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Cognitive, social, emotional, and subjective health benefits of computer use in adults: A 9-year longitudinal study from the Midlife in the United States (MIDUS)

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ABSTRACT

Computer use has been proposed to carry a host of benefits for cognitive function and socioemotional well-being in older adults. However, the literature on computer use remains equivocal as extant research suffers from mixed findings as well as methodological limitations, such as overreliance on cross-sectional designs, small sample sizes, and use of narrow criterions. The current studies ($N_{\text{Study 1}} = 3{,}294$, $N_{\text{Study 2}} = 2{,}683$) sought to address these limitations through the use of a large-scale, nationally representative, and longitudinal dataset. We found that frequency of computer use—over a period of approximately 9 years—longitudinally predicted positive changes in executive functioning, hedonic well-being, eudaimonic well-being, sense of control, optimism, self-esteem, and social relationships with family and friends. We also found that these cognitive and socioemotional benefits are associated with greater computer use over time. In contrast to studies showing that computer use promoted sedentary lifestyles or adverse physical health outcomes, we instead found that computer use longitudinally predicted better self-reported physical and mental health and reduced functional disabilities. The current findings attest to the promising benefits of computer use in promoting healthy cognitive and socioemotional functioning across midlife and old age.

The permeation of computers into the lives of modern humans is accompanied by an appreciation of their positive impacts on cognition and socioemotional well-being (Gatto & Tak, 2008; Wagner, Hassanein, & Head, 2010). These benefits of computer use have important implications for ageing. Older adults are susceptible to age-related problems, such as cognitive decline, low sense of control, low self-esteem, loneliness, poorer subjective well-being, and poorer health (e.g., Robins & Trzesniewski, 2005; Salthouse, 2009; Toh, Yang, & Hartanto, 2019). The positive effects of computers hint at the possibility that age-related deficits in older adults can potentially be reduced through increased computer usage. However, because extant research on the effects of computers suffers from mixed findings (e.g., Dickinson & Gregor, 2006; Fotheringham, Wonnacott, & Owen, 2000) as well as an overreliance on cross-sectional designs, small sample sizes, and narrow criteria, findings remain inconclusive. Using a large-scale, longitudinal, and comprehensive dataset, the current study aims to address these limitations through a holistic approach that focuses on the long-term influences of computer use on a multitude of cognitive, socioemotional, and health domains. In so doing, we extend previous research by providing a robust test of the possible benefits of computer use on a wide array of ageing-related outcome variables.

1. Ageing-related benefits of computer use

From a "use it or lose it" perspective, the preservation of healthy cognitive function depends on regular mental activity (Schooler, 2007). Thus, it has been suggested that age-related cognitive decline can be curtailed through stimulation from frequent computer use (Charness & Boot, 2009). Possible pathways range from exercising basic psychomotor and sensory skills, such as when users operate the mouse or locate icons on a screen, to various aspects of learning, memory, and executive functioning, such as when users figure out how to utilize computer processes to perform tasks (Tun & Lachman, 2010). Consistent with this view, computer use has been found to be associated with improved

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cognitive abilities in older adults (Slegers, van Boxtel, & Jolles, 2012; Tun & Lachman, 2010). Hence, older adults' cognitive functioning can potentially be trained and kept sharp through regular computer use.

Aside from cognitive benefits, computer use has also been proposed to benefit various sociopsychological capacities. Studies show that computer-savvy older adults tend to be empowered with a greater sense of control and self-esteem due to the control, independence, learning, and enjoyment afforded by being fluent with computers (e.g., Karavidas, Lim, & Katsikas, 2005; Shapira, Barak, & Gal, 2007; White et al., 1999). Computer-mediated communication platforms can also facilitate the maintenance of social networks, thereby enabling users to remain socially connected, upkeep social relationships, and avoid isolation and loneliness (Morrell, Mayhorn, & Bennett, 2000; Şar, Göktürk, Tura, & Kazaz, 2012; Szabo, Allen, Stephens, & Alpass, 2018). Through its effects on sociopsychological capacities, computer use may also be related to broader aspects of well-being, including subjective well-being (Diener, 1984) and psychological well-being (Ryff & Singer, 2006). Whereas the former involves positive and negative feelings and satisfaction judgments, the latter refers to the less hedonic aspects of healthy functioning, such as mastery and purpose in life (Rubin, 1987; Tov, 2018). To emphasize this distinction, we refer to them as hedonic and eudaimonic well-being, respectively. Although studies have yet to investigate the effects of computers on eudaimonic well-being, it is plausible that the empowering effects of computer fluency can promote environmental mastery, autonomy, personal growth, and purpose in older adults.

2. Issues with extant research

Although the foregoing analysis gives us strong reasons to expect that computer use will benefit older adults, mixed findings exist. Some studies indicate that computer use may have detrimental effects, such as poorer physical health (e.g., obesity, cardiovascular diseases, diabetes) due to physical inactivity (Fotheringham et al., 2000) as well as poorer mental health (Morrison & Gore, 2010), while many other studies have failed to find any effects of computer use on the socioemotional well-being of older people (e.g., Dickinson & Gregor, 2006; Hanson & Clarke, 2000).

These mixed findings could be due to the fact that many studies suffer from research design limitations. Most notably, the majority of studies rely heavily on cross-sectional designs (e.g., Karavidas et al., 2005; Morrell et al., 2000; Tun & Lachman, 2010; Şar et al., 2012). Although this allows us to identify construct-to-construct relationships at a single time point, the static nature of cross-sectional studies fails to elucidate the long-term changes and bidirectional influence of computer use and age-related deficits. For instance, it is conceivable that higher levels of well-being may facilitate the motivation to learn new skills and expand on existing intellectual resources (Fredrickson, 2001), including computer literacy. Some studies have employed longitudinal designs to investigate the effects of computer use across time (e.g. Almeida et al., 2012; Slegers et al., 2012), but these studies focus mostly on just one or very few outcome dimensions, leading to a narrow understanding of the multiple ways in which computer usage can benefit middle-aged and older adults. Furthermore, studies often use small samples from highly specific populations, such as adults from computer clubs (Karavidas et al., 2005) or nursery homes (Shapira et al., 2007), and thus may be unrepresentative and underpowered.

