a home defibrillator. Further, as the population continues to age, it is both socially important and cost effective to support the independence of older adults. Technology can play an important role in fostering this independence. To date, however, there is only limited evidence that this potential is being realized (National Research Council, 2004).

Similar to the findings of other studies (e.g., Ellis & Allaire, 1999), we found that the older and middle-aged adults in our sample had lower self-efficacy with respect to use of computers and more computer anxiety than did younger adults. This is an interesting finding given that a large percentage of the middle-aged (90%) and older people (84%) in our sample reported having experience with computers and that several studies (e.g., Campbell, 2004; Czaja & Sharit, 1998; Jay & Willis, 1992) have shown that experience with computers generally results in low anxiety and higher self-efficacy. The difference may come as a result of the nature of their experience. For example, experience may vary in terms of the nature of applications used, ease of system use, and overall success of the interaction.

Our findings also indicate that computer self-efficacy was an important predictor of general use of technology and that people with lower self-efficacy are less likely to use technology in general. This finding is consistent with the argument that people with lower self-efficacy display less motivation to engage in a task than do those with higher self-efficacy (Bandura, 1997). This finding also suggests that, when teaching people, especially older adults, it is important to use technology that allows them to experience success so that they build up confidence in their abilities. This might be accomplished by structuring training to allow for a gradual expansion of skills (Jay & Willis, 1992) and also speaks to the importance of providing feedback during training.

However, our structural regression models indicate that the effects of computer self-efficacy are mediated by computer anxiety, which was directly linked to breadth of computer experience and Web experience. These findings are in agreement with Brosnan (1999), who found that self-efficacy predicted computer anxiety, which in turn predicted word processor use. Our findings underscore the important role of anxiety with respect to technology adoption. In general, the people in our sample with higher computer anxiety were less likely to use technology or to have experience with computers and the Web. They also reported less breadth of both computer and Web experience. These findings parallel those of Ellis and Allaire (1999), who found that higher levels of computer anxiety were linked to less interest in computers. Our findings also show that computer anxiety partially mediates the influence of age on breadth of computer and Web experience. Further, we found a significant Age × Fluid Intelligence × Computer Anxiety interaction for breadth of Web experience. Notwithstanding high levels of fluid intelligence, computer anxiety has more of a debilitating effect on breadth of Web experience for older people. Anxiety has been associated with cognitive interference on a wide range of cognitive tasks (MacLeod, 1996). Attitudes are also believed to guide behavior (Regan & Fazio, 1977), so it likely that people with high levels of anxiety would be less likely to choose to use technology. In fact, the results indicate that although general use of technology has an impact of breadth of computer and Web experience, computer anxiety had a unique effect on these variables.

The fact that older adults—older women in particular—reported higher levels of computer anxiety suggests that computer training programs should focus on training techniques that reduce anxiety about using computers as well as provide computer skills training. Several studies have shown that providing supportive training can reduce anxiety about using technologies such as computers (Campbell, 2004; Jay & Willis, 1992). For example, it is important that training is conducted in a relaxed and supportive environment and that sufficient time is allowed so that trainees do not feel rushed (Fisk, Rogers, Charness, Czaja, & Sharit, 2004). In fact, a recent meta-analysis exploring the effects of training method and instructional factors on the performance of the older learner found that self-pacing accounted for the largest portion of the variance in performance (Callahan, Kiker, & Cross, 2003). Beier and Ackerman (2005) also found support for the notion that the learning performance of older adults can be facilitated in a self-paced learning environment.

It also may be helpful to provide older people with some type of stress inoculation training that teaches them to better deal with their performance anxiety. This type of training has been shown to result in improved performance among older adults (Hayslip, Maloy, & Kohl, 1995). As computer self-efficacy is an important predictor of computer anxiety, it is critical to ensure that older people receive encouraging feedback during training and experience some level of success. Interface design is also important in this regard. Perceived ease of use of computers is an important aspect of computer anxiety (e.g., Brosnan, 1999).

Our results also indicate that, in addition to attitudinal variables, cognitive abilities are important to technology adoption. This finding may be related to the fact that adoption of new technologies such as computers requires learning new skills. For example, people have to learn new ways of performing familiar tasks (communicating through e-mail vs. telephone), new procedural knowledge, and a new lexicon. In fact, in our study, there was a direct path between crystallized intelligence and breath of computer and Web experience. As suggested by Beier and Ackerman (2005), it may be that people who have higher levels of crystallized intelligence are more adept at knowledge acquisition. The relationship between cognitive abilities and technology adoption also points to the importance of ensuring that system interfaces are well designed and easy to use. For example, technology interfaces should place minimal demands on working memory and environmental supports such as cues, and reminders or navigational aids should be provided (see Fisk et al., 2004).

Overall, our findings provide further evidence that cognitive abilities are important to everyday activities. However, the fact that both attitudinal and cognitive variables simultaneously predict computer use indicates that competence in cognitive abilities is necessary but not sufficient for competence in everyday tasks. Diehl, Willis, and Schaie (1995) also found that, in addition to cognitive abilities, other factors such as age and health variables affect competence in everyday problem solving. Likewise, data from our previous studies (e.g., Czaja et al., 2001) show that, in addition to cognitive abilities, prior experience with computers is an important predictor of performance for a variety of computer-based work tasks. Beier and Ackerman (2005) likewise found that, in addition to fluid and crystallized intelligence, prior domain knowledge was an important predictor of learning new information about cardiovascular disease and xerography. The results from the present study show that general use of technology was a significant predictor of breadth of computer and Web experience. Although use of technology does not represent a direct measure of domain knowledge, it does represent a measure of general familiarity and experience with technology. This suggests that having general knowledge about technology and the role of technology in task performance is important to technology adoption.

