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Digital health literacy and online information-seeking behavior of Lebanese university students in the time of the COVID-19 pandemic and infodemic

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Abstract
This cross-sectional study evaluated digital health literacy (DHL) and web-based information-seeking behavior of Lebanese university students. A total of 602 students (60.1% female), 21.5 years (±4.1), participated in May-August 2020 in an online survey. We found that 76.2% used the Internet, in the past month, for COVID-19-related information. Those with a chronic health impairment more often had limited DHL for adding self-generated content (OR=0.448; 95 % CI=0.185, 1.085) and for determining relevance (OR=0.276; 95 %CI=0.114-0.670). Students in graduate studies had higher odds of having sufficient DHL for adding self-generated content (OR=2.328; 95 % CI=1.104, 4.909) and evaluating reliability (OR=2.318; 95 % CI=1.149, 4.679). Users of official sources of information had higher odds (OR=1.665; 95 % CI=1.065, 2.605) of having sufficient DHL for adding self-generated content. Regular users of social media had lower odds (OR=0.576; 95 % CI=0.358, 0.928) of having sufficient DHL for evaluating reliability. Self-efficacy, in this case one's potential to accomplish a search for reliable health information and adopt it in daily life, could improve with DHL. As such, health education needs to strengthen DHL competencies in university students, particularly among undergraduates, those relying on social media, and those with an existing health impairment.

Keywords
Digital health literacy, Lebanon, information-seeking behaviors, sources of health information, COVID-19

Introduction

As of August 2022, there have been over 570 million reported cases of, and over 6 million deaths worldwide due to, COVID-19 (WHO, 2022). Lebanon was no exception, with its first case in February 2020 (UNICEF Lebanon, 2020). Several measures were adopted to slow the spread of the virus, namely social distancing, closure of schools and airport, restriction on public gatherings and total lockdown. Despite these efforts, a resurgence of COVID-19 is reported reaching 6,000 daily cases in January 2021 (WHO, 2023).

Alongside the COVID-19 pandemic, an infodemic travelled faster than the virus (Cuan-Baltazar et al., 2020). The World Health Organization defines an infodemic as 'too much information including false or misleading information in digital and physical environments during a disease outbreak' (WHO, 2022). Both traditional mass media and social media contributed to the spread of misinformation (Zarocostas, 2020). In 2017, although Ebola-related misinformation was widespread on Instagram and Twitter, it was barely addressed by public health authorities (Guidry et al., 2017). YouTube was also a noteworthy source of misinformation during past pandemics involving H1N1, Ebola and Zika (Bora et al., 2018; Pandey et al., 2010; Pathak et al., 2015). Similarly, in the time of the COVID-19 pandemic, the infodemic was driven by an unprecedented amount of misinformation on social media (Cinelli et al, 2020a), along with a tendency for Internet users to acquire information that adhered to their worldviews (Bessi et al., 2015; Cinelli et al, 2020b). This abundance of misinformation on the Internet, combined with a lack of critical judgment, led to worrisome outcomes, notably panic shopping, stockpiling of medical supplies or drugs, and taking medicine without prescription (Cuan-Baltazar et al., 2020; Hou et al., 2020). It not only prompted engagement in inadequate behaviors, but also discouraged the adoption of evidence-based preventive measures such as social distancing (Kim & Tandoc, 2022).

A potential source of mistrust may have stemmed from the marked speed in changes in COVID-19-related recommendations and guidelines (Eysenbach, 2020), which depended on facts at the prime stages of the pandemic known as 'best evidence at the time' or 'BETs'. This meant that people could not keep up with the fast-paced changes in information. They also lacked mechanisms for fact-checking, which made it hard to discriminate between reliable and questionable knowledge (Augustaitis et al., 2021). The use of medical jargon may have also affected the public's comprehension of online content (Wei et al., 2016) and negatively influenced online information-seeking behavior. Moreover, a meta-analysis reported a positive correlation between health anxiety and online health information-seeking (McMullan et al., 2019).

The COVID-19 pandemic revealed existing health inequities by disproportionally hitting vulnerable populations such as the poor, the elderly and minority groups, mainly due to poor access to care and a higher prevalence of chronic conditions (Shadmi et al., 2020). These same groups may be failing to benefit from digital transformations that have the capacity to positively influence health (van Kessel et al., 2022a). Digital health innovations that provided continued access to critical health services whilst preserving social distancing and limiting exposure to the virus were inaccessible to these groups because of the digital divide (Crawford & Serhal, 2020). In fact, it has been reported that individuals who were more likely to seek health information online were young, of high educational and income levels, female, and belonging to the racial majority of any given society (Wang et al., 2021). This digital divide is believed to not only affect access to online health information but also to the mental grasp of the information retrieved (Bodie & Dutta, 2008). This may lead to unintended health consequences if mobile devices and the Internet were relied upon to halt the infodemic.

In addition to digital literacy, health literacy and digital health literacy have been proposed as fundamental skills to develop if people are to benefit from digital media as a source of health information and a means to sustain personal wellbeing (van Kessel, 2022b). Health literacy is defined as 'the degree to which individuals have the capacity to obtain, process, and understand basic health information and services needed to make appropriate health decisions' (IOM, 2004). Digital health literacy (DHL) determines how easily individuals make use of web-based information. It consists of a set of competencies that include operational and navigation skills, information searching, evaluation of reliability, determination of information relevance, addition of content, and protection of privacy (van der Vaart & Drossaert, 2017). DHL improves adherence to a healthy lifestyle and empowers people to make their own health decisions, ultimately improving health outcomes (Choukou et al., 2022). At the population level, this measure has shown that digitization of healthcare has led vulnerable subgroups of older or less educated individuals to face an added challenge in making use of Web-based information (van der Vaart & Drossaert, 2017). It is, therefore, equally important to build DHL competencies at the level of the public and at the level of professionals responsible for developing digital health resources or recommending their use (van Kessel et al., 2022a).

Theoretical Framework

Social cognitive theory emphasizes that human behavior is a result of an ongoing interaction between three main factors: person, environment, and behavior. This concept of triadic reciprocal determinism suggests that each of these factors can influence the others. Based on this theory, society, personality traits, and behavioral capabilities all play a role in individual decision-making (Glanz & Rimer, 2005). This explains human behavior and action when faced with any new condition, including health-related conditions (Bandura, 1998). McAlister et al. (2008) have demonstrated how different conceptual frameworks of social cognitive theory can be utilized to promote healthy and planned actions guided by the interaction between individual and environment under the concept of reciprocal determinism. These frameworks include outcome expectations, observational learning, incentive motivation, and self-efficacy. A change in outcome expectations, which are believed consequences of one's action, for example the satisfaction associated with condom use among individuals at high-risk of HIV infection, has been achieved through campaigns involving peer-modeling of consistent condom use especially with non-main partners (McAlister et al., 2000). These campaigns also involved observational learning as the intended audience learned from peer models how to use condoms appropriately and listened to their stories. Another framework uses incentive motivation to modify behavior, for example tobacco use, through punishments and rewards (Hopkins et al., 2001). By increasing the price of tobacco products, smoking cessation increases, and individuals feel indirectly rewarded for saving money. Yet another conceptual framework is self-efficacy, which refers to the belief in one's potential to accomplish a certain behavior by organizing and controlling one's actions and performance (Bandura, 1998). Self-efficacy supposes human agency, and predicts the extent of behavior change and improvement that can be achieved (Bandura & Adams, 1977). It has been used in studies on e-health literacy and has shown that improvements in self-efficacy in using e-health resources increased the chances of individuals reporting better handling of personal health concerns (Bunz, 2009; Saade & Kira, 2009; Simsek, 2011). Moreover, high Internet self-efficacy stimulates better online information searching strategies and superior learning outcomes from digital media platforms (Tsai & Tsai, 2003). In addition, social interaction as an environmental factor and health knowledge-seeking as a behavior have been associated to e-health literacy, with better health-seeking behavior positively influencing e-health literacy (Pourrazavi et al., 2020). Several strategies are believed to reinforce self-efficacy. These include: mastery experience or experiencing successful completion of a task, social modeling or creating the conditions for a behavior to be observed and imitated, alteration of one's emotional and physical reactions in order to minimize stress when faced with a challenging task, and finally, verbal persuasion or overcoming self-doubt through encouragement (Bandura & Adams, 1977).