In addition, confounding variables that may make an unforeseen contribution to the hypothesized effects of computer use (e.g., engagement in other cognitively or physically stimulating activities) are also seldom accounted for (e.g., Schlag, 2011; Shapira et al., 2007), thus further limiting the conclusiveness of these studies. For instance, in terms of demographic variables, age tends to be negatively associated with computer use (Cattaneo, Malighetti, & Spinelli, 2016; Zhang, Grenhart, McLaughlin, & Allaire, 2017) as well as cognitive, social, emotional, and health outcomes (Robins & Trzesniewski, 2005; Salthouse, 2009; Steptoe, Deaton, & Stone, 2015; Toh et al., 2019). Similarly, indicators of socioeconomic status (SES; e.g., education, household income, subjective status) tend to be positively associated with computer use (Chang, McAllister, & McCaslin, 2015) as well as cognitive, social, emotional, and health outcomes (Lyu & Burr, 2016; Read, Grundy, & Foverskov, 2016; Tan & Kraus, 2015). Beyond demographic factors, research has also shown that cognitively stimulating activities such as reading, writing, and playing word or card games may influence adults' cognition, health, and socioemotional well-being (Ferreira, Owen, Mohan, Corbett, & Ballard, 2015; Lampinen, Heikkinen, Kauppinen, & Heikkinen, 2006; Shah, Lin, Yu, & McMahon, 2017; Yates, Ziser, Spector, & Orrell, 2016). At the same time, frequency of computer use and other cognitively stimulating activities tend to be positively correlated because people who are generally active tend to engage in more cognitively stimulating activities (Parisi, Stine-Morrow, Noh, & Morrow, 2009). Without controlling for these covariates, it is not clear whether the benefits of computer use are driven by computer-specific activities or simply a byproduct of demographic and SES factors as well as cognitively stimulating activities that are unrelated to computer use. These limitations and mixed results render the overall findings inconclusive and hinder practitioners from deciding with confidence whether computer use should be encouraged as a means to empower older adults.

3. The current investigation

We aimed to simultaneously address the limitations of previous research through a large-scale longitudinal study comprising a nationally representative, non-clinical sample and a comprehensive array of measured variables. In two phases approximately a decade apart, participants were assessed for their computer use frequency, cognitive abilities, hedonic well-being, eudaimonic well-being, core self-evaluations (sense of control, optimism, self-esteem, and neuroticism), social relationships, physical and mental health, and engagement in cognitively and physically stimulating activities. This longitudinal and multidimensional approach enabled us to uncover the bidirectional longitudinal associations between computer use and various indicators of age-related functioning. In addition, our rich dataset allowed us to control for and rule out the effects of a wide array of potential confounds, including demographic factors, SES, and engagement in stimulating activities. Thus, in all our models, we controlled for these potential confounds to ensure that the cognitive, social, emotional, and health benefits observed in the current study were unique and specific to computer usage.

Based on our review of previous research, we expect frequent computer use to be associated with positive changes across a range of domains, including cognitive abilities, hedonic well-being, eudaimonic well-being, core self-evaluations, and social relationships. In view of Fotheringham et al.'s (2000) study which found prolonged computer use to be detrimental to health, we also considered that frequent computer use could lead to negative changes in health status and physical activities. Finally, we expect these effects of computer use to hold after controlling for potential confounds (i.e., demographic factors and other stimulating activities).

4. Method

4.1. Participants

Study 1. Participants were 3,294 adults who took part in the second (II) and third (III) waves of the study on Midlife in the United States (MIDUS). MIDUS II was conducted between 2004 and 2006 on a nationally representative, random-digit-dial sample of non-institutionalized, English-speaking adults. In MIDUS II, majority of our participants were midlife adults aged 40 to 65 (81.3%) followed by older adults aged above 65 (18.7%) and younger adults aged below 40 (9.1%)

From 2013 to 2014, MIDUS III was conducted as a follow-up to MIDUS II using the same methodology and assessments (see Ryff et al., 2016 for more details). The average time between the waves was approximately 9 years. We did not use specific inclusion criteria other than that participants were included as long as they participated in both MIDUS II and MIDUS III. The MIDUS data captures a wide spectrum of computer usage frequencies—from those who do not use computers at all to those who use computers daily (*never* = 20.2%, *once a month* = 3.9%, *several times a month* = 5.4%, *once a week* = 3.9%, *several times a week* = 14.4%, *daily* = 52.2%). Table 1 summarizes the descriptive statistics of our sample (see supplementary materials for more comprehensive descriptive statistics).

Study 2. Participants were 2683 adults who took part in the Cognitive Project component of MIDUS II and MIDUS III, which was conducted between 2004-2006 and 2013–2017, respectively. These participants were a subset of participants from Study 1 who agreed to participate in the subsequent Cognitive Project, which sought to assess cognitive function with a comprehensive battery of executive function and episodic memory tests. Similar to Study 1, the data in Study 2 includes a wide spectrum of computer usage frequencies (*never* = 19.9%, *once a month* = 3.8%, *several times a month* = 5.2%, *once a week* = 3.9%, *several times a week* = 14.7%, *daily* = 52.5%). Data collection for the MIDUS project was approved by the Education and Social/Behavioral Sciences and the Health Sciences Institutional Review Board at the University of Wisconsin-Madison. All participants provided informed consent and the data and materials can be publicly accessed via the Inter-University Consortium for Political and Social Research (http://www.icpsr.umich.edu).

4.2. Measures

Life satisfaction. Life satisfaction was measured using Prenda and Lachman's (2001) 6-item life satisfaction scale. Participants were asked to rate on a scale of 0 (*the worse possible*) to 10 (*the best possible*) how satisfied they were with their work, financial situation, health, relationship with partner, relationship with children, and overall life ($\alpha_{\text{MIDUS 1}} = 0.70$; $\alpha_{\text{MIDUS 2}} = 0.70$).

Positive and negative affect. Positive and negative affect were measured with a 9-item variant of the Positive and Negative Affect Schedule (Mroczek & Kolarz, 1998). On a scale of 1 (*all of the time*) to 5 (*none of the time*), participants rated the extent to which they had experienced positive (e.g., enthusiastic, proud; $\alpha_{\text{MIDUS 1}} = 0.85$; $\alpha_{\text{MIDUS 2}} = 0.86$) and negative emotions (e.g., upset, ashamed; $\alpha_{\text{MIDUS 1}} = 0.79$; $\alpha_{\text{MIDUS 2}} = 0.80$) in the past 30 days.

Eudaimonic well-being. Eudaimonic well-being was measured with Ryff's (1989) 42-item Psychological Well-Being Scale which comprises autonomy ($\alpha_{\text{MIDUS 1}} = 0.72$; $\alpha_{\text{MIDUS 2}} = 0.69$), environmental mastery ($\alpha_{\text{MIDUS 1}} = 0.78$; $\alpha_{\text{MIDUS 2}} = 0.80$), personal growth ($\alpha_{\text{MIDUS 1}} = 0.74$; $\alpha_{\text{MIDUS 2}} = 0.75$), positive relations with others ($\alpha_{\text{MIDUS 1}} = 0.78$; $\alpha_{\text{MIDUS 2}} = 0.77$), purpose of life ($\alpha_{\text{MIDUS 1}} = 0.70$; $\alpha_{\text{MIDUS 2}} = 0.72$), and self-acceptance ($\alpha_{\text{MIDUS 1}} = 0.85$; $\alpha_{\text{MIDUS 2}} = 0.84$). Each dimension consisted of six items and was rated on a scale of 1 (*strongly agree*) to 7 (*strongly disagree*).

Self-esteem. Self-esteem was measured with Rosenberg's (1965) Self-Esteem Scale. On scale of 1 (*strongly agree*) to 7 (*strongly* disagree), participants reported their agreement with statements such as "I certainly feel useless at times" ($\alpha_{\text{MIDUS 1}} = 0.77$; $\alpha_{\text{MIDUS 2}} = 0.76$).

