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Association between electronic device use and health status among a middle-aged and elderly population: a cross-sectional analysis in the UK Biobank

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Abstract

Aim Few previous studies have investigated the impact of multiple types of electronic devices on health status, and the moderating effects of gender, age, and BMI. Our aim is to examine the relationships between the use of four types of electronics and three health status indicators in a middle-aged and elderly population, and how these relationships varied by gender, age, and BMI.

Subject and methods Using data from 376,806 participants aged 40–69 years in the UK Biobank, we conducted a multivariate linear regression to estimate the association between electronic device use and health status. Electronics use was categorized as TV watching, computer use, computer gaming, and mobile phone use, and health status included self-rated health (SRH), multisite chronic pain (MCP), and total physical activity (TPA). Interaction terms were utilized to assess whether the above associations were modified by BMI, gender, and age. Further stratified analysis was performed to explore the role of gender, age, and BMI.

Results Higher levels of TV watching ($B_{SRH} = 0.056$, $B_{MCP} = 0.044$, $B_{TPA} = -1.795$), computer use ($B_{SRH} = 0.007$, $B_{TPA} = -3.469$), and computer gaming ($B_{SRH} = 0.055$, $B_{MCP} = 0.058$, $B_{TPA} = -6.076$) were consistently associated with poorer health status (all $P < 0.05$). Contrastingly, earlier exposure to mobile phones ($B_{SRH} = -0.048$, $B_{TPA} = 0.933$, $B_{MCP} = 0.056$) was inconsistent with health (all $P < 0.05$). Additionally, BMI ($B_{computer\ use-SRH} = 0.0026$, $B_{phone-SRH} = 0.0049$, $B_{TV-MCP} = 0.0031$, and $B_{TV-TPA} = -0.0584$) exacerbated the negative effects of electronics use, and male ($B_{phone-SRH} = -0.0414$, $B_{phone-MCP} = -0.0537$, $B_{phone-TPA} = 2.8873$) were healthier with earlier exposure to mobile phones (all $P < 0.05$).

Conclusion Our findings suggest that the adverse health effects associated with watching TV, computer use, and computer gaming were consistent and were moderated by BMI, gender, and age, which advances a comprehensive understanding of the association between multiple types of electronic devices and health status, and provides new perspectives for future research.

Keywords Electronic device use · Self-rated health · Multisite chronic pain · Total physical activity · Gender · BMI

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Introduction

As technology advances rapidly, electronic devices are becoming more widely used by middle-aged and elderly persons (Minagawa and Saito 2014). During the COVID-19 pandemic, people relied more on electronic devices to access digital health and social welfare services (Baldassar and Wilding 2020). It has been demonstrated that health is associated with electronics use (Rosenberg et al. 2015). Smartphone apps have promising potential to improve the cognitive abilities of older adults (Klimova and Valis 2017), especially in improving their working memory and reasoning skills, which will greatly facilitate activities of daily life

and contribute to overall longevity (Klimova 2016). Despite these benefits, the health risks posed by electronic devices should not be ignored. Several studies have found that time spent watching TV is associated with cardiometabolic biomarkers, poor cognitive performance, and all-cause mortality (Wilmot et al. 2012; Nang et al. 2013). It is thus particularly important and timely to better understand electronic device use and its relationship to health status in middle-aged and elderly persons, who tend to spend more time on electronics and have more leisure time after retirement (Harvey et al. 2015).

The frequency (Patterson et al. 2018), posture, accompanying behaviors (Cameron et al. 2016), and content interactivity (Andrade-Gomez et al. 2017) with respect to the use of different types of electronics have been shown to be associated with different health risks, but few studies have considered the impact of multiple types of electronic devices on health status. In addition, many studies have used only one type of indicator to measure health, such as physical activity, which may be problematic, as studies using various indicators of physical and mental health and functioning have shown different associations with electronics use (Cao et al. 2022). Therefore, this study incorporated a more comprehensive set of electronic device use, including TV watching, computer use, computer gaming, and mobile phone use, and selected the following three health status indicators that are closely related to the quality of life of older adults.

