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Predictors of Performance in Everyday Technology Tasks in Older Adults With and Without Mild Cognitive Impairment

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Abstract

Background and Objectives: The ability to use everyday technology has become a key competence for conducting activities of daily living, maintaining an autonomous life, as well as participating in society. However, studying this issue in older adults needs more attention, particularly among those with mild cognitive impairment (MCI).

Research Design and Methods: We assessed the performance of N = 80 older adults (M = 73 years) in a range of tasks representing important life domains, i.e., using a blood pressure monitor, a mobile phone, and an eBook reader. Thirty-nine participants had been diagnosed with MCI by experienced geropsychiatrists and 41 healthy controls were matched for age, sex, and education. Standardized observation based on video-recording and coding was combined with cognitive testing and assessment of social-cognitive variables (self-efficacy, perceived obsolescence, attitudes towards technology).

Results: Cognitively healthy participants outperformed those with MCI regarding completion time and errors. An interaction effect of device and study group indicated larger differences in completion time for tasks with multilayered interfaces. In hierarchical regression models, aggregated cognitive factors (fluid and memory component) predicted performance and interactions with education level emerged. Obsolescence, addressing a perceived lack of competence to cope with modern society, mediated the effect of cognitive status on performance, both regarding time (partial mediation, $adj.R^2$ = 28%) and errors (full mediation, $adj.R^2$ = 23%).

Discussion and Implications: Findings show that social-cognitive factors contribute to differences in performance on everyday technology tasks in addition to cognitive abilities. Training programs may profit from considering respective individual resources or limitations in the cognitive, personality-related or emotional-motivational domain.

Keywords: Cognition, Technology, Autonomy and self-efficacy, Task performance, MCI

Background and Objectives

For people of all ages, the ability to use everyday technology is crucial for conducting activities of daily living, living an autonomous life, as well as societal participation at large. For younger and older individuals alike, a range of cognitive abilities is relevant for handling complex technological systems (Arning & Ziefle, 2009; Czaja & Ownby, 2010). However, a major proportion of these abilities such as information processing speed and working memory show pronounced declining trajectories across the life span into old age (Craik & Salthouse, 2008). When it comes to cognitive pathology, early indicators of dementia-related disorders include significant losses in executive functioning and working memory abilities, which may considerably impede the use of technological devices (i.e., Slegers, van Boxtel, & Jolles, 2009). As Rogers and Fisk (2010) have pointed out, there is a general lack of outcome-oriented technology studies as well as of adequate methods regarding "direct observation of technology use difficulties" (p. 4), but this is especially the case for individuals with mild cognitive impairment (MCI).

The concept of MCI describes a transitional zone between normal cognitive function and mild dementia (Petersen, 2004) and is widely used in geropsychiatry and geriatric medicine, although there is some controversy over whether or not it constitutes a prodromal stage of dementia (Ritchie & Ritchie, 2012). Approximately 15%–20% of adults 65 years and older are supposed to be affected, with lower prevalence among the young-old and a sharp increase in advanced old age (Reischies & Wertenauer, 2011; Ritchie & Ritchie, 2012). Respective research is important, because MCI may lead to difficulties in handling everyday technology, which may threaten the often expressed aim to live independently at home and increase risks for institutionalization (Rogers & Fisk, 2010).

Theoretical Frameworks: Characteristics of Person and Technology

From a conceptual perspective, this study draws on Lawton's (1982) person–environment fit framework, particularly the *environmental docility hypothesis* which addresses the consequences of a mismatch between environmental demands (e. g., of a technological device) and a person's resources (e.g., cognitive abilities). In case of declining cognitive abilities the person–environment fit is at risk to be significantly reduced with the consequence of low technology performance, i.e., suboptimal or wrong use of a device (Schmidt, Claßen, & Wahl, 2017; Wahl, Iwarsson, & Oswald, 2012).

Furthermore, the principle *net resource release* suggested by Lindenberger and colleagues as a meta-criterion to evaluate (assistive) technology is critical to qualify the interface between available cognitive resources and technology use (Lindenberger, Lövdén, Schellenbach, Li, & Krüger, 2008). The principle implies that the use of a certain technological device or system is adaptive only as long as the handling costs (e.g., cognitive resource investments) are lower than the pay-offs in terms of released (cognitive) resources. As an illustration, Nehmer, Lindenberger, and Steinhagen-Thiessen (2010) stated that a car navigation system can help drivers to reach destinations more efficiently and with less mental effort, which releases cognitive resources and allows a driver to hold a conversation while driving. Net resource release may become a challenging aspect of technology use in older adults, because they need more cognitive resource investment than younger adults. In order to assess respective resource balances, Nehmer and colleagues (2010) also suggested considering objective performance parameters alongside subjective ratings.