We posit that self-efficacy relative to DHL defines the nature of one's interaction with the digital world and its various platforms and users. This affects one's knowledge acquisition and possibly leads to modifications in health behavior. Self-efficacy in DHL is dependent on one's ability to: adopt appropriate information-seeking behavior, use adapted search engines, and exert an effort in evaluating the reliability, relevance and applicability of information. We hypothesize that it is influenced by personal factors (age, sex, financial situation, educational level, and health impairment), environmental factors (access to digital resources, availability of search engines, basic computer literacy, and social support), and behavior (search for information and determination of its quality). Despite its possible role in countering the infodemic, research on DHL is scarce in the Middle East and North Africa. Thus, this study aimed to determine the levels and correlates of DHL among Lebanese university students through the lens of social cognitive theory with its central tenet, the concept of self-efficacy. We sought to determine DHL levels in relation to COVID-19; examine which online sources and topics were preferred to learn about the emerging disease; and identify the characteristics of students with low DHL.

Methodology

Study design and setting

Ethical approval was obtained from the Lebanese American University's Institutional Review Board (*IRB#*:LAU.SOM.CB4.8/May/2020) and from the Ethics Committees of participating universities. The primary investigator, a member of the COVID-HL network (https://covid-hl.eu/), established the first contact with the Presidents of the 37 universities in Lebanon. The solicitation email included a description of the study and the IRB approval. It also enclosed an 'invitation email', to be shared with university students, that explained the purpose of the study, and that participation was voluntary and anonymous. It provided a link to the online English consent form and survey, which were uploaded on our institution's e-platform with the help of the Department of Institutional Research and Assessment. A total of 18 universities accepted the invitation to take part in the study, 5 declined, and 14 did not respond, despite receiving a reminder. Universities shared the invitation with their student body via an internal mailing list. Data collection was carried out between May and August 2020. The survey was discontinued following the devastating explosion that shook Beirut in early August.

For a representative sample, we required 600 students, as per Cochran's formula (Cochran, 1977), with a confidence level of 95%, a population proportion of 0.5, and a margin of error of 0.04.

The questionnaire

The questionnaire gathered information on students' sociodemographic characteristics (sex, age, educational level, and satisfaction with financial situation), their information-seeking behavior (for self versus surrogate information-seeking), their DHL, sources used for online information, and COVID-related topics searched.

Digital Health Literacy (DHL)

Students were asked whether they had searched the Internet in the past four weeks for information on COVID-19 and related topics. Those who had searched for such information were invited to complete the DHL subscales that measured the following domains: information-searching, adding self-generated content, evaluating information reliability, and determining information relevance (van der Vaart & Drossaert, 2017). The original wording of the items was changed to provide a focus on COVID-19 (Dadaczynski et al., 2021). For example, 'When you search the Internet for information on health…' was changed to 'When you search the Internet for information on the coronavirus or related topics, …' Each DHL subscale consisted of three items with the options 'very difficult', 'difficult', 'easy' and 'very easy' scored 1 through 4. The score on each subscale was calculated as the average score on the three relevant items.

The DHL subscale on information searching asked students to rate the difficulty they had in making a choice based on the information they found online, in using the proper words or search query to look for information, and in finding the exact information they were looking for.

The DHL subscale on adding-self generated content asked students to rate the difficulty they faced in formulating clearly their question or health-related worry, in expressing their opinion or feelings in writing, and in ensuring that their message was understood by others as intended.

The DHL subscale for evaluating reliability focused on students' ease in deciding whether information was reliable, whether it was written with commercial interests in mind, and whether they were able to check different websites to see if they provided the same information.

The DHL on determining relevance asked students to rate how easy it was for them to decide if the information retrieved was applicable to them, if it could be put into practice in their daily lives, and if they actually used it to make health decisions relevant to coronavirus.

Online information-seeking behavior

Students were asked to indicate how often they used the following ten sources to obtain information on the coronavirus and related topics: websites of public bodies, for example the Lebanese Ministry of Public Health (MoPH), Wikipedia and other online encyclopedias, social media (e.g. Facebook, Instagram, Twitter), YouTube, blogs on health topics, online communities (e.g. Quora), health portals (e.g. the World Health Organization), and news portals (e.g. online newspapers). Each source had four possible answers: 'never', 'rarely', 'sometimes', and 'often'. Students were also asked which topics they searched for in the context of the coronavirus. Proposed topics included: current spread of the coronavirus, transmission routes, symptoms of the disease, individual measures to protect against infection, hygiene regulations, current situation assessments and recommendations, restrictions (e.g. stay-at-home orders, curfews, permission to drive personal vehicles based on even/odd license plates), economic and social consequences of the coronavirus, and dealing with psychological stress caused by the virus.

Statistical analysis

Data analysis was performed using SPSS for windows version 25 (IBM, SPSS Inc. Chicago, IL, USA). Sample characteristics were reported as frequency counts and percentages. Sources used in the search for information were re-categorized from four categories to two, with 'never' or 'rarely' as one category, and 'sometimes' or 'often' as another category. Two subgroups were created using the median split to have a subgroup for 'sufficient' and another for 'limited' DHL. Those who scored equal or greater than the median had 'sufficient' DHL. Variables were compared between students having sufficient DHL and those having insufficient levels, using the χ^2 test for categorical variables and Fisher's exact test when necessary. A probability of 0.05 was considered significant. Variables associated with sufficient DHL as the dependent variable were investigated, using binary logistic regression analysis. The adjusted odds ratio was calculated with a confidence interval of 95%.

Results

Sample characteristics

A total of 602 university students, mostly 18-21 year-olds (61.6%) and female (60.1%), participated in the survey. Table 1 summarizes the general characteristics of the study population. Participants were mostly at undergraduate level (75.6%), and some (5%) suffered from a chronic health impairment.

Table 1 General characteristics of the university students in our sample

Variables (N=602)	N (%)
Sex	
Female	362 (60.1)
Male	238 (39.5)
Diverse	2 (0.3)
Age	
18-21	371 (61.6)
22-25	192 (31.9)
>25	39 (6.5)
Educational Level	
Bachelor	455 (75.6)
Master	85 (14.1)
Other	62 (10.3)
Chronic health impairment	
No	572 (95.0)
Yes	30 (5.0)

Online information-seeking behavior

A total of 76.2% used the Internet in the past month to look for COVID-related information. The most frequently used sources were health portals (80.4%), social media (70.6%), news portals (67.1%), websites of public bodies (64.3%) and YouTube (52.3%). Fewer students used Wikipedia (43.8%), blogs on health topics (41.4%), and online communities such as Quora (32.5%).

Those who searched the Internet were mostly interested in knowing the current spread of the coronavirus (88.5%) and disease symptoms (74.5%). Participants were least interested in hygiene regulations (49.9%) and coping strategies (37.9%).

Students who searched for online information on COVID-19 were compared to those who did not search for information. There was no significant difference between the two groups, except for gender. Males were more likely than females to have searched for information online ($p=0.008$).