Self-rated health (SRH) is a globally recognized, easy-to-administer measure of health that captures multiple dimensions of health, including past health experiences and future health expectations (Simon et al. 2005). It is widely used in geriatrics because its responses appear to predict mortality, functional decline, health service utilization, and psychological health outcomes (Craigs et al. 2014). Multisite chronic pain (MCP) is prevalent and is associated with a higher risk of falls, which are one of the top 10 causes of death in older adults and are responsible for more than $19 billion in annual healthcare costs in the United States (Gorina et al. 2005; Leveille et al. 2009). Current evidence suggests that MCP is linked to poorer cognition (Weiner et al. 2006), and increased computer time was found to be associated with better cognitive performance in a longitudinal study of 2597 French older adults (Kesse-Guyot et al. 2012). However, no previous study has explored the impact of electronics use on MCP. The health benefits of physical activity are well documented, including reduced risk of cardiovascular disease, hypertension, and diabetes, and improved physiology in older adults with frailty or sarcopenia (Shiue 2015; Guthold et al. 2018). Hence, total physical activity (TPA) is used to assess the level of physical activity, which has been identified as a biomarker of life expectancy after retirement (Godfrey et al. 2014). The association between electronics use and physical activity has shown mixed results, with TV watching decreasing physical activity and computer use increasing physical activity (Kikuchi et al. 2014). However, there is limited research on the association between mobile phone use and physical activity in middle-aged and elderly persons.

Moreover, only a minority of studies have shown that the association between electronics use and health status varies by gender, age, and body mass index (BMI). Screen time was associated with obesity and with depressive symptoms in obese individuals (Goldfield et al. 2016), suggesting a possible effect of BMI. Some studies have shown age differences in electronics use (Rhodes et al. 2012) and sedentary rates (Hamrik et al. 2014). However, there are few studies on the moderating effects of gender, age, and BMI on the relationship between electronics use and health. This study fills the research gap in this direction.

Our investigation aimed to study the relationships between different types of electronics use (TV watching, computer use, computer gaming, mobile phone use) and different health status indicators (SRH, MCP, TPA) and how these relationships vary by gender, age, and BMI.

Methods

Population and study design

The UK Biobank is one of the most detailed, long-term prospective health research studies in the world. It is a large-scale biomedical database and research resource, including in-depth genetic and health information from half a million UK participants aged 40–69 in 2006 and 2010. Details of these procedures have been published previously (Sudlow et al. 2015). All participants provided detailed self-reported information on demographics, lifestyle, and health factors, alongside physical measurements.

The current study used baseline data from 376,806 participants. We excluded participants who had self-reported gender or genetic gender inconsistencies, and those who withdrew their consent. We also excluded genetically related individuals to obtain relatively independent single-nucleotide polymorphisms (SNPs) using King software. Furthermore, these individuals were restricted to "white British" based on self-reported ethnicity (UK Biobank Data-Field: 21000).

Health indicators

SRH (UK Biobank Data-Field 2178) was evaluated by a single question, "In general, how would you rate your overall health?", with possible answers "Excellent," "Good," "Fair," "Poor," "Do not know," and "Prefer not to answer". "Do not know" or "Prefer not to answer" was set to "missing" in

our analyses and excluded. A higher SRH score indicates a poorer health rating. This simple global question provides a useful and powerful summary of how individuals perceive their health status.

MCP is a derived chronic pain phenotype. Participants were asked via a touchscreen questionnaire about "pain types experienced in the last month" (UK Biobank Data-Field 6159), with the following possible answers: "None of the above"; "Prefer not to answer"; pain in seven different body sites (head, face, neck/shoulder, back, stomach/abdomen, hip, knee); or "all over the body." Participants who reported having pain were then asked (category ID 100048) whether this pain had lasted for 3 months or longer (defined as chronic pain). MCP was defined as the sum of body sites of chronic pain, recorded on a scale from 0 to 7. A higher MCP score indicates poorer health status.

TPA was assessed using questions adapted from the validated International Physical Activity Questionnaire (IPAQ) short form (Craig et al. 2003), covering frequency, intensity, and duration of three different levels of activity (walking, moderate, and vigorous). Weekly physical activity levels were measured by the Axivity AX3 wrist-worn triaxial accelerometer, where participants were instructed to wear the monitor on their right hip during all waking hours for seven consecutive days (Doherty et al. 2017). Metabolic equivalents (METs) were used to quantify the physical activity by weighting time with different energy expenditure. MET min/week of physical activity was referred to as "total physical activity." Poorer METs mean lower intensity of physical activity.

Electronic device use

Four indicators of electronic device use were included as predictor variables in our study, including TV watching, computer use, computer gaming, and mobile phone use. TV watching was assessed by the question "In a typical day, how many hours do you spend watching TV?" Computer use was measured by asking "In a typical day, how many hours do you spend using the computer?" Computer gaming frequency was evaluated through the question "Do you play computer games?" Responses were categorized as Never/rarely, Sometimes, Often, or Prefer not to answer. For our analysis, we retained only the Never/rarely and Often categories, and excluded other responses. Mobile phone use was assessed by asking "For approximately how many years have you been using a mobile phone at least once per week to make or receive calls?" Responses were originally classified into seven categories, including Never used mobile phone at least once per week, One year or less, Two to four years, Five to eight years, More than eight years, Do not know, and Prefer not to answer. For our analysis, we categorized the Never used mobile phone at least once per week as Never/

rarely, and merged Two to four years, Five to eight years, and More than eight years into the More than two years category. Other responses were excluded from the analysis.

