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Social Media Fatigue and Discontinuous Usage: A Meta-Analytic Structural Equation Modeling Based on the Stimulus-Organism-Response Model

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ABSTRACT

As social media permeates people's daily lives, an increasing number of users show different levels of discontinuous use behaviors. Guided by the Stimulus-Organism-Response model, this meta-analysis synthesizes 107 empirical studies (N=57,865) on the correlation between stimuli (social media overload and psychosocial stress), organism (social media fatigue) and response (social media discontinuous usage behaviors). This study was registered on PROSPERO (ID: CRD420251079070). The findings suggested that communication overload and technological overload show large level effects on social media fatigue, whereas social overload, information overload, fear of missing out, privacy concern and social comparison yield medium level effects. And the effect size of social media fatigue on discontinuous usage behaviors was also at a medium level. Variations in sample demographics, platform types, and the period background were found to significantly moderate the links between specific stimuli and social media fatigue. Furthermore, the results of the meta-analytic structural equation modeling analysis show that some of the social media overload and psychosocial stress stimuli have direct effects on social media discontinuous usage behaviors, and social media fatigue partially mediates the effects. The results offer theoretical insights into the mechanisms emphasizing social media discontinuous usage and offer practical implications for platform design and users' digital well-being.

Keywords: Social Media Fatigue, Social Media Discontinuous Usage Behaviors, Stimulus-Organism-Response Model, Social Media Overload, Psychosocial Stress.

INTRODUCTION

Nowadays, social media is becoming increasingly important to people's lives. Social media has evolved quickly and frequently provides consumers with a wealth of information and entertainment (Chung et al., 2019). Notwithstanding the growth, there have been significant obstacles that are frequently referred to as the "dark side" of social media (Dhir et al., 2021). Users are becoming less enthusiastic about social media as they continue to experience negative consequences. The phenomenon leads to social media fatigue and other psychological problems (Malik et al., 2020). This type of fatigue is usually linked to negative behaviors such as lurking (Ortiz et al., 2018), taking breaks (York & Turcotte, 2015), limiting posting (Neves et al., 2022) and moving platforms (Zhang et al., 2022). Social media discontinuous usage behavior has drawn the attention of scholars (Feng, 2025).

Some studies have found that the primary reason for the phenomenon of ceasing to use social media is fatigue (Islam et al., 2018; Qaisar et al., 2022; Zhang et al., 2020). Users of social media become exhausted due to psychological and social stressors like comparison, privacy, and fear of missing out (FOMO). They forecast the erratic utilization (Dhir et al., 2019; Liu & He, 2021; Wu-Ouyang, 2024). However, findings in the existing literature are different. While Xie and Tsai (2021) argued that information overload directly leads to discontinuous usage, Gao et al. (2018) found no such relationship. While some studies found no association between FoMO and fatigue (Bright & Logan, 2018), others found that it significantly predicts fatigue (Malik et al., 2020). Moreover, recent studies have examined various influence factors (Kim et al., 2023; Shao et al., 2022), but the most of research has neglected the mediating effects.

While earlier meta-analyses have examined a number of social media research topics, they have mostly concentrated on general usage patterns or psychological effects (Cunningham et al., 2021; Huang, 2022; Shannon et al., 2022). Although some studies have looked at the factors that influence users' intentions of discontinuance (Farooq et al., 2023; Feng et al., 2024), they have not made a distinction between extrinsic and intrinsic factors. To our knowledge, few prior research has systematically examined the structural pathways linking social media overload, psychosocial stress, fatigue, and discontinuous usage using meta-analytic structural equation modeling (MASEM).

Therefore, this study investigates the causes to discontinuous usage behaviors by employing MASEM based on the Stimulus-Organism-Response (SOR) theoretical framework. Specifically, this research (1) examines the interaction between social media overload factors (extrinsic stimuli) and psychosocial stress factors (intrinsic stimuli) and how these interactions influence discontinue using intentions; (2) applies the SOR model by regarding social media overload and psychosocial stress as stimuli (S), social media fatigue as the organism (O), and discontinuous usage behavior as the response (R); (3) investigates moderating roles of various factors in the correlations between stimuli and social media fatigue; and (4) identifies significant areas for future research.

Social Media Discontinuous Usage Behaviors

As the social media use increases problems keep escalating, increasingly more people are showing different levels of discontinuous use behaviors. Current studies reflect a declining size of social media users (Wang et al., 2021), since many users are consciously abandoning social media platforms (Oltra et al., 2025). Discontinuous usage means the act of the users who abandon or decline to go on using a technology after using it for some time (Rogers et al., 2014). Maier et al. (2015) felt that the usage pattern arises from the combined influence of technical and conversion pressures. There has been a suggestion to call this discontinuance behavior a "social media vacation" (Hanley et al., 2019). Various scholarly studies have reported differing patterns of social media discontinuance including reducing intensity of use (Masood et al., 2021), discontinuance completely (Masood et al., 2021), temporally discontinuing (Zhang et al., 2024), and discontinuing and switch to others (Zhang et al., 2022). This study includes all varieties of discontinuance behavior.

Social Media Fatigue

Ravindran et al. (2014) state that social media fatigue is a complicated and individualized feeling. It manifests as a user's weariness, irritation, frustration, lack of interest, and refusal to utilize social media. Fatigue is essentially a mental health condition brought on by excessive social media use. Negative feelings like boredom or a decline in interest in social connection accompany fatigue (Zheng & Ling, 2021). In this study, refers to the negative emotional state resulting from excessive use of social media.