Finally, our results indicate that there was still a strong, independent effect of age on the outcome measures not accounted for by attitudes and cognitive ability. Clearly, other variables not captured in this study are influencing the decisions that older adults make about adopting new technologies. One important factor may be perceived need for the technology. For example, we (Czaja, Guerrier, Nair, & Laudauer, 1993) studied use of e-mail among a sample of older women. Although all participants found it valuable, the perceived usefulness of the system and system reliability were more important factors in predicting use. Brosnan (1999) also found that the perceived usefulness of a word processing system was an important predictor of use. Other factors that may be relevant include the perceived effort associated with learning new technologies and economic resources. Recent studies have shown that the perceived cost of learning new technology is greater among older people than among younger people and that perceived effort has an influence on technology adoption (e.g., Melenhorst, Rogers, & Caylor, 2002). This notion also points to the need for interfaces that are easy to use and supportive training environments. Finally, older adults, particularly postretirement, vary enormously in wealth. Those who are less wealthy are less likely to purchase new technology devices and may be differentially likely to discount the value of new technology because of its costs. The influence of these factors in adoption of new technology is an important avenue for future investigation.

It is also important to emphasize that age differences in adoption and use of technology are probably best viewed as reactions of older generations to historical change rather than age-related declines per se. Today's older adults have matured in a time when computer technology was introduced, and their relative low use of computers probably reflects a form of cohort-specific obsolescence rather than developmental change in effective use of these types of systems. One implication of this view is that, as they grow older, today's younger adults are likely to have very different patterns of prior experience with, and attitudes toward, computer technology.

At the same time, however, normative developmental changes in fluid intelligence place additional constraints on the likelihood that older adults will adopt technology characterized by increased complexity of systems and technical manuals, new procedures, and so on. An excellent example is the evolving complexity of the cellular telephone. Such effects may help to explain why we observed some of the interactions involving age, ability, and attitudes. When older adults are high in ability, they are more likely to experience adverse effects of computer anxiety in inhibiting use. Be that as it may, one should not conclude that differences in adoption invariably represent a form of age-related decline, even if age-related declines in cognitive abilities influence use of computer technology.

Overall, our findings suggest that adoption of technology is a complex issue and is influenced by a variety of factors, including sociodemographic factors, attitudinal variables, and cognitive abilities. The relationships among these variables are complex, indicating that people's choices about using a particular technology cannot be explained solely by their age or education; they also require considerations of other psychological factors. This study also raises some interesting questions. For example, it would be interesting to examine whether reductions in anxiety and increased self-efficacy related to broader technology use and successful manipulations of attitudinal variables are maintained over time and generalize to new developments in technology. These questions are increasingly important given the rapid developments and deployment of technology in our society.

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Appendix A

Description of Core Battery of Measures

Measure	Form of administration	Description
Alphabet span (Craik, 1986)	Group	Participants were presented with a series of words. They were then required to write the words in alphabetical order.
Attitudes Towards Computer Questionnaire (Jay & Willis, 1992)	Group	A 35-item scale that assessed eight dimensions of attitudes toward computers (comfort, efficacy, gender equality, control, interest, dehumanization, and utility).
California Verbal Learning Test-Delayed (Delis, Kramer, Kaplan, & Ober, 1987)	Group	Participants were asked to recall as many words as they remembered from the original list after a 20-min delay.
California Verbal Learning Test-Immediate (Delis et al., 1987)	Group	Participants were presented with a list of words and asked to recall as many words as they remembered. This was repeated for five trials.
Computation span (Salthouse & Babcock, 1991)	Group	Participants were asked to solve arithmetic problems that were presented orally, while simultaneously trying to remember the solution for each of the problems.
Computer Anxiety Test (Loyd & Gressard, 1984)	Group	A 10-item scale that assessed general anxiety and comfort toward computers.
Choice reaction time (Wilkie, Eisdorfer, Morgan, Loewenstein, & Szapocnik, 1990)	Individual (computer based)	Participants were required to respond to a stimulus, which appeared on the screen (solid square), with their right or left hand, depending on the location of the stimulus. There was a total of 60 trials.
Cube Comparison Test (Ekstrom, French, Harman, & Dermen, 1976)	Group	A measure of spatial orientation where participants were required to identify whether two cubes are the same or different.
Digit Span Test (Wechsler, 1981)	Individual	Consists of two parts, In the first part, pairs of random-number sequences were read aloud, and the participant’s task was to repeat each sequence. In the second part, participants were presented with a series of digits and asked to recall them in reverse order.

