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Relating health information literacy self-efficacy to information technology use and health status: A large-scale study of Chinese undergraduates

Lier le sentiment d'auto-efficacité à la maîtrise de l'information en santé à l'utilisation de technologies de l'information et à l'état de santé : une étude à grande échelle d'étudiants chinois

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Résumé de l'article

L'objectif de cet article est de lier le sentiment d'auto-efficacité à la maîtrise de l'information en santé à l'utilisation de technologies et de l'information (TI) et à l'état de santé. En se basant sur une enquête sur le terrain auprès de 6 160 étudiants d'une université chinoise, nous avons constaté que le sentiment d'auto-efficacité à la maîtrise de l'information en santé était lié de manière significative à certaines caractéristiques sociodémographiques et relatives au mode de vie, à l'utilisation de TI et à l'état de santé. Certaines de ces caractéristiques ainsi que l'état de santé permettent d'identifier un faible sentiment d'auto-efficacité en maîtrise de l'information en santé chez certains individus, tandis qu'une utilisation quotidienne modérée des TI peut l'améliorer. Les conséquences théoriques et pratiques, de même que les limites et les travaux futurs, sont aussi abordés.

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Abstract: The purpose of this paper is to relate individuals' health information literacy (HIL) self-efficacy to their information technology (IT) use and health status. Using a large-scale field survey with 6,160 valid respondents from undergraduates in a Chinese university, we found that individuals' HIL self-efficacy was significantly related to some socio-demographics and lifestyle features, IT use, and health status. Meanwhile, some socio-demographics and lifestyle features and health status help identify low HIL self-efficacy individuals, while moderate daily IT use may improve HIL self-efficacy. Theoretical and practical implications, as well as limitations and future work, are also discussed.

Keywords: health information literacy, health status, technology use, large-scale field survey, undergraduates, China

Résumé : L'objectif de cet article est de lier le sentiment d'auto-efficacité à la maîtrise de l'information en santé à l'utilisation de technologies et de l'information (TI) et à l'état de santé. En se basant sur une enquête sur le terrain auprès de 6 160 étudiants d'une université chinoise, nous avons constaté que le sentiment d'auto-efficacité à la maîtrise de l'information en santé

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était lié de manière significative à certaines caractéristiques sociodémographiques et relatives au mode de vie, à l'utilisation de TI et à l'état de santé. Certaines de ces caractéristiques ainsi que l'état de santé permettent d'identifier un faible sentiment d'auto-efficacité en maîtrise de l'information en santé chez certains individus, tandis qu'une utilisation quotidienne modérée des TI peut l'améliorer. Les conséquences théoriques et pratiques, de même que les limites et les travaux futurs, sont aussi abordés.

Mots clés : maîtrise de l'information en santé, informatique de la santé, état de santé, technologies de l'information, utilisation des technologies

Introduction

The internet has become an important channel for young people to obtain health-related information with the proliferation of the internet in societies (Kim, Park, and Bozeman 2011). Online health information from nonmedical online sources is an important driver of patient-clinician information engagement (Moldovan-Johnson, Tan, and Hornik 2014). People can get free access to large amounts of online health information through user-generated content (UGC) via social media, health platforms, or mobile apps. Young people are increasingly using information technology (IT) to obtain health information and manage their health to improve their health status (Zhao, Fu, and Chen 2020). The United States government approved the Health Information Technology for Economics and Clinical Health Act in 2009, which endorsed more than $25 billion to promote health information technology (HIT) use in healthcare reform (HITECH Answers 2009). HIT also provides improved effectiveness and efficiency in health care systems in Canada for the communication, acquisition, and utilization of health information to reduce duplication of procedures (Snowdon et al. 2011).

The availability of large amounts of online health information also brings challenges for young people as not all information is trustworthy and reliable. Due to a lack of quality control, some online information seems to be less trustworthy than paper resources such as magazines and journals (Zhang, Zhang, and Li 2015). Young people need to have the capabilities to search and find the online health information they need and evaluate and comprehend this information as it can affect their health-related decisions (Eriksson-Backa et al. 2012; Hirvonen et al. 2016). As indicated in the literature, many young people lack knowledge of acquiring, identifying, and utilizing health information to solve health issues (Hirvonen et al. 2016; Robins, Holmes, and Stansbury 2010). Thus, there is a need to help young people develop health information literacy (HIL) self-efficacy in their lives (Dunn and Xie 2017).

Internet experience and IT-related abilities play important roles in developing HIL self-efficacy (Mokhtar, Majid, and Foo 2006). However, little research has attempted to investigate how IT usage affects individuals' HIL self-efficacy in IT usage habits, including the time and frequency of using mobile phones, PCs, and other devices. Also, current research has paid quite a lot of attention to the role of HIL self-efficacy in health management but ignored whether HIL self-efficacy is associated with individuals' health statuses (Pálsdóttir 2008). Health status is defined as a state of complete physical, mental, and social well-being, and not merely the absence of disease (World Health Organization 2000).

In this vein, this research project addresses the above-mentioned research gap through an empirical study of undergraduates. Based on a large-scale survey on 6,160 college students, this study endeavours to understand the associations among HIL self-efficacy, IT use, and undergraduates' health status. Specifically, the study strives to understand:

1. What is the relationship between HIL self-efficacy and IT use (i.e., the use of phones, computers, and mobile health applications (hereinafter referred to as mHealth apps)?
2. What is the relationship between HIL self-efficacy and health status (i.e., health status changes, eyesight changes, and insomnia problems)?
3. What is the relationship between HIL self-efficacy, socio-demographics, and lifestyle features (i.e., gender, age, annual family income, and internet experience)?

The rest of the paper presents a literature review followed by a description of the research methods used. A discussion of the data analysis and the research results is also provided. The paper concludes with some implications of this study and highlights the limitations as well.

Literature review

Health information literacy

HIL self-efficacy refers to the set of abilities needed to recognize health information needs, identify information sources, retrieve relevant information, assess health information quality, and analyze, understand, and use that information to support health-related decisions (Shipman, Kurtz-Rossi, and Funk 2009). The definition of HIL self-efficacy involves both health literacy (HL) and information literacy (IL) (Niemelä et al. 2012). HL refers to the degree to which people have the ability to acquire, handle, and comprehend basic health-related information and services needed to make proper health decisions (Institute of Medicine 2004). HL mainly describes the ability to make use of literacy skills in health contexts (Chinn 2011). This way of measuring HL is mainly suitable for the public with limited literacy (Niemelä et al. 2012) and not for the health information problems faced by the literate group in daily life (Niemelä et al. 2012; Mancuso 2009). IL refers to "a set of abilities requiring individuals to recognize when information is needed and have the ability to locate, evaluate, and use it effectively" (American Library Association 2001, 1). Different from basic HL and IL, HIL self-efficacy stresses the higher demands of social and cognitive competencies required to deal with the increasingly complex health information environment (Hirvonen et al. 2016; Polkinghorne and Wilton 2010; Chen and Williams 2009). In such environments, young people with enough essential HL and IL might lack the necessary abilities to seek, evaluate, and utilize health information under daily lived circumstances indicating inadequate HIL self-efficacy (Andrews et al. 2005; Enwald et al. 2016).