Digital health literacy and relation to other variables

The DHL subscales showed good reliability and internal consistency with Cronbach's alpha for information searching ($\alpha=0.799$), adding self-generated content ($\alpha=0.806$), evaluating reliability ($\alpha=0.758$) and determining relevance ($\alpha=0.798$). The subscale on protecting privacy was removed from the analysis because the coefficient was low ($\alpha <0.5$). Other researchers have reported a similar problem and omitted this subscale (Dadaczynski et al., 2021).

The results of the bivariate analyses for DHL subscales stratified by individual variables and online sources used to find information are presented in Table 2. University students with sufficient DHL for information searching were more often users of public bodies ($\chi^2(1)=7.487$, $p=0.006$). Graduate students ($\chi^2(2)=13.030$, $p=0{\cdot}001$), students who used websites of public bodies ($\chi^2(1)=13.030$, $p=0.001$), health portals ($\chi^2(1)=6.805$, $p=0.009$) and news portals ($\chi^2(1)=5.886$, $p=0.015$) more often had sufficient DHL for adding self-generated content. However, those with a chronic health impairment ($\chi^2(1)=4.451$, $p=0.035$) more often had limited DHL for adding self-generated content. No other sociodemographic difference could be found.

Graduate students ($\chi^2(2)=10.301$, $p=0.006$), and those who used websites of public bodies ($\chi^2(1)=5.555$, $p=0.018$), more often had sufficient DHL for evaluating reliability. On the other hand, frequent users of social media ($\chi^2(1)=5.818$, $p=0.016$) for information on the coronavirus more often had limited DHL for evaluating reliability.

Lastly, university students who used websites of public bodies ($\chi^2(1)=4.784$, $p=0.029$) and health portals ($\chi^2(1)=6.575$, $p=0.010$) for information on the coronavirus more often had sufficient DHL for determining relevance. On the other hand, those with a chronic health impairment ($\chi^2(1)=9.253$, $p=0.002$) more often had limited DHL for determining relevance.

Table 2 Digital health literacy (DHL) subscales by sociodemographic variables and COVID-related information-seeking behaviors

Variable (N=459)	Limited DHL for information searching	Sufficient DHL for information searching	p-value	Limited DHL for adding self-generated content	Sufficient DHL for adding self-generated content	p-value	Limited DHL for evaluating reliability	Sufficient DHL for evaluating reliability	p-value	Limited DHL for determining relevance	Sufficient DHL for determining relevance	p-value
	n (%)	n (%)		n (%)	n (%)		n (%)	n (%)		n (%)	n (%)	
Sex												
Female	68 (14.8)	193 (42)	0.925 [b]	97 (21.1)	164 (35.7)	0.379 [b]	113 (24.6)	148 (32.2)	0.865 [b]	79 (17.2)	182 (39.7)	0.667 [b]
Male	54 (11.8)	142 (30.9)		68 (14.8)	128 (27.9)		82 (17.9)	114 (24.8)		68 (14.8)	128 (27.9)	
Diverse	0 (0)	2 (0.4)		0 (0)	2 (0.4)		1 (0.2)	1 (0.2)		0 (0)	2 (0.4)	
Age												
18-21	77 (16.8)	204 (44.4)	0.347 [a]	110 (24)	171 (37.3)	0.057 [a]	126 (27.5)	155 (33.8)	0.302 [a]	98 (21.4)	183 (39.9)	0.194 [a]
22-25	40 (8.7)	106 (23.1)		49 (10.7)	97 (21.1)		60 (13.1)	86 (18.7)		42 (9.2)	104 (22.7)	
>25	5 (1.1)	27 (5.9)		6 (1.3)	26 (5.7)		10 (2.2)	22 (4.8)		7 (1.5)	25 (5.4)	
Educational level												
Bachelor	98 (21.4)	247 (53.8)	0.235 [a]	140 (30.5)	205 (44.7)	**0.001 [a]**	162 (35.3)	183 (39.9)	**0.006 [a]**	120 (26.1)	225 (49)	0.072 [a]
Master	12 (2.6)	53 (11.5)		15 (3.3)	50 (10.9)		19 (4.1)	46 (10.0)		17 (3.7)	48 (10.5)	
Other	12 (2.6)	37 (8.1)		10 (2.2)	39 (8.5)		15 (3.3)	34 (7.4)		10 (2.2)	39 (8.5)	
Satisfaction with financial situation												
Completely satisfied	14 (3.1)	43 (9.4)	0.874 [a]	16 (3.5)	41 (8.9)	0.363 [a]	25 (5.4)	32 (7.0)	0.747 [a]	13 (2.8)	44 (9.6)	0.278 [a]
Satisfied	65 (14.2)	171 (37.3)		85 (18.5)	151 (32.9)		104 (22.7)	132 (28.8)		78 (17.0)	158 (34.4)	
Not satisfied	43 (9.4)	123 (26.8)		64 (13.9)	102 (22.2)		67 (14.6)	99 (21.6)		56 (12.2)	110 (24.0)	
Chronic health impairment												
No	112 (24.4)	324 (70.6)	0.060 [a]	152 (33.1)	284 (61.9)	**0.035 [a]**	183 (39.9)	253 (55.1)	0.169 [a]	133 (29)	303 (66)	**0.002 [a]**
Yes	10 (2.2)	13 (2.8)		13 (2.8)	10 (2.2)		13 (2.8)	10 (2.2)		14 (3.1)	9 (2.0)	
Use of websites of public bodies												
Never or rarely	56 (12.2)	108 (23.5)	**0.006 [a]**	75 (16.3)	89 (19.4)	**0.001 [a]**	82 (17.9)	82 (17.9)	**0.018 [a]**	63 (13.7)	101 (22.0)	**0.029 [a]**
Sometimes or often	66 (14.4)	229 (49.9)		90 (19.6)	205 (44.7)		114 (24.8)	181 (39.4)		84 (18.3)	211 (46.0)	
Use of Wikipedia or other online encyclopedias												
Never or rarely	60 (13.1)	198 (43.1)	0.068 [a]	100 (21.8)	158 (34.4)	0.155 [a]	111 (24.2)	147 (32.0)	0.875 [a]	84 (18.3)	174 (37.9)	0.782 [a]
Sometimes or often	62 (13.5)	139 (30.3)		65 (14.2)	136 (29.6)		85 (18.5)	116 (25.3)		63 (13.7)	138 (30.1)	
Use of social media												
Never or rarely	30 (6.5)	105 (22.9)	0.173 [a]	42 (9.2)	93 (20.3)	0.163 [a]	46 (10.0)	89 (19.4)	**0.016 [a]**	50 (10.9)	85 (18.5)	0.137 [a]
Sometimes or often	92 (20.0)	232 (50.5)		123 (26.8)	201 (43.8)		150 (32.7)	174 (37.9)		97 (21.1)	227 (49.5)	
Use of YouTube												
Never or rarely	56 (12.2)	163 (35.5)	0.640 [a]	79 (17.2)	140 (30.5)	0.957 [a]	92 (20.0)	127 (27.7)	0.775 [a]	72 (15.7)	147 (32.0)	0.709 [a]
Sometimes or often	66 (14.4)	174 (37.9)		86 (18.7)	154 (33.6)		104 (22.7)	136 (29.6)		75 (16.3)	165 (35.9)	
Use of blogs on health topics												
Never or rarely	77 (16.8)	192 (41.8)	0.238 [a]	103 (22.4)	166 (36.2)	0.213 [a]	114 (24.8)	155 (33.8)	0.868 [a]	92 (20.0)	177 (38.6)	0.235 [a]
Sometimes or often	45 (9.8)	145 (31.6)		62 (13.5)	128 (27.9)		82 (17.9)	108 (23.5)		55 (12.0)	135 (29.4)	
Use of online communities												
Never or rarely	82 (17.9)	228 (49.7)	0.929 [a]	116 (25.3)	194 (42.3)	0.343 [a]	132 (28.8)	178 (38.8)	0.940 [a]	103 (22.4)	207 (45.1)	0.427 [a]
Sometimes or often	40 (8.7)	109 (23.7)		49 (10.7)	100 (21.8)		64 (13.9)	85 (18.5)		44 (9.6)	105 (22.9)	
Use of health portals												
Never or rarely	29 (6.3)	61 (13.3)	0.177 [a]	43 (9.4)	47 (10.2)	**0.009 [a]**	43 (9.4)	47 (10.2)	0.278 [a]	39 (8.5)	51 (11.1)	**0.010 [a]**
Sometimes or often	93 (20.3)	276 (60.1)		122 (26.6)	247 (53.8)		153 (33.3)	216 (47.1)		108 (23.5)	261 (56.9)	
Use of news portals												
Never or rarely	48 (10.5)	103 (22.4)	0.077 [a]	66 (14.4)	85 (18.5)	**0.015 [a]**	73 (15.9)	78 (17.0)	0.087 [a]	53 (11.5)	98 (21.4)	0.323 [a]
Sometimes or often	74 (16.1)	234 (51.0)		99 (21.6)	209 (45.5)		123 (26.8)	185 (40.3)		94 (20.5)	214 (46.6)	