Measure	Form of administration	Description
Digit Symbol Recall Test (Wechsler, 1981)	Group	After the standard Digit Symbol Substitution Test, participants were asked to recall the digit–symbol pairs from memory.
Digit Symbol Substitution Test (Wechsler, 1981)	Group	Participants were presented with a series of rows that pairs digits (1–9) with a nonsense symbol and were then required to fill in symbols below a row of digits.
Inference Test (Ekstrom, French, Harman, & Dermen, 1976)	Group	Participants were required to draw conclusions from information presented in statements.
Letter sets (Ekstrom, French, Harman, & Dermen, 1976)	Group	Participants were required to determine which of four sets of letters was unrelated to the others.
Meaningful memory (Institute for Personality and Ability Testing, 1982)	Group	Initially, participants were given a list of things to study. After 20 min, participants were asked to pick from a list of words a word that meant the same or about the same as the word that was described in the first list.
Multidimensional Aptitude Battery (Jackson, 1998)	Group	Participants were required to answer questions related to knowledge of diverse topics.
Nelson-Denney reading comprehension (Brown, Fischo, & Hanna, 1993)	Group	Participants were required to answer questions regarding the meaning of seven reading passages.
Number comparison (Ekstrom, French, Harman, & Dermen, 1976)	Group	The participants were required to inspect pairs of multidigit numbers and then indicate whether the pairs were the same or different.
Paper folding (Ekstrom, French, Harman, & Dermen, 1976)	Group	A measure of spatial visualization where participants were asked to visualize the folding and unfolding of pieces of paper. They were required to identify the figure being folded.
Self-efficacy (Rodin & McAvay, 1992)	Group	An eight-item paper-and-pencil questionnaire that assessed general self-efficacy.
Shipley vocabulary (Shipley, 1986)	Group	Participants were asked to circle the word that had the same meaning or most nearly the same meaning as a referent word.
Simple Reaction Time (Wilkie, Eisdorfer, Morgan, Loewenstein & Szapocnik, 1990)	Individual (computer based)	Participants used their dominant hand to press the keyboard when the stimulus (blue box) appeared.
Stroop Color–Word Association Test (Golden, 1978)	Individual	Paper-and-pencil test. Participants were required to separate the color names of color words.
Technology and computer/Web experience questionnaire	Group	A 14-item paper-and-pencil questionnaire that assessed use of technology and use/breadth of experience with computer technology and the Web.
Trail making test (Forms A & B) (Reitan, 1958)	Individual	Part A: Participant drew lines to connect consecutively numbered circles. Part B: Participant drew lines to connect alternating numbered and lettered circles.
WAIS–III Information (Wechsler, 1997)	Group	Participants were required to write responses to questions about factual information that dealt with general knowledge about common events, objects, places, and people.

Appendix B

Age-Group Differences in Cognitive Ability Measures

Ability measures	Younger *M*	Younger *SD*	Middle aged *M*	Middle aged *SD*	Older *M*	Older *SD*	*F* (2, 1107)	Age-group comparisons (α = .05)
Alphabet span simple	47.74	10.58	41.43	10.10	37.79	9.00	100.77***	Y > M > O
Choice RT Both hands (log)	−5.76	0.20	−5.92	0.29	−6.01	0.28	107.84***	Y > M > O
Computation span simple	41.20	15.33	34.62	14.86	28.75	12.46	80.40***	Y > M > O
CVLT-Delayed	13.67	2.46	11.37	3.44	10.61	4.14	119.27***	Y > M > O
CVLT-Immediate	60.36	10.05	52.98	11.93	49.17	11.20	111.60***	Y > M > O
Cube comparison correct	23.68	8.01	17.20	6.59	14.61	5.84	182.72***	Y > M > O
Digit symbol substitution	67.46	12.96	51.77	14.19	45.83	12.30	298.84***	Y > M > O
Digit symbol recall	7.46	1.97	6.19	2.45	4.43	2.40	191.71***	Y > M > O
Inference test correct	14.16	3.56	12.23	4.59	11.63	4.35	42.26***	Y > M, Y > O
Letter sets correct	21.40	4.90	16.86	5.85	14.78	5.64	167.61***	Y > M > O
MAB Information	25.69	6.38	23.54	7.60	24.34	7.41	8.34***	Y > M
Meaningful memory	15.29	4.14	12.39	4.93	11.46	4.79	75.11***	Y > M, Y > O
Number comparison correct	57.19	10.98	46.76	11.90	42.67	10.26	195.68***	Y > M > O
Paper folding correct	12.03	4.16	7.84	3.76	6.56	3.33	238.79***	Y > M > O
Reading comprehension	31.60	6.08	26.62	9.03	25.11	8.60	74.82***	Y > M, Y > O
Shipley vocabulary	30.02	4.21	32.15	6.05	34.47	4.62	98.09***	Y > M > O
Simple RT (log)	−5.57	0.22	−5.74	0.30	−5.85	0.27	117.50***	Y > M > O
Stroop color–word (log)	3.85	0.25	3.60	0.29	3.46	0.32	198.80***	Y > M > O
Trailmaking B-A (log)	−3.24	0.84	−3.59	0.68	−3.83	0.73	64.56***	Y > M > O

Ability measures	Younger		Middle aged		Older		F (2, 1107)	Age-group comparisons (α = .05)
	M	*SD*	*M*	*SD*	*M*	*SD*		
WAIS-III Information	19.34	4.55	19.39	5.28	20.64	4.63	11.25***	Y < O, M < O

Note. RT = reaction time; Y = younger; M = middle aged; O = older; CVLT = California Verbal Learning Test; MAB = Multidimensional Aptitude Battery.