Covariates

Other relevant covariates, including sociodemographic (age, gender, education attainment), socioeconomic status (Townsend Deprivation Index [TDI]) and lifestyle (smoking consumption, alcohol consumption, BMI), were also extracted. The frequency of cigarette smoking and alcohol drinking for each individual was defined by their self-reported amount of smoking and drinking, respectively. We used the reported maximum number of cigarettes (or pipes/cigars) consumed per day in the past or present. Similarly, we added up the average weekly consumption of different types of alcohol by participants. People who reported drinking less than once a week were asked about the average monthly amount of different types of alcohol. For these subjects, we added up their monthly alcohol consumption and divided by 4 to get their weekly consumption. BMI was calculated from weight (kg)/height(m)^2, based on actual weight and height. Measurements were taken at the assessment center. Education attainment was defined from the question, "Which of the following qualifications do you have? (You can select more than one)," under which eight options were provided. TDI was used as a measure of socioeconomic status, derived from the postal code of residence information on unemployment, car availability, owner occupation, and overcrowding. Higher values indicate greater deprivation.

Ethical approval

The UK Biobank has approval from the North West Multicentre Research Ethics Committee (MREC) as a Research Tissue Bank (RTB) approval. It also possesses a Human Tissue Authority (HTA) license. All participants gave broad consent to the use of their anonymized data and samples for any health-related research and further sub-studies.

Statistical analysis between electronic device use and health status

Multivariable linear regression models were used to estimate the association between electronic device use and health status. The instrumental variables were electronic device use including TV watching, computer use, computer gaming, and mobile phone use, and the outcome variables were health status including SRH, MCP, and TPA. We draw a directed acyclic graph utilizing the DAGitty program (www.dagitty.net) to identify possible confounders to build bias-minimized models (Supplementary Fig. S1). Additionally, three interaction terms were added to the model to assess

whether any associations between electronic device use and health status were modified by gender, age, and BMI. The same confounders included in the main models were adjusted for in the interaction model. Three models were constructed: (1) adjustment for age, gender, and the first 10 principal components of population structure; (2) model 1 plus adjustment for educational attainment, TDI, BMI, and the frequency of cigarette smoking and alcohol drinking; (3) model 2 plus adjustment for three interaction items of electronics use with age, gender, and BMI, respectively. The variance inflation factors (VIF) for each independent variable in models 1 and 2 were calculated to determine the degree of multicollinearity. The stratified analysis was performed to further explore the role of gender, age, and BMI. BMI was categorized into underweight < 18.5 kg/m^2, normal weight $= 18.5$–24.9 kg/m^2, overweight $= 25.0$–29.9 kg/m^2, and obesity ≥ 30.0 kg/m^2. Age stratification was based on the current retirement age in the UK: <65 years and ≥65 years (Hofacker et al. 2016). Gender was male and female. We also analyzed the main and interaction effects of electronic device use on health using models 2 and 3 in subgroups stratified by BMI and age, respectively, and only the main effect in subgroups stratified by gender. We also calculated the mean and standard deviation (SD) for continuous measures and the percentage for categorical variables. Owing to the large sample size, Pearson's χ^2 considered any small difference in group proportions to be significant, and

therefore, these results were not reported. Results are presented as beta coefficient (B) with 95% confidence intervals (CI) and adjusted R-squared. Significance was denoted at $P < 0.05$. All data analyses were performed using R 4.0.5.

Results

Study population

The descriptive characteristics of the sample are displayed in Supplementary Table S1. Among the 376,806 participants in the UK Biobank, different amounts of data were included in the regression analysis of different electronic device use and health status (Supplementary Table S2). Among participants, 53.72% were female, with an average age of 56.99 years (SD = 7.93).