From a sociological standpoint, the diffusion of (technological) innovation can be described as the process "in which an innovation is communicated through certain channels over time among the members of a social system" (Rogers, 2003, p.5). Adoption rate and success are assumed to depend on five attributes of innovations: (a) relative advantage, (b) compatibility (e.g., with needs, but also with previously introduced innovations/ideas), (c) complexity, (d) trialability, and (e) observability. For older adults, especially among those with MCI, new devices may be perceived as less advantageous in comparison with a familiar device. In particular, if the handling of a device differs from past experience and acquired skills, compatibility will presumably be rated lower alongside higher perceived complexity. Additionally, Rogers (2003) specified adopter categories that classify people on a scale from highest to lowest innovativeness: (a) innovators, (b) early adopters, (c) early majority, (d) late majority, and (e) laggards. Among these, laggards are the last to adopt an innovation, typically have an aversion to change, tend to be focused on traditions and to be oldest of all adopters.

Linking Cognitive Abilities to Technology-Based Performance

The relatively high prevalence of MCI mentioned above illustrates that a considerable number of older adults who still live independently at home may be at risk for making errors on tasks that have a high cognitive load. With respect to perceived difficulty to use everyday technology, older adults with MCI have been shown to rank between cognitively healthy individuals and groups with mild dementia (Malinowsky, Almkvist, Kottorp, & Nygård, 2010; Nygård, Pantzar, Uppgard, & Kottorp, 2012). Moreover, older adults with MCI were less likely to develop enhanced confidence and efficacy in a systematic training program regarding computer use in comparison to cognitively healthy counterparts (Wild et al., 2012). However, participants with MCI are capable of participating and they benefit, to some extent, from computer-based and other training programs (i.e., Barnes et al., 2009; Unverzagt et al., 2007; Willis & Belleville, 2015).

Among cognitively healthy older adults, several cognitive abilities have been linked to technology-based performance. Seminal research was conducted by the CREATE (*Center for Research and Education on Aging and Technology Enhancement*) consortium with respect to computer usage, showing positive links between task performance and measures of episodic memory, working memory, executive functioning, processing speed and spatial abilities (i.e., Charness, Kelley, Bosman, & Mottram, 2001; Czaja et al., 2013; Sharit, Taha, Berkowsky, Profita, & Czaja, 2015; Taha, Czaja, Sharit, & Morrow, 2013). There is also evidence that complex user interfaces (i.e., higher numbers of levels in hierarchical menus) are more challenging for older adults (Docampo Rama, de Ridder, & Bouma, 2001; Ziefle & Bay, 2005). Such performance differences may partly overlap with or be explained by age-related differences in working memory or spatial ability (Freudenthal, 2001).

However, research into the area of technology and cognition so far mostly concentrated on the "young-old," predominantly including participants between 60 and 70 years. Moreover, study populations were largely highly educated and experienced with technology, indicating a research gap with regard to less privileged individuals and those with MCI. Going further, social-cognitive factors such as attitudes and beliefs that may influence technology-related behavior have not been consequently investigated as additional psychological predictors or mediators of the cognition-performance link.

The Role of Social-Cognitive Factors for Technology Use

In addition to meta-criteria such as net resource release, social-cognitive variables may be important for successful technology use in the case of MCI as well as cognitively healthy aging. Although the label "laggards" may imply very late adoption and probably worse performance on technology-based tasks, the present work intends a differentiated investigation of individual beliefs and attitudes among older adults and their relation to performance. First, for *general self-efficacy*—people's beliefs about their ability to cope with a variety of demands—positive associations with the frequency of internet usage in old age were found (Erickson & Johnson, 2011). Domain-specific internet self-efficacy scales were associated with the intention to use computers and breadth of usage (Czaja et al., 2006; Lam & Lee, 2006) and with perceived ease of use regarding online community websites (Chung, Park, Wang, Fulk, & McLaughlin, 2010). Task performance has, to our knowledge, not yet been simultaneously linked to self-efficacy and cognition among older adults, but positive associations have been demonstrated among students and people aged about 50 years (Arning & Ziefle, 2009; Brosnan, 1998).

Second, with respect to *attitudes towards technology*, the most influential and robust framework is the technology acceptance model (TAM; Davis, 1989; Venkatesh & Bala, 2008) with its multiple extensions. The role of attitudes in predicting technology use has been widely established, including older populations (i.e., Czaja & Nair, 2006; Umemuro, 2004). However, for task performance in older age, empirical evidence regarding the influence of attitudes is, to our knowledge, so far missing (see also the multidisciplinary review by Wagner, Hassanein, & Head, 2010).