*** $p < .001$.

Acknowledgements

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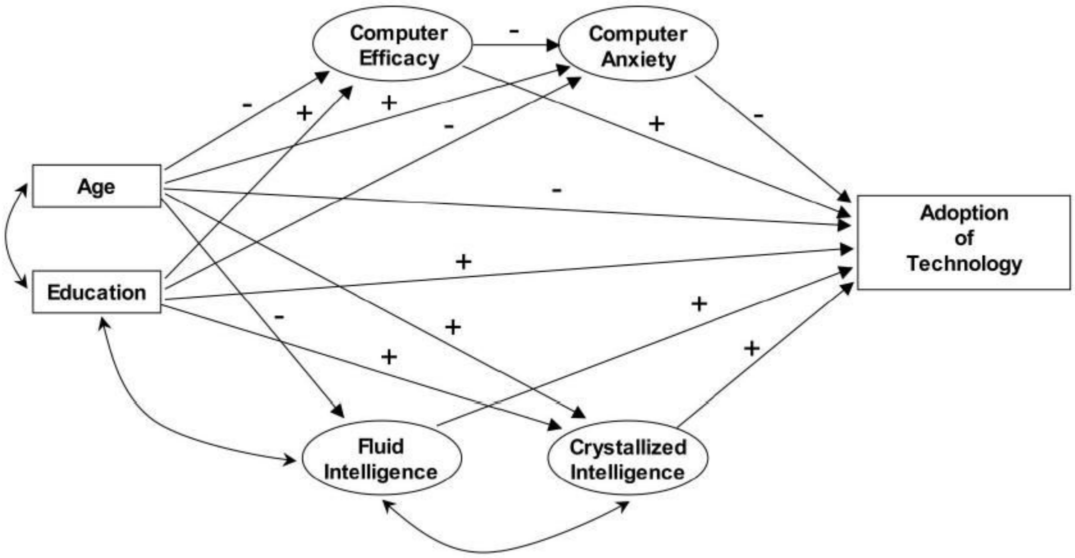

Figure 1.
Hypothesized model of the relationships among social/demographic variables, computer attitude variables, cognitive ability variables, and adoption of technology.

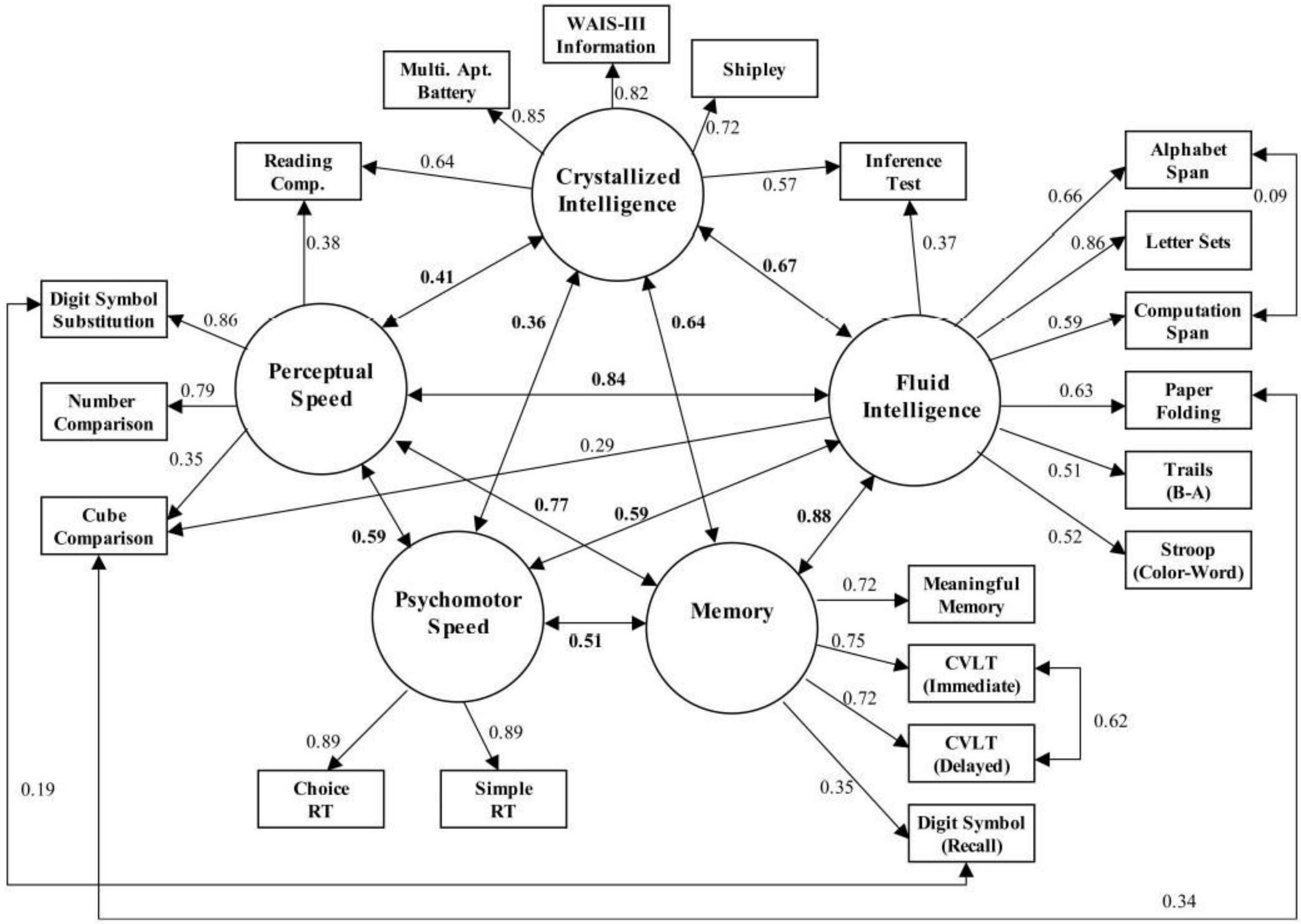

Figure 2.
Standardized factor loadings and factor correlations for the final five-factor ability model. WAIS–III = Wechsler Adult Intelligence Scale–III.