The relationship between electronics use and health status

The multicollinearity analysis of models 1 and 2 reported that the VIF of the included factors were all less than 5. As shown in Table 1, significant associations were observed between TV watching and health status (all $P < 1.0 \times 10^{-9}$), including SRH (B = 0.056, 0.055 to 0.058), MCP (B = 0.044, 0.041 to 0.047), and TPA (B = −1.795, −1.983 to

Table 1 Association between electronic device use and health status

		TV watching		Computer use		Computer gaming		Mobile phone use	
		Beta (95% CI)	Adj. R^2	Beta (95% CI)	Adj. R^2	Beta (95% CI)	Adj. R^2	Beta (95% CI)	Adj. R^2
Self-reported health	Model 1	0.101(0.099–0.103) ***	0.052	0.020 (0.015–0.025) ***	0.004	0.174 (0.161–0.187) ***	0.008	−0.015 (−0.022 to −0.009) ***	0.005
	Model 2	0.056 (0.055–0.058) ***	0.129	0.007 (0.001–0.013) *	0.096	0.055 (0.040–0.069) ***	0.116	−0.048 (−0.055 to −0.040) ***	0.118
	Model 3	0.153 (0.137–0.168) ***	0.130	−0.090 (−0.143 to −0.038) ***	0.096	0.277 (0.139–0.414) ***	0.116	−0.117 (−0.192 to −0.041) **	0.119
Multisite chronic pain	Model 1	0.080 (0.078–0.083) ***	0.019	0.020 (0.013–0.028) ***	0.007	0.179 (0.160–0.198) ***	0.006	0.094 (0.084–0.104) ***	0.006
	Model 2	0.044 (0.041–0.047) ***	0.036	0.008 (−0.001 to 0.017)	0.024	0.058 (0.036–0.081) ***	0.033	0.056 (0.044–0.067) ***	0.033
	Model 3	−0.023 (−0.046 to 0.001)	0.037	0.038 (0.004–0.115)	0.024	0.331 (0.124–0.538) **	0.033	0.044 (−0.070 to 0.158)	0.033
Total physical activity	Model 1	−1.034 (−1.179 to −0.889) ***	0.007	−3.818 (−4.246 to −3.390) ***	0.012	−8.437 (−9.663 to −7.210) ***	0.006	0.799 (0.188–1.411) *	0.006
	Model 2	−1.795 (−1.983 to −1.607) ***	0.024	−3.469 (−3.978 to −2.960) ***	0.028	−6.076 (−7.568 to −4.583) ***	0.022	0.933 (0.188–1.679) *	0.022
	Model 3	8.207 (6.618–9.795) ***	0.025	1.896 (−2.718 to 6.512)	0.029	12.562 (−1.435 to 26.560)	0.022	7.417 (−0.067 to 14.901)	0.022

Model 1 was adjusted for age, gender, and the first 10 principal components of the population structure. Model 2 was adjusted not only for the factors in model 1 but also for educational attainment, Townsend Deprivation Index, BMI, and the frequency of cigarette smoking and alcohol drinking. Model 3 was adjusted not only for the factors in model 2 but also for three interaction items of electronic device use with age, gender, and BMI, respectively. *** $P \leq 0.001$, ** $P \leq 0.01$, * $P \leq 0.05$.

−1.607). Increased computer use was associated with higher SRH (B = 0.007, 0.001 to 0.013, P = 0.023), and lower TPA (B = −3.469, −3.978 to −2.960, $P < 1.00 \times 10^{-9}$). Frequent computer gaming was linked to higher SRH (B = 0.055, 0.040 to 0.069, $P = 2.95 \times 10^{-7}$), higher MCP (B = 0.058, 0.036 to 0.081, $P < 1.00 \times 10^{-9}$), and lower TPA (B = −6.076, −7.568 to −4.583, $P < 1.00 \times 10^{-9}$). Earlier exposure to mobile phones was linked to lower SRH (B = −0.048, −0.055 to −0.040, $P = 2.95 \times 10^{-7}$), higher MCP (B = 0.056, 0.044 to 0.067, $P < 1.00 \times 10^{-9}$), and higher TPA (B = 0.933, 0.188 to 1.679, P = 0.014).

Modulating effect of gender, age, and BMI

BMI

BMI moderated the relationship between TV watching time and two health status indicators (Table 2 and Fig. 1): MCP (B = 0.0031, $P < 1.00 \times 10^{-9}$), TPA (B = −0.0584, $P = 1.7 \times 10^{-3}$); the relationship between computer use time and SRH (B = 0.0026, $P = 7.09 \times 10^{-5}$); and the relationship between mobile phone use and SRH (B = 0.0049, $P = 4.96 \times 10^{-9}$). In addition, its modulating effects on TV watching time and SRH (B = −0.0062, $P = 3.41 \times 10^{-9}$) and on

computer use time and SRH (B = −0.0434, $P = 1.75 \times 10^{-4}$) were observed in normal-weight people (Table 3).