Third, *perceived obsolescence,* a promising construct in life-span psychology defined as a gradual loss of social integration and perceived lack of competence to deal with the demands of modern society (Brandtstädter & Wentura, 1994; Kaspar, 2004), may additionally explain differences in technology-based performance. So far, there is no empirical evidence linking perceived obsolescence to performance outcomes, and cognitive impairment has not been set into this context either. However, for MCI and perceived obsolescence alike, associations with loneliness, depressive symptoms and affective valence were found (Brandtstädter & Wentura, 1994; Kaspar, 2004), and higher perceived obsolescence was found to be associated with less technological equipment at home (Friesdorf & Heine, 2007). Extending this first evidence, we expect that perceived obsolescence may mediate the linkage between cognitive performance and technology use in old age.

Finally, a major gap in the existing technology and aging literature is that most studies addressing performance (and not only usage) focus on computer and internet applications. In contrast, more "simple" everyday technologies such as blood pressure monitors or (nonsmart) mobile phones are seldom investigated, although optimal performance in using such devices might be closely related to core quality of life domains such as health, communication, or leisure time (Schulz et al., 2015; van Bronswijk, Bouma, & Fozard, 2002).

Study Aims and Hypotheses

We examined task performance in everyday technologies representing the areas of health (blood pressure monitor), communication (mobile phone), and leisure (eBook reader) among older adults with and without MCI. We also investigated the role of cognitive and social-cognitive factors in terms of their incremental value to explain variability in task performance. We expected higher cognitive abilities, higher self-efficacy and lower perceived obsolescence to be significantly associated with better performance in technology-based tasks. As attitudes towards technology do not imply competence beliefs, we did not expect close correlations with performance.

Moreover, as individuals with MCI might experience stronger feelings of obsolescence due to perceived difficulties in dealing with the challenges of our modern society, we predict perceived obsolescence to be a mediating factor of the association between cognitive status and technology performance.

Research Design and Methods

Recruitment and Sample

In order to predetermine effect size, we referred to studies that also used performance-based instruments for comparisons between older adults with MCI and healthy controls. With respect to instrumental activities of daily living, which can be seen as superordinate category for technology handling, large effect sizes have been reported (i.e., Giovannetti et al., 2008: d = 1.2; Goldberg et al., 2010: d = 0.86). Regarding the perceived difficulty of everyday technology (self-reported), medium to large effect sizes between groups with and without MCI were found (i.e., Nygård, et al., 2012: d = 0.82) with a minimum of d = 0.66 (Malinowsky, et al., 2010) which was therefore used as estimation for power analysis (G*Power; Faul, Erdfelder, Buchner, & Lang, 2009). Assuming a two-tailed α of 0.05 and power of 80%, the required sample size was 76.

A total of N = 80 retired older adults were included; 50% were female, and their age ranged from 58 to 88 years (M = 73, SD = 5.3). About one-third could be classified as having either a low (27.5%), medium (37.5%), or high education level (35.0%), with either 8–9, 10–11, or 12–13 years of education. Sixty-seven percent of the participants (with and without MCI in equal parts) had been enrolled in a previous study on mobility (Wahl et al., 2013) that was completed several years before our data collection started. In that former study, cognitively healthy individuals had been drawn randomly from official public registers in 2008 and individuals with MCI had been identified by experienced geropsychiatrists and psychologists in the memory clinics of the Psychiatric Clinic of Heidelberg University and the Central Institute of Mental Health, Mannheim. Those who had agreed to be approached for potential future studies and met our inclusion criteria (i.e., had not developed dementia) were contacted again. The remaining participants were recruited via a local lecture series on aging-related topics and again by approaching the memory clinics. One hundred and twenty-one potential participants received postal information on study content during the assessment period (spring 2012 until autumn 2014), followed by a telephone call to clarify exclusion criteria, namely dementia (n = 6 excluded), severe sensory or health impairment (n = 10), or living in a nursing home (n = 0). Moreover, n = 16 individuals could not be reached and n = 9 stated that they were not interested.

Of our final 80 participants, n = 39 fulfilled the diagnostic criteria for MCI (Petersen, 2004) supported by psychometric assessment, functional magnetic resonance imaging and analyses of cerebrospinal fluid. The MCI group scored between 23 and 28 points in the Mini-Mental State Examination (MMSE; Folstein, Folstein, & McHugh, 1975) used for global cognitive screening. The group of n =41 cognitively unimpaired participants did not differ in age, education, sex, instrumental activities of daily living, vision, or hearing ability and reached 29 or 30 MMSE-points.

