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ARTICLE

The Association between eHealth Literacy and Depression among Young and Middle-Aged Adults: Mediations of Lifestyle Behaviors

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ABSTRACT: Background: Young and middle-aged adults are susceptible to depression, which may impose health and economic burdens on both individuals and society. eHealth literacy is the ability for individuals to obtain health information through digital channels, which may be beneficial to their mental health. This study aims to investigate the association between eHealth literacy and depression, as well as the mediating roles of lifestyle behaviors. **Methods:** The study adopted a cross-sectional survey to collect data from 1280 young and middle-aged participants (Mean_{age} = 39.55 years, 56.72% females) in China. The Chinese version of the eHealth Literacy Scale (eHEALS) and the 10-item Center for Epidemiologic Studies Depression Scale (CESD-10) were used to measure eHealth literacy and depression, respectively. Correlation analysis and ordinary least squares regression were conducted to analyze the data. A parallel-mediation model was established to examine the mediating roles of four lifestyle behaviors: smoking, alcohol consumption, sleeping, and exercising. **Results:** The results showed that eHealth literacy was significantly negatively associated with depression among young and middle-aged adults in China ($\beta = -0.294$, 95%CI [−0.330, −0.258], $p < 0.001$). In addition, the results statistically suggest the mediating roles of smoking ($\beta = -0.010$, 95%CI [−0.019, −0.002]), alcohol consumption ($\beta = -0.010$, 95%CI [−0.021, −0.002]), sleeping ($\beta = -0.017$, 95%CI [−0.026, −0.009]), and exercising ($\beta = -0.016$, 95%CI [−0.026, −0.007]) in the association between eHealth literacy and depression. **Conclusions:** These results suggest that higher levels of eHealth literacy are associated with lower levels of depression, indicating that eHealth literacy could be beneficial to mental health. Healthy lifestyle behaviors in terms of smoking, alcohol consumption, sleeping, and exercising may be mediators in the association.

KEYWORDS: eHealth literacy; depression; lifestyle behavior; smoking; alcohol consumption; sleeping; exercising

1 Introduction

Depression is a noticeable challenge faced by humanity. According to new data from the World Health Organization (WHO) in 2025, more than 1 billion people worldwide are living with mental health disorders [1]. Depression is one of the most common mental health disorders. Approximately 332 million people globally suffer from depression, accounting for about 4.4% of the world's population [2]. The number of people with depression has been increasing since 1990, and this trend has become particularly evident since the COVID-19 pandemic [3]. For example, in the first year of the COVID-19 pandemic, the global prevalence of depression increased by 25% [4]. Depression is one of the primary contributors to the global burden of mental diseases [2,5], as it is closely associated with an increased risk of suicide, which in turn places pressure on the healthcare system, economic productivity, and even social stability [6,7]. Therefore, exploring effective ways to prevent and address depression is of great significance for global health, economic development, and social stability.

The rapid advancement of digital technology is offering potential solutions for treating depression by significantly transforming people's lifestyles [8]. eHealth literacy is individuals' ability to obtain health-related information through digital channels [9]. High eHealth literacy could support individuals in acquiring more and better health-related information and knowledge through digital channels such as search engines, online forums, and generative artificial intelligence [10]. Based on this information, individuals can better understand their health conditions and develop healthier lifestyle behaviors, thereby achieving improved physical and mental health outcomes, such as lower rates of chronic diseases and depression [11,12]. However, there are still several gaps in the existing research on eHealth literacy and depression. First, the association between eHealth literacy and depression remains unclear. Several studies have examined this association within certain periods (e.g., during the COVID-19 pandemic) or among certain populations (e.g., older adults or adolescents) [13–15]. However, research focusing on the association between eHealth literacy and depression among young and middle-aged adults after the COVID-19 pandemic remains limited. Second, the mediating role of lifestyle behaviors in the association between eHealth literacy and depression has not been empirically demonstrated. Although existing studies pointed out that developing healthy lifestyle behaviors, accessing social support, and seeking mental health services may serve as potential mediators between eHealth literacy and depression [16], few studies have empirically examined the mediating roles of certain lifestyle behaviors (e.g., smoking, alcohol consumption, sleeping, and exercising) in the association between eHealth literacy and depression. This study aims to address the above research gaps.

1.1 Association between eHealth Literacy and Depression

Depression refers to a condition in which individuals exhibit a depressed mood, unhappiness, or loss of interest in usual activities, sometimes accompanied by other psychological or somatic symptoms [17]. At the physiological level, depression is prospectively associated with obesity, cardiac disease, and suicide, while at the social level it may have negative impacts on education, employment, and social interactions [18]. In addition, the loss of working days caused by depression imposes economic costs on both individuals and society [19–21]. Given these adverse effects, the effective prevention of depression is of great importance for both individuals and society. Identifying the correlative factors of depression is a prerequisite for implementing targeted preventive actions. Existing literature suggests that the antecedents of depression can be broadly categorized into four categories. First, at the biological level, genetics may contribute to depression [22]. Second, demographic factors (e.g., gender, age, and marital status) are associated with depression [23,24]. Third, the likelihood of depression is significantly associated with social factors including economic conditions, healthcare, education, and community context [25]. Fourth, the likelihood of depression may also be influenced by lifestyle behaviors, such as smoking, alcohol consumption, and exercising [26]. However, existing literature has paid relatively limited attention to how emerging technologies in the digital era, such as the Internet and intelligent health applications, are associated with depression.

