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Social networking sites use and life satisfaction: a moderated mediation model of e-health literacy, fatigue, uncertainty, and stress

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Abstract

Excessive social media use during health crises can lead to information overload and psychological distress, yet the mechanisms underlying this relationship remain unclear. This study investigated how social networking sites (SNS) affected life satisfaction during the COVID-19 pandemic in Iran and whether this relationship was explained by SNS fatigue, uncertainty about disease, and stress. The research also examined whether e-health literacy was a protective factor in this process. Results confirmed that SNS use negatively affected life satisfaction through a sequential pathway of increased fatigue, uncertainty, and stress. E-health literacy moderated the initial link between SNS use and fatigue, with higher literacy weakening this relationship. The results demonstrate the complex relationship between SNS use and wellbeing during health crises and highlight the potential protective role of e-health literacy.

Clinical trial number

Not applicable

Keywords Social networking sites, Life satisfaction, E-health literacy, SNS fatigue, Stress

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Introduction

The COVID-19 pandemic reportedly changed how people access information, with social networking sites (SNS) becoming central sources of information for people amid global uncertainty [1]. SNS refers to online platforms and apps that enable users to interact, form virtual communities, and share news and information [2]. As experienced in many countries, the pandemic increased Iranians' use of SNS in general and, more specifically, to seek health information [3]. In Iran, WhatsApp, Telegram, and Instagram are the most widely used social media platforms, with 88.5% of Iranians reporting social media use [4, 5].

This increased SNS usage during the pandemic created a significant problem as users were exposed to increased volumes of often contradictory, false or misleading health information, an issue that has been referred to as an *infodemic* [6]. SNS platforms serve as primary channels for infodemics due to their algorithmic amplification of content, minimal quality control, and rapid sharing capabilities. Unlike traditional media with editorial oversight, SNS allows information to spread with limited verification, creating an environment where users can encounter contradictory health claims, pseudoscientific treatments, and competing expert opinions simultaneously [7, 8].

In Iran, this issue was further intensified by challenges in accessing timely COVID-19 vaccines, which fueled greater reliance on SNS for health-related updates, treatment options, and preventive measures. As uncertainty about healthcare policies and vaccine availability persisted, the demand for SNS as a primary information source surged, exposing users to even greater information overload. This has raised concerns about the impact of excessive information and misinformation on users' mental health, wellbeing, and life satisfaction [9, 10, 11]. Research on SNS effects shows conflicting results - some studies demonstrate that SNS usage improves life satisfaction [12, 13], whereas others indicate excessive usage causes adverse psychological impacts, such as *techno-exhaustion* [14, 15]. Reviews suggest these varying effects depend on how SNS are used, how often, and by whom [16].

Two theoretical frameworks help explain the mechanisms behind these effects. The stressor-strain-outcome (SSO) theory explains how excessive use of SNS (stressor) leads to SNS fatigue (strain), which causes stress (outcome) [17]. Similarly, cognitive dissonance theory reveals how exposure to inconsistent information on SNS produces psychological discomfort [18, 19].

A significant gap in current research involves understanding protective factors that might mitigate these negative outcomes. E-health literacy - the capability to effectively seek, understand, appraise, and apply health-related information from electronic sources [20] may serve this protective function. People with inadequate e-health literacy often feel overwhelmed and confused when exploring health information online, as they struggle to navigate, interpret, and effectively assess information quality. The prime theoretical construct of e-health literacy is self-efficacy, representing an individual's belief in their capability to organize and execute a plan of action in specific situations [21, 22]. Users with low e-health literacy likely experience greater uncertainty and anxiety when facing information overload compared to those who can effectively process information.

Most studies have investigated the direct relationship between e-health literacy and various health outcomes (e.g., hospitalization, mortality, health care cost, and health information seeking) [23, 24]. However, limited evidence exists regarding e-health literacy's role in managing the infodemic and its impact on life satisfaction during disease outbreaks. This gap is particularly relevant given how people increasingly use social media for health information. Studies show changing patterns in health information seeking, with greater reliance on internet sources in Iran [25] and globally [8]. Research indicates that 85% of participants use social media for health information, though concerns about reliability persist [26]. Even healthcare professionals increasingly use social media to exchange medical knowledge, with 53% and 35% reporting such use to enhance their practices [27].

To address this research gap, this study has two objectives: First, to investigate the serial mediating role of SNS fatigue, uncertainty, and stress about COVID-19 in the relationship between SNS use and life satisfaction during the pandemic in Iran; second, to assess the moderating role of e-health literacy in the relationship between SNS use and SNS fatigue.

Literature review

H1 *There is a relationship between SNS use and life satisfaction.*

Research on the relationship between SNS use and users' psychological wellbeing has found conflicting results [14, 28, 29]. For instance, early research demonstrated that SNS use through increasing social support positively impacts life satisfaction [30]. In contrast, some studies have shown that some SNS characteristics (e.g., information overload) negatively impact psychological wellbeing [17]. Considering the conflicting findings of past studies, this study develops a two-tailed hypothesis to test if SNS use during the pandemic is related to life satisfaction.