Sense of control. Sense of control was measured with Lachman and Weaver's (1998) 12-item Sense of Control scale. On a scale of 1 (*strongly agree*) to 7 (*strongly disagree*), participants rated their self-perceived efficacy in achieving personally important goals (personal mastery) and their perception of obstacles beyond their control that interfere with reaching those goals (perceived constraints) ($\alpha_{\text{MIDUS 1}} = 0.87$; $\alpha_{\text{MIDUS 2}} = 0.87$).

Optimism. Dispositional optimism was measured with the 6-item revised Life Orientation Test (Scheier, Carver, & Bridges, 1994). On a

Table 1
Descriptive statistics of MIDUS II and MIDUS III samples.

	MIDUS II (2004–2006)		MIDUS III (2013–2014)	
	M (*SD*)	Range	*M* (*SD*)	Range
Demographic				
Mean age (years)	54.54 (11.35)	30–84	63.64 (11.35)	39–93
Sex (% of male)	45.1%		45.1%	
Education[a]	7.48 (2.49)	1–12	7.51 (2.51)	1–12
Household income (in $1000)	75.86 (61.23)	0–300	86.87 (67.50)	0–300
Subjective social status	6.56 (1.80)	1–10	6.60 (1.80)	1–10
Daily Activities				
Computer use frequency	4.45 (2.02)	1–6	4.81 (1.90)	1–6
Reading frequency	5.46 (1.04)	1–6	5.28 (1.25)	1–6
Word games frequency	2.43 (1.77)	1–6	2.98 (2.03)	1–6
Card games frequency	2.10 (1.40)	1–6	2.08 (1.52)	1–6
Attending lectures frequency	1.75 (1.07)	1–6	1.62 (1.02)	1–6
Writing frequency	2.58 (1.71)	1–6	2.42 (1.68)	1–6
Hedonic well-being				
Life satisfaction	7.58 (1.21)	1–10	7.58 (1.33)	1–10
Positive affect	3.61 (0.74)	1–5	3.55 (0.77)	1–5
Negative affect	1.53 (0.51)	1–5	1.49 (0.54)	1–5
Eudaimonic well-being				
Autonomy	37.19 (7.01)	10–49	37.28 (6.69)	10–49
Environmental mastery	38.51 (7.36)	11–49	38.49 (7.51)	10–49
Personal growth	39.03 (6.69)	14–49	38.30 (6.85)	14–49
Positive relations	40.93 (6.84)	14–49	40.63 (6.74)	14–49
Purpose in life	39.10 (6.74)	10–49	38.10 (7.02)	8–49
Self-acceptance	38.43 (8.23)	7–49	38.06 (8.15)	7–49
Core Self-evaluations				
Self-esteem	38.08 (7.35)	11–49	37.69 (7.12)	12–49
Sense of control	5.59 (0.97)	1–7	5.44 (1.02)	1–7
Optimism	23.49 (4.74)	6–30	23.30 (4.56)	6–30
Neuroticism	2.05 (0.62)	1–4	2.06 (0.62)	1–4
Social relationships				
Perceived support from family	3.53 (0.57)	1–4	3.51 (0.58)	1–4
Perceived support from friends	3.31 (0.64)	1–4	3.30 (0.64)	1–4
Contact with friends	5.64 (1.68)	1–8	5.51 (1.76)	1–8
Having more close friends	5.56 (1.80)	1–7	5.38 (1.87)	1–7
Subjective health				
Self-rated physical health	3.67 (0.94)	1–5	3.43 (1.04)	1–5
Self-rated mental health	3.89 (0.90)	1–5	3.63 (0.95)	1–5
Self-rated functional disabilities	1.69 (0.81)	1–4	1.98 (0.95)	1–4
Objective health				
Body mass index	27.84 (5.70)	14–82	28.20 (6.13)	16–79
Number of chronic diseases	2.28 (2.36)	0–30	3.25 (3.15)	0–20

(*continued on next page*)

Table 1 (*continued*)

	MIDUS II (2004–2006)		MIDUS III (2013–2014)	
	M (*SD*)	Range	*M* (*SD*)	Range
Physical activities				
Vigorous physical activities	3.51 (1.94)	1–6	3.48 (1.98)	1–6
Moderate physical activities	4.27 (1.79)	1–6	4.20 (1.85)	1–6
Light physical activities	5.16 (1.41)	1–6	5.10 (1.48)	1–6
Cognitive functions				
Executive functions (*z*-scored)	0.23 (0.91)	−2.80–3.36	−0.15 (0.74)	−5.62–2.02
Episodic memory (*z*-scored)	0.14 (0.95)	−3.08–4.10	−0.04 (0.99)	−2.93–3.63

*Note. SD*s are shown in parentheses. For all variables, scores were computed such that higher scores indicate higher value. Descriptive statistics were presented before imputation.

[a] Education attainment was rated on a scale of 1 (*No school*) to 12 (*Ph.D, ED. D, MD, LLB, LLD, JD, or other professional degree*).

scale of 1 (*agree a lot*) to 5 (*disagree a lot*), participants reported their agreement with statements such as "In uncertain times, I usually expect the best" ($\alpha_{\text{MIDUS 1}} = 0.77$; $\alpha_{\text{MIDUS 2}} = 0.80$).

Neuroticism. Trait neuroticism was measured with the 4-item neuroticism subscale of the MIDUS Big Five Scale (Prenda & Lachman, 2001). On a scale of 1 (*a lot*) to 4 (*not at all*), participants reported their agreement with self-descriptive adjectives such as moody and nervous ($\alpha_{\text{MIDUS 1}} = 0.74$; $\alpha_{\text{MIDUS 2}} = 0.71$).

Perceived social support. Perceived social support in the domains of family and friends was measured using an adapted version of Walen and Lachman's (2000) 8-item Social Support Scale. Four items assessed participants' perceptions of support availability from family members ($\alpha_{\text{MIDUS 1}} = 0.83$; $\alpha_{\text{MIDUS 2}} = 0.83$) while another four items assessed participants' perceptions of support availability from friends ($\alpha_{\text{MIDUS 1}} = 0.83$; $\alpha_{\text{MIDUS 2}} = 0.86$). The items were rated on a scale of 1 (*a lot*) to 4 (*not at all*).

Friendship quality. Friendship quality was indexed by frequency of contact with friends and number of close friends. Participants' frequency of contact with friends was measured by asking participants how often they interacted with their friends in terms of visits, phone calls, letters, or email on a scale of 1 (*several times a day*) to 8 (*never or hardly ever*). Number of close friends was measured by asking participants to indicate on a scale of 1 (*strongly agree*) to 7 (*strongly disagree*) the extent to which they agreed that they only have a few close friends to share their concerns with.

Subjective health. Self-rated physical health was measured by asking participants to indicate the general quality of their physical health while self-rated mental health was measured by asking participants to indicate the general quality of their mental and emotional health. Both items were rated on a scale of 1 (*excellent*) to 5 (*poor*). Self-rated functional disabilities was measured with Katz, Ford, Moskowitz, Jackson, and Jaffe's (1963) 7-item Instrumental Activities of Daily Living scale. Each item asked participants to report their difficulty in performing a specific practical activity of daily life on a scale of 1 (*a lot*) to 4 (*not at all*).