Health literacy refers to the ability to access, understand, evaluate, and apply health information to maintain and promote health [27–29]. eHealth literacy is an extension of health literacy in the digital era, and it refers to the ability to search, understand, evaluate, and apply information about health through electronic channels such as the Internet and generative artificial intelligence [30–32]. Individuals with higher eHealth literacy could access more and higher-quality health information. Such information may help individuals detect depression in a timely manner and adopt measures—such as lifestyle modifications and medication—to prevent and address depression [10,16]. Moreover, higher eHealth literacy enables individuals to access external resources including mental health services and social supports, which may enable them to cope more effectively with depression [33,34]. Existing studies have shown that individuals with higher eHealth literacy are more likely to have better mental health conditions and lower prevalence of psychological disorders such as anxiety and depression [13–15,35].

1.2 Mediating Roles of Lifestyle Behaviors

Existing research has shown that eHealth literacy is associated with lifestyle behaviors such as smoking, alcohol consumption, sleeping, and exercising. In the digital era, an increasing number of organizations provide health information through digital channels such as the Internet, and more individuals obtain such information through these channels [36,37]. For individuals, it is not sufficient merely to have access to this information, and they must also be able to understand and evaluate it, thus applying it effectively [38]. eHealth literacy refers to individuals' ability to obtain, understand, evaluate, and apply health information through digital channels [30–32]. The Knowledge-Attitude-Practice (KAP) model suggests that the process of behavioral change consists of three stages: knowledge acquisition, attitude formation, and behavioral change [39]. Among these, knowledge acquisition provides the foundation for behavioral change, while attitude formation serves as the driving force for behavioral change [40]. Within the context of eHealth literacy, the ability to obtain health information facilitates knowledge acquisition, the ability to understand and evaluate health information promotes attitude formation, and the ability to apply health information corresponds to behavioral change. From an economic perspective, eHealth literacy may also be regarded as a type of health-related human capital. Individuals with higher eHealth literacy may possess greater capacities to obtain, understand, evaluate, and apply health information from digital channels, thereby potentially making more informed decisions about mental health. Better mental health could be beneficial for individuals to provide longer-term and higher-quality labor to the labor market. In addition, eHealth literacy may help reduce information frictions in the digital environment of health information. Information friction refers to additional costs arising from incomplete or asymmetric information. eHealth literacy may help individuals reduce information search costs and improve the efficiency of health information processing, which may be favorable to health equity.

Therefore, individuals with higher eHealth literacy are able to access more and higher-quality health information, which may be beneficial to their mental health outcomes [10]. In contrast, individuals with lower eHealth literacy may encounter difficulties in understanding and accessing health information, which may be unfavorable to their mental health management [16]. Based on the above arguments, amounts of evidence has empirically indicated that eHealth literacy is significantly associated with lifestyle behaviors such as smoking, alcohol consumption, sleeping, and exercising [41–44].

Existing research also indicates that lifestyle behaviors could be physiologically, neurologically, psychologically, or socially associated with depression. In terms of the physiological association, exercising could reduce depression by lowering biomarkers such as inflammation and cortisol [45]. In terms of the neurological association, smoking, alcohol consumption, and sleep may be associated with depression by influencing the development of the prefrontal cortex, which is tightly related to neurogenesis [46,47]. In terms of psychological associations, individuals with higher levels of exercise tend to have greater psychological resilience and better psychological adjustment, and tend to report lower levels of depression [48]. In terms of social associations, smoking and alcohol consumption could be related to depression by contributing to educational or employment failures [49]. Based on the above, a series of evidence has indicated that lifestyle behaviors in terms of smoking, alcohol consumption, sleeping, and exercising are significantly associated with depression [45–49].

In summary, this study posits that smoking, alcohol consumption, sleeping, and exercising play mediating roles in the association between eHealth literacy and depression.

1.3 Current Study

Due to the rapid intensification of economic and social competition, young and middle-aged adults in China face substantial occupational and academic pressures [50–54]. These pressures may lead to depression, which could translate into health and economic burdens for both individuals and society [20–22]. At the same time, the rapid development of digital technologies in China has provided important channels for individuals to access information for managing mental health. Among the Chinese population, young and middle-aged adults are sensitive to and receptive to digital technologies [55]. Based on this background, the association between eHealth literacy and depression, as well as the potential mediating roles of lifestyle behaviors, among young and middle-aged adults in China warrants attention. First, this study hypothesizes that eHealth literacy is negatively associated with depression among young and middle-aged adults in China (**H1**). Second, this study develops a parallel-mediation model to explain the mediating roles of lifestyle behaviors in this association, which is shown in Fig. 1. Specifically, this study hypothesizes that smoking (**H2**), alcohol consumption (**H3**), sleeping (**H4**), and exercising (**H5**) play mediating roles in the association between eHealth literacy and depression.