H2*. SNS use is positively related to SNS fatigue.*

SNS fatigue has been recently described as mental exhaustion and subjective feelings of tiredness induced by overusing social networks [17, 31, 32, 33]. Extant literature has identified specific antecedents of SNS fatigue, including psychological stressors (e.g., fear of missing out, social comparison) and behavioral factors (e.g., compulsive checking behaviors) [31, 32, 34]. Research has also demonstrated that different types of SNS overload contribute to fatigue, specifically social overload (excessive social demands), information overload (overwhelming content volume), and communication overload (unmanageable message frequency) [31, 32, 35]. When cognitive demands exceed working memory capacity, information processing becomes impaired, leading to difficulties in comprehension, retention, and recall of new information [36]. This cognitive overload impedes the brain's ability to filter and organize incoming data effectively. SNS fatigue relates to subjective exhaustion, disinterest, and mental

depletion that emerge when the volume and complexity of social media information surpasses an individual's cognitive processing capacity [32, 35]. This state represents a stress response to prolonged cognitive demands. Increased time spent on social media platforms exposes users to an accelerating stream of content can be taxing on cognitive processes such as impaired attention, reduced comprehension, and decision-making difficulties [32].

H3 *E-health literacy moderates the relationship between the use of SNS and SNS fatigue.*

The surge in the public's use of SNS to acquire information on diseases exposes users to large volumes of information [37, 38, 39] and contradictory or invalid information with no scientific basis [40]. SNS platforms can amplify an infodemic due to their minimal content verification and rapid sharing capabilities.

E-health literacy functions as a cognitive filter that helps users process health information encountered on SNS [41]. Individuals with higher e-health literacy possess specific skills for navigating this content: They can recognize credible sources, understand scientific terminology, contextualize statistical information, and identify logical inconsistencies in health claims. These capabilities allow them to process information more efficiently, reducing the cognitive resources required to make sense of contradictory content.

People with low e-health literacy are more likely to comprehend e-health information incorrectly and have difficulties differentiating between low-quality and high-quality information [42]. Research has shown that individuals with high health literacy require less cognitive capability to sort out information than those with low health literacy, who risk experiencing cognitive overload [43]. Without effective filtering mechanisms, individuals with low e-health literacy must expend significantly more cognitive effort to reconcile conflicting information, accelerating resource depletion and fatigue. E-health literacy helps individuals distinguish relevant information from conflicting messages on social media and reduces the dissonance created by the overload of contradictory information, especially during an infodemic [44]. Therefore, e-health literacy may moderate the relationship between SNS use and fatigue, as the literature suggests that people with higher e-health literacy feel less SNS fatigue [21].

H4 *Fatigue due to SNS use is positively related to uncertainty.*

Literature has shown that in the context of previous natural or human-caused disasters, excessive consumption of news and information via media platforms has been associated with higher levels of stress, anxiety, and depression [45]. When the volume of information exceeds a person's cognitive processing capacity, they cannot effectively categorize and interpret new information. This ultimately creates an atmosphere of confusion and uncertainty.

Brashers, Brashers et al. [46] noted that exposure to excessively inconsistent information could complicate individuals' coping ability and increase uncertainty. As social media fatigue is rooted in the experience of information overload, it is expected that SNS fatigue produces uncertainty.

While both fatigue and uncertainty can result from information overload, cognitive processing theory suggests a sequential rather than parallel relationship between them. SNS fatigue represents a state of cognitive resource depletion resulting from information processing demands that exceed available capacity [36]. This depleted cognitive state then impairs an individual's ability to effectively evaluate and make sense of information, leading to uncertainty. According to limited capacity models of information processing, when cognitive resources are exhausted through prolonged or intensive social media use (fatigue), the ability to organize, categorize, and make judgments about information quality decreases, resulting in increased uncertainty. This theoretical foundation could explain why fatigue would likely precede uncertainty rather than both developing simultaneously [45, 46].

H5 *There is a positive relationship between uncertainty about disease and stress.*

Research has revealed that uncertainty as an environmental or psychological factor is considered a potent stressor that reduces psychological wellbeing and leads to stress disorder [47, 48]. Moreover, empirical evidence has shown that uncertainty about illness causes stress due to various reasons (e.g., the novelty of the disease and incomplete knowledge of the medical community [49]. While the reliance on online sources to obtain health information has risen during the COVID-19 pandemic, the *infodemic* strengthened uncertainty and caused stress responses.

H6 *There is a negative relationship between stress about the COVID-19 disease and life satisfaction.*

The association between stress and life satisfaction has been a critical topic of research, which has found that stress negatively impacts life satisfaction [50]. The transactional theory of stress, developed by, suggests that in coping with a stressful situation, an individual appraises internal/external stressors to ensure they do not exceed their resources to endanger their wellbeing. The theory explains that the overload of contradictory information due to SNS use may influence individuals to perceive they have inadequate resources to cope with COVID-19.

Consequently, a perceived lack of resources will intensify a stressful event, negatively influencing individuals' well-being and life satisfaction [51].