Objective health. Objective health was indexed in terms of body mass index (BMI), which was determined through participants' self-reported weight and height, and presence of chronic diseases, which was operationalized as the total number of chronic diseases participants experienced in the past 12 months.

Physical activities. Frequency of physical activities was assessed via two items where participants were asked about their frequency of engaging in vigorous physical activities (e.g., competitive sports like running, vigorous swimming, lifting heavy objects), moderate physical activities ("light tennis, low impact aerobics, brisk walking"), and light physical activities ("bowling, archery, fishing") during summer. The items were rated on a scale of 1 (*several times a week*) to 6 (*never*).

Socioeconomic status. SES was indexed in terms of education attainment, household income, and subjective social status. Participants rated their education attainment on a scale of 1 (*No school*) to 12 (*Ph.D, ED. D, MD, LLB, LLD, JD, or other professional degree*). Household income was measured based on participants' household total income through wages, pension, social security, and other financial sources. Participants' subjective social status was measured using the MacArthur scale (Adler, Epel, Castellazzo, & Ickovics, 2000), which uses an image of a ladder on which participants indicate their self-perceived social standing in their community by choosing the most appropriate rung on the ladder ranging from 1 (reflects lowest SES) to 10 (reflects highest SES).

Computer use and other activities. Participants reported their frequency of computer use, reading, playing word games, playing cards and other games, attending lectures and courses, and writing on a scale of 1 (*daily*) to 6 (*never*).

Cognitive ability. Executive functions and episodic memory were measured in Study 2 using the Brief Test of Adult Cognition by Telephone (BTACT; Tun & Lachman, 2006), which is a battery of cognitive function tests comprising the Immediate Word List Recall Task, Backward Digits Span, Categorical Fluency, Stop and Go Switch Task (SGST), Number Series, Backward Counting Task, and Delayed Word List Recall. As validated by Lachman and Tun (2008), episodic memory was measured in terms of performance on the immediate word list recall and delayed word list recall, while executive function was measured in terms of performance on the backward digit span, categorical fluency, number series, backward counting, and SGST.

4.3. Data analysis

The current study sought to examine the bidirectional longitudinal relations between frequency of computer use and various domain criterions, including executive functions, episodic memory, hedonic well-being, eudaimonic well-being, core self-evaluations, social relationships, subjective health, objective health, and physical activities. To do so, for each domain, we employed a two-wave cross-lagged design and structural equation modelling using maximum likelihood estimation with robust standard errors (MLR) with M*plus* version 7.4, which is robust to non-normality and non-independence of observations (Asparouhov, 2005). The models included autoregressive paths, cross-sectional paths between frequency of computer use and domain criterions, and cross-lagged reciprocal paths between frequency of computer use and domain criterions. To handle missing data, we used full information maximum likelihood, which has been demonstrated to be unbiased, efficient, and thus superior to traditional ad hoc missing-data techniques in structural equation models (Enders & Bandalos, 2001).

Each domain criterion was operationalized as a latent variable and estimated via multiple well-established indicators. The latent variable of hedonic well-being was indicated by life satisfaction, positive affect, and negative affect; eudaimonic well-being was indicated by autonomy, environmental mastery, personal growth, positive relations with others, purpose in life, and self-acceptance; core self-evaluations was indicated by self-esteem, sense of control, optimism, and neuroticism; social relationships was indicated by support from family, support from friends, frequency of contact with friends, and number of close friends; subjective health was indicated by self-rated physical health, self-rated mental health, and self-rated functional disabilities; objective health status was indicated by number of chronic diseases, BMI, and waist-to-hip ratio; and physical activities was indicated by the partaking of physically vigorous activities during summer. For cognitive functions, we estimated a two-factor model with executive functions and episodic memory as latent variables based on the validated two-factor model in BTACT (Lachman & Tun, 2008). Executive function was indicated by performance on the backward digit span, categorical fluency, number series, backward counting, and SGST; and episodic memory was

Table 2
Tests of measurement invariance across MIDUS II and III.

	Model	χ^2	df	CFI	TLI	RMSEA	SRMR
Study 1							
Hedonic well-being	Configural	14.097	13	1.000	1.000	.005	.007
	Metric	20.035	15	.999	.998	.010	.015
	Scalar	63.453	17	.991	.986	.029	.016
Eudaimonic well-being	Configural	860.419	67	.964	.952	.060	.050
	Metric	883.361	72	.964	.954	.058	.053
	Scalar	971.976	77	.960	.953	.059	.055
Core self-evaluations	Configural	200.348	27	.985	.975	.044	.035
	Metric	217.477	30	.984	.976	.044	.040
	Scalar	266.345	33	.980	.972	.046	.045
Social relationships	Configural	208.783	27	.968	.947	.045	.039
	Metric	224.533	30	.966	.949	.044	.043
	Scalar	253.946	33	.961	.947	.045	.045
Subjective health	Configural	206.756	13	.973	.943	.067	.053
	Metric	217.660	15	.972	.948	.064	.054
	Scalar	322.756	17	.958	.931	.074	.050
	Partial Scalar	258.396	16	.967	.942	.068	.055
Objective health	Configural	19.193	3	.995	.974	.040	.016
	Metric	19.203	3	.995	.974	.040	.016
	Scalar	19.703	4	.995	.981	.035	.015
Physical activities	Configural	116.992	13	.983	.963	.049	.034
	Metric	123.219	15	.982	.967	.047	.037
	Scalar	125.534	17	.982	.971	.044	.038
Study 2							
Cognitive functions	Configural	474.720	85	.976	.967	.041	.038
	Metric	488.428	89	.976	.967	.041	.039
	Scalar	947.300	94	.948	.934	.058	.059
	Partial Scalar	505.443	93	.975	.968	.041	.040

Note. df = degrees of freedom, *CFI* = comparative fit index, *TLI* = Tucker-Lewis index, *RMSEA* = root mean square error of approximation, *SRMR* = standardized root mean square residual.

indicated by performance on the immediate word list recall and delayed word list recall. To evaluate model fit, we followed an established criterion where an acceptable fit is indicated when the root mean square error of approximation (RMSEA) is below 0.08, Bentler's comparative fit index (CFI) and Tucker-Lewis index (TLI) values are above 0.90, and the standardized root mean square residual (SRMR) is below 0.08 (Brown, 2015; Hair, Black, Babin, & Anderson, 2011).

We first ensured that our constructs held conceptually over time by examining their configural (equality in factor structure), metric (equality in factor loadings), and scalar (equality in latent intercepts) invariances (Biesanz, 2012). Testing for measurement invariance is necessary to ensure that the measurement properties of our latent variables are stable over time, and that the changes in the latent variables are not due to changes in measurement properties. Following Cheung and Rensvold's (2002) recommendations, invariance would be established if changes in CFI are less than 0.01 (ΔCFI < 0.01) between models when adding constraints.

While holding the optimal equality constraints, we estimated three models for each domain criterion, each with an additional set of covariates to ensure the robustness of the hypothesized longitudinal relations from the potential confounding effects of demographics, SES, and other cognitively stimulating activities. In the first model, we estimated the cross-lagged model without controlling for any covariates to provide unadjusted estimates of the longitudinal bidirectional relations between computer use and each criterion after 9 years. In the second model, we controlled for demographic variables at Time 1, including age at

Table 3
Standardized cross-lagged path coefficients of computer use and latent variables of socioemotional and health outcomes.