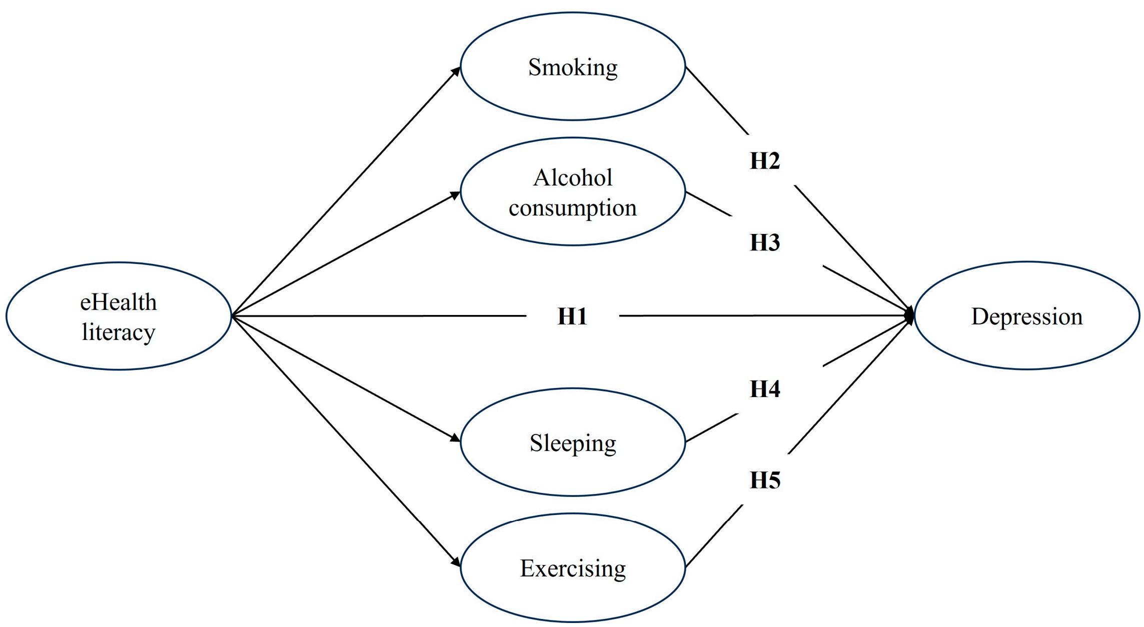

Figure 1: The conceptual model.

2 Methods

2.1 Participants and Procedures

We recruited 1317 young or middle-aged adults aged from 18 to 60 using convenience sampling in eight provinces of China (Hebei, Inner Mongolia, Shanxi, Shandong, Fujian, Jiangxi, Guizhou, and

Guangxi) from 12 to 22 March 2026. An online questionnaire based on the Credamo survey platform (https://www.credamo.com/#/) was sent to residents, who voluntarily completed the questionnaire. 32 participants who left half of the questionnaire unanswered and 5 participants who provided incorrect answers to the attention check item were excluded, resulting in 1280 participants included in the formal analysis (Mean_{age} = 39.55 years, SD_{age} = 10.53, 56.72% females). The descriptive information of samples in terms of gender, educational attainment, employment status, marital status, and income level is shown in Table 1. The samples included individuals from different groups divided by gender, educational attainment, employment status, marital status, and income level.

The study design and the procedure used to collect data were approved by the Medical Ethics Committee of Tsinghua University (THU-01-2026-0014), and the ethics approval was obtained before 12 March 2026. All participants approved informed consents.

2.2 Measures

2.2.1 Sociodemographic Information

Sociodemographic information was measured by 6 self-constructed items about participants' age, gender, educational attainment, employment status, marital status, and income level. All of the items about sociodemographic information were included as control variables in the following analysis. The item measuring age was an open-ended question in which participants reported their age. The items measuring gender, educational attainment, employment status, marital status, and income level were multiple-choice questions, and the meanings of their values are shown in Table 1.

Table 1: Descriptive information and meanings of variable values.

Variables	Values	Meanings	Frequency (%)
Gender	0	Female	726 (56.72%)
	1	Male	554 (43.28%)
Educational attainment	0	College or below	575 (44.92%)
	1	Bachelor's degree or higher	705 (55.08%)
Employment status	0	Unemployed or students	179 (13.98%)
	1	Employed	1101 (86.02%)
Marital status	0	Without a Spouse	284 (22.19%)
	1	With a Spouse	996 (77.81%)
Income level	0	≤5000 CNY	718 (56.09%)
	1	>5000 CNY	562 (43.91%)

2.2.2 eHealth Literacy

eHealth literacy was measured using the Chinese version of eHEALS [56]. The scale consists of 8 items, for example, "I know how to find helpful health information on the Internet". Each item was rated on a 5-point scale, ranging from "1 = completely untrue" to "5 = completely true". The mean score of the 8 items was used in the formal analysis, with higher scores indicating higher levels of eHealth literacy. The Cronbach's alpha was 0.96 in the current dataset, indicating good validation [57].

2.2.3 Depression

Depression was measured using the Chinese version of CESD-10 [58]. The scale consists of 10 items. For 8 items about negative feeling (e.g., "I felt depressed"), each of them was rated by a 4-point scale about the frequency of a certain feeling over the past week, with "1 = 0 day", "2 = 1–3 days", "3 = 4–6 days", and "4 = 7 days". 2 items on positive feelings (e.g., "I was happy") were coded in reverse, with "1 = 7 days", "2 = 4–6 days", "3 = 1–3 days", and "4 = 0 days". The mean score of 10 items was used in the formal analysis, with higher scores indicating higher levels of depression. The Cronbach's alpha was 0.84 in the current dataset, indicating good validation [57].