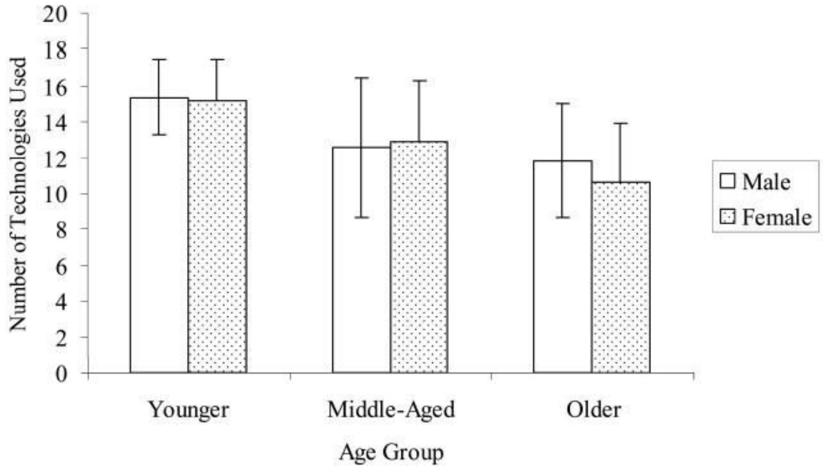

Figure 3.
General use of technology according to age group and gender.

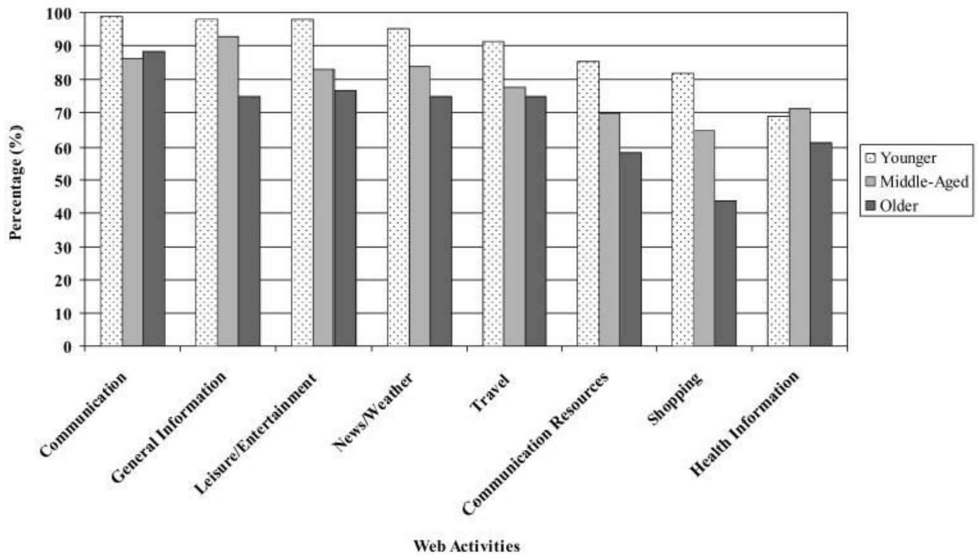

Figure 4.
Web activities by age group.

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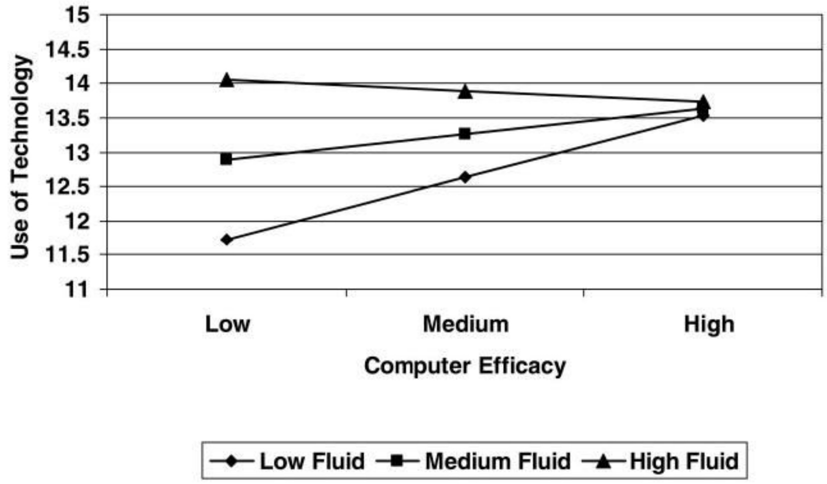

Figure 5.
Interaction of Fluid × Computer efficacy for use of technology.