Gender

Gender moderated the relationship between mobile phone use and all three health status indicators (Table 2 and Fig. 1): SRH (B = −0.0414, $P = 3.91 \times 10^{-8}$), MCP (B = −0.0537, $P = 2.58 \times 10^{-6}$), TPA (B = 2.8873, $P = 1.11 \times 10^{-4}$); the relationship between time watching TV and two health status indicators: SRH (B = 0.0163, $P < 1.00 \times 10^{-9}$), TPA (B = 1.1106, $P = 4.82 \times 10^{-10}$); the relationship between computer gaming and two health status indicators: SRH (B = 0.0375, $P = 1.43 \times 10^{-2}$), MCP (B = −0.0825, $P = 3.52 \times 10^{-4}$); and the relationship between computer use time and TPA (B = −1.6741, $P = 1.46 \times 10^{-3}$). There was no statistical association between computer use and MCP in the total population, but it was found in the female population (Table 4).

Age

Age moderated the relationship between computer gaming and all three health status indicators (Table 2 and Fig. 1): SRH (B = −0.0054, $P = 4.15 \times 10^{-9}$), MCP (B = −0.0037, $P = 8.32 \times 10^{-3}$), TPA (B = −0.2851, $P = 2.03 \times 10^{-3}$); the

Table 2. Main effects and interaction effects of electronic device use

		X	SEX*X	AGE*X	BMI*X
Self-reported health	TV watching	0.056 (0.055–0.058) ***	0.0163 (0.0129–0.0197) ***	−0.0017 (−0.002 to −0.0015) ***	−0.0002 (−0.0002 to −0.0002)
	Computer use	0.007 (0.001–0.013) ***	−0.0085 (−0.0203 to 0.0033)	0.0006 (−0.0001 to 0.0013)	0.0026 (0.0013–0.0038) ***
	Computer gaming	0.055 (0.040–0.069) ***	0.0375 (0.0075–0.0675) *	−0.0054 (−0.0072 to −0.0036) ***	0.0022 (−0.0006 to 0.0052)
	Mobile phone use	−0.048 (−0.055 to −0.040) ***	−0.0414 (−0.0562 to −0.0266) ***	−0.0007 (−0.0018 to 0.0004)	0.0049 (0.0033–0.0066) ***
Multisite chronic pain	TV watching	0.044 (0.041–0.047) ***	−0.0032 (−0.0084 to 0.0021)	−0.0003 (−0.0007 to 0)	0.0031 (0.0026–0.0037) ***
	Computer use	0.008 (−0.001 to 0.017)	−0.0347 (−0.052 to −0.0171) ***	−0.0003 (−0.0014 to 0.0008)	0.0003 (−0.0016 to 0.0021)
	Computer gaming	0.058 (0.036–0.081) ***	−0.0825 (−0.1277 to −0.0372) ***	−0.0037 (−0.0064 to −0.0001) ***	−0.0001 (−0.0052 to 0.0036)
	Mobile phone use	0.056 (0.044–0.067) ***	−0.0537 (−0.0761 to −0.0313) ***	0.0004 (−0.0012 to 0.0020)	0.0006 (−0.0019 to 0.0031)
Total physical activity	TV watching	−1.795 (−1.983 to −1.607) ***	1.1106 (0.7609–1.4603) ***	−0.1557 (−0.1781 to −0.1333) ***	−0.0584 (−0.0949 to −0.0219) ***
	Computer use	−3.469 (−3.978 to −2.960) ***	−1.6741 (−2.7049 to −0.6433) ***	−0.1198 (−0.1834 to −0.0562) ***	0.0779 (−0.0354 to 0.1913)
	Computer gaming	−6.076 (−7.568 to −4.583) ***	−1.2900 (−4.3200 to 1.7401)	−0.2851 (−0.4662 to −0.1041) ***	−0.0659 (−0.3702 to 0.2383)
	Mobile phone use	0.933 (0.188–1.679) *	2.8873 (1.4234–4.3512) ***	−0.1366 (−0.2418 to −0.0313) *	0.0099 (−0.1571 to 0.1769)