HIL self-efficacy concerns the necessary capabilities in health and should be investigated among different populations due to its importance in the internet age (Enwald et al. 2016). Previous research has explored HIL self-efficacy among different groups like senior high school students (Niemelä et al. 2012), college students (Banas 2008; Ivanitskaya, O'Boyle, and Casey 2006; Nengomasha et al. 2015; Putnam, Kitts, and Pulcher 2010; Fu, Chen, and Zheng 2020), young people (Hirvonen et al. 2016), senior citizens (Yates 2013), and patients with diseases (Eriksson-Backa et al. 2012; Lloyd, Bonner, and Dawson-Rose 2014).

Prior studies on HIL self-efficacy have shown that individuals with higher education levels are reported to have higher HIL self-efficacy among university students (Ivanitskaya, O'Boyle, and Casey 2006), adults (Ek and Heinström 2011), and seniors (Eriksson-Backa et al. 2012). Niemelä et al. (2012) found that female upper secondary school students have higher HIL self-efficacy and therefore are more willing to search for and receive health information through multiple channels than male students. However, the HIL self-efficacy differences in terms of gender appear to decline with the increase of age (Tseng and Lin 2008). Therefore, women may be more concerned about health information when they are young, but men grow concerned about increased health risks when they get older (Tseng and Lin 2008) at which point men will enhance their HIL self-efficacy to help prevent health risks (Enwald et al. 2016). Some studies on HIL self-efficacy have also explored how health institutions and libraries can help develop individuals' HIL self-efficacy (Ivanitskaya et al. 2012; Shipman, Kurtz-Rossi, and Funk 2009). A summary of prior studies on the factors related to HIL self-efficacy is presented in Table 1.

Authors	Research Methods	Research subjects	Research findings
Banas 2008	Questionnaire survey	University students (N=98)	HIL self-efficacy is significantly associated with the frequency of internet use and risk-response states.
Eriksson-Backa et al. 2012	Questionnaire survey	Older people (N=281)	HIL self-efficacy is significantly associated with self-rated current health, education level, seeking activity, and interest in health information.
Nengomasha et al. 2015	Questionnaire survey	College students (N=271)	User's HIL self-efficacy influences the selection of health information sources.
Xu et al. 2019	Cross-sectional survey	Patients (N=200)	Patients living in cities, with duration of disease longer than 5 years, and above a secondary school education had higher HIL self-efficacy than other patients.
Hirvonen et al. 2016	Questionnaire survey	Young men (N=1,633)	HIL self-efficacy among young men is significantly related to father's occupation.
Kuhberg-Lasson and Mayer 2017	Questionnaire survey	Vocational students (N=352)	HIL self-efficacy significantly related to extraversion and education. Meanwhile, education plays a mediating role in the relationship between HIL self-efficacy and openness.
Enwald et al. 2015	Questionnaire survey	Young men (N=824)	Higher HIL self-efficacy was related to the selection of fear appeal message alternatives in the inactivity context.
Ivanitskaya, O'Boyle, and Casey 2006	Questionnaire survey	College students (N=243)	HIL self-efficacy is determined by the abilities of information retrieval and information source identification.
Enwald et al. 2017	Questionnaire survey	Older People (N=918)	Poor self-estimated HIL self-efficacy is likely to be reported by older people who have less experience using or have negative attitudes towards mobile IT.

Table 1: A summary of prior studies on the factors related to HIL self-efficacy

Prior research has not considered family income, life satisfaction, and other socio-demographics and lifestyle features in HIL self-efficacy research. The current study addresses this gap by including annual family income (Hirvonen et al. 2016), internet experience (Banas 2008), the frequency of health information seeking (Renahy, Parizot, and Chauvin 2010), the frequency of exercise (Booth et al. 2001), daily exercise time (Booth et al. 2001) and the frequency of staying up late (Amschler and McKenzie 2005). Meanwhile, life satisfaction, which can effectively reflect individuals' health satisfaction is also included in our study (Ernsting et al. 2017). Therefore, this study can provide more clues about the relationships between HIL self-efficacy and socio-demographics and lifestyle features.

Health-related literacy self-efficacy and technology use

Health-related literacy self-efficacy is relevant to the social and cognitive abilities needed to deal with complex health information circumstances (Hirvonen et al. 2016). Rapid developments in IT promote the utilization of health information and IT use can also help improve HIL self-efficacy (Mokhtar, Majid, and Foo 2006). The internet and IT both act as important tools for young people to search for health-related information (Webster and Willliams 2005). Given that the internet provides an environment in which people may post health information freely, some statements can be exaggerated, misleading, or outright fabricated (Pearson 2003). Using simple search terms in search engines cannot offer reliable access to health information (Eysenbach et al. 2002). Users need to have a certain level of HIL self-efficacy in order to access health information efficiently. Technology use is critical for improving health-related literacy in different populations (Enwald et al. 2017; Tennant et al. 2015). Tennant et al. (2015) found that older people who use the Web 2.0 and IT devices have higher HL than those who do not use them. Manganello et al. (2017) showed that adults with low HL were more likely to use mHealth apps and social networking sites to obtain health information but less likely to use search engines. Jensen et al. (2010) found that HL skills of low-income adults were positively related to IT use like search engines, email, and online health information seeking. However, few have delved into the relationship between some characteristics in IT usage and HIL self-efficacy such as screen size and platform preferences for seeking health information. A summary of prior studies on the relationship between health-related literacy and technology use is presented in Table 2.

Authors	Research Methods	Research subjects	Main findings
Cho, Park, and Lee 2014	Questionnaire survey	Adults (N=765)	The effects of HL on mHealth app use were mediated by mHealth app use efficacy.
Enwald et al. 2017	Questionnaire survey	Older People (N=918)	Older people who prefer to use mobile IT have more confidence in their ability to obtain health information and comprehend health-related terms.
Chen et al. 2018	Questionnaire survey	Adults (N=600)	Lower HL was associated with lower possibilities of using health websites for health information and higher possibilities of using social media, television, and blogs.
Ivanitskaya et al. 2012	Questionnaire survey	Health preprofessional students (N=308)	IT use skills, information evaluation skills, and library skills can contribute to the development of HIL self-efficacy.

Bailey et al. 2015	Secondary analysis	Patients (N=1,077)	Patients with adequate HL were more likely to own a mobile phone or smartphone than those with low or marginal HL.