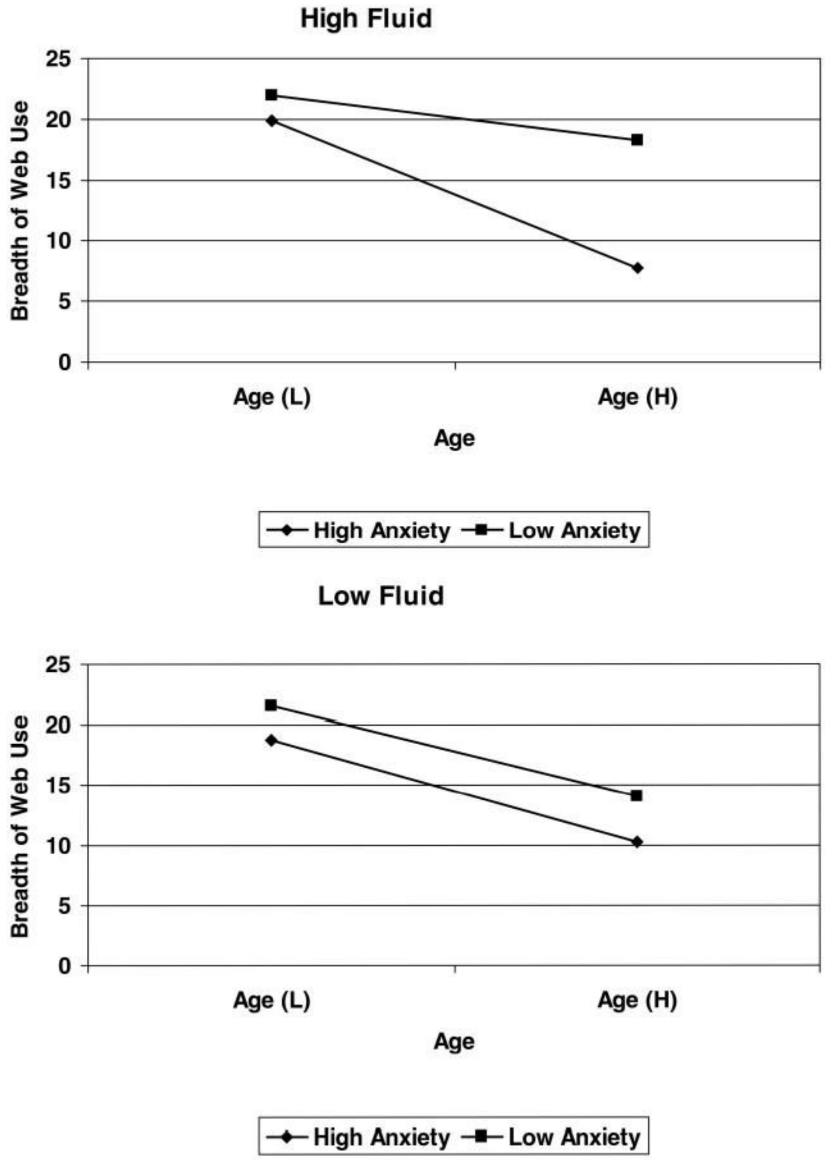

Figure 6.
Interaction of Age × Computer anxiety for high fluid intelligence and low fluid intelligence for breadth of World Wide Web use.

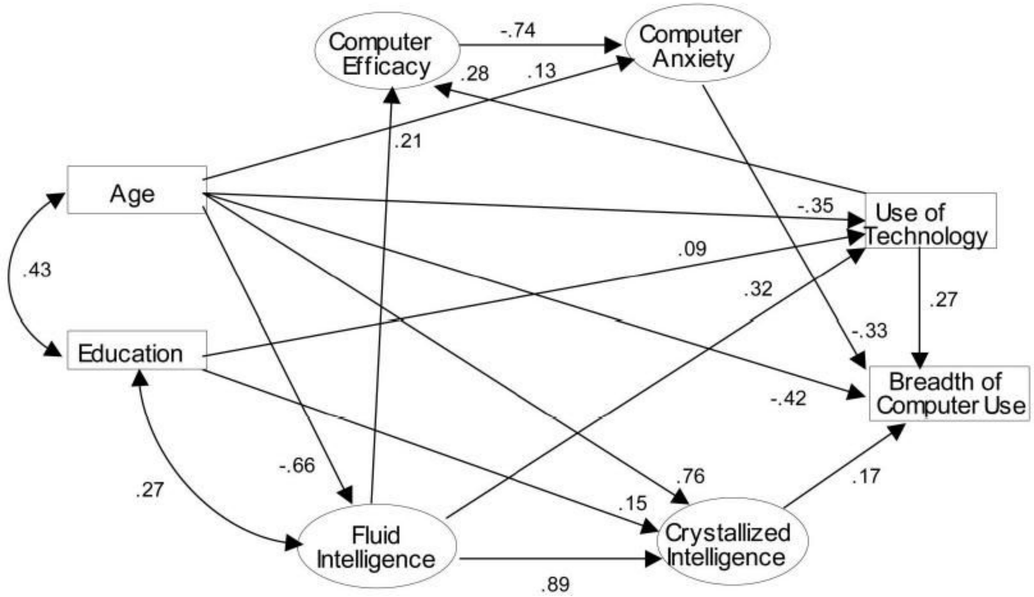

Figure 7.
The final structural model for general breadth of computer use, with standardized regression weights.