2.2.4 Lifestyle Behaviors

Lifestyle Behaviors were measured by four self-constructed items about participants' lifestyle behaviors in terms of smoking, alcohol consumption, sleeping, and exercising. The item measuring smoking behavior was "How many days in the past week did you smoke", with "0 = Yes" and "1 = No". The item measuring alcohol consumption behavior was "How many days in the past week did you consume alcohol", with "1 = 7 days", "2 = 4–6 days", "3 = 1–3 days", and "4 = 0 day". The joint consensus statement of the American Academy of Sleep Medicine and the Sleep Research Society recommends that adults obtain 7 h or more of sleep per night [59], so the item measuring sleeping behavior was "How many days in the past week did you sleep at least 7 h", with "1 = 0 day", "2 = 1–3 days", "3 = 4–6 days", and "4 = 7 days." WHO guidelines recommend that adults engage in at least 150 min of physical activity per week, equivalent to exercising at least 30 min per day across an average of 5 days per week [60]. Therefore, the item measuring exercising behavior was "How many days in the past week did you exercise for at least 30 min", with "1 = 0 days", "2 = 1–3 days", "3 = 4–6 days", and "4 = 7 days". For all of these variables, higher scores indicated healthier lifestyle behaviors. Considering that participants recruited through online convenience sampling may be unwilling to complete long or complex questionnaires, we adopted the above four self-constructed single-item questions rather than existing multi-item questions to measure their lifestyle behaviors. This measurement could reduce respondent burden and questionnaire length in the context of an online survey, thereby improving participants' willingness to respond and the quality of their responses.

2.3 Data Analysis

The data was analyzed in four steps. First, Harman's single-factor test was conducted as a preliminary diagnostic for common method bias (CMB). The first unrotated factor accounted for 28.265% of the total variance, which was below the commonly used threshold. However, Harman's test cannot fully rule out potential CMB, and the following findings should be interpreted with caution. Second, the Pearson correlation analysis was used to investigate the associations between eHealth literacy, depression, smoking habit, alcohol consumption habit, sleeping habit, exercising habit, and sociodemographic items. Third, ordinary least squares regression was used to investigate the association between eHealth literacy and depression. Fourth, regression was conducted using Model 4 of the PROCESS macro in SPSS 27.0 (IBM Corp., Armonk, NY, USA) to investigate the mediating roles of smoking, alcohol consumption, sleeping, and exercising in the association between eHealth literacy and depression. The 5000-times bootstrapping method and 95% confidence interval (CI) were used to estimate the indirect effects. The threshold for statistical significance used in the above analysis was two-tailed $p < 0.05$.

3 Results

3.1 Results of Correlation Analysis

In the preliminary analysis, correlation analysis was conducted to describe the bivariate associations among depression, eHealth literacy, smoking, alcohol consumption, sleeping, exercising, age, gender, educational attainment, employment status, marital status, and income level.

The results of the correlation analysis are presented in Table 2. It can be observed that eHealth literacy has a significantly negative association with depression score (r = −0.477, $p < 0.001$), which indicates that individuals with higher levels of eHealth literacy on average report lower levels of depression, providing preliminary support for **H1**.

In addition, eHealth literacy has significantly positive correlations with healthy smoking habit (r = 0.165, $p < 0.001$), healthy alcohol consumption habit (r = 0.173, $p < 0.001$), healthy sleeping habit (r = 0.235, $p < 0.001$) and healthy exercising habit (r = 0.264, $p < 0.001$). This suggests that individuals with higher levels of eHealth literacy are more likely to have healthy habits in terms of smoking, alcohol consumption, sleeping, and exercising. At the same time, depression has significantly negative correlations with healthy habits in terms of smoking (r = −0.197, $p < 0.001$), alcohol consumption (r = −0.189, $p < 0.001$), sleeping (r = −0.292, $p < 0.001$), and exercising (r = −0.295, $p < 0.001$). This indicates that individuals who have healthier habits in terms of smoking, alcohol consumption, sleeping, and exercising have lower levels of depression. These findings provide preliminary support for **H2** to **H5**.

3.2 Results of Regression Models

Regression was used to estimate the association between eHealth literacy and depression. In the regression model, the dependent variable was depression, the core independent variable was eHealth literacy, and control variables included age, gender, educational attainment, employment status, marital status, and income level. The results of the regression models are presented in Table 3. As shown in Model 1 of Table 3, eHealth literacy has a significantly negative association with depression (β = −0.303, 95%CI [−0.337, −0.268], $p < 0.001$), when control variables are not included. As shown in Model 3 of Table 3, eHealth literacy still has a significantly negative association with depression (β = −0.294, 95%CI [−0.330, −0.258], $p < 0.001$), when control variables are included. Comparing Model 2 and Model 3 of Table 3, the inclusion of eHealth literacy in the regression model with only control variables increases the R^2 from 0.053 to 0.258, indicating that eHealth literacy has an important explanatory power for depression. These results suggest that individuals with higher levels of eHealth literacy have lower levels of depression, which supports **H1**.

3.3 Results of Mediation Analysis

Regression was also used to investigate the potential mediating roles of lifestyle behaviors. Specifically, Model 4 of the PROCESS macro in SPSS with 5000 bootstrap samples to examine the mediating roles of smoking, alcohol consumption, sleeping, and exercising.