	Model 1		Model 2		Model 3	
	Estimate	SE	Estimate	SE	Estimate	SE
Computer use as antecedent						
Computer use$_{(T1)}$ → Hedonic well-being$_{(T2)}$	.078**	.018	.050*	.021	.049*	.021
Computer use$_{(T1)}$ → Eudaimonic well-being$_{(T2)}$	.081**	.015	.048**	.017	.043*	.017
Computer use$_{(T1)}$ → Core self-evaluations$_{(T2)}$	.076**	.015	.031†	.017	.031†	.018
Computer use$_{(T1)}$ → Social relationships$_{(T2)}$	.069**	.020	.056*	.022	.058*	.022
Computer use$_{(T1)}$ → Subjective health$_{(T2)}$	.086**	.017	.053**	.019	.058**	.019
Computer use$_{(T1)}$ → Objective health$_{(T2)}$	.035	.026	.027	.025	.020	.026
Computer use$_{(T1)}$ → Physical exercise$_{(T2)}$	.099**	.021	.016	.022	.012	.023
Computer use as consequence						
Hedonic well-being$_{(T1)}$ → Computer use$_{(T2)}$	-.017	.018	.061**	.022	.062**	.022
Eudaimonic well-being$_{(T1)}$ → Computer use$_{(T2)}$	.008	.015	.052**	.017	.052**	.017
Core self-evaluations$_{(T1)}$ → Computer use$_{(T2)}$	.014	.016	.069**	.018	.069**	.018
Social relationships$_{(T1)}$ → Computer use$_{(T2)}$	.011	.017	.038*	.018	.038*	.019
Subjective health$_{(T1)}$ → Computer use$_{(T2)}$	.101**	.016	.094**	.016	.095**	.017
Objective health$_{(T1)}$ → Computer use$_{(T2)}$	-.112**	.030	-.063*	.025	-.066*	.026
Physical exercise$_{(T1)}$ → Computer use$_{(T2)}$	.111**	.016	.077**	.016	.077**	.016

Note. Model 2 controlled for age, sex, education, household income, and subjective social status. Model 3 additionally controlled for frequency of reading, playing word and card games, attending lectures and courses, and writing. †$p < .10$ * $p < .05$, **$p < .01$.

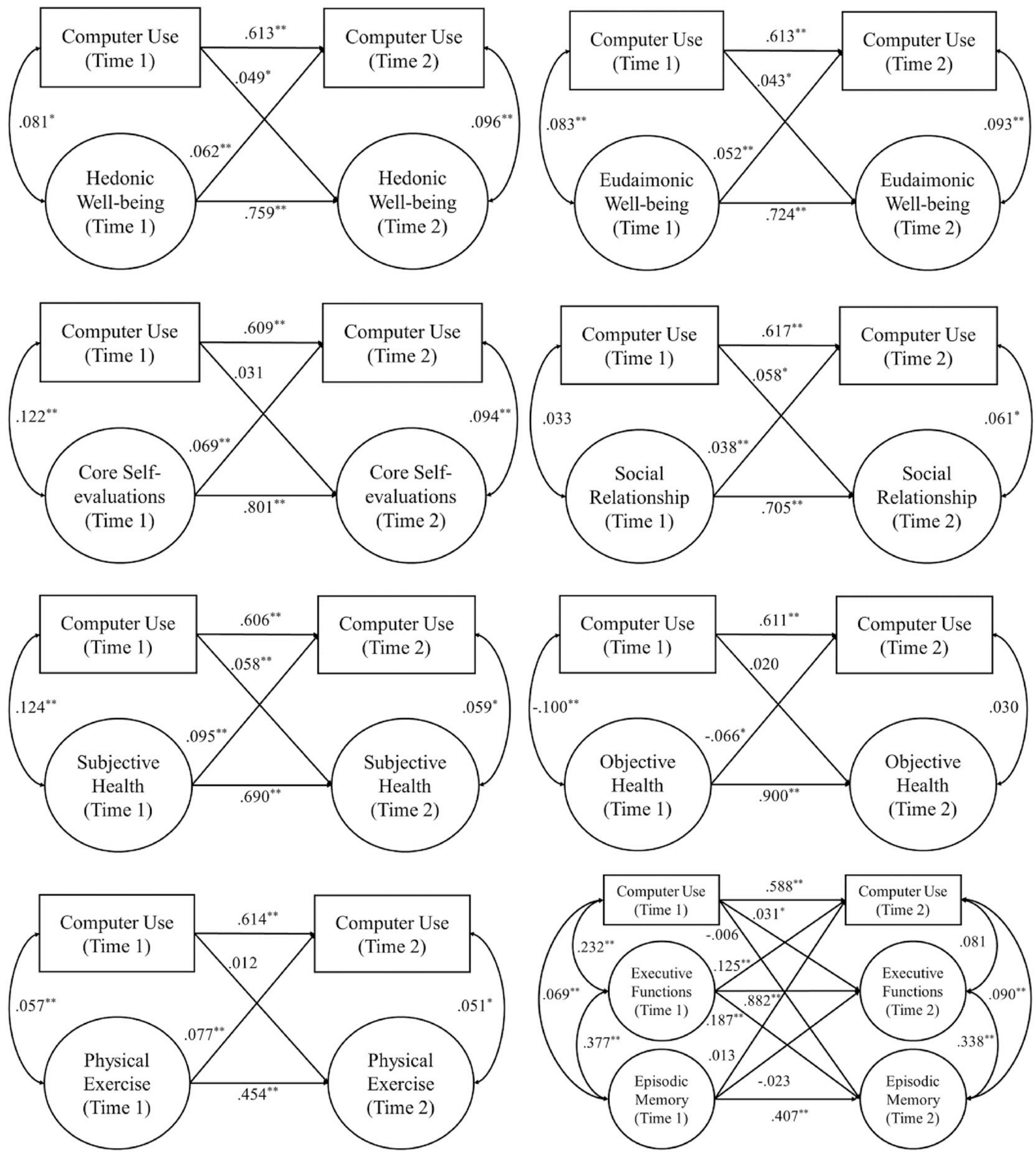

Fig. 1. Cross-lagged panel models in Studies 1 and 2 after controlling for age, sex, education, household income, subjective social status, and frequency of reading, playing word and card games, attending lectures and courses, and writing. The factor indicators and autocorrelations among indicator residuals are not displayed to sustain graphical clarity. The analyses were conducted while holding the optimal equality constraints (full or partial scalar invariance). The numbers represent standardized coefficient estimates. *p < .05 **p < .01.

assessment, sex, household income, education attainment, and subjective social status. In the third model, we controlled for frequency of reading, frequency of playing word games, frequency of playing cards and other games, frequency of attending lectures and courses, and frequency of writing in all analyses to ensure that the estimates were not confounded by daily activities other than computer use. These confounding variables were accounted for by controlling for their effects on computer use and our outcome criterions at Time 1 and Time 2.