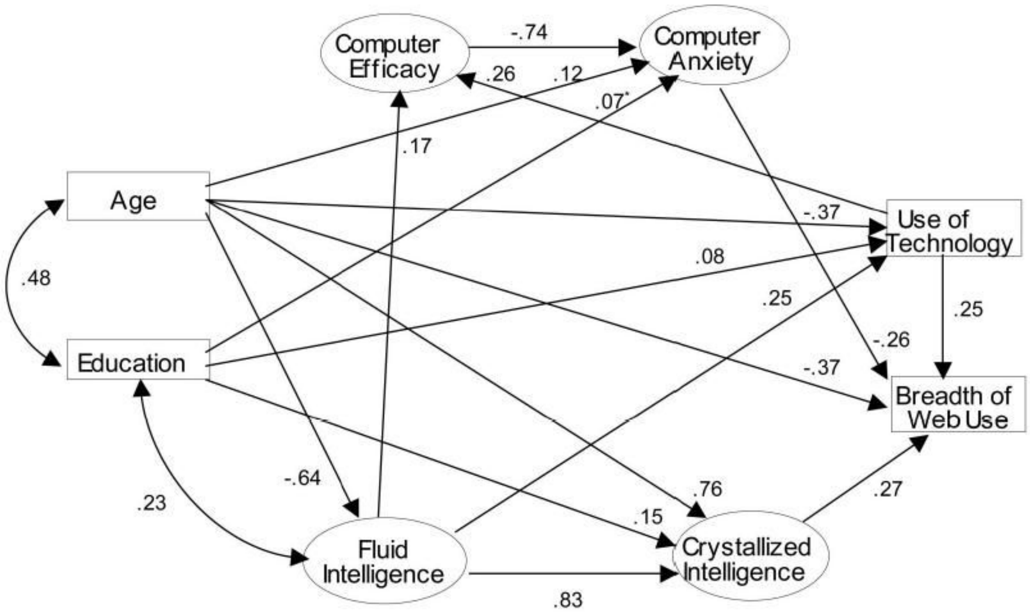

Figure 8.
The final structural model for general breadth of Web use, with standardized regression weights.

Table 1

Sample Description

	Younger	Middle aged	Old
Number	470	273	461
Age (*M*, *SD*)	22.02 (4.69)	49.93 (4.50)	70.49 (5.12)
Gender			
Male	177	97	180
Female	239	176	281
Education***			
≤ High school	19%	13%	15%
Some college	74%	40%	31%
College degree	4%	21%	22%
Postcollege degree	3%	26%	33%
Occupational status***			
Retired	< 1%	11%	83%
Students	78%	8%	< 1%
Employed full-time	11%	30%	4%
Employed part-time	5%	14%	8%
Other	5%	38%	5%
Ethnicity***			
White/European Americans	52%	57%	81%
Black/African Americans	15%	25%	11%
Hispanic/Latino Americans	17%	13%	5%
Other	17%	6%	3%
General health***			
Poor, fair	5%	13%	11%
Good, very good	69%	72%	73%
Excellent	27%	16%	16%
Health compared with other people of same age**			
Poor, fair	10%	15%	8%
Good, very good	65%	63%	65%
Excellent	25%	22%	27%
Satisfaction with health**			
Not at all, not very satisfied	9%	16%	9%
Neither satisfied nor dissatisfied	10%	9%	11%
Somewhat satisfied, extremely satisfied	81%	76%	80%
Health problem limited routine activities***			
Never, seldom	88%	66%	70%
Sometimes	9%	23%	25%
Often, always	3%	11%	5%

** $p < .01$.

*** $p < .001$.

Table 2

Age-Group Differences in Ability Factor Scores

Ability measures	Young *M*	Young *SD*	Middle-aged *M*	Middle-aged *SD*	Old *M*	Old *SD*	*F* (2, 1132)	Age-group comparisons (α = .05)
Crystallized intelligence	−.13	.77	−.09	1.00	.18	.86	19.42***	Y < O, M < O
Fluid intelligence	.52	.58	−.12	.62	−.46	.58	301.68***	Y > M > O
Memory	.49	.56	−.09	.74	−.44	.74	203.23***	Y > M > O
Perceptual speed	.68	.73	−.21	.81	−.56	.69	317.46***	Y > M > O
Psychomotor speed	.50	.70	−.11	.97	−.44	.90	131.22***	Y > M > O

Note. Y = young; M = middle-aged; O = old.

*** $p < .001$.

Table 3

Analysis of Variance for Computer Attitude Scales by Age Group and Gender

Variable and source	*df*	*F*	η^2	*p*
Anxiety				
Age group	2	75.91	.114	.000
Gender	1	18.51	.015	.000
Age Group × Gender	2	3.05	.005	.048
Efficacy				
Age group	2	51.05	.079	.000
Gender	1	6.35	.005	.012
Age Group × Gender	2	.66	.001	.520
Interest				
Age group	2	3.80	.006	.023
Gender	1	4.78	.004	.029
Age Group × Gender	2	.70	.001	.499
General				
Age group	2	2.38	.004	.093
Gender	1	6.63	.006	.010
Age Group × Gender	2	3.67	.006	.026

Table 4

Hierarchical Regressions With R^2 and Increment in R^2: Use of Technology

Variable	R^2	Adjusted R^2	ΔR^2	ΔF
Education	.000	−.001	.000	.085
Ethnicity	.015	.012	.015	8.292***
Cognitive abilities	.307	.304	.292	222.037***
Computer attitudes	.365	.360	.058	48.900***
Age	.429	.425	.064	121.129***
Significant two-way interactions (e.g., Age × Computer Efficacy)	.449	.441	.020	5.586***
Age × Cognitive Abilities × Computer Attitudes	.455	.446	.006	10.850**

** $p < .01$.

*** $p < .001$.

Table 5

Summary of the Final Regression Model for Use of Technology

Independent variables	**β**	***F***	***df***	***p***
Education	.357	17.63	1	.000
Age	−.074	136.63	1	.000
Ethnicity: Black/African American	−.614	8.48	1	.004
Fluid intelligence	.727	29.62	1	.000
Crystallized intelligence	.245	4.70	1	.030
Computer anxiety	−.565	22.98	1	.000
Computer efficacy	.391	12.85	1	.000
Age × Crystallized Intelligence	.010	4.29	1	.039
Age × Computer Anxiety	−.012	3.95	1	.047
Age × Computer Efficacy	−.015	6.04	1	.014
Education × Age	−.009	5.24	1	.022
Fluid Intelligence × Computer Anxiety	−.276	4.40	1	.036
Fluid Intelligence × Computer Efficacy	−.519	17.38	1	.000
Age × Fluid Intelligence × Computer Anxiety	−.015	10.85	1	.001

Note. R^2 = .455; adjusted R^2 = .450.