Ethical approval was obtained from the Ethics Review Board of the Faculty of Behavioral and Cultural Studies at Heidelberg University in September 2011. Written informed consent was received from all participants upon enrollment.

Measures

We conducted home-visits (mean duration = 2 hr) that included established cognitive tests, questionnaires on social-cognitive variables, and standardized tasks with everyday technology.

Cognitive Testing

Cognitive abilities were assessed with a battery of established neuropsychological tests. We applied the Trail Making Test (A and B) to measure visual attention and task switching (Reitan, 1979), the Digit Span Backward Test to assess working memory capacity, the Digit Symbol Substitution Test for processing speed, the Retell Stories Subtest 1 and 2 for logical memory (Wechsler, 2000), and the Paper Folding Test to assess visuo-spatial abilities (Ekstrom, French, Harman, & Dermen, 1976). Correlation analyses for the cognitive tests showed high associations, leading us to a preceding exploratory factor analysis (principal axis factoring) in order to reduce the number of predictors for the regression analyses and to avoid multicollinearity. An oblique Promax-rotation revealed a two-factor solution explaining 79.9% of variance, the correlation between the two rotated factors was r = .67. As those tests based on predominantly fluid abilities showed high loadings on the first factor (Digit Span: .83, Trails B–A: −.83, Digit Symbol Substitution: .86, and Paper Folding: .76) it was labeled “fluid component” (66.7% explained variance). The second factor was labeled “memory component” due to high loadings of respective tests (delayed recall items of MMSE: .60, logical memory 1: .77, logical memory 2: .93; 13.2% explained variance). A table containing factor loadings is available on request.

Social-Cognitive Variables

General self-efficacy was assessed using the unidimensional scale of Schwarzer & Jerusalem (1999) which includes 10 items (example: “I can usually handle whatever comes my way”; Cronbach’s α = .91). Responses are given on a 4-point scale ranging from 1 (“not true”) to 4 (“completely right”). *Perceived Obsolescence* was assessed via the respective subscale in Brandstädter and Wentura’s questionnaire on experiencing time and future (1994). It includes five items (“For me, life has become more and more complicated, more difficult to comprehend”; Cronbach’s α = .79). Responses are given on a 5-point scale from 1 (“not at all”) to 5 (“very true”). *Attitudes towards technology* were assessed using a five-item questionnaire (Hampel, Mollenkopf, Weber, & Zapf, 1991) with two items loading on an emotional evaluation component (“Technology threatens people more than it helps them”) and three items loading on a rational component (“If you would like to maintain a modern standard of living, then you must keep pace with technological developments, whether you want to or not”). Responses are given on a 5-point scale from 1 (“not at all”) to 5 (“very true”); the composite scale was used with Cronbach’s α = .71.

Performance in Everyday Technology Tasks

For the assessment of performance regarding everyday technology, participants were asked to perform specified tasks with the three selected devices depicted in Figure 1 covering the technology domains of health, communication, and leisure. They received standardized written instructions of 150 words for each device. In detail, tasks covered operating a blood pressure monitor (three main tasks including 12 substeps; examples: switch memory bank, read pulse rate; menu style: single-layered interface), a nonsmart mobile phone (three tasks, 14 substeps; examples: set alarm clock, select phone book, enter number; three hierarchical layers), and an eBook reader (three tasks, 10 substeps; examples: browse to specified page, select largest font size; two hierarchical layers). Tasks had been broken down into discrete and sequential substeps in a prior task analysis based on a scheme suggested by Rogers and colleagues using the example of a blood glucose meter (Rogers, Mykityshyn, Campbell, & Fisk, 2001). In order to objectively document performance with respect to our outcome measures number of errors and completion time, participants' hands and the devices were videotaped. The resulting video sequences were rated by two independent observers who coded errors for each substep (i.e., font size correct: yes/ no) with an interrater agreement of 93.4% (Cohen's κ = .76). The rating procedure was pretested in a feasibility study based on 33 sequences (Schmidt & Wahl, 2012) with a κ of .80.

Additional items assessed technology ownership and usage frequency (23-item list) and usability ratings that are not part of the present study but have been reported previously (Schmidt, 2015).

Statistical Analyses

Statistical analyses were performed using SPSS version 24.0. In addition to regression analyses, we conducted relative weight analyses which allow partitioning the explained variance among multiple predictors (Tonidandel & LeBreton, 2011), as opposed to the indices commonly produced by multiple regression which fail to appropriately partition variance to correlated predictors. Although mediation analysis has been recommended to be applied primarily in longitudinal studies (Maxwell & Cole, 2007), we argue that in our quasiexperimental design the independent variable (diagnosis) and the mediator (perceived obsolescence) precede our dependent variables, i.e., experimentally elicited task performance criteria.