Table 2: A summary of prior studies on the relationship between health-related literacy and technology use

HIL self-efficacy and health status

HIL self-efficacy can benefit the health management of multiple populations. Individuals who lack HIL self-efficacy may avoid health-related information and therefore cannot carry out effective health management (Enwald et al. 2016). Enwald et al. (2015) found that HIL self-efficacy was negatively related to non-preference of fear appeals) while Hirvonen et al. 2015 noted an avoidance of information concerning physical activity. Hirvonen et al. (2016) found that HIL self-efficacy can promote health management among young men for aerobic fitness, muscle mass, body fat, and waist size. Yates (2013) indicated that HIL self-efficacy helps people stay informed about bodily information and discern valid health information. Eriksson-Backa et al. (2012) found that older people with higher HIL self-efficacy show a higher willingness to seek health information and manage health status. Most work explores the role of HIL self-efficacy for an individual's health management, which in turn improves their health status. However, the relationship between HIL self-efficacy and specific health status regarding factors like eyesight and insomnia among students, has rarely been explored (Shantakumari et al. 2014; Rosen et al. 2016). Eyesight is closely related to an individual's health status at the student stage (Annals of Eye Science 2018). Therefore, it is meaningful to explore whether HIL self-efficacy is potentially associated with health status (e.g., eyesight and insomnia). Staying up late is different from insomnia in the manuscript. Staying up late means that the user actively goes to sleep late, but insomnia means that the user passively finds it difficult to fall asleep. A summary of prior studies on the relationship between health-related literacy and health status is presented in Table 3.

Authors	Research Methods	Research subjects	Main findings
Wu et al. 2016	Longitudinal study	Patients (N=575)	HL self-efficacy helps to carry out better health management and can mediate the relationship between health status and age.
Suka et al. 2015	Questionnaire survey	Adults (N=1,218)	HL self-efficacy might influence health status indirectly through facilitating health management because people with high HL can get sufficient information using various sources.
Xu et al. 2019	Cross-sectional survey	Patients (N=200)	HIL self-efficacy can promote the health management of patients with permanent cystostomy by improving the ability to obtain online health information and make informed decisions.
Richter et al. 2019	Questionnaire survey	Patients (N=206)	Patients with higher HL self-efficacy reported better health status (i.e., fewer depressive symptoms) and a better quality of life.
Vozikis, Drivas, and Milioris 2014	Questionnaire survey	University students (N=1,516)	HL self-efficacy does not associate significantly with health status; however, HL associates significantly with the consumption of alcohol, smoking, and physical workouts.

Table 3: A summary of prior studies on the relationship between health-related literacy and health status

In the literature, the sample size of most previous studies is relatively small; in most cases, less than 1,000 participants. A large sample size might explain HIL self-efficacy more accurately (i.e., mean value) and avoid misleading statistics caused by outliers (Zamboni 2018). Overall, existing research conclusions on HIL self-efficacy were inconsistent. All of these reasons motivate the current study (Berkman et al. 2011; Hirvonen et al. 2016; Richter et al. 2019). Additionally, few studies have explored the association of HIL self-efficacy with subdimensions of IT use (e.g., phone screen size, mobile operating systems) and health status (e.g., long-term medications, insomnia problems). However, health-related abilities are closely related to IT use like phone use (Kaplan 2006; Matthew-Maich et al. 2016; Whitehead and Seaton 2016), computer use (Hermes et al. 2019), mHealth app use (Whitehead and Seaton 2016), and phone screen size (Matthew-Maich et al. 2016). Individuals are facing increasing health information issues related to long-term medications (Whitehead and Seaton 2016), insomnia (Moghe et al. 2014; Hermes et al. 2019), and eyesight changes (Moghe et al. 2014). Therefore, our study focuses on how HIL self-efficacy associates with subdimensions of IT use and health status.

Method

Data collection

The study was conducted at a Chinese university with a population of more than 30,000 undergraduate students. Undergraduates at the university were randomly chosen to participate in the study. Before administering the questionnaire, a pilot test was performed to strengthen the readability and the validity of the proposed instrument. The questionnaire was revised following the feedback from the pilot test. Then the final version of the questionnaire was published on the university's questionnaire platform on the official website of the Physical Education (PE) department. The university's PE department conducts sports tests for all the undergraduate students every year. When students logged into the official website of the PE department to view their results of sports tests, the questionnaire was distributed randomly according to their login time. Students participated in the survey voluntarily. Ethical approval was obtained from the corresponding author's affiliated institution. At the beginning of the questionnaire, we declared the confidentiality of our study and indicated its purpose was only for academic research. We ensured that all participants' names would not be identified in any reports of the completed study and data were analyzed at an aggregated level. At the beginning of the questionnaire, we indicated that this study was only for academic research, and the questionnaire was collected after informed consent forms were signed by students. In all, 6,948 questionnaire forms were returned. As some participants gave many consistent answers to different questions, we removed incomplete questionnaires and questionnaires with a standard deviation of less than 0.6, which indicated unreliable responses. This resulted in 6,160 valid samples retained for later data analysis.

Measures

The questionnaire measured participants' IT use, health status, socio-demographics and lifestyle features, and HIL self-efficacy. First, HIL self-efficacy was assessed by a screening tool designed by Niemelä et al. (2012). Participants were required to report on their HIL self-efficacy based on a five-statement measurement (see Appendix A). Life satisfaction has been defined as a construct representing an overall assessment of an individual's quality of life (Pavot and Diener 1993, 2008). The measurement of life satisfaction for this study was taken from the work of Pavot and Diener (2008) (see Appendix A). A 7-point Likert scale was adopted to measure the two constructs of HIL self-efficacy and life satisfaction ranging from "1-strongly disagree" to "7-strongly agree."

IT use was assessed by the hours using computers and mobile phones, the hours and frequency using mHealth apps, the platform seeking health information, the size of the phone screen, and the operating system of mobile phones. The phone screen and the operating system of the phone have been shown to affect the retrieval and utilization of health information (see Raptis et al. 2013 and Sweeney and Crestani 2006), thereby impacting HIL. Health status was examined by assessing physical health status, long-term medication use, eyesight changes, insomnia problems, and health changes. A considerable number of young people are living with chronic illness and need long-term medication (Pérez et al. 2019). Meanwhile, the relationship between HIL and specific health status such as eyesight and insomnia among students, has rarely been explored (Shantakumari et al. 2014; Rosen et al. 2016). Eyesight is closely related to an individual's health status at the student stage, especially for countries with high myopia like China, Japan, South Korea, and Singapore (World Health Organization 2017). Therefore, it is meaningful to explore whether HIL is potentially associated with health status as measured by eyesight and insomnia. In addition, age, annual family income, internet experience, the frequency of exercise, daily exercise duration, the frequency of staying up late, the frequency of health information seeking, and life satisfaction were measured to capture the respondents' socio-demographics and lifestyle features.

Statistical analysis

IBM SPSS Statistics 22.0 for Mac was utilized for statistical analyses on the 6,160 questionnaires included in the analysis. The minimum and maximum values of HIL self-efficacy are 5 and 35 points, respectively. To delve deeper, the HIL self-efficacy sum variable was separated into three classifications: low (≤15 points), basic (16–25 points), and high (≥26 points). The majority of participants had basic HIL self-efficacy (58.3%), or 3,592 participants. The number of individuals with low HIL self-efficacy was 1,266, or 20.6% of the respondents, while the number of individuals with high HIL self-efficacy was 1,302, accounting for 21.1% of the samples.