5. Results

5.1. Study 1

Prior to estimating the structural model for the longitudinal associations between computer use and our domain criterions, we tested for longitudinal measurement invariance. The factors were specified to have nondirectional covariance relationships and all the autocorrelations among measurement residuals across time were estimated. The measurement invariance results for all our domain criterion variables are presented in Table 2 (see supplementary materials for the factor loadings of all our measurement models). Results indicated that the configural, metric, and scalar invariance models fit the data well (RMSEAs < 0.08, CFIs > 0.90., TLIs > 0.90, and SRMRs < 0.08). More importantly, our model comparisons demonstrated scalar invariance over time for hedonic well-being, eudaimonic well-being, social relationships, and physical exercise (ΔCFIs < 0.01). However, our model did not achieve scalar invariance for subjective health (ΔCFI $= 0.014$). Hence, we specified a test of partial scalar invariance on the basis of metric invariance (Byrne, Shavelson, & Muthén, 1989) by relaxing the intercept of one indicator and comparing ΔCFI one at a time until all indicators have been tested. From this test, we found that a modified model with relaxed constraints on the intercepts of functional disabilities fitted the data well, thus indicating partial scalar invariance for subjective health (ΔCFI $= 0.005$).

Table 4
Standardized cross-lagged path coefficients of frequency of computer use in predicting changes for each indicator of socioemotional and health outcomes.

Domains	Model 1		Model 2		Model 3	
	Estimate	SE	Estimate	SE	Estimate	SE
Hedonic well-being						
Computer use$_{(T1)}$ → Life satisfaction$_{(T2)}$	.062**	.016	.040*	.018	.041*	.019
Computer use$_{(T1)}$ → Positive affect$_{(T2)}$	.055**	.016	.045*	.019	.039*	.020
Computer use$_{(T1)}$ → Negative affect$_{(T2)}$	-.057**	.018	-.055**	.020	-.056**	.021
Eudaimonic well-being						
Computer use$_{(T1)}$ → Autonomy$_{(T2)}$	.055**	.015	.052**	.017	.050**	.018
Computer use$_{(T1)}$ → Environmental mastery$_{(T2)}$	.093**	.016	.073**	.016	.071**	.019
Computer use$_{(T1)}$ → Personal growth$_{(T2)}$	.123**	.016	.068**	.018	.057**	.018
Computer use$_{(T1)}$ → Positive relations$_{(T2)}$	.070**	.015	.063**	.017	.061**	.018
Computer use$_{(T1)}$ → Purpose in life$_{(T2)}$	.102**	.016	.054**	.017	.042*	.018
Computer use$_{(T1)}$ → Self-acceptance$_{(T2)}$	.032*	.014	.014	.016	.007	.017
Core self-evaluations						
Computer use$_{(T1)}$ → Self-esteem$_{(T2)}$	.072**	.016	.045*	.018	.041*	.018
Computer use$_{(T1)}$ → Sense of control$_{(T2)}$	.116**	.016	.052**	.018	.050**	.018
Computer use$_{(T1)}$ → Optimism$_{(T2)}$	.053**	.015	.036*	.017	.037*	.017
Computer use$_{(T1)}$ → Neuroticism$_{(T2)}$	-.042**	.015	-.029	.017	-.021	.018
Social relationships						
Computer use$_{(T1)}$ → Family support$_{(T2)}$	.054**	.017	.065**	.020	.065**	.020
Computer use$_{(T1)}$ → Friend support$_{(T2)}$	.010	.020	.016	.019	.010	.020
Computer use$_{(T1)}$ → Contact with friends$_{(T2)}$	.091**	.019	.082**	.021	.073**	.021
Computer use$_{(T1)}$ → Having more close friends$_{(T2)}$	.073**	.018	.059**	.020	.056**	.020
Subjective health						
Computer Use$_{(T1)}$ → Self-rated physical health$_{(T2)}$	.111**	.016	.069**	.018	.075**	.018
Computer Use$_{(T1)}$ → Self-rated mental health$_{(T2)}$	.124**	.016	.087**	.019	.089**	.019
Computer Use$_{(T1)}$ → Self-rated functional disabilities$_{(T2)}$	-.117**	.016	-.038*	.017	-.041*	.017
Objective health						
Computer use$_{(T1)}$ → Body mass index$_{(T2)}$	.028*	.011	.003	.012	-.002	.012
Computer use$_{(T1)}$ → Number of chronic diseases$_{(T2)}$	-.043*	.017	.001	.019	-.004	.020
Physical activities						
Computer use$_{(T1)}$ → Vigorous physical activities$_{(T2)}$	.086**	.019	.006	.020	.001	.021
Computer use$_{(T1)}$ → Moderate physical activities$_{(T2)}$	.126**	.019	.027	.021	.020	.022
Computer use$_{(T1)}$ → Light physical activities$_{(T2)}$	.157**	.021	.073**	.023	.057*	.024

Table 3 shows the results of our cross-lagged panel models after converting all lagged relationships into directional predictive paths while holding the optimal equality constraints. All autoregressive paths were statistically significant ($ps < .001$). In our unadjusted models (Model 1), we found that computer use significantly predicted positive changes across all criterion variables ($ps < .01$) except for objective health ($p = .173$). After controlling for demographics, education, income, and subjective social status (Model 2), computer use remained a significant predictor of positive changes in hedonic well-being, eudaimonic well-being, social relationships, and subjective health ($ps < .05$). The results remained robust even after controlling for 5 different types of cognitively stimulating activities, suggesting that these positive changes are uniquely associated with computer use (Model 3; see Fig. 1).[1] Computer use was not linked to any decline in objective health or physical exercise. Following up on our findings, we conducted separate cross-lagged panel models for each factor's sub-indicators (Table 4). In summary, we found that computer use was a significant predictor of positive changes in life satisfaction, positive affect, autonomy, environmental mastery, personal growth, positive relations, purpose in life, self-esteem, sense of control, optimism, and self-rated physical and mental health. Computer use also significantly predicted a decrease in negative affect and functional disabilities. We did not observe any relations between computer use and changes in self-acceptance, neuroticism, BMI, number of chronic diseases, and physical activit ies.

Socioemotional and health factors were also found to predict changes in computer use. As shown in Tables 3 and 5, after controlling for covariates (Models 2 and 3), hedonic well-being, eudaimonic well-being, core self-evaluations, social relationships, subjective health, and physical exercise were positively associated with more computer use over time. In contrast, lower objective health was associated with higher computer use over time.

5.2. Study 2

We also tested for longitudinal measurement invariance of the BTACT. As shown in Table 2 and consistent with past research (Lachman & Tun, 2008), the two-factor model (executive functions and episodic memory) fitted the data well. However, the changes in CFI for the BTACT only suggests metric (ΔCFIs = 0.000) but not scalar invariance (ΔCFIs = 0.028). Hence, we tested for partial scalar invariance on the basis of metric invariance (Byrne et al., 1989). We relaxed the constraints on the intercepts of the performance in SGST as the items had the least residual variance. The modified model fitted the data well, thus indicating partial scalar invariance for the BTACT (ΔCFI = 0.001).