Note: n (%)=number and proportion of individuals, [a] Chi-square test of independence; [b] Fisher's Exact Test; In bold the significant differences at $p<0.05$

Binary logistic regression and DHL subscales

Binary logistic regression analyses for having sufficient DHL with potential explanatory variables (sex, age, educational level, satisfaction with financial situation, chronic health impairment, and use of different information sources) are presented in Table 3.

Table 3 Odds Ratio of having sufficient DHL

Variables		**Adj. OR (95% CI) for having sufficient DHL for information searching**		**Adj. OR (95% CI) for having sufficient DHL for adding self-generated content**		**Adj. OR (95% CI) for having sufficient DHL for evaluating reliability**		**Adj. OR (95% CI) for having sufficient DHL for determining relevance**	
		Adj. OR	**(95% CI)**	**Adj. OR**	**(95% CI)**	**Adj. OR**	**(95% CI)**	**Adj. OR**	**(95% CI)**
Sex	Female	1		1		1		1	
	Male	1.029	(0.654, 1.619)	1.212	(0.791, 1.858)	1.033	(0.689, 1.549)	0.891	(0.581, 1.366)
	Diverse	Infinity	-	Infinity		0.988	(0.051, 19.035)	Infinity	-
Age	18-21	1		1		1		1	
	22-25	0.886	(0.513, 1.529)	0.859	(0.511, 1.442)	0.796	(0.483, 1.310)	1.109	(0.653, 1.885)
	>25	1.449	(0.475, 4.422)	1.450	(0.509, 4.132)	0.891	(0.356, 2.231)	1.571	(0.573, 4.310)
Educational level	Bachelor	1		1		1		1	
	Master	1.688	(0.760, 3.751)	2.328	(1.104, 4.909)*	2.318	(1.149, 4.679)*	1.348	(0.650, 2.795)
	Other	1.219	(0.554, 2.683)	2.372	(1.052, 5.350)*	2.074	(1.002, 4.293)*	1.780	(0.790, 4.007)
Satisfaction with the financial situation	Completely satisfied	1		1		1		1	
	Satisfied	0.917	(0.459, 1.835)	0.727	(0.371, 1.425)	1.087	(0.592, 1.998)	0.655	(0.326, 1.317)
	Not satisfied	0.965	(0.467, 1.994)	0.602	(0.299, 1.210)	1.239	(0.655, 2.344)	0.606	(0.294, 1.251)
Use of websites of public bodies	Never or rarely	1		1		1		1	
	Sometimes or often	1.665	(1.036, 2.676)*	1.665	(1.065, 2.605)*	1.393	(0.905, 2.144)	1.462	(0.926, 2.308)
Use of Wikipedia or other online encyclopedias	Never or rarely	1		1		1		1	
	Sometimes or often	0.619	(0.390, 0.984)*	1.242	(0.803, 1.921)	1.033	(0.682, 1.564)	0.935	(0.600, 1.455)
Use of social media	Never or rarely	1		1		1		1	
	Sometimes or often	0.740	(0.434, 1.263)	0.697	(0.424, 1.144)	0.576	(0.358, 0.928)*	1.571	(0.962, 2.564)
Use of YouTube	Never or rarely	1		1		1		1	
	Sometimes or often	1.067	(0.663, 1.718)	1.068	(0.685, 1.664)	1.108	(0.725, 1.693)	1.069	(0.679, 1.682)
Use of blogs on health topics	Never or rarely	1		1		1		1	
	Sometimes or often	1.434	(0.871, 2.361)	1.301	(0.821, 2.063)	1.050	(0.676, 1.630)	1.148	(0.719, 1.834)
Use of online communities	Never or rarely	1		1		1		1	
	Sometimes or often	1.058	(0.624, 1.795)	1.201	(0.731, 1.975)	1.056	(0.660, 1.691)	1.094	(0.659, 1.814)
Use of health portals	Never or rarely	1		1		1		1	
	Sometimes or often	1.008	(0.573, 1.773)	1.347	(0.792, 2.289)	1.000	(0.595, 1.680)	1.529	(0.899, 2.602)
Use of news portals	Never or rarely	1		1		1		1	
	Sometimes or often	1.597	(1.002, 2.544)*	1.629	(1.049, 2.530)*	1.542	(1.009, 2.356)*	1.094	(0.700, 1.708)
Chronic health impairment	No	1		1		1		1	
	Yes	0.448	(0.185, 1.085)	0.412	(0.169, 1.003)	0.561	(0.234, 1.345)	0.276	(0.114, 0.670)*

Note: Adjusted OR at 95% CI for all included explanatory factors *Significant at $p < 0.05$

The odds of having sufficient DHL for information searching was higher in more frequent users of websites of public bodies (OR=1.665; 95% CI=1.036-2.676) and news portals (OR=1.597; 95% CI=1.002-2.544) but was lower in more frequent users of Wikipedia and online encyclopedias (OR=0.619; 95% CI=0.390-0.984).

The odds of having sufficient DHL for adding self-generated content was higher in students at graduate level (OR=2.328; 95% CI=1.104-4.909) or higher (OR=2.372; 95% CI=1.052-5.350). Additionally, the frequent use of websites of public bodies (OR=1.665; 95% CI=1.065-2.605) and news portals (OR=1.629; 95% CI= 1.049-2.530) was predictive of sufficient DHL for adding self-generated content.

The odds of having sufficient DHL for evaluating reliability was 2.318 times higher in graduate students and 2.074 times higher in those with more years of education. It also appeared that students who used social media often or sometimes as information sources were more likely to have limited DHL for evaluating reliability (OR=0.576; 95% CI=0.358-0.928) whereas those who used news portals were more likely to have sufficient DHL (OR=1.542; 95% CI=1.009-2.356).

Lastly, students suffering from a chronic health impairment were less likely to have sufficient DHL for determining relevance (OR=0.276; 95% CI=0.114-0.670). Other variables did not seem to explain the level of DHL for determining relevance.