Table 2: Correlation analysis of variables.

	1	2	3	4	5	6	7	8	9	10	11	12
1. Depression	1											
2. eHealth	−0.477***	1										
3. Healthy smoking	−0.197***	0.165***	1									
4. Healthy alcohol	−0.189***	0.173***	0.606***	1								
5. Sleep	−0.292***	0.235***	0.115***	0.112***	1							
6. Exercise	−0.295***	0.264***	0.156***	0.162***	0.328***	1						
7. Age	−0.114***	−0.045	−0.163***	−0.167***	0.068**	0.202***	1					
8. Gender	0.054*	−0.036	−0.341***	−0.287***	−0.043	−0.049*	0.087***	1				
9. Educational attainment	−0.153***	0.185***	−0.003	−0.057**	0.129***	0.052*	−0.115***	−0.016	1			
10. Employment status	−0.031	0.052*	0.030	0.005	−0.011	−0.001	0.139***	−0.048*	0.225***	1		
11. Marital status	−0.073***	−0.047*	−0.026	−0.044	0.047*	0.148***	0.655***	−0.012	−0.089***	0.267***	1	
12. Income level	−0.141***	0.118***	−0.147***	−0.214***	0.147***	0.035	0.164***	0.066**	0.242***	0.0120	0.075***	1

Note: N = 1280. *p < 0.05, **p < 0.01, ***p < 0.001.

Table 3: Regression analysis of the association between eHealth literacy and depression.

Independent Variable	**Dependent Variable: Depression**		
	Model 1	**Model 2**	**Model 3**
eHealth	−0.303***		−0.294***
	(0.018)		(0.018)
Age		−0.007***	−0.007***
		(0.002)	(0.002)
Gender		0.080*	0.060*
		(0.032)	(0.028)
Educational attainment		−0.174***	−0.093**
		(0.036)	(0.032)
Employment status		0.042	0.063
		(0.052)	(0.045)
Marital status		−0.007	−0.029
		(0.052)	(0.048)
Income level		−0.103**	−0.055
		(0.034)	(0.031)
Constant	2.872***	2.083***	3.143***
	(0.070)	(0.081)	(0.103)
N	1280	1280	1280
R^2	0.228	0.053	0.258

Note: Standard errors are reported in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001.

The results of each regression model are shown in Table 4. When smoking, alcohol consumption, sleeping, and exercising are used as dependent variables, eHealth literacy has significantly positive associations with smoking (β = 0.064, 95%CI [0.044, 0.084], $p < 0.001$), alcohol consumption (β = 0.142, 95%CI [0.098, 0.186], $p < 0.001$), sleeping (β = 0.219, 95%CI [0.161, 0.277], $p < 0.001$), and exercising (β = 0.285, 95%CI [0.230, 0.339], $p < 0.001$). When depression is used as the dependent variable, all of eHealth literacy (β = −0.241, 95% CI [−0.278, −0.204], $p < 0.001$), smoking (β = −0.151, 95%CI [−0.271, −0.032], $p = 0.013 < 0.05$), alcohol consumption (β = −0.071, 95%CI [−0.138, −0.004], $p = 0.039 < 0.05$), sleeping (β = −0.077, 95%CI [−0.111, −0.042], $p < 0.001$), and exercising (β = −0.057, 95%CI [−0.089, −0.026], $p < 0.001$) have significantly negative associations with depression. These results are consistent with those of the correlation analysis, statistically suggesting the potential mediating roles of smoking, alcohol consumption, sleeping, and exercising in the association between eHealth literacy and depression. In addition, we calculated the variance inflation factor (VIF) for each independent variable in the regression model including all independent variables to assess the potential impact of multicollinearity. The results show that the maximum VIF value was 1.96, which was well below the commonly used threshold of 10, statistically suggesting that the multicollinearity was not serious.

Table 4: Regression analysis of mediating roles of smoking, alcohol consumption, sleeping, and exercising on the association between eHealth literacy and depression.

Independent Variables	Dependent Variables				
	Smoke	Alcohol	Sleep	Exercise	Depression
eHealth	0.064*** (0.010)	0.142*** (0.022)	0.219*** (0.030)	0.285*** (0.028)	−0.241*** (0.019)
Smoke					−0.151* (0.061)
Alcohol					−0.071* (0.034)
Sleep					−0.077*** (0.017)
Exercise					−0.057*** (0.016)
Age	−0.006*** (0.001)	−0.010*** (0.002)	0.006 (0.003)	0.019*** (0.003)	−0.007*** (0.002)
Gender	−0.215*** (0.019)	−0.340*** (0.036)	−0.090 (0.051)	−0.107* (0.050)	−0.009 (0.029)
Educational attainment	−0.017 (0.020)	−0.087* (0.038)	0.171** (0.055)	0.109* (0.053)	−0.082** (0.031)
Employment status	0.012 (0.031)	0.003 (0.060)	−0.170* (0.080)	−0.199* (0.079)	0.040 (0.043)
Marital status	0.081** (0.029)	0.124* (0.058)	0.069 (0.085)	0.114 (0.081)	0.004 (0.046)
Income level	−0.082*** (0.019)	−0.245*** (0.036)	0.169** (0.055)	−0.086 (0.054)	−0.077* (0.031)
Constant	0.920*** (0.057)	3.762*** (0.119)	1.804*** (0.167)	0.410** (0.142)	3.709*** (0.145)
N	1280	1280	1280	1280	1280
R^2	0.178	0.173	0.084	0.126	0.313