Data are shown as beta (95% CI). *** $P \leq 0.001$, ** $P \leq 0.01$, * $P \leq 0.05$.
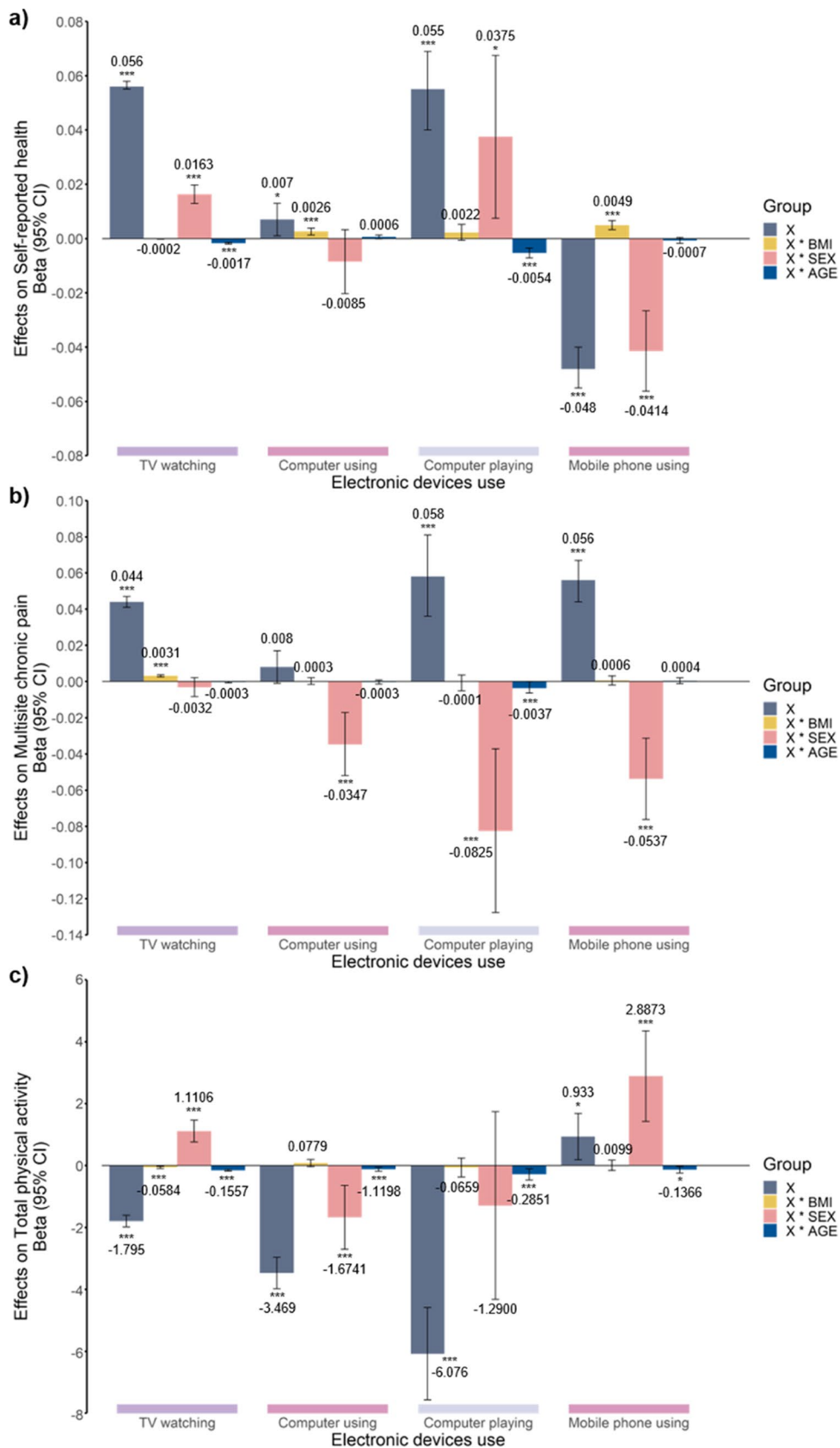
Data were shown as Beta (95% CI). *** $P \leq 0.001$, ** $P \leq 0.01$, * $P \leq 0.05$.

Fig. 1 Main effects and interaction effects of electronic device use

relationship between TV watching time and two health status indicators: SRH (B = −0.0017, $P < 1.00 \times 10^{-9}$), TPA (B = −0.1557, $P < 1.00 \times 10^{-9}$); the relationship between computer use time and TPA (B = −0.1198, $P = 2.21 \times 10^{-4}$); and the relationship between mobile phone use and TPA (B = −0.1366, $P = 1.10 \times 10^{-2}$). In addition, its moderating effect on mobile phone use and SRH (B = −0.0014, $P < 1.00 \times 10^{-9}$) was shown in people under 65 years old (Table 3). Notably, age no longer moderated any of the correlations in those over 65 years of age. More results of the subgroup analysis are presented in Supplementary Table S3–4.

Discussion

We examined the associations between the use of four types of electronics and three health status indicators in a middle-aged and elderly population, which reflects a more comprehensive relationship between the intensity of electronics use and health status. We found that more TV watching, computer use, and computer gaming were consistently associated with poorer health status, including higher SRH, lower TPA, and higher MCP. However, the health effects associated with mobile phone use were inconsistent, with lower SRH, higher TPA, and higher MCP. Furthermore, some of these associations were moderated by BMI, gender, and age.