Discussion

Chronic health impairment was predictive of limited DHL for adding self-generated content and for determining relevance. This is an important personal factor to take into consideration when aiming to increase Internet self-efficacy. This finding concurs with the literature, since chronic disease (Bouclaous et al., 2021), decreased physical functioning (Wolf et al., 2005) and improper chronic disease self-care (Schillinger, 2002) have been associated with lower levels of health literacy. During the pandemic, people with chronic conditions needed timely access to health information that was specific to their disease because they were experiencing an increased risk of mortality, morbidity and critical complications from COVID-19 (Onder et al., 2020). Their need remained largely unmet causing major dissatisfaction with online health information among people with chronic conditions; however, a higher level of DHL seemed to predict higher information satisfaction (Kor et al., 2020).

The most used sources of information on coronavirus and related topics were health portals. However, prior research has shown that television was the top source of information, closely followed by social media (Melki et al., 2020). This may be due to differences in participant age groups. While our sample was predominantly 18-to-21-year-olds, Melki et al. had a higher proportion of 31- to 45-year-olds. This could indicate that different age groups turned to different platforms for information, and a switch from television to smartphones and laptops had occurred in the younger generation. Smartphone use was reported to have a positive effect on online health information-seeking behavior, and consequently on quality of life, especially among younger users and caregivers (Ghahramani and Wang, 2020). It may also be indicative of health literacy level, since those who use the Internet for health information tend to have higher levels of health literacy than those who use more conventional sources like television and newspapers (Özkan et al., 2021). Younger individuals preferred using commercial websites for obtaining health information, whereas seniors sought health information from academic websites (Jia et al., 2021), and this confirms the association between socio-demographic characteristics and type of health websites used. Higher socioeconomic status has been associated with higher health literacy levels and better adherence to guidelines for preventive behaviors during the COVID-19 pandemic (Guo et al, 2021).

Current and up-to-date information needs to be made available to individuals who do not have access to online sources of information, or do not have the appropriate literacy level or competency in foreign languages for understanding online health information (Tangcharoensathien et al., 2020). Nevertheless, data visualizations in social media interventions may help with interpretation of health information: for example, the use of infographics or pictographs ease comprehension of health-related concerns, and facilitate decision-making and participation in personal health management (Riviera-Romero et al., 2022). Health professionals may also refer the public to reliable or 'provider-approved' resources online (LaValley et al., 2017), and guide patients in their search for health information.

More than a third of the students were dissatisfied with their financial situation. This was expected in light of the recent economic and financial crises that struck the country as of October 2019. After failed attempted lockdowns starting March 2020, and the massive Beirut port explosion of August 4, 2020, Lebanon had to deal with the human tragedy along with an exacerbated economic crisis (World Bank, 2020). Shortly after, confirmed COVID-19 cases greatly increased beyond 16,000 by end of August 2020 (WHO, 2022).

There was no significant sex difference in relation to DHL as opposed to findings from other countries (Rosário et al., 2020; Okan et al., 2020). However, this is in accordance with work on health literacy in Lebanon (Bouclaous et al., 2021) in which sex was not a significant predictor in the adult population. It was reported that 43.8% of Lebanese adults had inadequate or problematic comprehensive health literacy (CHL), which is the ability to acquire health information from different media, judge its reliability, and use it to make health decisions that would protect from illness or improve health (Bouclaous et al., 2021). This information is relevant to the current study, given that the participants of the prior study were asked to rate the difficulty they faced in judging whether the information on health risks in the media was reliable (from TV or the Internet), in deciding how to protect themselves from illness based on information in the media (newspapers, leaflets and the Internet), and in understanding information in the media on how to get healthier (from the Internet and magazines). We found a similar proportion of students with limited DHL for information searching (26.6%), for self-generated content (35.9%), for evaluating reliability (42.7%), and for determining relevance (32%). CHL was positively correlated with education, income, and health status. This also comes to support our current results related to higher educational level, higher satisfaction with financial situation, and no chronic health condition being associated with sufficient DHL levels.

Graduate students (master's degree, Ph.D., Pharm.D. or M.D.) were more likely to have sufficient DHL for adding self-generated content and evaluating reliability. This may be explained by higher knowledge of COVID-19 symptoms and risks, and lower extent of belief in incorrect information and widespread myths among more educated individuals (Melki et al., 2020). We might infer that higher educational levels allowed individuals to better formulate health-related questions when navigating online, and have enough knowledge about the topic to test the credibility of information and sources. In fact, individuals with higher education or an elevated financial situation may have higher levels of health literacy, which would translate into a higher likelihood of seeking online health information (Wang et al., 2021). Notably, self-efficacy plays an important role in enabling students to seek and understand information, in addition to allowing them to adopt and appreciate different opinions and ideas through interactions in the online environment (Jeon and Kim, 2022).

The use of official public websites was associated with sufficient DHL on all four subscales. This could be explained by the tendency of students with sufficient DHL to look for information that is credible, evidence-based and comprehensive. In addition, students who reported frequent use of social media were less likely to have sufficient DHL for evaluating information reliability. This is similar to findings reported in the literature (Rosário et al., 2020; Okan et al., 2020). Smartphones have made access to online health information almost effortless, but misleading information, driven by social media, has led to undesirable health outcomes, increased healthcare spending, and deadly consequences (Chong et al., 2020), because individuals with low health literacy would engage in risky behavior, increasing their chances of catching and spreading the virus. Similar results were reported in Slovenia, where students with lower DHL mostly used social media and blogs (Vrdelja et al., 2021). Conversely, in Greece, the limited use of social media helped in slowing the virus spread (Skarpa & Garoufallou, 2021). Our results are similar to those from Denmark, where university students who used social media had limited ability to evaluate the reliability of information compared to those who used it to a lesser extent (Bak et al., 2022). This supports our assumption that seeking health information from credible sources, which is a health-related behavior, is associated with higher levels of DHL.

Since low DHL is a direct contributor to the spread of COVID-19-related online misinformation (Bin Naeem & Boulos, 2021), strengthening DHL could encourage protective practices and decrease the risk of exposure to the virus. It may be possible to design a social media intervention that would develop DHL in those who depend on this resource for health information. In fact, there are encouraging signs that social media posts can be a powerful tool for promoting health equity when information is culturally relevant, and disseminated effectively to bypass physical and geographic barriers (Ramirez et al., 2021; Welch et al. 2016). However, the usage and utility of such interventions may be affected by digital health inequities caused by age, level of education, access to social media, health literacy level, socioeconomic status or culture (Friis-Healy et al., 2021). For this reason, a deliberate effort should be made to design digital tools that foster accuracy, comprehensiveness and accessibility of online health information and services as well as comprehension at any DHL level (Wei et al., 2016; LaValley et al., 2017; Demirci et al., 2021). In Lebanon, the government sought to develop the public's media literacy skills through partnership between the Ministry of Information and local TV stations that spread COVID-19 information using infomercials (https://factchecklebanon.nna-leb.gov.lb), in addition to the training of youth actors as information ambassadors in communities and on social media (UNDP Lebanon, 2020).

Students searched the least for information on how to deal with psychological stress caused by COVID-19. This observation may have changed with time due to the protracted nature of the pandemic and increasing media coverage. Already, there was a mismatch between the COVID-19 discourse of front-line health workers and the public in relation to risk and uncertainty (Brown, 2020): while the former described an overwhelmed health system, a need to triage patients, and provide intensive care treatment to all, the latter perceived a high relative risk only among the old and the sick, and relative safety in belonging to mainstream society.

Among the factors associated with online health information-seeking behavior, quality of information, usefulness, and trust in the Internet seemed to have the greatest effect (Wang et al., 2021). Moreover, individuals were more likely to search for online health information when they had high self-efficacy and trust (Wang et al., 2021). This was all the more relevant in countries with low information communication technologies, where regulation of online health-related content and monitoring of its quality were at the infancy stage (Bloom et al., 2017). In these contexts, individuals often had reservations about the health information posted online and needed to count on their own judgment to assess the quality and adequacy of information (Alpay et al., 2009). Interestingly, the importance of trustworthiness of the Internet dropped when individuals searched for online information on specific health topics (e.g. HIV, cancer) rather than general health information; in this case, even the associations between individuals' education and income levels and their online health-seeking behavior faded while the main concern shifted towards finding information that met a particular need or interest (Lee & Hawkins, 2016). Other attributes that encouraged people to seek health information online were convenience, anonymity, and privacy to search for sensitive health topics.