Note: Standard errors are reported in parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

The results of the separate analysis of the mediating roles of four lifestyle behaviors are shown in Table 5 and Fig. 2. It can be observed that the total magnitude of the association between eHealth literacy and depression is −0.294. Among these, the total magnitude of these four mediations is −0.053, accounting for 18.027% of the total magnitude. First, eHealth literacy is associated with depression via smoking (Mediation 1), with a magnitude value of −0.010, accounting for 18.868% of the total indirect association. Second, eHealth literacy is associated with depression via alcohol consumption (Mediation 2), with a magnitude value of −0.010, accounting for 18.868% of the total indirect association. Third, eHealth literacy is associated with depression via sleeping (Mediation 3), with a magnitude value of −0.017, accounting for 32.075% of the total indirect association. Fourth, eHealth literacy is associated with depression via exercising (Mediation 4), with a magnitude value of −0.016, accounting for 30.189% of the total indirect association. Each of the four mediations has a significant level, with a 95%CI that does not include 0.

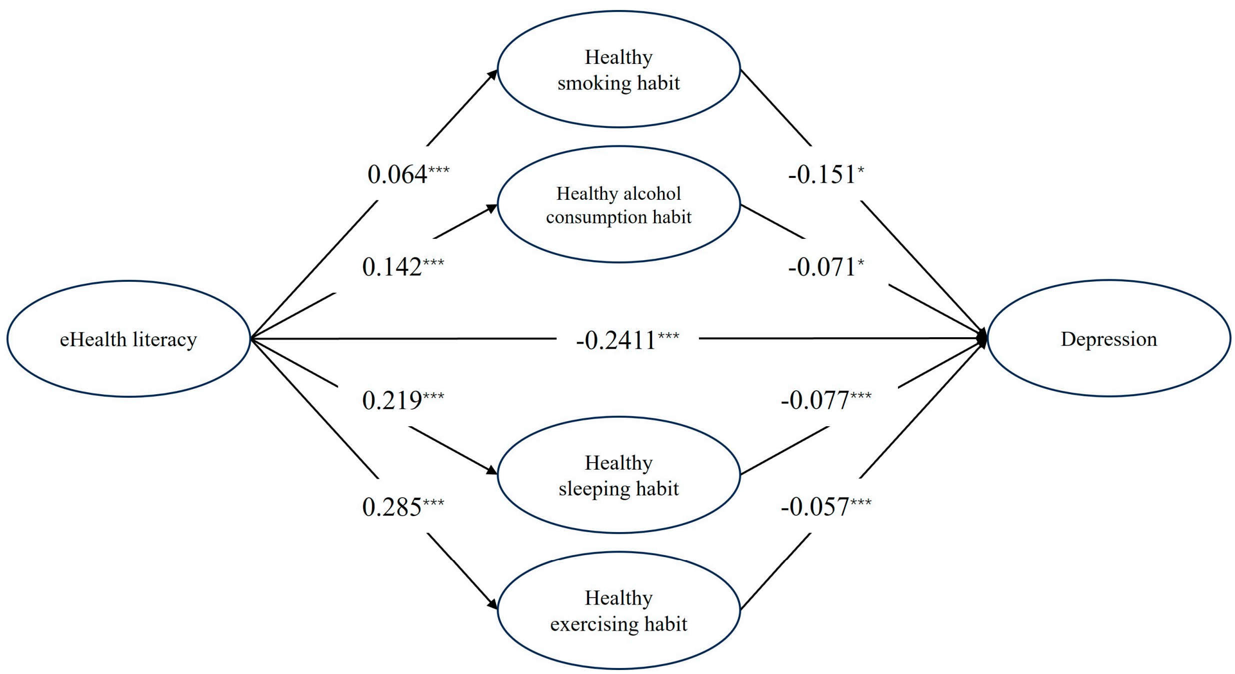

Figure 2: The mediating roles of lifestyle behaviors. Note: $^{*}p < 0.05$, $^{***}p < 0.001$.

Table 5: Separate analysis of the mediating roles of four lifestyle behaviors.

Mediation	Effect	Boot SE	95% CI Boot LLCI	95% CI Boot ULCI	Relative Mediation
					Ratio in total association:
Total mediation	−0.053	0.007	−0.068	−0.040	18.027%
					Ratio in total indirect association:
Mediation 1: Smoking	−0.010	0.004	−0.019	−0.002	18.868%
Mediation 2: Alcohol consumption	−0.010	0.005	−0.021	−0.002	18.868%
Mediation 3: Sleeping	−0.017	0.005	−0.026	−0.009	32.075%
Mediation 4: Exercising	−0.016	0.005	−0.026	−0.007	30.189%

Note: Boot SE, bootstrap standard error; Boot LLCI, bootstrap lower limit of confidence interval; Boot ULCI, bootstrap upper limit of confidence interval.