H7 *SNS Fatigue, uncertainty, and stress sequentially mediate the relationship between the use of SNS and life satisfaction.*

Similar to past research on stress in the context of information technology, this study uses the stressor-strain-outcome (SSO) theory to underpin the relationship between SNS use and life satisfaction. Based on SSO, excessive time spent on SNS (stressor) sequentially prompts SNS fatigue, uncertainty, and stress (strain), which further leads to reduced life satisfaction (outcome).

The proposed sequential ordering follows a cognitive-affective processing pattern established in psychological research. First, exposure to large amounts of contradictory and ambiguous information due to increased SNS use results in cognitive resource depletion, referred to as SNS fatigue [52]. This cognitive exhaustion then impairs information processing capabilities, making it difficult for individuals to reconcile conflicting information about the disease, thereby creating uncertainty. Research in cognitive psychology supports this progression, as fatigue-induced cognitive impairment compromises an individual's ability to evaluate information coherently [36, 43].

Subsequently, this uncertainty is a psychological stressor contributing to stress responses. Psychological research has established that uncertainty about health threats specifically triggers stress responses as a reaction to perceived threats from unknown or unpredictable circumstances [47, 48]. This cognitive-to-affective progression from fatigue to uncertainty to stress represents a theoretically grounded causal sequence rather than parallel or alternative orderings of these variables.

While an extensive body of literature has examined the relationship between SNS use and wellbeing (e.g., life satisfaction), stemming from theory and previous research, this study offers a more complex model where SNS fatigue, uncertainty, and stress mediate the effect of SNS use on life satisfaction among SNS users. Previous research in disaster contexts supports this progression, demonstrating how information processing demands create cognitive strain, perceptual confusion, and emotional distress [45].

Table 1 Participants' demographic characteristics

Characteristic	*N*	%
Sex		
Female	282	53.2
Male	248	46.8
Education level		
Primary or Secondary School	22	4.2
Completed Secondary School/Diploma	113	21.3
Bachelor's Degree	216	40.8
Postgraduate Degree	179	33.8
Employment status		
Unemployed	108	20.4
Student	64	12.1
Part-time emloyment	104	19.6
Full-time employment	254	47.9
Currently Employed in Healthcare?		
Yes	157	29.6
No	373	70.4
Impact of the pandemic on Emloyment		
Lost job	94	17.7
Lost part of job	123	23.2
Shifted to online work	162	30.6
Business growth	51	9.6

Methods

Research design

In this cross-sectional study, data from Iranian adults were obtained through an online survey distributed via the social media platforms Telegram and Facebook in 2021. These platforms were chosen because they are among Iran's most popular social networks, allowing access to a diverse sample of SNS users. The survey was administered during the COVID-19 pandemic when Iran was experiencing its third wave of infections, a period characterized by high information seeking about the disease through social media channels.

Participants

The study participants were individuals who used social networks. In total, 530 Iranians with an average age of 35.57 years ($SD = 10.31$; Range = 18 to 70) participated. The sample consisted of 282 females (53.2%) and 248 males (46.8%) (Table 1).

Measures

SNS use Respondents were asked to indicate how many hours they spend on social media platforms daily [53].

E-health literacy An eight-item e-health Literacy Scale [21] was used, such as "I know how to find helpful health resources on the Internet." Participants were invited to answer items on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Fatigue due to SNS Three items adapted from Dhir et al. [17] on a 7-point Likert scale varying from 1 (strongly disagree) to 7 (strongly agree) (e.g., "I am frequently overwhelmed by the amount of information available on social media").

Uncertainty about the COVID-19 disease This study adopted a short form of the Mishel Uncertainty in Illness Scale (SF-MUIS), which consisted of five items and was validated by Hagen et al. [54] (e.g., "I have a lot of questions about the COVID-19 disease without answers"). Responses were recorded on a 7-point Likert-type scale varying from 1 (strongly disagree) to 7 (strongly agree).

Stress The stress dimension of the Depression Anxiety and Stress Scales was used (e.g., "I found it hard to wind down") [55]. Responses to the seven items of the stress dimension were scored using a 4-point Likert scale from 0 (Did not apply to me at all) to 3 (Applied to me very much or most of the time).

Life satisfaction A single item, "All things considered, how satisfied are you with your life?" was used. The response was recorded utilizing an 11-point scale ranging from 0 "totally dissatisfied" to 10 "totally satisfied" [56].

Procedure

The study employed a voluntary response sampling approach, recruiting participants through announcements posted on public Telegram channels and Facebook groups popular among Iranian users. Telegram, which is widely used in Iran, allows users to join public channels where information is broadcast to subscribers. The research announcements contained information about the study's purpose, estimated completion time (approximately 15 min), and a link to the survey. Participation was voluntary, and no incentives were offered.

Before participating, individuals were screened based on inclusion criteria. All participants were [1] 18 years or older [2], current users of at least one social networking site [3], users of social media for COVID-19 health information seeking, and [4] able to provide informed consent. After screening, eligible participants completed the online survey containing demographic questions and measures for all variables in the research model. Upon completion of all measures, participants were thanked for their participation and provided with contact information for the researchers.