To show the sample characteristics, we computed the mean and standard deviation (S.D.) values for continuous variables. Meanwhile, we also calculated the percentages for categorical variables. The significant difference between various groups is examined by Analysis of Variance (ANOVA), Student's t-test, and Pearson correlations. To weigh the magnitude of differences in socio-demographics and lifestyle features, self-reported IT use, and self-rated health status, the size of the effect of the variables was computed using eta squared ($\eta 2$), which is an effect size measure for ANOVA results. Based on the recommendation of Cohen (1988), $\eta 2=0.02$ represents a small effect size, $\eta 2=0.13$ represents a medium effect size, and $\eta 2=0.26$ represents a large effect size.

Results

Sample characteristics

To ensure the reliability of our measuring variable, Cronbach's alpha (α) was applied to weigh the internal consistency of the HIL self-efficacy scale. The α value for HIL self-efficacy was 0.925 above the threshold of 0.7 (Hays and Revicki 2005). The mean and standard deviation values of HIL self-efficacy are 20.9 and 6.9, respectively. In our survey, participants consisted of 3,294 (53.5%) males and 2,866 (46.5%) females, mainly between 19 and 24 years old (95.2%). The breakdown of annual household income showed that 24.7% of participants made less than 20,000 ($2,982) while 23.7% made somewhere between 20,000-50,000 local currency ($2,982-$7,455). Most participants (79.8%) had internet experience of over three years. Some of the participants sought health information less than once a week (36.9%). More than half of the participants performed sports 1-2 times a week (53.1%). Less than half of the participants exercised 0.5-1.0 hour every day (42.8%). About one-third of the participants stayed up late 1-2 times a week (35.6%). Table 4 shows specific socio-demographics and lifestyle features.

Variable (N)		N=6160								
		Mean (S.D.)	Low HIL self-efficacy N (%)	Basic HIL self-efficacy N (%)	High HIL self-efficacy N (%)	Total N (%)	pa	pb	Pearson correlation	Effect sizes η2
Gender	male	20.4(7.2)	775(12.6)	1872(30.4)	647(10.5)	3294(53.5)	/	<0.001	0.075***	/
	female	21.5(6.5)	491(8.0)	1720(27.9)	655(10.6)	2866(46.5)				
Age	≤18	20.0(6.7)	31(0.5)	78(1.3)	22(0.3)	131(2.1)	0.002	/	-0.019 Ns.	0.002
	19	21.2(6.4)	107(1.7)	394(6.4)	130(2.1)	631(10.2)				
	20	21.2(6.9)	199(3.2)	549(8.9)	231(3.8)	979(15.9)				
	21	20.8(7.0)	242(3.9)	686(11.1)	230(3.7)	1158(18.8)				
	22	21.1(7.0)	248(4.0)	730(11.9)	289(4.7)	1267(20.6)				
	23	21.0(6.9)	261(4.2)	755(12.3)	269(4.4)	1285(20.9)				
	24	20.5(7.1)	135(2.2)	299(4.9)	107(1.7)	541(8.8)				
	≥25	19.6(6.5)	43(0.7)	101(1.6)	24(0.4)	168(2.7)				
Annual family income in local currency (US dollars)	< 20,000 ($2,982)	19.7(7.5)	425(6.9)	820(13.3)	277(4.5)	1522(24.7)	<0.001	/	0.107***	0.013
	20,000-50,000 ($2,982-$7,455)	20.8(6.3)	286(4.6)	903(14.65)	272(4.4)	1461(23.7)				
	50,000-100,000 ($7,455-$14,910)	21.4(6.2)	234(3.8)	893(14.5)	297(4.8)	1424(23.1)				
	100,000-200,000 ($14,910-$29,820)	21.8(6.7)	199(3.2)	685(11.1)	296(4.8)	1180(19.2)				
	> 200,000 ($29,820)	21.7(7.9)	122(2.0)	291(4.7)	160(2.6)	573(9.3)				
Internet experience	< 0.5 year	17.1(9.9)	118(1.9)	91(1.5)	46(0.7)	255(4.1)	<0.001	/	0.119***	0.017
	0.5 year-1 year	20.0(6.9)	85(1.4)	176(2.9)	50(0.8)	311(5.1)				
	1 year-2 years	20.0(7.0)	67(1.1)	162(2.6)	47(0.8)	276(4.5)				
	2 years-3 years	20.6(6.1)	79(1.3)	250(4.0)	73(1.2)	402(6.5)				
	>3 years	21.3(6.7)	917(14.9)	2913(47.3)	1086(17.6)	4916(79.8)				
The frequency of health information seeking	< once a week	19.3(7.1)	636(10.3)	1303(21.2)	331(5.4)	2270(36.9)	<0.001	/	0.181***	0.038
	1-2 times a week	21.3(6.1)	328(5.3)	1194(19.4)	406(6.6)	1928(31.3)				
	3-5 times a week	22.4(5.9)	73(1.2)	364(5.9)	151(2.45)	588(9.5)				
	almost every day	22.5(7.3)	229(3.7)	731(11.9)	414(6.7)	1374(22.3)				
The frequency of exercise	never	17.6(8.4)	256(4.1)	307(5.0)	84(1.4)	647(10.5)	<0.001	/	0.171***	0.038
	1-2 times a week	20.8(6.4)	655(10.6)	1981(32.15)	636(10.3)	3272(53.1)				

	3-5 times a week	21.8(6.6)	302(4.9)	1116(18.1)	465(7.6)	1883(30.6)				
	6-7 times a week	23.0(7.4)	53(0.9)	188(3.1)	117(1.9)	358(5.8)				
Daily exercise duration	< 0.5 hour	20.0(7.0)	658(10.7)	1519(24.7)	456(7.4)	2633(42.8)	<0.001	/	0.119***	0.016
	0.5 hour-1 hour	21.5(6.5)	450(7.3)	1588(25.8)	599(9.7)	2637(42.8)				
	1 hour-2 hours	21.8(6.7)	131(2.1)	439(7.1)	204(3.3)	774(12.5)				
	>3 hours	23.3(9.4)	27(0.4)	46(0.8)	43(0.7)	116(1.9)				
The frequency of staying up late	never	20.5(7.1)	151(2.4)	387(6.3)	123(2.0)	661(10.7)	<0.001	/	-0.033**	0.005
	1-2 times a month	21.2(6.2)	248(4.0)	900(14.6)	291(4.7)	1439(23.4)				
	1-2 times a week	21.3(6.5)	394(6.4)	1313(21.3)	485(7.9)	2192(35.6)				
	3-5 times a week	20.8(6.8)	279(4.5)	718(11.7)	262(4.2)	1259(20.4)				
	6-7 times a week	19.6(9.2)	194(3.2)	274(4.4)	141(2.3)	609(9.9)				
Life satisfaction	extremely dissatisfied with life (5-9)	10.5(7.9)	273(4.5)	76(1.2)	20(0.3)	369(6.0)	<0.001	/	0.512***	0.291
	dissatisfied with life (10-14)		207(3.4)	281(4.6)	48(0.7)	536(8.7)				
	slightly dissatisfied with life (15-19)		372(6.0)	853(13.8)	159(2.5)	1384(22.5)				
	neutral (20)		115(1.9)	676(11.0)	82(1.3)	873(14.2)				
	slightly satisfied with life (21-25)		157(2.5)	1126(18.3)	367(6.0)	1650(26.8)				
	satisfied with life (26-30)		79(1.3)	425(6.9)	337(5.4)	841(13.6)				
	extremely satisfied with life (31-35)		63(1.0)	155(2.5)	289(4.7)	507(8.2)				