Figure 1. Blood pressure monitor (smartLAB profi, HMM GmbH), mobile phone (emporiaTALKpremium, Emporia) and eBook reader (OYO, Thalia).

Results

We first report the results of group comparisons in cognitive abilities, social-cognitive variables and task performance as well as correlations among these variables. Second, results of hierarchical regression analyses for the explanation of performance criteria are presented.

Group Differences and Correlational Results

Group comparisons using *t* tests and Mann–Whitney *U* tests revealed higher scores in all tests for specific cognitive abilities among healthy controls compared to those with MCI (Cohen's $d > 0.80$; indicating large effect sizes). In addition, cognitively healthy participants reported higher general self-efficacy ($M = 3.46$, $SD = 0.40$ vs $M = 2.82$, $SD = 0.46$; $t(78) = 6.66$, $p < .001$, $d = 1.49$) and lower perceived obsolescence than individuals with MCI ($M = 1.56$, $SD = 0.55$ vs $M = 2.24$, $SD = 0.83$; $t(65) = -4.27$, $p < .001$, $d = 0.96$). Attitudes toward technology were equally positive on the respective scale from 1 to 5 and did not differ between groups ($M = 4.10$, $SD = 0.74$ vs $M = 4.01$, $SD = 0.63$; $t(78) = 0.60$, $p > .05$). With regard to technology ownership and usage patterns, participants owned 13 devices on average (range = 6–19). Blood pressure monitors were used on a weekly basis by 25% of our participants, mobile phones by 47% and eBook readers by 0%; scores did not differ by cognitive status.

Regarding overall task performance, cognitively healthy participants outperformed those with MCI in terms of completion time and number of errors with large effect sizes (d[minutes] = 0.82, $t(71) = -4.67$, $p < .001$; d[errors] = 0.86, $t(66) = -3.84$, $p < .001$), meaning that participants with MCI made more mistakes ($M = 6.51$, $SD = 3.47$) and needed more time ($M = 10.44$ min, $SD = 2.45$) than healthy controls (errors: $M = 3.98$, $SD = 2.26$, min: $M = 8.26$, $SD = 1.76$). Device-specific performance by study group is depicted in Figure 2. A 2 × 3 mixed analysis of variance with study group as between-subjects factor and device as within-subjects factor revealed an interaction effect of device and study group indicated larger differences in completion time (but not errors) for tasks that required

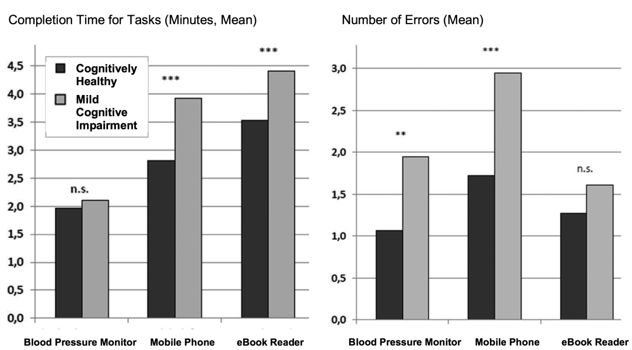

Figure 2. Performance in technology-based tasks (device-specific) by study group. *Note*: $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$.

navigating hierarchical menu structures, namely with the mobile phone and eBook reader ($F(2, 77) = 8.55$, $p <. 01$, partial $\eta^2 = .10$).

Correlation analyses indicated that higher scores on the two condensed cognitive components, higher self-efficacy, and lower perceived obsolescence were significantly associated with better performance (i.e., less time needed and fewer errors), both with regard to overall and (most) device-specific criteria (Table 1). General attitudes toward technology were unrelated to task performance.

Prediction of Task Performance

Hierarchical regression models explaining overall performance criteria are presented in Table 2, with relative weights (RW) indicating the respective amount of explained variance per predictor (right column). Study group was not entered as predictor to avoid multicollinearity due to large overlaps with the cognitive components. Sociodemographic variables were entered in the first step, aggregated cognitive components in the second, and interaction effects with at least marginal contribution in the third step. Age showed no significant contribution, sex explained a small amount of variance in completion time favoring women, and higher education was beneficial both in terms of a direct influence regarding fewer errors and in terms of interaction effects with cognitive components.