Data analysis

The samples were randomly split into two datasets, each comprising 265 responses. An exploratory factor analysis (EFA) was conducted with maximum likelihood estimation and Promax rotation on the first dataset using SPSS version 26. The Kaiser–Meyer–Olkin (KMO) and Bartlett's test of sphericity was used to check the appropriateness of the sample to conduct the factor analysis. Items with a factor loading of less than 0.5 were removed (Sharif & Nia, 2018). A maximum likelihood confirmatory factor analysis (CFA) was conducted to confirm the factor structure of the second dataset.

Several model fit indices were employed to evaluate the model fit to the data. The measurement model was revised following the modification indices. Cronbach's alpha, composite reliability (CR), and maximal reliability greater than 0.7 indicate good internal consistency and construct reliability [69]. For convergent validity, each construct's average variance extracted (AVE) needs to be more than 0.5 [57]. For discriminant validity, this study followed the Fornell and Larcker [58] criterion, where the AVE of each construct should be greater than its respective maximum squared variance (MSV). Also, this study used the Heterotrait Monotrait Ratio of Correlations (HTMT) matrix analysis to evaluate the discriminant validity of all constructs. There are no discriminant validity concerns when the HTMT values are below 0.85 [59].

Next, an imputation technique replaced the constructs with their latent variable score. Partial correlation analyses were conducted to test the correlations between the constructs while controlling for the effects of age, education level, and healthcare job. While age and education serve as control variables in many studies, healthcare-related jobs are also included in the context of the current study. Finally, the structural model was developed to test the hypotheses. The direct and indirect associations between the constructs were tested using the bootstrapping approach with 2000 replications. The interaction effect of e-health literacy and SNS use was computed and assessed to examine the moderation effect. This study used AMOS software version 27 to assess both measurement and structural models. All tests were two-tailed, and p-values of less than 0.05 were deemed statistically significant.

Results

The maximum likelihood EFA ($n = 265$) revealed four factors accounting for 63.994% of the variance. The first item of fatigue was due to SNS use, and item 8 of stress was eliminated due to low factor loading. The KMO value of 0.887, and the significant Bartlett's test of sphericity ($\chi^2 = 4010.259$, $df = 231$, $p < .001$) indicated that the sampling was adequate. Next, a CFA was conducted on the second dataset ($n = 265$) to verify and validate the factor structure obtained from the EFA. The results of the initial measurement model showed that the model did not fit the data well, as evidenced by: ($\chi^2(203) = 605.070$, $p < .05$, $\chi^2/df = 2.981$, CFI = 0.904, NFI = 0.863, RFI = 0.844, SRMR = 0.052, and RMSEA (90% confidence interval (CI)) = 0.087 (0.079–0.095)]. According to the modification indices, five pairs of item measurement errors were freely covaried to improve the model fit. These adjustments reflected nuanced relationships within the constructs. For stress, the modifications between items 2

and 5 highlighted a link between over-reactivity to situations and difficulty in calming down afterwards, indicative of challenges in emotional regulation. In terms of uncertainty, adjustments between items 1 and 2 set a broader framework for understanding uncertainty about COVID-19, while other items delved into more specific areas within this context. Within the domain of e-health literacy, modifications between items 1 and 2 reflected a distinction between general awareness of health resources on the Internet and specific knowledge of where to find them. Similarly, adjustments between items 3 and 4 captured the relationship between knowing how to find health information online and the ability to utilize it effectively for self-help. Finally, adjustments between items 7 and 8 represented the link between discerning the quality of online health resources and the confidence in using them for decision-making. These modifications provided a more refined understanding of the underlying constructs, contributing to the overall improvement of the CFA model fit [($\chi^2(198) = 363.745$, $p < .05$, $\chi^2/df = 1.837$, CFI = 0.960, NFI = 0.917, RFI = 0.904, SRMR = 0.049, and RMSEA (90% confidence interval (CI)) = 0.056 (0.047–0.065)]. All factor loadings were greater than 0.5 and statistically significant (Table 2). The results showed good internal consistency and reliability for all constructs, where Cronbach's alpha ranged from 0.753 to 0.940, CR ranged from 0.777 to 0.931, and maximal reliability ranged from 0.888 to 0.947. The AVE ranged from 0.602 to 0.696, demonstrating good convergent validity. Moreover, the MSV of each construct