Note: [a] Analysis of Variance; [b] t-test; *p<0.05, **p<0.01, ***p<0.001

Table 4. Socio-demographics and lifestyle features of the study population (n=6160) across the different categories of HIL self-efficacy

As for IT use, most of the participants used mobile phones for 1-3 hours every day ($M_{HIL\ self\text{-}efficacy}$=21.4, S.D.=6.2), and most of the participants also used computers for 1-3 hours every day ($M_{HIL\ self\text{-}efficacy}$=21.4, S.D.=6.2). Participants who played on mobile phones before going to bedtime for less than 0.5 hour had the highest HIL self-efficacy ($M_{HIL\ self\text{-}efficacy}$=21.4, S.D.=6.5). Participants who used mHealth apps 6-7 times every week demonstrated the highest HIL self-efficacy ($M_{HIL\ self\text{-}efficacy}$=23.8, S.D.=6.6). Those who used mHealth apps for more than 2 hours every week showed the highest HIL self-efficacy ($M_{HIL\ self\text{-}efficacy}$=24.3, S.D.=6.8). Students who preferred to seek health information through mobile platforms ($M_{HIL\ self\text{-}efficacy}$=21.5, S.D.=6.2) had higher HIL self-efficacy than participants who preferred PC platforms ($M_{HIL\ self\text{-}efficacy}$=19.3, S.D. =8.6). As the size of the phone screen increased, the value of HIL self-efficacy for participants kept increasing. Most participants' phone screen sizes ranged from 5 to 6 inches ($M_{HIL\ self\text{-}efficacy}$=21.7, S.D.=6.6). The average HIL self-efficacy level of iOS users ($M_{HIL\ self\text{-}efficacy}$=20.9, S.D.=7.5) was the same as that of Android users ($M_{HIL\ self\text{-}efficacy}$=20.9, S.D.=6.4). Table 5 presents the mean and standard deviation values of the undergraduates' IT use.

Variable (N)		N=6160								
		Mean (S.D.)	Low HIL self-efficacy N (%)	Basic HIL self-efficacy N (%)	High HIL self-efficacy N (%)	Total N (%)	pa	pb	Pearson correlation	Effect sizes η2
Daily duration of using mobile phones	<0.5 hour	16.1(10.8)	308(5.0)	998(16.2)	373(6.0)	1679(27.2)	<0.001	/	0.107***	0.028
	0.5 hour-1 hour	20.3(6.8)	327(5.3)	1069(17.4)	365(5.9)	1761(28.6)				
	1 hour-3 hours	21.4(6.2)	312(5.1)	1116(18.1)	399(6.5)	1827(29.7)				
	3 hours-5 hours	21.0(6.3)	161(2.6)	322(5.2)	107(1.7)	590(9.6)				
	>5 hours	21.4(6.9)	158(2.6)	87(1.4)	58(0.9)	303(4.9)				
Daily duration of using computers	<0.5 hour	19.7(8.4)	256(4.15)	475(7.7)	196(3.2)	927(15.0)	<0.001	/	0.039**	0.007
	0.5 hour-1 hour	21.1(6.4)	297(4.8)	842(13.7)	315(5.1)	1454(23.6)				
	1 hour-3 hours	21.4(6.2)	339(5.5)	1264(20.5)	436(7.1)	2039(33.1)				
	3 hours-5 hours	20.8(6.6)	212(3.4)	573(9.3)	194(3.2)	979(15.9)				
	>5 hours	21.0(7.5)	162(2.6)	438(7.1)	161(2.6)	761(12.4)				
The duration of using mobile phones for entertainment before going to bedtime	never	17.4(10.4)	188(3.0)	152(2.5)	88(1.4)	428(6.9)	<0.001	/	0.056***	0.199
	<0.5 hour	21.4(6.5)	334(5.4)	991(16.1)	394(6.4)	1719(27.9)				
	0.5 hour-1 hours	21.1(6.2)	439(7.1)	1548(25.1)	507(8.3)	2494(40.5)				
	1 hours-2 hours	20.9(6.5)	205(3.3)	661(10.8)	204(3.3)	1070(17.4)				
	>2 hours	21.3(7.8)	100(1.6)	240(3.9)	109(1.8)	449(7.3)				
The weekly frequency of using mHealth apps	never	19.5(7.4)	741(12.0)	1478(24.0)	457(7.4)	2676(43.4)	<0.001	/	0.217***	0.048
	less than once a week	20.7(6.1)	289(4.7)	841(13.7)	235(3.8)	1365(22.2)				
	1-2 times a week	22.3(5.7)	119(2.0)	642(10.4)	240(3.9)	1001(16.3)				
	3-5 times a week	22.6(6.1)	56(0.9)	234(3.8)	129(2.1)	419(6.8)				

	6-7 times a week	23.8(6.6)	61(1.0)	397(6.4)	241(3.9)	699(11.3)				
The weekly duration of using mHealth apps	<0.5 hour	20.2(7.1)	886(14.4)	2154(35.0)	709(11.5)	3749(60.9)	<0.001	/	0.170***	0.029
	0.5 hour-1 hours	21.3(6.1)	281(4.6)	865(14.0)	290(4.7)	1436(23.3)				
	1 hours-2 hours	22.5(6.2)	64(1.0)	345(5.6)	141(2.3)	550(8.9)				
	>2 hours	24.3(6.8)	35(0.6)	228(3.7)	162(2.6)	425(6.9)				
Which way do you prefer to seek health information	PC platforms	19.3(8.6)	476(7.7)	728(11.8)	305(4.95)	1509(24.5)	/	<0.001	0.136***	/
	Mobile platforms	21.5(6.2)	790(12.8)	2864(46.5)	997(16.2)	4651(75.5)				
The size of the phone screen	<3 inches	14.4(10.3)	165(2.7)	81(1.3)	39(0.6)	285(4.6)	<0.001	/	0.113***	0.050
	3 inches-4 inches	20.1(6.3)	222(3.6)	473(7.7)	131(2.1)	826(13.4)				
	4 inches-5 inches	21.4(6.3)	350(5.7)	1261(20.5)	414(6.7)	2025(32.9)				
	5 inches-6 inches	21.7(6.6)	353(5.8)	1203(19.5)	525(8.5)	2081(33.8)				
	>6 inches	22.0(7.5)	33(0.6)	112(1.8)	58(0.9)	203(3.3)				
	I don't know	20.7(6.6)	143(2.3)	462(7.5)	135(2.2)	740(12.0)				
The operating system of mobile phones	iOS	20.9(7.5)	480(7.8)	1216(19.7)	483(7.8)	2179(35.4)	NS (0.250)	/	0.012 NS	/
	Android	20.9(6.4)	745(12.1)	2254(36.6)	768(12.4)	3767(61.1)				
	Windows Phone	22.1(6.9)	20(0.3)	64(1.1)	26(0.4)	110(1.8)				
	Symbian	22.7(6.6)	2(0.0)	11(0.2)	5(0.1)	18(0.3)				
	Blackberry	22.8(8.0)	2(0.0)	7(0.1)	5(0.1)	14(0.2)				
	Other operating systems	18.8(9.4)	11(0.2)	15(0.2)	5(0.1)	31(0.5)				
	I don't know	22.4(8.4)	6(0.1)	25(0.4)	10(0.2)	41(0.7)				