This research was subject to limitations. Reporting was exclusive to university students, limiting the generalizability of our findings since young adults include students in technical school or in the labor market. The sample had more females than males, and a higher participation from Beirut and Mount Lebanon than the periphery. The use of an online survey may have excluded students with infrequent access to the Internet during lockdown, those on university summer break or reading period, and those who had lower digital competencies. In addition, data collection was conducted in the early stages of the crisis when infection rates were at a minimum, fear and awareness of COVID-19 were still limited, and restrictions were less stringent. It is possible that the wave of COVID-19, with its exponential rise in cases and the overstretched Lebanese health system, may have driven information-seeking behavior towards ways to stop the spread of the virus and variants, and the efficiency of vaccines, all of which could alter the levels of DHL for information-seeking and for relevance of information. In addition to measuring DHL, it would have been interesting to include a scale that assesses health literacy in general. Lastly, the cross-sectional design prevented us from establishing causal relationships between variables.

Strengthening self-efficacy in DHL can increase one's confidence in navigating online resources, promote healthy behaviors, and prevent the spread of disease. Our findings highlight the need for credible and accessible health education programs that strengthen DHL in Lebanese university students, including their capacity to search for health information, evaluate its reliability and relevance, and be able to add self-generated content. Self-efficacy can be increased by improving DHL skills on social media through the use of educational videos that demonstrate how to use the Internet, how to ask relevant questions and display good online health communication skills, how to judge the quality of information retrieved from different websites, and how to make appropriate health decisions based on this information. Another way to achieve this could be by providing social support within online communities, and motivating individuals to adopt healthy behaviors, through peer celebrities and influencers. Interventions should target students who do not use official sources for health information, those at undergraduate level, and students with existing chronic conditions. Further research is recommended in order to gain understanding of risk governance in Lebanon, and ways to build trust, relay evidence-based decisions, and enhance risk communication.

References

Alpay, L., Verhoef, J., Xie, B., Te'eni, D., & Zwetsloot-Schonk, J. H. (2009). Current Challenge in Consumer Health Informatics: Bridging the Gap between Access to Information and Information Understanding. *Biomedical informatics insights*, *2*(1), 1–10. https://doi.org/10.4137/bii.s2223

Augustaitis, L., Merrill, L. A., Gamarel, K. E., & Haimson, O. L. (2021). Online Transgender Health Information Seeking: Facilitators, Barriers, and Future Directions. Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems. Yokohama, Japan. https://doi.org/10.1145/3411764.3445091

Bak, C. K., Krammer, J., Dadaczynski, K., Orkan, O., von Seelen, J., Prinds, C., Søbjerg, L. M., & Klakk, H. (2022). Digital Health Literacy and Information-Seeking Behavior among University College Students during the COVID-19 Pandemic: A Cross-Sectional Study from Denmark. *International Journal of Environmental Research and Public Health*, *19*(6), 3676. https://doi.org/10.3390/ijerph19063676

Bandura, A. (1998). Health promotion from the perspective of social cognitive theory. *Psychology & Health*, *13*(4), 623–649. https://doi.org/10.1080/08870449808407422

Bandura, A., & Adams, N. E. (1977). Analysis of self-efficacy theory of behavioral change. *Cognitive Therapy and Research*, *1*(4), 287–310. https://doi.org/10.1007/bf01663995

Bessi, A., Coletto, M., Davidescu, G.A., Scala, A., Caldarelli, G., Quattrociocchi, W. (2015). Science vs conspiracy: collective narratives in the age of misinformation. *PLoS ONE* 10, e0118093 (2015). https://doi.org/10.1371/journal.pone.0118093

Bin Naeem, S., Boulos, M. (2021). Covid-19 misinformation online and Health Literacy: A brief overview. *International Journal of Environmental Research and Public Health*, *18*(15), 8091. https://doi.org/10.3390/ijerph18158091

Bloom, G., Berdou, E., Standing, H., Guo, Z., & Labrique, A. (2017). ICTs and the challenge of health system transition in low and middle-income countries. *Globalization and Health, 13*(1), 56. https://doi.org/10.1186/s12992-017-0276-y

Bodie, G. D., & Dutta, M. J. (2008). Understanding health literacy for strategic health marketing: EHealth literacy, health disparities, and the digital divide. *Health Marketing Quarterly, 25*(1-2), 175-203. https://doi.org/10.1080/07359680802126301

Bora, K., Das, D., Barman, B., & Borah, P. (2018). Are internet videos useful sources of information during global public health emergencies? A case study of YouTube videos during the 2015-16 Zika virus pandemic. *Pathogens and Global Health*, *112*(6), 320–328. https://doi.org/10.1080/20477724.2018.1507784

Bouclaous C, Salem S., Ghanem A, Saade N., El Haddad J., Bou Malham M., Al Osta S., Matar K., Nassar E., Yared G., Khiami M., Eid MJ. Health literacy levels and predictors among Lebanese adults visiting outpatient clinics in Beirut. *HLRP: Health Literacy Research and Practice* 2021;5(4):e295–e309. https://doi.org/10.3928/24748307-20211012-02

Brown, P. (2020). Studying COVID-19 in light of critical approaches to risk and uncertainty: research pathways, conceptual tools, and some magic from Mary Douglas. *Health, Risk & Society,* 22(1), 1-14. https://doi.org/10.1080/13698575.2020.1745508

Bunz, U. (2009). A generational comparison of gender, computer anxiety, and computer-email-web fluency. *SIMILE: Studies In Media & Information Literacy Education*, *9*(2), 54–69. https://doi.org/10.3138/sim.9.2.003

Choukou, M. A., Sanchez-Ramirez, D. C., Pol, M., Uddin, M., Monnin, C., & Syed-Abdul, S. (2022). COVID-19 infodemic and digital health literacy in vulnerable populations: A scoping review. *Digital Health*, *8*, 205520762210769. https://doi.org/10.1177/20552076221076927

Chong, Y. Y., Cheng, H. Y., Chan, H. Y. L., Chien, W. T., & Wong, S. Y. S. (2020). COVID-19 pandemic, infodemic and the role of eHealth literacy. *International Journal of Nursing Studies*, *108*, 103644. https://doi.org/10.1016/j.ijnurstu.2020.103644

Cinelli, M., Quattrociocchi, W., Galeazzi, A., Valensise, C. M., Brugnoli, E., Schmidt, A. L., Zola, P., Zollo, F., Scala, A. (2020). The COVID-19 social media infodemic. *Scientific Reports*, 10, article 16598. https://doi.org/10.1038/s41598-020-73510-5

Cinelli, M., Brugnoli, E., Schmidt, A. L., Zollo, F., Quattrociocchi, W., & Scala, A. (2020). Selective exposure shapes the facebook news diet. *PloS One*, 15(3), e0229129-e0229129. https://doi.org/10.1371/journal.pone.0229129

Cochran, W. G. (1977). Sampling techniques (3rd ed.). New York: John Wiley & Sons.