Regarding the effects of television and computer use on lower TPA and higher SRH, these results were broadly consistent with previous studies. Television and computer time are characteristic indicators of sedentary behavior. A comprehensive analysis of a large UK-based prospective study showed a linear dose–response relationship between sedentary time and 14 noncommunicable diseases, including cardiometabolic diseases, diabetes, and depression (Cao et al. 2022). Some studies have shown that sedentariness reduces voluntary energy expenditure, inhibits skeletal muscle activation, and leads to reduced venous and arterial blood flow, all of which may contribute to impaired glucose metabolism (Bellettiere et al. 2019). Furthermore, sedentary behavior impedes direct communication between individuals, reduces social interaction (Kraut et al. 1998; Huang et al. 2020), reduces exercise practice (Gujral et al. 2017), and ultimately increases the risk of depression. In contrast to television and computer, earlier exposure to mobile phones was associated with lower SRH and higher TPA, which implies healthy outcomes. This may be because the posture of mobile phone use is more diverse and not limited to a sedentary state. Individuals who had earlier access to cell phones may have had greater access to information about health and wellness, as well as easier access to healthcare resources. A meta-analysis provided modest evidence to support the effectiveness of smartphone apps in increasing physical activity (Romeo et al. 2019). Numerous studies have shown that smartphone apps can serve as effective cognitive training and health management tools for healthy aging to promote physical and mental health (Klimova and Valis 2017; Romeo et al. 2019). Moreover, people with earlier access to cell phones may have had stronger social connections, which could have contributed to better health outcomes. However, it is important to note that the overall impact of phone use on health is still a subject of ongoing research, and no definitive answer has been reached yet.

We also found that increased use of electronics was associated with higher MCP. Some studies have identified several risk factors independently associated with MCP, including depression and poor physical performance (Thapa et al. 2019). Studies have also confirmed the links between depression and television (Huang et al. 2020), computer (Zhang et al. 2022), and mobile phone use (Zhang et al. 2022). Although there are potential linking mechanisms between them, the relationship between MCP and electronics use has not been studied. The associations between different electronics use and health outcomes are not identical, so the specific reasons for these differences remain to be explored. In short, it can be suggested that controlling the amount of time spent on television and computer can be beneficial for middle-aged and elderly adults.

Our results showed that BMI exacerbated the negative health associations of electronics use. Studies have demonstrated that higher TV and computer use are associated with higher BMI (Vandelanotte et al. 2009; Cameron et al. 2016; Celis-Morales et al. 2018). Additionally, screen time was associated with lower overall and psychosocial health-related quality of life among overweight and obese adolescents (Goldfield et al. 2015). A possible explanation is that electronics use is accompanied by poorer dietary habits, making it closely associated with overweight and obesity (Cameron et al. 2016), and ultimately with poor health outcomes. Interestingly, we found that BMI attenuated the negative effects of TV watching and computer gaming on SRH in the subgroup of normal-weight people. A study that implicitly supports our view showed that the effect of screens on energy intake differs between normal-weight and overweight participants (Marsh et al. 2014). These results imply that although controlling BMI in general can help reduce the adverse health associations of electronics use, increasing BMI within the normal weight range will have beneficial effects. Therefore, it may be appropriate to develop BMI-specific intervention programs for electronics use.

We found more favorable health effects associated with mobile phone use among men, but did not find a consistent health effect of gender on other electronics use. There is evidence that there are gender differences in the association between health and mobile phone use, possibly due in part to gender differences in some health indicators and

Table 3 Summary of significant results for moderating effects in BMI and age subgroups

Subgroup	Health status	Beta (95% CI)
Age ≤65 years		
Age * TV watching	SRH	−0.0015 (−0.0018 to −0.0012) ***
Age * Computer gaming	SRH	−0.0064 (−0.0086 to −0.0042) ***
Age * Mobile phone use	SRH	−0.0014 (−0.0027 to 0) *
Age * Computer gaming	MCP	−0.0048 (−0.0081 to −0.0015) ***
Age * TV watching	TPA	−0.1404 (−0.1681 to −0.1126) ***
Age * Computer use	TPA	−0.1413 (−0.2137 to −0.0689) ***
Age * Computer gaming	TPA	−0.2888 (−0.5099 to −0.0677) *
BMI - Normal weight		
BMI * TV watching	SRH	−0.0062 (−0.0082 to −0.0041) ***
BMI * Computer gaming	SRH	−0.0434 (−0.0660 to −0.0207) ***
BMI * Mobile phone use	SRH	0.0124 (0.0046–0.0203) **
BMI - Overweight		
BMI * Mobile phone use	SRH	0.0093 (0.0013–0.0172) *
BMI - Obesity		
BMI * TV watching	MCP	0.0034 (0.0020–0.0050) ***

Data are shown as beta (95% CI). *** $P \leq 0.001$, ** $P \leq 0.01$, * $P \leq 0.05$.