Table 2 Measurement model assessment

Constructs/Items	EFA factor loading	CFA factor loading	α	CR	MAX_R	AVE	MSV
Fatigue due to SNS use			0.753	0.777	0.888	0.643	0.202
Item 2: I am frequently overwhelmed by amount of information available on the Internet.	0.745	0.728					
Item 3: Amount of information available on the Internet makes me tense & overwhelmed.	0.791	0.769					
Uncertainty about COVID-19 disease			0.918	0.919	0.935	0.696	0.017
Item 1: I have a lot of questions about COVID-19 without answers.	0.709	0.611					
Item 2: I understand everything explained to me about COVID-19.	0.832	0.556					
Item 3: The doctors say things to me about COVID-19 that can have many meanings.	0.843	0.830					
Item 4: There are so many different types of staff; it's unclear who is responsible for what.	0.899	0.786					
Item 5: The purpose of each treatment is clear to me.	0.870	0.643					
E-health literacy			0.940	0.931	0.947	0.630	0.004
Item 1: I know what health resources are available on the Internet.	0.677	0.654					
Item 2: I know where to find helpful health resources on the Internet.	0.866	0.777					
Item 3: I know how to use the health information I find on the Internet to help me.	0.885	0.747					
Item 4: I know how to find helpful health resources on the Internet.	0.899	0.838					
Item 5: I have the skills I need to evaluate the health resources I find on the Internet.	0.822	0.881					
Item 6: I know how to use the Internet to answer my questions about health.	0.847	0.924					
Item 7: I can tell high quality health resources from low quality health resources on the Internet.	0.779	0.752					
Item 8: I feel confident in using information from the Internet to make health decisions.	0.747	0.742					
Stress			0.896	0.913	0.922	0.602	0.202
Item 1: I found it hard to wind down.	0.661	0.726					
Item 2: I tended to over-react to situations.	0.645	0.786					
Item 3: I felt that I was using a lot of nervous energy.	0.771	0.852					
Item 4: I found myself getting agitated.	0.846	0.864					
Item 5: I found it hard to calm down after something upset me.	0.845	0.782					
Item 6: I found myself getting impatient.	0.738	0.741					
Item 7: I felt that I was rather touchy.	0.685	0.659					

α: Cronbach's alpha, CR: Composite reliability, MAX_R: Maximum reliability,

AVE: Average variance extracted, MSV: Maximum squared variance

α, *CR*, MAX_R > *0.0.7; AVE* > *0.5*, *AVE* > *MSV*

Table 3 Discriminant validity assessment using the Fornell-Larcker criterion and HTMT matrix

		Fatigue due to SNS use	Uncertainty about COVID-19 disease	E-health literacy	Stress
Fornell-Larcker criterion	Fatigue due to SNS use	0.795			
	Uncertainty about COVID-19 disease	0.114*	0.833		
	E-health Literacy	−0.121*	−0.056	0.802	
	Stress	0.414***	0.218***	−0.130**	0.760
Heterotrait-monotrait ratio of correlations (HTMT)	Uncertainty about COVID-19 disease	0.152			
	E-health literacy	0.108	0.052		
	Stress	0.411	0.220	0.123	

*$p<0.05$, **$p<0.01$, ***$p<0.001$

Table 4 The results of correlation analysis

Variables	[2]	[3]	[4]	[5]	[6]
[1] SNS use	0.162***	0.137**	0.087*	0.256***	−0.090*
[2] Fatigue due to SNS use		0.155***	−0.110*	0.483***	−0.076
[3] Uncertainty about COVID-19 disease			−0.069	0.268***	−0.061
[4] E-health literacy				−0.123**	0.041
[5] Stress					0.359***
[6] Life satisfaction					

*$p<0.05$, **$p<0.01$, ***$p<0.001$

The results controlled for age, education level, and employment in healthcare

(ranging from 0.004 to 0.202) was lower than its corresponding AVE, fulfilling discriminant validity criteria for all constructs. Also, the findings of the Fornell-Larcker and the HTMT matrix analysis showed discriminant validity for all constructs (Table 3).

The results of the partial correlation analysis using the latent variable score of all constructs after controlling for the effects of age, education level, and healthcare job, showed positive relationships between SNS use, fatigue due to SNS use, uncertainty about COVID-19 disease, and stress (Table 4). E-health literacy was negatively related to fatigue due to SNS use and stress. Moreover, life satisfaction was positively correlated with stress and negatively related to SNS use.

The structural model showed a good fit [χ^2 [6] = 6.628, χ^2/df = 1.105, CFI = 0.998, IFI = 0.999, NFI = 0.985, SRMR = 0.014, RMSEA = 0.014(0.001–0.060)] (Table 5). The results of assessing the total effect model indicated a significant negative relationship between SNS use and life satisfaction ($\beta = -0.091$, $p<.05$), supporting H1. The results of a direct effects assessment showed support for the relationship between SNS use and fatigue due to SNS use ($\beta = 0.162$, $p<.001$), which supported H2. Moreover, the relationship between the interaction of e-health literacy and SNS use with fatigue due to SNS use was statistically significant ($\beta = -0.099$, $p<.05$). This finding supported H3 on the moderating role of e-health literacy on the relationship between SNS use and fatigue due to SNS use. In other words, e-health literacy buffered the positive relationship between SNS use and fatigue due to SNS use. The moderating result of H3 was plotted in Fig. 1. Also, the relationships between fatigue due to SNS use and uncertainty about the COVID-19 disease ($\beta = 0.129$, $p<.01$), uncertainty about the COVID-19 disease and stress ($\beta = 0.176$, $p<.001$), as well as stress and life satisfaction ($\beta = -0.413$, $p<.001$) were statistically significant, which supported H4, H5, and H6, respectively. Furthermore, the results supported the serial mediation of fatigue due to SNS use, uncertainty about the COVID-19 disease, and stress in the relationship between SNS use and life satisfaction ($\beta = -0.002$, $p<.01$), supporting H7. The non-significant relationship between SNS use and life satisfaction in the mediation model ($\beta = -0.004$, $p=.923$) indicated full mediation. The model explained 30% of the stress variance and 15% of the variance of life satisfaction. Figure 2 shows the findings of the structural model assessment.