The two cognitive components explained additional 25% of variance with respect to overall completion time and additional 13% with respect to errors. For completion time, the fluid component was particularly relevant (RW: fluid = 42.8%, memory = 22.9% of adj.R^2) whereas for errors, the memory component was slightly more important (RW: fluid = 25.5%, memory = 33.6%). Interaction effects of education and both cognitive components were found for the time criterion, and an interaction of education and the memory component was also found for the number of errors. For participants with lower memory scores, significant differences in completion time between persons with low and high education level emerged, favoring the higher educated group ($p < .05$), whereas for participants with higher memory scores, completion time was not further related to education. Higher fluid abilities reduced completion time among participants with medium and higher education level, but not for participants with low education level ($p < .05$). Regarding errors, the memory component was of particular relevance for participants with low education level, as higher memory scores buffered performance showing reduced error rates in this group ($p < .01$), but not among those with higher education. For illustration of the interaction effects see Supplementary Figure 1.

Beyond the inclusion of demographic and cognitive components, self-efficacy and attitudes did not explain additional variance with respect to overall performance criteria in the total sample. However, for cognitively healthy individuals, additional 13% of variance in completion time could be explained by self-efficacy in the third step. Likewise, device-specific analyses revealed significant contributions of self-efficacy regarding completion time for the mobile phone and the eBook reader.

Finally, we tested if perceived obsolescence served as a mediator regarding the link between study group (cognitively healthy vs MCI) and task performance, while controlling for education and technology ownership (Figure 3). A partial mediation was found for completion time ($adj.R^2$ = 28%) and a full mediation for error rate ($adj.R^2$ = 23%). Technology ownership initially contributed to variance explanation regarding completion time (but not errors) and lost its significance with the inclusion of perceived obsolescence. Although not a priori hypothesized due to the missing empirical link between MCI and general self-efficacy, an analogous model was tested for self-efficacy as mediator. However, no mediating effect was observed.

Discussion and Implications

A primary aim of the present study was to explore the role of MCI for performance in tasks with everyday technology. Therefore, participants with MCI and cognitively healthy counterparts were compared regarding completion time and error rate in a selection of everyday tasks, i.e., a blood pressure monitor, a mobile phone, and an eBook reader. Results indicate worse overall performance of the MCI group with large effect sizes for both performance criteria, suggesting meaningful differences between groups in key competencies for conducting activities of daily living and remaining as autonomous as possible. In line with previous findings in young and middle age (Ziefle & Bay, 2005), the two devices with higher complexity in terms of layered interfaces generated larger differences in completion time, but not in error rate. Of note, participants with MCI even committed more errors using the "simple" single-layered blood pressure monitor than healthy controls (medium-sized effect). However, frequent errors included incorrect arm positon or placement of the cuff and were therefore unrelated to interface design, or were due to missing default time windows when switching memory banks. Although the higher number of errors within the MCI group may have higher practical relevance in daily life than their slower completion time, it should be noted that default time windows are quite common (i.e., cash machines).

A second goal was to identify factors associated with task performance. Results of multivariate regression models point to the limited role of chronological age per se as a predictor of performance, whereas education level was more relevant, especially for the prediction of errors and in terms of interaction effects with cognitive factors. Hence, higher education can be interpreted as a protecting factor that buffers performance deficits in the case of lower cognitive abilities, or as resource that shows reciprocal effects with higher cognitive abilities and generates better performance.

Table 1. Correlations of Global and Device-Specific Performance with Sociodemographic, Cognitive, and Social-Cognitive Variables