Similar to Study 1, we conducted cross-lagged panel models while holding the optimal equality constraints. As shown in Table 6, computer use remained a significant predictor of positive changes in executive functions after controlling for covariates. When each cognitive task was analyzed individually, we found that computer use consistently predicted increased positive changes in performance for all executive function tasks, including the backward digit span, categorical fluency, number series, backward counting, and SGST ($ps < .001$). However, computer use was not a significant predictor of changes in episodic memory, especially when we controlled for cognitively stimulating

[1] We also conducted an additional analysis with a single comprehensive model of multiple latent domain outcomes, including hedonic well-being, eudaimonic well-being, social relationships, subjective health, and physical exercise. Consistently, we observed significant cross-lagged paths of computer use at Time 1 on all the latent domain outcomes at Time 2 (hedonic well-being, eudaimonic well-being, social relationships, subjective health; $ps < .05$), except for physical exercise (see supplementary materials for more details).

Table 5
Standardized cross-lagged path coefficients of socioemotional and health outcomes in predicting changes for each indicator of socioemotional and health outcomes.

Domains	Model 1		Model 2		Model 3	
	Estimate	SE	Estimate	SE	Estimate	SE
Hedonic well-being						
Life satisfaction$_{(T1)}$ → Computer use$_{(T2)}$	-.017	.016	.029	.017	.030	.017
Positive affect$_{(T1)}$ → Computer use$_{(T2)}$	-.007	.014	.039**	.015	.039**	.015
Negative affect$_{(T1)}$ → Computer use$_{(T2)}$	.010	.016	-.039*	.016	-.040*	.016
Eudaimonic well-being						
Autonomy$_{(T1)}$ → Computer use$_{(T2)}$	-.030*	.014	-.003	.014	-.004	.014
Environmental mastery$_{(T1)}$ → Computer use$_{(T2)}$	-.017	.014	.033*	.014	.033*	.015
Personal growth$_{(T1)}$ → Computer use$_{(T2)}$	.050**	.015	.064**	.015	.064**	.015
Positive relations$_{(T1)}$ → Computer use$_{(T2)}$	-.007	.014	.031*	.015	.031*	.015
Purpose in life$_{(T1)}$ → Computer use$_{(T2)}$	.032*	.014	.044**	.015	.044**	.015
Self-acceptance$_{(T1)}$ → Computer use$_{(T2)}$	.002	.015	.040*	.016	.040*	.016
Core self-evaluations						
Self-esteem$_{(T1)}$ → Computer use$_{(T2)}$	.005	.015	.053**	.015	.053**	.015
Sense of control$_{(T1)}$ → Computer use$_{(T2)}$	.021	.014	.038**	.015	.038**	.015
Optimism$_{(T1)}$ → Computer use$_{(T2)}$	.018	.015	.054**	.015	.053**	.015
Neuroticism$_{(T1)}$ → Computer use$_{(T2)}$	.009	.014	-.035*	.015	-.035*	.015
Social relationships						
Family support$_{(T1)}$ → Computer use$_{(T2)}$	-.009	.015	.017	.014	.017	.015
Friend support$_{(T1)}$ → Computer use$_{(T2)}$	.030*	.014	.030*	.014	.030*	.014
Contact with friends$_{(T1)}$ → Computer use$_{(T2)}$	.005	.015	.017	.014	.017	.014
Having more close friends$_{(T1)}$ → Computer use$_{(T2)}$	-.009	.015	.014	.014	.013	.014
Subjective health						
Self-rated physical health$_{(T1)}$ → Computer use$_{(T2)}$	.089**	.014	.076**	.014	.077**	.014
Self-rated mental health$_{(T1)}$ → Computer use$_{(T2)}$	.049**	.014	.059**	.014	.060**	.014
Self-rated functional disabilities$_{(T1)}$ → Computer use$_{(T2)}$	-.107**	.016	-.057**	.016	-.057**	.016
Objective healthrowhead						
Body mass index$_{(T1)}$ → Computer use$_{(T2)}$	-.013	.015	-.010	.014	-.010	.014
Number of Chronic diseases$_{(T1)}$ → Computer use$_{(T2)}$	-.074**	.016	-.042**	.016	-.043**	.016
Physical activities						
Vigorous activities$_{(T1)}$ → Computer use$_{(T2)}$	.107**	.014	.056**	.014	.054**	.014
Moderate activities$_{(T1)}$ → Computer use$_{(T2)}$	.103**	.015	.068**	.014	.067**	.015
Light activities$_{(T1)}$ → Computer use$_{(T2)}$	.051**	.014	.036*	.014	.036*	.014

Note. Model 2 controlled for age, sex, education, household income, and subjective social status. Model 3 additionally controlled for frequency of reading, playing word and card games, attending lectures and courses, and writing. Across all predictors and criterion variables, higher scores indicate a higher level of the construct. *$p < .05$, **$p < .01$.

activities in our models. Furthermore, our cross-lagged panel models also revealed that executive functions, but not episodic memory, significantly predicted positive changes in computer use over 9 years.

6. Discussion

Based on a 9-year longitudinal analysis, we found reciprocal relations between computer use frequency and a multitude of positive outcomes, including executive functions, social relationships, well-

Table 6
Standardized cross-lagged path coefficients of computer use and the latent variables of cognitive outcomes in Study 2.

	Model 1		Model 2		Model 3	
	Estimate	SE	Estimate	SE	Estimate	SE
Cross-lagged paths for the latent variables of executive functions and episodic memory						
Computer use$_{(T1)}$ → Executive functions$_{(T2)}$	.046**	.016	.028†	.015	.031*	.016
Computer use$_{(T1)}$ → Episodic memory$_{(T2)}$	.039	.021	.000	.020	-.006	.021
Executive functions$_{(T1)}$ → Computer use$_{(T2)}$	.193**	.023	.115**	.029	.125**	.030
Episodic memory$_{(T1)}$ → Computer use$_{(T2)}$	.031	.018	.015	.020	.013	.020
Cross-lagged paths for the individual indicators of executive functions						
Computer use$_{(T1)}$ → Backward digit span$_{(T2)}$	.144**	.018	.073**	.020	.060**	.020
Computer use$_{(T1)}$→ Categorical fluency$_{(T2)}$	.131**	.016	.056**	.018	.049**	.019
Computer use$_{(T1)}$ → Number series$_{(T2)}$	.156**	.016	.067**	.017	.063**	.017
Computer use$_{(T1)}$→ Backward counting$_{(T2)}$	.083**	.012	.050**	.013	.052**	.013
Computer use$_{(T1)}$ → SGST$_{(T2)}$	.108**	.020	.073**	.022	.074**	.023
Backward digit span$_{(T1)}$ → Computer use$_{(T2)}$	.070**	.015	.044**	.015	.043**	.015
Categorical fluency$_{(T1)}$ → Computer use$_{(T2)}$	.097**	.015	.040*	.016	.040*	.016
Number series$_{(T1)}$ → Computer use$_{(T2)}$	.115**	.015	.066**	.016	.068**	.016
Backward counting$_{(T1)}$ → Computer use$_{(T2)}$	.127**	.016	.046**	.017	.048**	.017
SGST$_{(T1)}$ → Computer use$_{(T2)}$	.094**	.018	.042*	.017	.043*	.018
Cross-lagged paths for the individual indicators of episodic memory						
Computer use$_{(T1)}$ → Immediate word list recall$_{(T2)}$	.139**	.018	.044*	.019	.030	.019
Computer use$_{(T1)}$ → Delayed word list recall$_{(T2)}$	.110**	.018	.036†	.020	.028	.020
Immediate word list recall$_{(T1)}$ → Computer use$_{(T2)}$	.092**	.015	.048**	.015	.048**	.016
Delayed word list recall$_{(T1)}$ → Computer Uue$_{(T2)}$	.089**	.015	.039*	.015	.039*	.016