Note: [a] Analysis of Variance; [b] t-test; *p<0.05, **p<0.01, ***p<0.001

Table 5: Self-reported IT use across the different categories of HIL self-efficacy among undergraduates (n=6160)

As for health status, participants' HIL self-efficacy was positively related to physical health status. Participants who reported their physical health status was good owned the highest HIL self-efficacy ($M_{HIL\ self\text{-}efficacy}$=21.5, S.D.=7.6). Participants who did not need long-term medication had higher HIL self-efficacy ($M_{HIL\ self\text{-}efficacy}$=21.1, S.D.=6.7) than those who needed long-term medication ($M_{HIL\ self\text{-}efficacy}$=18.5, S.D. =8.8). Most participants rarely had insomnia problems ($M_{HIL\ self\text{-}efficacy}$=21.1, S.D.=6.4). The eyesight of most participants remained stable ($M_{HIL\ self\text{-}efficacy}$=21.2, S.D.=6.6). The same applies to changes in health status. The health status of most participants kept stable over the past six months ($M_{HIL\ self\text{-}efficacy}$=20.9, S.D.=6.5). Table 6 presents the mean and standard deviation values of health status.

Variable (N)		N=6160								
		Mean (S.D.)	Low HIL self-efficacy N (%)	High HIL self-efficacy N (%)	High HIL self-efficacy N (%)	Total N (%)	pa	pb	Pearson correlation	Effect sizes η2
Physical health status	Poor	19.2(7.1)	105(1.7)	202(3.3)	52(0.8)	359(5.8)	<0.001	/	0.083***	0.007
	Normal	20.7(6.2)	653(10.6)	2042(33.2)	574(9.3)	3269(53.1)				
	Good	21.5(7.6)	508(8.2)	1348(21.9)	676(11.0)	2532(41.1)				
Taking long-term medication due to illness	Yes	18.5(8.8)	119(1.9)	147(2.4)	59(1.0)	325(5.3)	/	<0.001	0.084***	/
	No	21.1(6.7)	1147(18.6)	3445(55.9)	1243(20.2)	5835(94.7)				
Instances of insomnia	often	20.4(7.4)	78(1.3)	197(3.2)	58(0.9)	333(5.4)	NS (0.192)	/	0.002 NS	/
	occasionally	21.0(6.2)	333(5.4)	1076(17.5)	329(5.3)	1738(28.2)				
	rarely	21.1(6.4)	524(8.5)	1553(25.2)	570(9.3)	2647(43.0)				
	never	20.8(8.2)	331(5.4)	766(12.4)	345(5.6)	1442(23.4)				
Is your eyesight better or worse than six months ago	worse	20.9(6.6)	511(8.3)	1533(24.9)	514(8.3)	2558(41.5)	<0.001	/	0.026***	0.008
	no change	21.2(6.6)	618(10.0)	1933(31.4)	705(11.5)	3256(52.9)				
	better	18.5(10.3)	137(2.2)	126(2.0)	83(1.4)	346(5.6)				
Do you think you are healthier than six months ago	unhealthier	20.9(6.6)	309(5.0)	907(14.7)	291(4.7)	1507(24.5)	NS (0.784)	/	0.009 NS	/
	no change	20.9(6.5)	694(11.3)	2115(34.3)	701(11.4)	3510(57.0)				
	healthier	21.1(8.3)	264(4.3)	569(9.2)	310(5.0)	1143(18.5)				

Note: [a] Analysis of Variance; [b] t-test; *p<0.05, **p<0.01, ***p<0.001

Table 6: Self-reported health status across the different categories of HIL self-efficacy among undergraduates (n=6160)

The relationship between HIL self-efficacy and socio-demographics and lifestyle features

ANOVA, t-test, and Pearson correlations were conducted to test the relationship between HIL self-efficacy and the study's included socio-demographic and lifestyle measures. Most of the socio-demographic and lifestyle features except age in our research were significantly associated with HIL self-efficacy (see Table 4). HIL self-efficacy was significantly and positively associated with gender ($r=0.075^{***}$), and females had higher HIL self-efficacy scores than males ($p<0.001^{***}$). HIL self-efficacy was insignificantly associated with age ($r=-0.019$, n.s.). HIL self-efficacy showed a tendency to increase first and then decrease as an individual's age increased ($p=0.041^{*}$). HIL self-efficacy was positively associated with annual family income ($p<0.001^{***}$; $r=0.107^{***}$). HIL self-efficacy ($p<0.001^{***}$; $r=0.119^{***}$) was significantly and positively related to internet experience. HIL self-efficacy exhibited a positive correlation with health information seeking ($p<0.001^{***}$; $r=0.181^{***}$). HIL self-efficacy was significantly and positively related to frequency of exercise ($p<0.001^{***}$; $r=0.171^{***}$). HIL self-efficacy had a strong positive correlation with daily exercise duration ($p<0.001^{***}$; $r=0.119^{***}$). HIL self-efficacy was significantly and negatively related to the frequency of staying up ($p<0.001^{***}$; $r=-0.033^{**}$).

Based on effect sizes in Cohen (1988), small effect sizes were observed for age ($\eta2=0.002$), annual family income ($\eta2=0.013$), internet experience ($\eta2=0.017$), daily exercise duration ($\eta2=0.016$), and the frequency of staying up late ($\eta2=0.005$). Small to medium effect sizes were observed for the frequency of health information seeking ($\eta2=0.038$) and the frequency of exercise ($\eta2=0.038$).

The Cronbach's alpha (ɑ) value for life satisfaction was 0.926, which rests above the threshold of 0.7 (Hays and Revicki 2005). The minimum and maximum value of life satisfaction were 5 and 35, respectively. The mean value of life satisfaction was 20.9 (S.D.=7.0). As is shown in Table 4, life satisfaction was significantly and positively related to HIL self-efficacy ($F=83.769$, $p<0.001^{***}$). A large effect size was observed for life satisfaction ($\eta2=0.291$). The details are shown in Table 4.