4 Discussion

4.1 Main Findings

Young and middle-aged adults in China face substantial occupational and academic pressures, which may lead to depression [50–54], and impose health and economic burdens on both individuals and society [20–22]. The development of digital technologies provides potential solutions to this issue. eHealth literacy is the ability related to whether young and middle-aged adults in China can use digital channels to obtain health information and thereby promote mental health [30–32]. This study investigated the association between eHealth literacy and depression among young and middle-aged adults in China, as well as the mediating roles of four lifestyle behaviors. The results suggest that eHealth literacy is negatively associated with depression. Furthermore, the findings statistically suggest the mediating roles of smoking, alcohol consumption, sleeping, and exercising in the association between eHealth literacy and depression. These findings not only reveal the potential benefits of eHealth literacy, but also provide new perspectives for policymakers and health-related organizations in the field of mental health.

4.2 Interpretations of Findings

4.2.1 Interpretation of Association between eHealth Literacy and Depression

This study found a significantly negative association between eHealth literacy and depression among young and middle-aged adults in China. In other words, individuals with higher eHealth literacy are more likely to report lower levels of depression, whereas those with lower eHealth literacy are more likely to report higher levels of depression. This finding is consistent with previous studies conducted in other population groups [13–15]. In the digital era, an increasing number of organizations provide health information through digital channels such as the Internet. At the same time, more individuals obtain such information through these digital channels. Existing research indicates that young and middle-aged adults are particularly receptive to these digital channels [55].

eHealth literacy refers to individuals' ability to obtain, understand, evaluate, and apply health information from digital channels [30–32]. This type of ability is highly related to whether individuals can effectively use health information from digital channels to maintain their mental health. Individuals with higher eHealth literacy could access more and higher-quality health information through digital channels and make more effective use of them to prevent depression, which may be beneficial to their mental health [10]. In contrast, individuals with lower eHealth literacy may encounter difficulties in understanding and evaluating health information from digital channels, which may be unfavorable to their mental health [16]. Therefore, eHealth literacy is negatively associated with depression.

The magnitude of the association between eHealth literacy and depression was noticeable. Numerically, the estimated coefficient of eHealth literacy in the regression model was −0.2939, statistically indicating that a one-unit increase in eHealth literacy measured by the eHEALS was associated with an average decrease of 0.2939 units in depression measured by the CESD-10. Comparatively, eHealth literacy, like important socioeconomic factors that have been shown in previous studies (e.g., educational attainment and income level) [61,62], is negatively associated with depression, which indicates the potential benefits of eHealth literacy in the field of mental health. It should be noted that the above interpretation of the magnitude of the association between eHealth literacy and depression may not fully capture the complexity of the relevant information. More precise estimation and comparison of the magnitude may require future studies employing more refined measurements.

4.2.2 Interpretation of Mediating Roles of Lifestyle Behaviors

The results of this study statistically suggest the mediating roles of smoking, alcohol consumption, sleeping, and exercising in the association between eHealth literacy and depression among young and middle-aged adults in China.

Specifically, eHealth literacy is significantly positively associated with healthy habits in terms of smoking, alcohol consumption, sleeping, and exercising. The KAP model provides an explanation for these results. The KAP model conceptualizes the process of behavioral change as consisting of three stages: knowledge acquisition, attitude formation, and behavioral change [39]. Knowledge acquisition forms the foundation of behavioral change, while attitudes provide the motivation for such change [40]. eHealth literacy encompasses individuals' ability to obtain, understand, and evaluate health information from digital channels. This ability could increase individuals' knowledge, while the ability to understand and evaluate such health information enables individuals to form scientific beliefs about healthy lifestyle behaviors, which in turn motivate the adoption of healthy lifestyle behaviors. Higher eHealth literacy may also reflect stronger human capital. Individuals with higher levels of eHealth literacy may have better mental health, which may help them provide longer-term and higher-quality labor to the labor market. Moreover, eHealth literacy may represent an ability that helps reduce information frictions related to health. In the digital environment of health information, the quantity and quality of information may be similar for all individuals, whereas individuals' abilities to process such information may differ, which may contribute to health inequities. Individuals with higher eHealth literacy may face fewer difficulties in obtaining, understanding, evaluating, and applying health information, which may be beneficial to equity in the health field. In general, eHealth literacy is significantly associated with smoking, alcohol consumption, sleeping, and exercising.

Furthermore, these lifestyle behaviors could have physiological, neurological, psychological, and social associations with depression. First, smoking and alcohol consumption could be neurologically and socially associated with depression. In terms of neurogenesis, smoking and alcohol consumption may contribute to abnormal development of the prefrontal cortex, which may disrupt neurogenesis and trigger depression [47]. In terms of social relationships, smoking and alcohol consumption may lead to educational and occupational failures, which are potential contributors to depression [49]. Second, sleep could be neurologically associated with depression, as adequate sleep could help maintain the development of the prefrontal cortex [46]. Third, exercising could be physiologically and psychologically associated with depression. In terms of physiology, appropriate exercise could help reduce biomarkers associated with depression, such as inflammation and cortisol [45]. In terms of psychology, higher levels of exercise are often associated with greater psychological resilience and better psychological adjustment, which may make individuals less likely to experience depression [48].

It should be noted that although the mediating roles of these four lifestyle behaviors were statistically significant, their total magnitude was small. Therefore, these four lifestyle behaviors partially mediated the association between eHealth literacy and depression, and there may be other mediating factors (e.g., salt and oil control, diet, and physical examinations) in the association, which is recommended to be investigated by future research.

4.3 Contributions and Implications

This study could contribute to existing knowledge from several aspects.