Variables	*M*	*SD*	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 Age	72.69	5.27	.08	.05	−.21^{+}	−.21^{+}	−.26*	−.02	.36**	.11	.11	.21^{+}	.12	.05	.02	.19^{+}	.00	−.06
2 Sex[a]	--	--		−.03	.24*	.06	−.15	.18	−.04	.02	.18	.09	.12	.19^{+}	.12	.04	.00	.23*
3 Education[b]	--	--			.24*	.46***	30**	.27*	−.22^{+}	.06	−.28*	.02	−.27*	−.33**	−.36**	−.17	−.38**	−.25*
4 Technology Ownership[c]	13.45	3.94				.31**	.23*	.37**	−.49***	.18	−.37**	−.29*	−.40***	−.20^{+}	−.24*	−.23*	−.29**	−.04
5 Fluid Component[d]	0.00	1.00					.67***	.42***	−.48***	.17	−.56***	−.22*	−.53***	−.52***	−.42***	−.42***	−.37**	−.15
6 Memory Component[d]	0.00	1.00						.45***	−.48***	.05	−.48***	−.24*	−.42***	−.48***	−.45***	−.47***	−.34**	−.19^{+}
7 General Self-Efficacy[e]	3.15	.53							.57***	.29**	−.37**	−.17	−.31**	−.39***	−.33**	−.30**	−.37**	−.06
8 Perceived Obsolescence[f]	1.89	.77								−.28*	.44***	.29**	.39***	.38**	.40***	.43***	.34**	.13
9 Attitudes toward Technology[f,g]	4.05	.69									−.14	−.01	−.07	−.27*	−.04	−.10	−.11	.11
10 Overall Completion Time (Minutes)	9.34	2.33										.56***	.83***	.84***	.60***	.42***	.54***	.39***
11 Blood Pressure M. (Minutes)	2.03	.62											.36**	.26*	.25*	.27*	.23*	.15
12 Mobile Phone (Minutes)	3.36	1.36												.67***	.57***	.37**	.53***	.36**
13 eBook Reader (Minutes)	3.97	.90													.56***	.42***	.45***	.39***
14 Overall Number of Errors	5.23	3.17														.75***	.83***	.67***
15 Blood Pressure M. (Errors)	1.50	1.43															.42***	.23*
16 Mobile Phone (Errors)	2.33	1.53																.36**
17 eBook Reader (Errors)	1.44	1.26																

Note: $N = 80$.

[a]50% female, 0=female, 1=male; [b]1=low (27.5%), 2=medium (37.5%), 3=high education level (35.0%), with either 8–9, 10–11, or 12–13 years of education; [c]Number of technological devices owned, range: 6–19; [d]factor scores, aggregated cognitive components; [e]possible scores: 1–4; [f]possible scores: 1–5. [g]For attitudes towards technology we used the overall scale, as both subscales (emotional and rational component) showed very similar correlation patterns with performance criteria.

$^{+}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table 2. Hierarchical Regression Analysis Predicting Performance in Technology-Based Tasks on the Basis of Aggregated Cognitive Components

		Completion time (over all devices)				Number of errors (over all devices)			
Step	Predictor	$\beta_{\text{step 1}}$	$\beta_{\text{step 2}}$	$\beta_{\text{step 3}}$	*RW%*	$\beta_{\text{step 1}}$	$\beta_{\text{step 2}}$	$\beta_{\text{step 3}}$	*RW%*
1	Age	.10	−.05	−.07	*0.8*	.03	−.08	−.09	*1.2*
	Sex[a]	.16	.19⁺	.21*	*7.2*	.10	.08	.10	*3.5*
	Education[b]	−.28*	−.00	−.01	*6.6*	−.36**	−.19⁺	−.20⁺	*21.6*
2	*Aggregated Cognitive Factors*								
	Fluid Component		−.48**	−.47**	*42.8*		−.15	−.15	*25.5*
	Memory Component		−.14	−.11	*22.9*		−.30*	−.27*	*33.6*
3	*Interactions*[c]								
	Education × Fluid			−.28*	*5.2*			−.17	*2.6*
	Education × Memory			.38*	*14.6*			.26*	*12.0*
ΔR^2		.11*	.25***	.08*		.14**	.13**	.04⁺	
$adjR_{cum}^2$		.08	.32	.39		.11	.23	.24	

Note: N = 80; method = stepwise.
RW% = Relative weights, percentage of R^2 explained by the respective predictor.
[a]0=female, 1=male; [b]1=low, 2=medium, 3=high education level, with either 8–9, 10–11, or 12–13 years of education; [c]Further interaction terms were tested but did not significantly contribute to variance explanation.
⁺p < .10, *p < .05, **p < .01, ***p < .001.

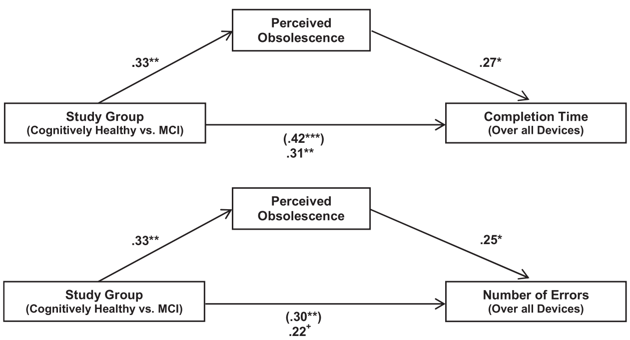

Figure 3. Perceived obsolescence mediates the relationship of study group and technology performance criteria.

Note: standardized regression coefficients (β); numbers in brackets depict the respective β prior to introduction of the mediator (perceived obsolescence); both models were adjusted for education and technology ownership as a measure of general experience with technology. 0=Cognitively Healthy, 1=MCI; *p < .05, **p < .01, ***p < .001.