Discussion

The proliferation of the *Permanently Online*, *Permanently Connected* mindset during the pandemic likely led to feeling overwhelmed due to the influx of conflicting information [60]. This study shows that general SNS use during COVID-19 infringed upon users' life satisfaction (H1). Indeed, more time spent on SNS use was associated with psychological effects such as fatigue, uncertainty about COVID-19, and stress, which reduced life satisfaction. The results here corroborate those confirming the opposing sides of SNS use, such as higher levels of technostress that ultimately decrease life satisfaction [61]. With a surge in time spent on SNS, users are more likely to be exposed to misinformation or information overload. These make individuals feel fatigued and confused, hindering their ability to interpret or find the right information and negatively impacting life satisfaction [17].

Results from this study align with recent research showing that the rise in emotional fatigue is associated with using SNS (H2) [17]. Past literature has found that SNS users are overwhelmed by overburdening streams of ever-changing information [37]. According to the limited capacity model of motivated mediated message

Table 5 The results of structural model assessment

Paths	Standardized path coefficients	95% confidence interval	
		Lower bound	Upper bound
Total effect			
SNS use → Life Satisfaction	−0.091*	−0.158	−0.018
Direct effects			
SNS use → Fatigue due to SNS use	0.162***	0.088	0.235
SNS use → Uncertainty◆	0.112**	0.041	0.183
SNS use → Stress	0.177***	0.113	0.240
SNS use → Life satisfaction	−0.004	−0.071	0.067
Fatigue due to SNS use → Uncertainty◆	0.129**	0.050	0.197
Fatigue due to SNS use → Stress	0.412***	0.349	0.474
Fatigue due to SNS use → Life satisfaction	0.118**	0.034	0.200
Uncertainty◆ → Stress	0.176***	0.116	0.239
Uncertainty◆ → Life satisfaction	0.029	−0.042	0.099
Stress → Life satisfaction	−0.413***	−0.497	−0.331
E-health literacy → Fatigue due to SNS use	−0.161***	−0.235	−0.091
General SNS use * E-health literacy → Fatigue due to SNS use	−0.099*	−0.177	−0.027
Indirect effects			
SNS use → Fatigue due to SNS use → Uncertainty◆	0.021**	0.004	0.046
SNS use → Fatigue due to SNS use → Uncertainty◆ → Stress	0.003**	0.001	0.011
SNS use → Fatigue due to SNS use → Uncertainty◆ → Life Satisfaction	0.001	−0.001	0.004
SNS use → Fatigue due to SNS use → Stress	0.066***	0.031	0.111
SNS use → Fatigue due to SNS use → Life Satisfaction	0.019**	0.002	0.047
SNS use → Fatigue due to SNS use → Stress → Life Satisfaction	−0.028***	−0.015	−0.037
SNS use → Uncertainty◆ → Stress	0.020**	0.005	0.044
SNS use → Uncertainty◆ → Life Satisfaction	0.003	−0.002	0.018
SNS use → Uncertainty◆ → Stress → Life Satisfaction	−0.008**	−0.002	−0.014
SNS use → Stress → Life Satisfaction	−0.073***	−0.056	−0.079
Fatigue due to SNS use → Uncertainty◆ → Stress	0.023**	0.006	0.047
Fatigue due to SNS use → Uncertainty◆ → Life Satisfaction	0.004	−0.021	0.020
Fatigue due to SNS use → Stress → Life Satisfaction	−0.170**	−0.173	−0.157
Fatigue due to SNS use → Uncertainty◆ → Stress→ Life Satisfaction	−0.009**	−0.003	−0.016
Uncertainty◆ → Stress → Life Satisfaction	−0.073**	−0.058	−0.079
SNS use → Fatigue due to SNS use → Uncertainty◆ → Stress → Life Satisfaction	−0.002**	−0.004	−0.001

*$p<0.05$, **$p<0.01$, ***$p<0.001$; ◆ Uncertainty about COVID-19 disease; The results controlled for age, education level, and employment in healthcare.