Table 4 Association between electronic device use and health status by gender

		Female	Male
Self-reported health	TV watching	0.051 (0.049–0.054) ***	0.061 (0.058–0.063) ***
	Computer use	0.012 (0.003–0.021) *	0.004 (−0.004 to 0.011)
	Computer gaming	0.039 (0.018–0.060) ***	0.074 (0.052–0.095) ***
	Mobile phone use	−0.020 (−0.030 to −0.010) ***	−0.075 (−0.086 to −0.064) ***
Multisite chronic pain	TV watching	0.047 (0.043–0.052) ***	0.041 (0.037–0.044) ***
	Computer use	0.025 (0.011–0.040) ***	−0.004 (−0.014 to 0.007)
	Computer gaming	0.089 (0.055–0.123) ***	0.034 (0.005–0.063) *
	Mobile phone use	0.080 (0.064–0.097) ***	0.035 (0.019–0.050) ***
Total physical activity	TV watching	−1.801 (−2.033 to −1.570) ***	−1.790 (−2.083 to −1.497) ***
	Computer use	−2.557 (−3.303 to −1.811) ***	−3.981 (−4.677 to −3.285) ***
	Computer gaming	−5.970 (−7.840 to −4.101) ***	−6.653 (−8.972 to −4.334) ***
	Mobile phone use	0.864 (−0.036 to 1.763)	1.214 (0.023–2.404) *

Data are shown as beta (95% CI). *** $P \leq 0.001$, ** $P \leq 0.01$, * $P \leq 0.05$.

sedentary characteristics (Lee et al. 2017). Contrary to our findings that males with earlier access to mobile phones were healthier, a study among older Japanese showed that mobile phone use was associated with lower levels of depressive symptoms in older women, but not in older men (Minagawa and Saito 2014). The reason for the opposite results may be related to the characteristics of depression. However, further research is still needed to clarify the health associations and mechanisms of the interaction between gender and electronics use.

Strengths and limitations

The large sample size allowed us to estimate the correlations with high precision and enabled us to extensively explore the association between various types of electronics use and health, as well as the effects of gender, BMI, and age on this association. Many of the previous relevant studies were conducted in smaller populations with a less comprehensive selection of electronic products, leaving them with limited insight into variable correlations. Another contribution of this study is that we used three health indicators that are strongly associated with the quality of life of middle-aged and elderly persons, and for the first time examined the relationship between electronics

use and MCP. In addition, our findings complement the limited research on the moderating effects of gender, BMI, and age on the association between electronics use and health.

However, some limitations must be acknowledged. Firstly, the data collected on electronics usage was based on self-reports, which may have led to biases and inaccuracies in the data. Secondly, the study sample only included middle-aged and elderly individuals of European ancestry, so further research is needed to test the generalizability of the findings to other populations and age groups. Thirdly, the study was cross-sectional in design, making it difficult to establish causal effects, and longitudinal studies would be of interest. Lastly, the relationship between mobile phone use and health outcomes is complex and is influenced by various factors, including lifestyle factors like diet, exercise, and sleep quality. While the study accounted for socioeconomic status, it did not consider other lifestyle factors and only evaluated mobile phone use for calls, not other activities such as texting or internet browsing. Therefore, further research is needed to better understand the relationship between mobile phone use and health outcomes.

Conclusions

The correlations between the four types of electronics use and the three health outcomes were different, but the adverse health associations with TV watching, computer use, and computer gaming were consistent, and were moderated by BMI, gender, and age. Our findings advance a comprehensive understanding of the association between multiple types of electronic devices and health status in middle-aged and elderly persons, emphasize the moderating role of BMI, gender, and age, and provide new perspectives for future research.

Declarations

Ethics approval This study was conducted using data from the UK Biobank, which has obtained ethical approval from the National Health Service (NHS) Research Ethics Service (reference number 11/NW/0382). The UK Biobank has also obtained informed consent from all participants, and all data were anonymized to protect the privacy of the participants.

Consent to participate Not applicable.

Consent for publication All the authors have read and approved the final version of the manuscript.

Competing interests The authors report no financial interests or potential conflicts of interest.

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