First, it identifies the significantly negative association between eHealth literacy and depression among young and middle-aged adults in China. Given this population's high susceptibility to depression and strong acceptance of digital channels, identifying the relationship between eHealth literacy and depression is of great importance for promoting their mental health.

Second, this study finds the mediating roles of smoking, alcohol consumption, sleeping, and exercising in the association between eHealth literacy and depression. This finding provides an explanation enhancing the plausibility of the observed statistical association.

Third, the findings of this study have important practical implications for various stakeholders, such as policymakers, enterprises, healthcare institutions, and individuals. These stakeholders could take actions based on the findings of this study that eHealth literacy and healthy lifestyle behaviors may be beneficial to mental health.

The findings of this study have the following implications for multiple stakeholders.

First, these findings demonstrate to policymakers the potential benefits of eHealth literacy in the field of mental health. Policymakers could improve individuals' eHealth literacy by developing policies or providing community services, that enable individuals to obtain more health information from digital channels and use such information in a better manner, which may be beneficial to their mental health.

Second, enterprises and healthcare institutions could utilize digital channels such as the Internet to provide health information for individuals. With the development of digital technology and the improvement of individuals' eHealth literacy, more and more individuals can access health information through these digital channels, which may help them form healthier lifestyles.

Third, young and middle-aged adults could improve their eHealth literacy and proactively use digital channels to obtain health information. Based on such information, they could develop a healthier lifestyle in terms of smoking, alcohol consumption, sleeping, and exercising, which may be favorable to their mental health.

4.4 Limitations and Future Research

This study also has several limitations.

First, there is a limitation about the measurement. Variables in this study were self-reported and collected in the same instrument. Although Harman's method was adopted to examine CMB, the bias caused by CMB could not be totally excluded, and it may lead to an overestimation of the correlation. In addition, sleep and exercise were measured by the number of days meeting thresholds in the past week, without considering sleep quality or exercise intensity, which may lose some information about lifestyle behaviors. Moreover, the four lifestyle behaviors were measured using self-constructed single-item questions. Although single-item questions may reduce respondent burden and questionnaire length to improve participants' willingness to respond and the quality of their responses, internal reliability cannot be statistically tested for single items. We suggest future research employ more appropriate measurements (e.g., behavioral tracking data or multiple-item measurements) to reduce measurement bias and examine the findings of this study.

Second, there is a limitation in the sampling. We collected data from eight provinces in China using online convenience sampling. The sampling approach may lead to selection bias because residents with higher levels of digital literacy and digital access were more likely to see and be willing to complete the online questionnaire, which may result in insufficient representation of residents with lower eHealth literacy. Additionally, the sample obtained by a convenience sampling method is inherently non-probability based, which may not be representative of the general young and middle-aged population. Therefore, the generalization of the findings to other populations should be made with caution.

Third, there was a limitation regarding the variables controlled in this study. Although this study found a significant association between eHealth literacy and depression, this relationship may be mixed with other correlated traits, such as cognitive ability, noncognitive skills, digital access, and personality traits. For example, high digital literacy and digital access may be highly correlated to both eHealth literacy and depression. However, these potentially correlated traits were not controlled in this study, which may lead to the overestimation of the association between eHealth literacy and depression. Future research could try to measure and control these variables to obtain a purer magnitude of the relationship between eHealth literacy and depression.

Fourth, there was a limitation about potential endogeneity caused by reverse causality, omitted variables, and simultaneity. For reverse causality, depression may also influence eHealth literacy. Individuals with lower levels of depression may have greater motivation to seek health information through digital channels, manifesting higher eHealth literacy. For omitted variables, some factors that may simultaneously influence eHealth literacy and depression were not measured and controlled, such as cognitive ability, digital access, personality traits, and noncognitive skills. For simultaneity, lifestyle behaviors and depression may influence each other. For example, poor sleep and exercising may contribute to depression, while depression may also negatively affect sleep quality and exercising. Therefore, the results of this study should be interpreted as correlations rather than causal relationships, and future research could use longitudinal data and experimental design to address endogeneity and examine the findings of this study.

Fifth, there was a limitation in terms of model setting. Smoking behavior and alcohol consumption showed a relatively high correlation in the correlation analysis, which may be attributable to multicollinearity or potential sequential mediation. Although the VIF values indicated that multicollinearity among variables was not serious, the parallel-mediation model adopted in this study cannot capture potential sequential mediations. In addition, the PROCESS models used in this study to examine mediations relied on several strong assumptions, such as that mediators are conditionally exogenous. Due to data limitations, the conditional exogeneity of mediators was not empirically demonstrated. Therefore, this study did not interpret the relevant findings as causal mechanisms but rather as statistically potential mediating roles of lifestyle behaviors. Future research could collect more comprehensive data to examine causal mechanisms and construct alternative models to investigate whether sequential mediations exist.

5 Conclusions

Given the high susceptibility to depression and strong acceptance of health information from digital channels among young and middle-aged adults, this study investigates the association between eHealth literacy and depression in this population group. Evidence from China shows that there is a significantly negative association between eHealth literacy and depression among young and middle-aged adults. Furthermore, smoking, alcohol consumption, sleep, and exercise may play mediating roles in the association. The findings of this study highlight the importance of eHealth literacy in the field of mental health. In addition, the results suggest that improving these behaviors may be beneficial to mental health.

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