Table 6

Final Hierarchical Logistic Regression Model: Computer Experience

Variable	β	Wald test	Exp (*B*)
Education	.227	6.305	1.255
Ethnicity: Black/African American	−1.229	20.462	.293
Ethnicity: Hispanic/Latino	−.826	5.144	.438
Fluid intelligence	.644	12.543	1.905
Computer anxiety	−.745	37.765	.475
Age	−.046	17.611	.955

Note. Nagelkerke's R^2 = .341. Exp (B) = estimated odds ratio.

Table 7

Hierarchical Regressions With R^2 and Increment in R^2: Breadth of Computer Use

Variable	R^2	Adjusted R^2	ΔR^2	ΔF
Gender	.026	.025	.026	26.655***
Education	.043	.041	.016	16.493***
Cognitive abilities	.308	.305	.265	187.422***
Computer anxiety	.452	.449	.144	255.999***
Age	.579	.577	.128	296.687***
Significant two-way interactions (e.g., Crystallized Intelligence × Computer Anxiety)	.585	.581	.006	3.560**
Age × Cognitive Abilities × Computer Anxiety	.590	.586	.005	11.551**

** $p < .01$.

*** $p < .001$.

Table 8

Summary of the Final Regression Model for Breadth of Computer Use

Independent variables	β	*F*	*df*	*p*
Gender	.105	18.54	1	.000
Education	.065	19.10	1	.000
Age	−.022	316.20	1	.000
Fluid intelligence	.056	4.26	1	.039
Crystallized intelligence	.110	22.59	1	.000
Computer anxiety	−.312	211.55	1	.000
Fluid Intelligence × Computer Anxiety	.059	5.28	1	.022
Crystallized Intelligence × Computer Anxiety	−.076	11.44	1	.001
Age × Fluid Intelligence × Computer Anxiety	−.003	11.55	1	.001

Note. R^2 = .590; adjusted R^2 = .586.

Table 9

Final Hierarchical Logistic Regression Model: Web Experience

Variable	β	Wald test	Exp (B)
Education	.201	7.979	1.222
Ethnicity: Black/African American	−.934	14.544	.393
Fluid intelligence	.854	17.396	2.348
Crystallized intelligence	.416	11.143	1.516
Computer anxiety	−.741	55.654	.477
Age	−.068	55.657	.935
Age × Fluid Intelligence	−.025	8.087	.975

Note. Nagelkerke's R^2 = .499. Exp (B) = estimated odds ratio.

Table 10

Hierarchical Regressions With R^2 and Increment in R^2: Breadth of Web Use

Variable	R^2	Adjusted R^2	ΔR^2	ΔF
Cognitive abilities	.174	.172	.174	87.862***
Computer attitudes	.282	.278	.108	62.978***
Age	.381	.377	.099	133.723***
Significant two-way interactions (e. g., Age × Computer Efficacy)	.390	.383	.009	2.518*
Age × Cognitive Abilities × Computer Attitudes	.400	.392	.010	13.178***

* $p < .05$.

*** $p < .001$.

Table 11

Final Multiple Regression Model for Breadth of Web Use

Independent variables	β	*F*	*df*	*P*
Age	−.183	142.180	1	.000
Crystallized intelligence	2.312	66.599	1	.000
Computer anxiety	−2.389	58.660	1	.000
Computer efficacy	.565	3.883	1	.049
Age × Computer Anxiety	−.055	11.940	1	.001
Age × Computer Efficacy	−.037	5.100	1	.024
Fluid Intelligence × Computer Anxiety	−.745	4.522	1	.034
Fluid Intelligence × Computer Efficacy	−.763	4.699	1	.030
Age × Fluid Intelligence × Computer Anxiety	−.042	13.178	1	.000

Note. R^2 = .400; adjusted R^2 = .392.

Table 12

Standardized Effects of Variables on Breadth of Computer Use and Breadth of Web Use

Variable	Standardized effect		
	Total	Direct	Indirect
Breadth of computer use (R^2 = .64)			
Education	.055**	.000	.055**
Age	−.657**	−.417**	−.240**
Crystallized intelligence	.169**	.169**	.000
Fluid intelligence	.312**	.000	.312**
Use of technology	.341**	.273**	.068**
Computer efficacy	.242**	.000	.242**
Computer anxiety	−.328**	−.328**	.000
Breadth of web use (R^2 = .46)			
Education	.064***	.000	.064***
Age	−.516**	−.368**	−.148**
Crystallized Intelligence	.270**	.270**	.000
Fluid intelligence	.330**	.000	.330**
Use of technology	.299**	.249**	.049***
Computer efficacy	.193**	.000	.193**
Computer anxiety	−.260***	−.260***	.000

** $p < .01$.

*** $p < .00$.