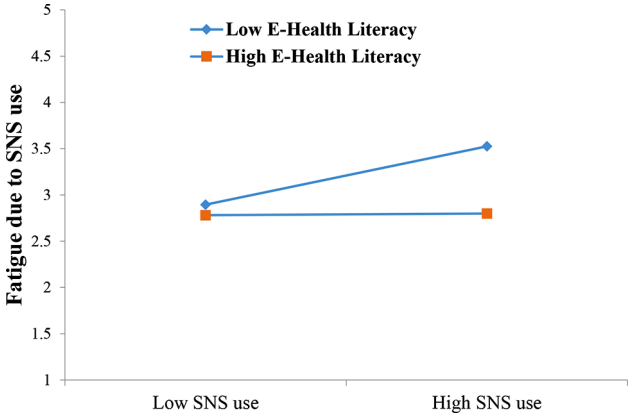


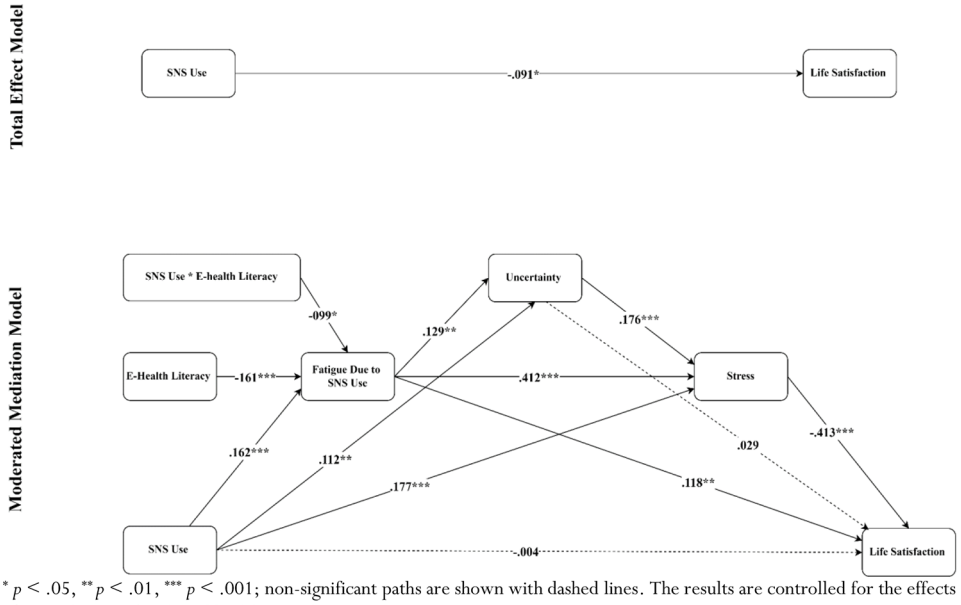
Fig. 1 The moderating effect of E-Health literacy on the relationship between SNS use and fatigue due to SNS use *$p<0.05$, **$p<0.01$, ***$p<0.001$; non-significant paths are shown with dashed lines. The results are controlled for the effects of age, education level, and healthcare job

processing (LC4MP) [62], individuals have a limited capacity to encode, store, and retrieve incoming information. With excess information, individuals may be fatigued after spending more time on SNS [35].

Also, the findings of this research indicate that the intensity of the negative link between the general use of SNS and SNS fatigue is dependent on e-health literacy (H3). The time spent on SNS has a stronger positive effect on SNS fatigue among those with low-level e-health literacy. Indeed, e-health literacy buffers the relationship between general SNS use and fatigue. These results imply that SNS users with low levels of e-health literacy are vulnerable to experiencing negative psychological states. This finding contributes to the existing literature by shedding light on e-health literacy as an essential life skill. As social media platforms have become a regular component in every field, including healthcare environments, the required skills associated with technology seem imperative.

One of the major contributions of this study lies in discovering the positive association between SNS fatigue and the uncertainty about COVID-19 (H4). This is the first study to highlight the link between SNS fatigue and uncertainty to our knowledge. It was found that SNS fatigue is associated with uncertainty about various aspects of the COVID-19 disease. Since many unknown factors about COVID-19 exist, circulated information on SNS might influence uncertainty. Since information on the number of days of hospitalization or symptoms from the virus varies, individuals feel uncertain about various aspects of COVID-19.

Subsequently, the results of this study showed that information uncertainty as a stressor was associated with higher levels of stress (H5). This is consistent with Lin et al.'s (2020) recent study that declared that individuals' stress in responding to the COVID-19 pandemic may be



* $p < .05$, ** $p < .01$, *** $p < .001$; non-significant paths are shown with dashed lines. The results are controlled for the effects of age, education level, and healthcare job

Fig. 2 The results of the structural model assessment

exacerbated by information uncertainty. This study corroborates the finding that uncertainty impacts stress [63]. In Iran, the contradictory information provided to the public by various stakeholders through virtual networks led people to lose faith [64]. It aggravated the confusion among individuals on how to find accurate information about COVID-19 treatment costs, amongst other types of information.

Similarly, the finding on the negative relationship between stress and life satisfaction (H6) was consistent with previous research. SNS fatigue, uncertainty, and stress-mediated the relationship between SNS use and life satisfaction (H7). SNS fatigue may lead to a surge in uncertainty about COVID-19, stress, and life dissatisfaction. This depicts the underlying mechanism that could explain the relationship between the use of SNS and life satisfaction, leading to this study's main theoretical contribution. According to cognitive overload theory, exposure to information overload and *infodemic* in SNS undermine the individuals' cognitive abilities to process information, leading to negative psychological states. Likewise, from the perspective of SSO theory, the use of SNS is regarded as a stressor that causes strain on life satisfaction. In a nutshell, SNS fatigue, uncertainty about COVID-19 disease, and stress serve as sequential mediators that link the general use of SNS to life satisfaction.