Note. Model 2 controlled for age, sex, education, household income, and subjective social status. Model 3 additionally controlled for frequency of reading, playing word and card games, attending lectures and courses, and writing. †$p < .10$ * $p < .05$, **$p < .01$.

being, and physical and mental health, that are crucial for optimal functioning in older adults. In the domain of cognitive abilities, computer use frequency prospectively predicted executive functioning but not episodic memory. Hence, through the activation of learning, memory, and psychomotor processes, computer use may serve as a form of mental stimulation that can train and maintain cognitive abilities, such as executive functions. In contrast, the null findings for episodic memory may be due to the resistance of autobiographic memory to the effects of cognitive training (Melby-Lervåg & Hulme, 2013). Our findings are consistent with previous propositions that computer use may attenuate age-related cognitive declines (Gatto & Tak, 2008; Wagner et al., 2010). Therefore, given that executive functions are especially crucial in day-to-day operations during older adulthood (Vaughan & Giovanello, 2010), computer use may be a means to preserve healthy functioning with advancing age.

Beyond cognitive abilities, we also found that computer use has salubrious effects on other domains of life. With respect to relational well-being, computers may facilitate social connectedness through communication outlets such as social media and other messaging platforms, which help to alleviate the social isolation, withdrawal, and loss of social support that accompany old age (Morrell et al., 2000; Zhang, Greenhart, McLaughlin, & Allaire, 2017). In particular, our results suggest that computer use can help to maintain support from family, contact with friends, and having more close friends. As social activities with close others are especially important for well-being during later adulthood (Djundeva, Dykstra, & Fokkema, 2018; Pinquart & Sörensen, 2000), computer use could be a feasible way to improve and maintain social engagement. We also found that computer use positively predicted autonomy, environmental mastery, personal growth, positive relations, and purpose in life. Moreover, frequent computer use is related to improvements on some aspects of core self-evaluations, such as self-esteem, sense of control, and optimism, but not reduced neuroticism. Collectively, social relationships, eudaimonic well-being, sense of control, self-esteem, and optimism likely augment hedonic well-being (Ferguson & Goodwin, 2010). Indeed, we found higher computer use frequency to be associated with greater life satisfaction, higher positive affect, and lower negative affect.

In the domain of health, our results reveal that computer use was not related to engagement in physical activities, obesity, or chronic health problems, thereby indicating that computer use is not detrimental to physical or mental health. This finding challenges previous research suggesting that computer use, as a form of sedentary activity, contributes to health and mental problems (e.g., Fotheringham et al., 2000). Instead, we found higher frequency of computer use to be associated with better self-reported physical and mental health. This may be because individuals who use computers more often have elevated levels of well-being and psychological resources which, in turn, is concomitant with greater self-reported physical and mental health. Indeed, past research has demonstrated that people with higher levels of happiness and sense of control tend to report better physical health, possibly through higher frequency of healthy behaviors (e.g., regular exercise) and enhanced cardiovascular and immune functioning (Diener, Pressman, Hunter, & Delgadillo-Chase, 2017; Pressman, Gallagher, & Lopez, 2013; Taylor, Kemeny, Reed, Bower, & Gruenewald, 2000). In essence, the positive effects of computer use on participants' cognitive functioning and socioemotional well-being did not come at a cost to their physical or mental health.

Interestingly, we also found that various life domains such as executive functions, hedonic well-being, eudaimonic well-being, core self-evaluations, social relations, and self-reported physical and mental health prospectively predict computer use. For instance, higher levels of executive functioning likely promote the ability to acquire and augment existing computer literacy. Further, hedonic well-being, eudaimonic well-being, and positive core self-evaluations may lead to higher frequency of computer use through enhanced motivation to expand one's intellectual repertoire (Fredrickson, 2001), which can include computer proficiency. In terms of social relations, individuals with higher social well-being may use social media and messaging applications on computers more frequently to maintain social connectedness. In the domain of health, greater self-reported and objective physical and mental health as well as physical activities likely engender better well-being and overall quality of life (Pressman et al., 2013; Taylor et al., 2000; Wiese, Kuykendall, & Tay, 2017) which, in turn, facilitate computer skill acquisition and competence. Importantly, the current study is the first to demonstrate that the reciprocal relations between computer use and our outcomes of interest allude to a positive feedback loop whereby increased computer use affects multiple life domains which, in turn, increase future computer use frequency.

Our study is not without limitations. Although cross-lagged panel models offer some advantages over cross-sectional models, our ability to make causal inferences remains limited as longitudinal studies do not entirely rule out potential third factors. Future research with experimental designs is necessary to allow for more conclusive inferences about causal mechanisms. In addition, given that the MIDUS dataset indexed general computer use, it remains unknown how specific uses of computer programs and applications affect cognitive abilities, well-being, and health. For example, frequency of social media use may be more strongly associated with social relations and emotional well-being (Hartanto & Yang, 2016; Orben & Przybylski, 2019; Szabo et al., 2018), whereas playing video games may be more closely related to higher-order cognitive abilities such as executive functions (Waris et al., 2019). Moreover, our measure of computer use is limited due to the use of single-item measure (Nunnally & Bernstein, 1994). However, it is noteworthy that the single-item computer use had a relatively high test-retest reliability across an interval of approximately 9 years ($r = 0.727$). Lastly, as the MIDUS dataset was based on predominantly American participants in middle and late adulthood, our findings may have limited generalizability. Therefore, future research should seek to replicate and validate our findings with samples from other age cohorts and cultures.

Nevertheless, our study bears several notable strengths. First, unlike past studies that have relied on cross-sectional designs, the longitudinal analysis employed here affords a better understanding of the effects of computer use on crucial outcome variables as well as the feedback effects of various life domains on computer use. Second, we were able to rule out a variety of potential confounds (including income and general activity levels), thereby increasing our confidence in the validity of our stated relationships. Third, relative to previous research, the larger and more representative sample used in the current study grants higher precision and reliability in the estimation of effect sizes (Button et al., 2013). Fourth, by examining multiple outcomes, our findings offer a comprehensive and holistic understanding of how computer use impacts cognitive, well-being, and health domains. In summary, our robust findings highlight frequent computer use as a protective factor against cognitive decline and attest to the efficacy of computers in promoting healthy functioning during midlife and old age.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2019.106179.

Note. Model 2 controlled for age, sex, education, household income, and subjective social status. Model 3 additionally controlled for frequency of reading, playing word and card games, attending lectures and courses, and writing. Across all predictors and criterion variables, higher scores indicate a higher level of the construct. *p < .05, **p < .01.

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