Crawford, A., & Serhal, E. (2020). Digital health equity and COVID-19: The innovation curve cannot reinforce the social gradient of health. *Journal of Medical Internet Research*, *22*(6), e19361. https://doi.org/10.2196/19361

Cuan-Baltazar, J. Y., Muñoz-Perez, M. J., Robledo-Vega, C., Pérez-Zepeda, M. F., & Soto-Vega, E. (2020). Misinformation of COVID-19 on the Internet: Infodemiology study. *JMIR Public Health and Surveillance*, *6*(2), e18444. https://doi.org/10.2196/18444

Dadaczynski, K., Okan, O., Messer, M., Leung, A.Y.M., Rosário, R., Darlington, E., Rathmann K. (2021). Digital health literacy and web-based information-seeking behaviors of university students in Germany during the COVID-19 pandemic: Cross-sectional survey study. *Journal of Medical Internet Research*, 23(1), e24097. https://doi.org/10.2196/24097

Demirci, Ş., Uğurluoğlu, Ö., Konca, M., & Çakmak, C. (2021). Socio-demographic characteristics affect health information seeking on the internet in turkey. *Health Information and Libraries Journal*, 38(4), 304-312. https://doi.org/10.1111/hir.12358

Eysenbach, G. (2020). How to Fight an infodemic: The four pillars of infodemic management. *Journal of Medical Internet Research*, *22*(6), e21820. https://doi.org/10.2196/21820

Friis-Healy, E. A., Nagy, G. A., & Kollins, S. H. (2021). It is time to REACT: Opportunities for digital mental health apps to reduce mental health disparities in racially and ethnically minoritized groups. *JMIR Mental Health*, 8(1), e25456-e25456. https://doi.org/10.2196/25456

Ghahramani, F., & Wang, J. (2020). Impact of smartphones on quality of life: A health information behavior perspective. *Information Systems Frontiers, 22*(6), 1275-1290. https://doi.org/10.1007/s10796-019-09931-z

Glanz, K., & Rimer, B. (2005). *Theory at a Glance: A guide for health promotion practice.* U.S. Dept. of Health and Human Services, National Cancer Institute.

Guidry, J. P. D., Jin, Y., Orr, C. A., Messner, M., & Meganck, S. (2017). Ebola on Instagram and Twitter: How health organizations address the health crisis in their social media engagement. *Public Relations Review*, *43*(3), 477–486. https://doi.org/10.1016/j.pubrev.2017.04.009

Guo, Z., Zhao, S. Z., Guo, N., Wu, Y., Weng, X., Wong, J. Y. H., Lam, T. H., & Wang, M. P. (2021). Socioeconomic Disparities in eHealth Literacy and Preventive Behaviors During the COVID-19 Pandemic in Hong Kong: Cross-sectional Study. *Journal of Medical Internet Research*, *23*(4), e24577. https://doi.org/10.2196/24577

Hopkins, D. P., Husten, C. G., Fielding, J. E., Rosenquist, J. N., & Westphal, L. L. (2001). Evidence reviews and recommendations on interventions to reduce tobacco use and exposure to environmental tobacco smoke. *American Journal of Preventive Medicine*, *20*(2), 67–87. https://doi.org/10.1016/s0749-3797(00)00298-1

Hou, Z., Du, F., Zhou, X., Jiang, H., Martin, S., Larson, H., & Lin, L. (2020). Cross-country comparison of public awareness, rumors, and behavioral responses to the COVID-19 epidemic: infodemiology study. *Journal of Medical Internet Research*, 22(8), e21143. https://doi.org/10.2196%2F21143

Institute of Medicine. (2004). *Health Literacy: A Prescription to End Confusion*. Washington, DC: The National Academies Press, https://doi.org/10.17226/10883

Jeon, J., & Kim, S. (2022). The mediating effects of digital literacy and self-efficacy on the relationship between learning attitudes and ehealth literacy in nursing students: A cross-sectional study. *Nurse Education Today*, 113, 105378-105378. https://doi.org/10.1016/j.nedt.2022.105378

Jia, X., Pang, Y., & Liu, L. S. (2021). Online Health Information Seeking Behavior: A Systematic Review. *Healthcare*, *9*(12), 1740. https://doi.org/10.3390/healthcare9121740

Kim, H. K., & Tandoc, E. C., Jr (2022). Consequences of Online Misinformation on COVID-19: Two Potential Pathways and Disparity by eHealth Literacy. *Frontiers in Psychology*, *13*, 783909. https://doi.org/10.3389/fpsyg.2022.783909

Kor, P. P. K., Leung, A. Y. M., Parial, L. L., Wong, E. M. L., Dadaczynski, K., Okan, O., Amoah, P. A., Wang, S. S., Deng, R., Cheung, T. C. C., & Molassiotis, A. (2020). Are People With Chronic Diseases Satisfied With the Online Health Information Related to COVID-19 During the Pandemic? *Journal of Nursing Scholarship*, *53*(1), 75–86. https://doi.org/10.1111/jnu.12616

LaValley, S. A., Kiviniemi, M. T., & Gage-Bouchard, E. A. (2017). Where people look for online health information. *Health Information and Libraries Journal*, 34(2), 146-155. https://doi.org/10.1111/hir.12143

Lee, S. Y., & Hawkins, R. P. (2016). Worry as an uncertainty-associated emotion: Exploring the role of worry in health information seeking. *Health Communication*, 31(8), 926-933. https://doi.org/10.1080/10410236.2015.1018701

McAlister, A. L., Perry, C. L., & Parcel, G. S. (2008). How individuals, environments, and health behaviors interact: Social cognitive theory. In K. Glanz, B. K. Rimer, & K. Viswanath (Eds.), *Health behavior and health education: Theory, research, and practice* (pp. 169–188). Jossey-Bass.

McAlister, A., Johnson, W., Guenther-Grey, C., Fishbein, M., Higgins, D., & O'Reilly, K. (2000). Behavioral journalism for HIV prevention: Community newsletters influence risk-related attitudes and behavior. *Journalism & Mass Communication Quarterly*, *77*(1), 143–159. https://doi.org/10.1177/107769900007700111

McMullan, R. D., Berle, D., Arnáez, S., & Starcevic, V. (2019). The relationships between health anxiety, online health information seeking, and cyberchondria: Systematic review and meta-analysis. *Journal of Affective Disorders, 245*, 270-278. https://doi.org/10.1016/j.jad.2018.11.037

Melki, J., Hitti, E., Abou Zeid, M., El Takach, A., Hadid, D., Ghandour, L., Naamani, D., Karakira, Kassab, A.H., El Amin, J., Tabbara, R. & Farhat, S. (2020). Mitigating infodemics: A working paper on media and communication uses in Lebanon during the COVID-19 pandemic. *Media/Digital Literacy Program*. Institute of Media Research and Training, Volume 1, Issue 2, Lebanese American University, Beirut, Lebanon.