With focus on social-cognitive variables, we found significant correlations of performance criteria with self-efficacy and perceived obsolescence, but not with attitudes towards technology. This is in line with our expectation that psychological factors related to perceived (lack of) competence would exhibit stronger associations with performance than more distal attitudes, that in turn have been linked frequently to acceptance dimensions (Charness & Boot, 2009; Mitzner et al., 2010). Although our sample was rather inexperienced with technology, the reported attitudes were very positive (M_{total} = 4.05 out of 5), reflecting the need to take a more differentiated view instead of labeling older adults as laggards with aversion to innovation.

Self-efficacy, although significantly correlated, did not reveal incremental value in variance explanation beyond cognitive components. Complementary analyses indicated additional variance explanation in completion time (overall, mobile phone and eBook reader) due to self-efficacy for cognitively healthy individuals only. This might be explained by the fact that self-efficacy was uncorrelated to cognition in this group, whereas among participants with MCI a closer overlap with the memory component was found, which may have led to a larger amount of shared explained variance in task performance. Finally, perceived obsolescence remained significant after controlling for technology ownership and study group, and the mediating influence on the association of diagnosis (cognitively healthy vs MCI) and performance demonstrates that there are important psychological factors alongside cognition that operate in the context of technology handling.

Limitations and Further Research

Some limitations should be considered for broader generalization and application of present results. In the strict sense, our findings are limited to performance issues with the selected devices, although they were chosen to represent three relevant areas of technology. Related, as the sequence of tasks and devices was held constant, effects due to the order of testing cannot be ruled out. For generalization, more research is needed to replicate the found patterns of cognitive abilities, social-cognitive variables and performance measures on tasks with different devices. Since our sample size was rather low, especially for the number of predictors included in the analyses, the presented findings require replication in larger samples.

To address changes in cognitive abilities or increases in perceived obsolescence and their influence on long-term performance in technology-based tasks, longitudinal studies are needed. Furthermore, similar (quasi-)experimental designs would profit from pre-post-measurements of tailored domain-specific (i.e., everyday technology) self-efficacy beliefs, in order to explore changes triggered by mastery experience (Bandura, 1997). As familiarity and foreseeability of task demands were rather low in our inexperienced sample we opted for general self-efficacy ratings instead of task-specific beliefs. Further extensions could involve measures for technology literacy or proficiency (Boot et al., 2015) in order to extend our measures of technology ownership and general experience with technology.

Apart from that, the explicit inclusion of expert-diagnosed participants with MCI and the design combining established cognitive tests, questionnaires on social-cognitive factors and objective task performance data are major strengths of our study. We further intended to overcome the limitation of highly educated and technology-experienced study populations. By assessing cognitive abilities through paper-and-pencil tests (and not also "technology-based" on PCs), we were able to reduce common-method biases and therefore avoid overestimation of the actual association of cognition and performance with technology.

Practical Implications and Outlook

Instead of providing simulated computer-based tasks in a laboratory, we aimed to generate high ecological validity by using common and available devices and assessing task performance in participants' natural environment (see also Bielak, Hatt, & Diehl, 2017). With regard to adult education, training programs may profit from taking into account the individual resources, peculiarities and limitations of the older persons - be it in the cognitive, personality-related or emotional-motivational domain. Practical relevance can also be derived for the assessment of complex activities of daily living in so-called smart homes or for the diagnostic field of performance-based measures, where tasks with everyday technology might be used as early indicators of subliminal cognitive impairment. Handling of technology can be interpreted as combination of several simultaneous cognitive tasks, or as a motor-cognitive dual-tasks, that are particularly sensitive to detect deficits coming with age (Riby, Perfect, & Stollery, 2004). Recent studies involving direct (performance-based) assessments of IADL demonstrate higher sensitivity in comparison with common proxy or self-report procedures (Jekel et al., 2015; Puente, Terry, Faraco, Brown, & Miller, 2014). Alongside such rather resource-intensive tests in the lab, an unobtrusive monitoring of technology-based tasks and usage patterns in a person's environment might be advantageous. There is also first evidence that MCI may translate into changed patterns regarding computer use (Kaye et al., 2014). Moreover, within such a longitudinal monitoring including a broader range of everyday technologies, it could be explored in what sense frequent technology use has cognitively stimulating effects and can act as protective factor (as described in the engagement hypothesis), or in turn, reduce perceived obsolescence.

Supplementary Data

Supplementary data are available at *The Gerontologist* online.

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Conflict of Interest

None reported.

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