The relationship between HIL self-efficacy and IT use

In addition to the operating system of mobile phones, other measurement items related to IT use were significantly associated with HIL self-efficacy (see Table 5). The results of analyses showed that HIL self-efficacy was positively associated with daily duration of using mobile phones ($p<0.001^{***}$; $r=0.107^{***}$), daily duration of using computers ($p<0.001^{***}$; $r=0.039^{***}$), the duration playing mobile phones ($p<0.001^{***}$; $r=0.056^{***}$), the weekly frequency of using mHealth apps ($p<0.001^{***}$; $r=0.217^{***}$), the weekly duration of using mHealth apps ($p<0.001^{***}$; $r=0.170^{***}$), the platform preference for health information seeking ($p<0.001^{***}$; $r=0.136^{***}$), and the size of the phone screen ($p<0.001^{***}$; $r=0.113^{***}$), but not the operating system of mobile phones ($p=0.110$ Ns.; $r=0.012$ Ns.).

Based on the work of Cohen (1988), a small effect size was observed for the daily duration of using computers ($\eta2=0.007$). Small to medium effect sizes were observed for the daily duration of using mobile phones ($\eta2=0.028$), the weekly frequency of using mHealth apps (η2=0.048), the weekly duration of using mHealth apps (η2=0.029), and the size of the phone screen (η2=0.050). Medium to large effect size was observed for the duration of playing mobile phones before sleeping (η2=0.199). The details are shown in Table 5.

The relationship between HIL self-efficacy and health status

For health status, HIL self-efficacy had insignificant correlations with insomnia problems and health change (see Table 6). Nevertheless, HIL self-efficacy significantly and positively correlated with physical health status ($p<0.001$***; $r=0.083$***). HIL self-efficacy was significantly related to long-term medication. People who did not need long-term medication due to illness had higher HIL self-efficacy than those on medication ($p<0.001$***; $r=0.084$***). HIL self-efficacy showed a significant correlation with better or worse eyesight, and people with the highest HIL self-efficacy had stable eyesight ($p<0.001$***; $r=0.026$***). Based on Cohen (1988), small effect sizes were observed for physical health status (η2=0.007) and eyesight change (η2=0.008). The details are shown in Table 6.

Discussion

The prevalence of the internet has profoundly changed the ways people obtain health information. HIL self-efficacy plays a crucial role in the acquisition of health information in people's daily life. By examining the correlation of HIL self-efficacy with socio-demographics and lifestyle features, IT use, and health status, our study contributes new insights on improving HIL self-efficacy and reducing the IT dark side, which refers to the various adverse consequences introduced by IT use like mobile phone and computer use (Tarafdar, Gupta, and Turel 2013).

The results showed that most of the socio-demographics and lifestyle features except age significantly correlated with HIL self-efficacy among undergraduates, such as gender, age, annual family income, internet experience, and life satisfaction, as is shown in Table 4. Female undergraduates had higher HIL self-efficacy than male undergraduates. This result is consistent with prior studies, which indicate females have higher HIL self-efficacy and are more willing to search and obtain health information from various sources (Enwald et al. 2016; Niemelä et al. 2012). Johnston et al. (2008) showed that men, in general, had less motivation than women to boost and keep good health status. One plausible reason could be that men's utilization of public health services is lower than that of women (Johnston et al. 2008). Among socio-demographics and lifestyle features, age had a minimal correlation with HIL self-efficacy implying that HIL self-efficacy remains relatively stable at the undergraduate level. Annual family income positively relates to HIL self-efficacy. The results are in line with previous research that indicates information-seeking behaviour changes depending on socio-economic status (Suri et al. 2014). People with better family conditions have more opportunities to receive health education, which enhances HIL self-efficacy. As mentioned by Hirvonen et al. (2016), family members' occupation can significantly affect HIL self-efficacy. High-income families have more channels to obtain high-quality health information. Internet experience is positively associated with HIL self-efficacy.

Rich internet experience helps individuals to locate better online health information needed (Banas 2008).

HIL self-efficacy was positively related to the frequency of exercise and daily exercise duration. Engaging in physical activity is one of the most important ways to enhance general well-being including physical, mental, and emotional well-being (Li, Lu, and Wang 2009). It has been reported that participating in daily physical activities can reduce lifestyle-related disease risks related to weight and chronic diseases (Warburton, Nicol, and Bredin 2006). Moreover, HIL self-efficacy was also positively related to the frequency of staying up late. Sleep plays a major part in body functioning (Ziporyn et al. 2017). Staying up late can lead to decreased sleep quality. Poor sleep habits negatively affect an individual's physical and mental health alike (Pilcher, Ginter, and Sadowsky 1997; Wong et al. 2013; Majeno et al. 2018). Furthermore, high levels of anxiety, stress, and depression were significantly associated with decreased sleep quality (Zochil and Thorsteinsson 2017). Undergraduates who stayed up late frequently tend to have lower HIL self-efficacy. Individuals evaluate their life satisfaction by appealing to preset criteria (i.e., health satisfaction) they have designed for themselves. HIL self-efficacy had a strong positive correlation with life satisfaction. One possible reason is that individuals with high HIL self-efficacy report a higher level of health, which is positively related to life satisfaction (Ernsting et al. 2017; Hirvonen et al. 2016). Therefore, undergraduates should improve their abilities to manage their health status by raising HIL self-efficacy and therefore improving their life satisfaction (Dunn and Xie 2017).

IT use provides not only benefits to individuals (Rockmann and Gewald 2017) but also numerous adverse outcomes (Tarafdar, Gupta, and Turel 2013). As is shown in Table 5, HIL self-efficacy positively correlated with the daily duration of using mobile phones and computers. As duration increases, HIL self-efficacy increases first and then stays the same or decreases. We argue that there are a couple of possible reasons for our finding. On the one hand, because HIL self-efficacy refers to the ability to seek and obtain health information online (Hirvonen et al. 2016), the operating duration of mobile phones and computers can improve the proficiency of searching health information. On the other hand, excessive daily IT use will lead to decreasing levels of physical activity or increasing levels of sedentary activity and therefore can affect adolescents' physical well-being, e.g., through possible weight gain (Subrahmanyam and Šmahel 2011). Higher HIL self-efficacy is negatively associated with long-term mobile or computer use. Likewise, the duration of playing mobile phones before sleeping has the strongest correlation with HIL self-efficacy. HIL self-efficacy also increases first and then stays the same or decreases as duration increases. Certain IT use can increase information retrieval capabilities, thereby positively associating with HIL self-efficacy. However, IT overuse to be a cause of unfavorable physical and mental wellbeing. Specifically, excessive use of mobile phones before bedtime might negatively impact sleep and consequently affect physical and mental wellbeing (Yildirim and Correia 2015).