Okan, O., Bollweg, T. M., Berens, E.-M., Hurrelmann, K., Bauer, U., & Schaeffer, D. (2020). Coronavirus-related health literacy: A cross-sectional study in adults during the COVID-19 infodemic in Germany. *International Journal of Environmental Research and Public Health*, *17*(15), 5503. https://doi.org/10.3390/ijerph17155503

Onder, G., Rezza, G., & Brusaferro, S. (2020). Case-fatality rate and characteristics of patients dying in relation to COVID-19 in Italy. *Journal of the American Medical Association*, 323(18), 1775–1776. https://doi.org/10.1001/jama.2020.4683

Özkan, S., Tüzün, H., Dikmen, A. U., Aksakal, N. B., Çalışkan, D., Taşçı, Ö., & Güneş, S. C. (2021). The Relationship Between Health Literacy Level and Media Used as a Source of Health-Related Information. *Health Literacy Research and Practice*, *5*(2), e109–e117. https://doi.org/10.3928/24748307-20210330-01

Pandey, A., Patni, N., Singh, M., Sood, A., & Singh, G. (2010). YouTube as a source of information on the H1N1 influenza pandemic. *American Journal of Preventive Medicine*, *38*(3), e1–e3. https://doi.org/10.1016/j.amepre.2009.11.007

Pathak, R., Poudel, D. R., Karmacharya, P., Pathak, A., Aryal, M. R., Mahmood, M., & Donato, A. A. (2015). YouTube as a source of information on ebola virus disease. *North American Journal of Medical Sciences, 7*(7), 306-309. https://doi.org/10.4103/1947-2714.161244

Pourrazavi, S., Kouzekanani, K., Bazargan-Hejazi, S., Shaghaghi, A., Hashemiparast, M., Fathifar, Z., & Allahverdipour, H. (2020). Theory-based e-health literacy interventions in older adults: A systematic review. *Archives of Public Health*, *78*(1). https://doi.org/10.1186/s13690-020-00455-6

Ramirez, A. G., Aguilar, R. P., Merck, A., Despres, C., Sukumaran, P., Cantu-Pawlik, S., & Chalela, P. (2021). Use of #SaludTues tweetchats for the dissemination of culturally relevant information on latino health equity: Exploratory case study. *JMIR Public Health and Surveillance*, 7(3), e21266-e21266. https://doi.org/10.2196/21266

Rivera-Romero, O., Gabarron, E., Miron-Shatz, T., Petersen, C., & Denecke, K. (2022). Social media, digital health literacy, and digital ethics in the light of health equity. Yearbook of Medical Informatics, https://doi.org/10.1055/s-0042-1742503

Rosário, R., Martins, M. R. O., Augusto, C., Silva, M. J., Martins, S., Duarte, A., Fronteira, I., Ramos, N., Okan, O., & Dadaczynski, K. (2020). Associations between COVID-19-related digital health literacy and online information-seeking behavior among Portuguese university students. *International Journal of Environmental Research and Public Health*, *17*(23), 8987. https://doi.org/10.3390/ijerph17238987

Saade, R., & Kira, D. (2009). Computer Anxiety in E-Learning: The Effect of Computer Self-Efficacy. *Journal of Information Technology Education: Research*, *8*, 177–191. https://doi.org/10.28945/166

Schillinger, D., Grumbach, K., Piette, J., Wang, F., Osmond, D., Daher, C, Palacios, J., Sullivan, G.D., & Bindman, A.B. (2002). Association of health literacy with diabetes outcomes. *Journal of the American Medical Association, 288*(4), 475-482. https://doi.org/10.1001/jama.288.4.475

Shadmi, E., Chen, Y., Dourado, I., Faran-Perach, I., Furler, J., Hangoma, P., Hanvoravongchai, P., Obando, C., Petrosyan, V., Rao, K. D., Ruano, A. L., Shi, L., de Souza, L. E., Spitzer-Shohat, S., Sturgiss, E., Suphanchaimat, R., Uribe, M. V., & Willems, S. (2020). Health equity and COVID-19: Global perspectives. *International Journal for Equity in Health, 19*(1), 104-104. https://doi.org/10.1186/s12939-020-01218-z

Simsek, A. (2011). The relationship between computer anxiety and computer self-efficacy. *Contemporary Educational Technology*, *2*(3). https://doi.org/10.30935/cedtech/6052

Skarpa, P. E., & Garoufallou, E. (2021). Information seeking behavior and covid-19 pandemic: A snapshot of Young, middle aged and senior individuals in Greece. *International Journal of Medical Informatics*, *150*, 104465. https://doi.org/10.1016/j.ijmedinf.2021.104465

Tangcharoensathien, V., Calleja, N., Nguyen, T., Purnat, T., D'Agostino, M., Garcia-Saiso, S., Landry, M., Rashidian, A., Hamilton, C., AbdAllah, A., Ghiga, I., Hill, A., Hougendobler, D., van Andel, J., Nunn, M., Brooks, I., Sacco, P.L., De Domenico, M., Mai, P., Gruzd, A., Alaphilippe, A., Briand, S. (2020). Framework for managing the COVID-19 infodemic: Methods and results of an online, crowdsourced WHO technical consultation. *Journal of Medical Internet Research*, 22(6), e19659. https://doi.org/10.2196/19659

The World Bank. (2020). The world bank in Lebanon-Overview. https://www.worldbank.org/en/country/lebanon/overview

Tsai, M.-J., & Tsai, C.-C. (2003). Information searching strategies in web-based Science Learning: The role of internet self-efficacy. *Innovations in Education and Teaching International*, *40*(1), 43–50. https://doi.org/10.1080/1355800032000038822

UNICEF Lebanon. (2020, March 6). Spreading facts, not fear, in the fight against coronavirus in Lebanon [Press release]. https://www.unicef.org/lebanon/press-releases/spreading-facts-not-fear-fight-against-coronavirus-lebanon.

UNDP Lebanon. (2020, May 22). UN combats spread of fake news at local and national levels [Press release]. https://www.lb.undp.org/content/lebanon/en/home/presscenter/pressreleases/pr22-05.html

van der Vaart, R., & Drossaert, C. (2017). Development of the digital health literacy instrument: Measuring a broad spectrum of health 1.0 and health 2.0 skills. *Journal of Medical Internet Research*, 19(1):e27. https://doi.org/10.2196/jmir.6709

van Kessel, R., Hrzic, R., O'Nuallain, E., Weir, E., Wong, B. L. H., Anderson, M., Baron-Cohen, S., & Mossialos, E. (2022). The digital health paradox: International policy perspectives to address the increased health inequalities for people living with disabilities. *Journal of Medical Internet Research, 24*(2), e33819-e33819. https://doi.org/10.2196/33819

van Kessel, R., Wong, B. L. H., Clemens, T., & Brand, H. (2022). Digital health literacy as a super determinant of health: More than simply the sum of its parts. *Internet Interventions*, *27*, 100500. https://doi.org/10.1016/j.invent.2022.100500

Vrdelja, M., Vrbovšek, S., Klopčič, V., Dadaczynski, K., & Okan, O. (2021). Facing the growing covid-19 infodemic: Digital Health Literacy and information-seeking behaviour of university students in Slovenia. *International Journal of Environmental Research and Public Health*, *18*(16), 8507. https://doi.org/10.3390/ijerph18168507

Wang, X., Shi, J., & Kong, H. (2021). Online Health Information Seeking: A Review and Meta-Analysis. *Health Communication*, *36*(10), 1163–1175. https://doi.org/10.1080/10410236.2020.1748829

Wei, X.; Du, Z.; Zhang, S. Analysis of barriers to health information seeking and utilizing in patients with diabetes. *Cross-Cultural Communication*. 2016, 12, 48–51.

Welch, V., Petkovic, J., Pardo Pardo, J., Rader, T., & Tugwell, P. (2016). Interactive social media interventions to promote health equity: An overview of reviews. *Health Promotion and Chronic Disease Prevention in Canada, 36*(4), 63-75. https://doi.org/10.24095/hpcdp.36.4.01

Wolf, M. S., Gazmararian, J. A., & Baker, D. W. (2005). Health literacy and functional health status among older adults. *Archives of Internal Medicine, 165*(17), 1946-1952. https://doi.org/10.1001/archinte.165.17.1946

World Health Organization. (n.d.). *Infodemic*. World Health Organization. Retrieved August 14, 2022, from https://www.who.int/health-topics/infodemic#tab=tab_1

World Health Organization. (n.d.). *Lebanon: WHO coronavirus disease (covid-19) dashboard with vaccination data*. Retrieved February 8, 2023, from https://covid19.who.int/region/emro/country/lb

Zarocostas, J. (2020). How to fight an infodemic. *The Lancet*, *395*(10225), 676. https://doi.org/10.1016/S0140-6736(20)30461-X