Limitations and future research

This study shows the value of integrating a possible moderator and mediator into a single theoretical framework to better understand the psychological development behind SNS use in the COVID-19 pandemic. This study is not without limitations. Firstly, using self-report techniques to measure e-health literacy and the use of SNS may not fully capture the participants' actual status and potentially introduce social desirability bias. Our voluntary response sampling through social media platforms may have introduced selection bias, as participants who were more active on SNS or had stronger opinions about COVID-19 information might have been more likely to participate. Secondly, using the cross-sectional research design makes it difficult to determine causality and establish temporal precedence among the variables. Thirdly, the current study participants are from Iran, which restricts the generalizability of the findings to other cultures.

A further limitation is the single-item approach to understanding life satisfaction. While this study examines psychological mediators and moderators of SNS use on life satisfaction, it is important to acknowledge that life satisfaction is influenced by multiple factors that include micro-level factors such as genes, neural mechanisms, and physiological processes, as well as macro-level elements, including socio-cultural norms, public health systems, and environmental conditions [65]. While valuable for participants' time, the single-item approach used in this study cannot fully capture the multidimensional nature of life satisfaction. Future research would benefit from cross-scale integration that connects these micro-level physiological foundations with the macro-level societal contexts in which individuals operate. Such integration could provide a deeper understanding of how SNS use influences wellbeing across different dimensions and contexts, enhancing the relevance of such findings

beyond psychology to fields such as public health, sociology, and neuroscience.

Several otherresearch directions emerge from these findings. longitudinal studies could address questions such as: How do the relationships between SNS use, e-health literacy, and psychological outcomes evolve over time? Do individuals develop adaptive strategies to manage information overload as a pandemic progresses? Such research would benefit from multiple measurement points (e.g., early, middle, and late pandemic phases) to capture developmental trajectories and potential adaptation processes.

Whereas future cross-cultural research could examine how cultural values regarding information-seeking and uncertainty avoidance influence the fatigue-uncertainty-stress pathway and whether collectivistic versus individualistic societies differ in how social media impacts psychological wellbeing during crises.

Implications

The currentstudy demonstrated that e-health literacy significantly moderates the relationship between SNS use and SNS fatigue, with higher e-health literacy reducing the strength of this relationship. By moderating this relationship, e-health literacy indirectly influences the pathway to life satisfaction through our sequential mediation model of fatigue, uncertainty, and stress. While our study did not test a direct relationship between e-health literacy and life satisfaction, our findings suggest that enhancing e-health literacy serves as an important protective mechanism, particularly when people are faced with high volumes of health information [66].

Based on these findings, specific interventionscould be developed to enhance users' abilities to crtically evaluate health information online. Such interventions could include digital literacy programs for schools and universities, targeted online courses for adults, and public health campaigns that teach specific skills such as verifying credible sources and understanding medical terminology and statistics [67]. Our findings also suggest that s these interventions should be developed with consideration to community factors (i.e., access to technology and cultural attitudes toward health information) and individual characteristics (i.e., age, education level, and existing digital skills) to ensure tailored approaches for individuals to best utilize health information encountered on social media platforms [68].

Conclusions

The findings showed that SNS fatigue, uncertainty about COVID-19, and stress-mediated the effect of SNS use on life satisfaction during the pandemic. Moreover, e-health literacy buffered the impact of SNS use on fatigue, such that the impact was weaker for those with higher levels of e-health literacy.

This study demonstrateds the sequential pathway through which excessive social media use affects life satisfaction. The results suggest that SNS use first leads to fatigue due to cognitive resource depletion, contributing to uncertainty about disease-related information as users struggle to reconcile conflicting content. This uncertainty subsequently acts as a stressor, triggering stress responses that ultimately reduce life satisfaction.

Identifying e-health literacy as a protective factor is a significant contribution to understanding how individual differences influence responses to information overload during health crises [42, 43]. The moderation effect found in this study suggests that developing e-health literacy skills might help reduce the negative psychological impacts of SNS use during pandemics and other public health emergencies where the public are facted with large amounts of information [41].

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Author contributions

N.N, S.P and H.SH designed the study. P.R & H.SH contributed the data collection. S.P & H.SH conducted the data analysis and interpretation of the data. O.E, L.SH & K.A were involved in drafting the manuscript. All authors critically revised the manuscript and approved the final version.

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Data availability

Due to the privacy of the research participants, the data generated during the current study are not publicly available but are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

The present study was performed in accordance with the international ethical standards of the Declaration of Helsinki. This study was approved by the ethics committee of Mazandaran University of Medical Sciences (IR.MAZUMS.REC.1399.008). Participants were informed that their participation was voluntary and that their responses would be published anonymously as group data. They completed the online informed consent form.

Consent for publication

Not Applicable.

Competing interests

The authors declare no competing interests.

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