HIL self-efficacy was positively related to the weekly frequency and duration of using mHealth apps. Use of the apps differed from the usage of mobile phones and computers mentioned above. As the frequency and duration of using mHealth apps increased, users' HIL self-efficacy kept increasing. Consumers increasingly use mHealth apps for self-monitoring (Gill, Kamath, and Gill 2012). The frequency and duration of using mHealth apps will increase users' proficiency for searching and evaluating health information and thus is positively associated with HIL self-efficacy. The HIL self-efficacy of undergraduates who preferred to search for health information through mobile phones was higher than those who tended to seek health information through PC platforms. There are several possible reasons driving this finding. Firstly, the unequal acquisition of health information has caused many young adults with finite resources to be more susceptible to health consequences, especially in developing countries. Mobile internet provides unique chances to solve the issue owing to the popularity of mobile phones among young adults and the high volume of these devices. Secondly, according to the *Mobile Healthcare Market Research Report* (iiMedia Research 2020), the number of users in the mobile healthcare market in China has grown steadily throughout the world. The mobile health market accounted for $46,048 million in 2019 and is expected to hit $230,419 million by 2027 (Allied Market Research 2020). Users prefer to obtain health information through mobile (Allied Market Research 2020), and our findings point out that mobile phone use has a greater impact on HIL self-efficacy than computer use.

It is interesting to find that the phone screen size was significantly related to HIL self-efficacy. The HIL self-efficacy of undergraduates positively correlated with the mobile screen size. Large screens are associated with better usability including the reduced effort of use and improved task performance (Sweeney and Crestani 2006; Maniar et al. 2008). The larger mobile screen can help users browse more health information at the same time and reduce the visual burden that occurs during the health information search process. Screen size can be incorporated into the design of mHealth apps. HIL self-efficacy was not significantly associated with the operating system of mobile phones. With the continuous optimization of operating systems, the user experience tends to be homogeneous. Mobile phones with different operating systems have less impact on health information searches.

HIL self-efficacy was significantly and positively related to physical health status. Undergraduates with higher HIL self-efficacy have an increased ability to obtain and utilize health information and thus keeping good health. Furthermore, HIL self-efficacy was also significantly associated with long-term medication. The ability to seek, comprehend, assess, and utilize health information may help users maintain good health and reduce dependence on medicines. HIL self-efficacy was significantly related to better or worse eyesight. Participants with unchanged eyesight (HIL self-efficacy=21.2) were reported to have the highest average HIL self-efficacy, followed by participants with worse eyesight (HIL self-efficacy=20.9) and better eyesight (HIL self-efficacy=18.5) in the past six months. Two reasons might explain the findings. First, higher HIL self-efficacy helps users maintain eyesight stability. Second, HIL self-efficacy only plays an indirect role in the eyesight change. Eyesight changes are mainly due to habits associated with eye use and strain (Shantakumari et al. 2014). For instance, recent years reveal a reported upsurge in IT-related health problems among university students such as tired eyes, a burning sensation in the eyes, and headaches (Shantakumari et al. 2014).

It is interesting to find that health change and insomnia problems were insignificantly related to HIL self-efficacy. We argue that HIL self-efficacy has an indirect relationship with health change and insomnia. Sleep-related HL, which can increase awareness of and access to evidence-based therapy for insomnia, can help individuals deal with insomnia (Liu et al. 2016). Users with a higher HIL self-efficacy could obtain the needed health information more efficiently and thus might get more effective help regarding health issues such as insomnia.

Implications

This study contributes to new insights in understanding the relevance regarding HIL self-efficacy and IT use and health status based on a population-based sample of undergraduates. Our findings promote the stream of HIL self-efficacy research on two counts. On the theoretical front, this study investigates the influencing factors of HIL self-efficacy of undergraduates from the perspective of IT use and health status. Based on thousands of questionnaires, IT use may act as a potential contributor to the formation of HIL self-efficacy abilities, which in turn promotes an individual's health status. Additionally, we emphasized the IT dark side among undergraduates suggesting that IT use in the formation of HIL self-efficacy is complex and more research on the IT dark side is needed. This study highlighted that, alongside the numerous benefits that IT innovations afford, there are various adverse consequences on physical and psychological well-being caused by IT use. Thus, this study provides a useful reference for future research.

On the practical front, our research provides suggestions to help college students develop a healthy, resilient lifestyle (Latham and Gross 2011; Ishimura, Howard, and Moukdad 2007). Specifically, our results offer a cautionary lesson to promote thinking about HIL self-efficacy and health status in a digital environment. Smartphones and other devices are extensively used in every aspect of our daily lives. On the one hand, students should be encouraged to make full use of IT, especially mHealth apps, to enhance the search and utilization of health information. On the other hand, young people should avoid the adverse impacts of IT use on health status (Fu et al. 2020) such as staying up to use IT devices. Meanwhile, college students can be advised to strengthen the frequency and duration of physical exercise and the HIL self-efficacy score could be used as a foundation for health counseling (Hirvonen et al. 2016). For the health management department in educational institutions, undergraduates with different HIL self-efficacy standards and IT use habits ought to be considered when developing e-health services (Enwald et al. 2017). The health management department should pay special attention to college students who need long-term medication. We believe that university librarians may contribute to helping students improve their HIL as well. For example, librarians could conduct relevant IT courses for teaching students with different health statuses, socio-demographics, and lifestyle features, how to search for and evaluate credible online and offline health information.

Limitations and Future Study

This study has a few limitations. First, only three sets of factors influencing HIL self-efficacy of undergraduates were considered in our study, including socio-demographics and lifestyle features, IT use, and health status. Interesting findings may be achieved by including more factors in future studies such as individuals' social capital and learning abilities. Second, this was an empirical study based on self-reported questionnaire survey data. Future research should test the universality of the findings. Face-to-face interviews that elicit students' explanations for staying up and smartphone overuse could also facilitate further interpretation. Third, the study is based on examining undergraduates at a university. Cautions should be taken when extending the research findings to students from other backgrounds. Meanwhile, since the population of this study is undergraduate students who are generally young, cautions should also be taken when extending the research findings to other age groups. Moreover, the results may serve as a basis for health information tailoring, counseling, and services, especially among young people or college students. More meaningful conclusions could be drawn by incorporating more populations into the analysis. The official website does not calculate the total number of questionnaires issued, so the response rate cannot be calculated.

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Construct	Item
HIL self-efficacy	1. I like to get health information from a variety of sources.
	2. I know where to seek health information.
	3. It is easy to assess the reliability of health information in printed sources (magazines and books).
	4. It is easy to assess the reliability of health information on the Internet.
	5. I apply health-related information to my own life and/or that of people close to me.
Life satisfaction	1. In most ways, my life is close to my ideal.
	2. The conditions of my life are excellent.
	3. I am satisfied with my life.
	4. So far, I have gotten the important things I want in life.
	5. If I could live my life over, I would change almost nothing.

Appendix A: The measurement of key variables