LITERATURE REVIEW AND RESEARCH MODEL

SOR Model

The stimulus-organism-response (SOR) theory describes the impact of stimuli on cognition and emotions and therefore leading to behavioral responses (Mehrabian, 1974). Scholars prefer to use it while dissecting environmental influence on cognition and human behavior (Chan et al., 2017). The SOR model helps to elucidate the function of discontinuous usage patterns. People give up the continuous use of social media due to fatigue (Faisal et al., 2024; Liu et al., 2021). The model explains the way some stimuli can cause individuals to get exhausted by social media and drop its use. As seen in **Figure 1**, the SOR model served as the foundation for the construction of the research model.

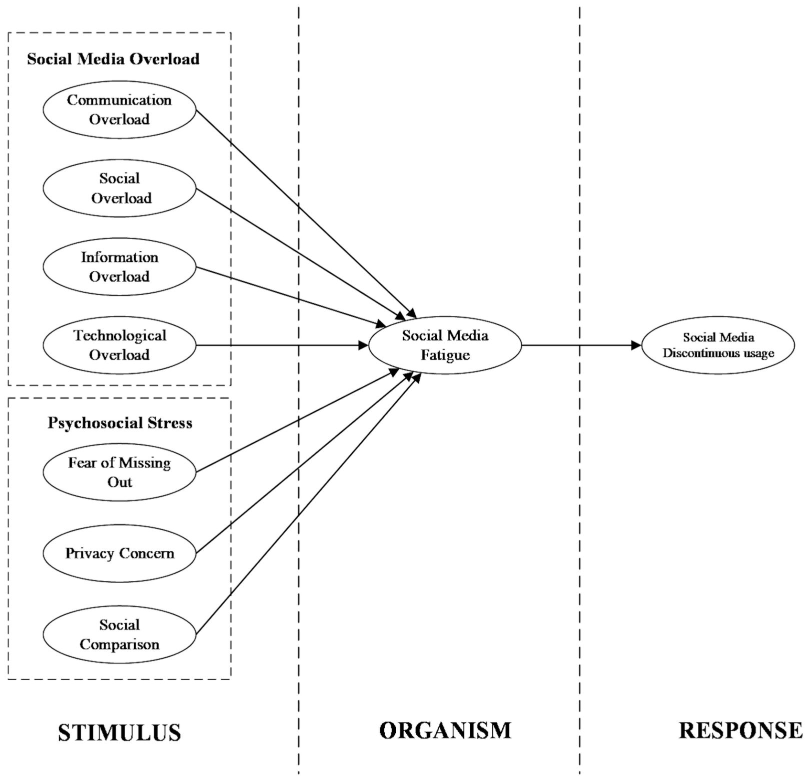

Figure 1. Research Model

External Stimuli and Internal Stimuli (S)

Environmental stimuli refer to the factors include external stimuli or internal stimuli. Both of them are examined in this study. External stimuli mainly include social overload, communication overload, information overload, and technology overload. Internal stimuli include social comparison, privacy concerns, and FOMO.

Excessive use of social media can harm users' well-being and mental state (Shahrazad et al., 2025). Excessive use tends to bring about information overload, wherein users are presented with more information than they are able to process (Bright et al., 2015). Overload results in fatigue, along with other adverse effects (Pang, 2021). Users are also confronted with too much social demand and, hence, social overload (Zhang et al., 2016). This has been linked to fatigue and discontinuous use (Li et al., 2018). Additionally, communication overload is also an important stimulus (Pang & Liu, 2024). Over-communication on social media can exhaust user energy (Cao & Sun, 2018). Complexity of platforms can also create technology overload, as users need to invest time in learning the usage of platforms (Cho, 2015; Fu & Li, 2022).

Psychosocial stress is another important stimulus. FoMO is fear of missing others' experiences (Przybylski et al., 2013). FoMO is prevalent in social media use (Xie et al., 2024). Many studies attribute fatigue to FoMO (Jabeen et al., 2023; Tandon et al., 2021). Moreover, social media has become a prevailing source of social comparison (Sabatini & Sarracino, 2015). It can decrease self-esteem and heighten fatigue (Jarman et al., 2021). The growing usage of social media also accelerated privacy and security concerns (Zhang et al., 2022). People who are concerned about privacy experience greater stress and fatigue (Dhir & Midha, 2014; Li et al., 2022).

Fatigue as Organism (O) and Discontinuous Usage Behaviors as Response (R)

Based on the SOR model, social media fatigue is an internal organism reaction to environmental stimuli, whereas discontinuous usage is a behavioral response of an individual. Following previous studies, people who experience fatigue after performing a particular behavior will be motivated to look for changes in the behavior (Podsakoff et al., 2007). Adopting grounded theory, Zhang et al. (2020) emphasized the combined contribution of situational and individual factors in causing fatigue and leading to discontinuous use behavior. Further, social fatigue can also intensify people's depressive and anxious mood states, which can lead to social media avoidance (Zong et al., 2019). Therefore, this study supposes that fatigue, as provoked by extrinsic and intrinsic drivers, presents the case for discontinuous usage.

Moderators

Differences in the findings of earlier research on these variables may be due to the effect of various participant populations and situational contexts. This study examines four potential moderating variables: gender, sample characteristics, platform type, and period background.

Gender. Women and men behave differently on social media discontinuance behaviors. Women are more prone to social media overload and fatigue than men (Bontcheva et al., 2013). Social media overload, though, enhances men's propensities to abandon the use of it than women (Zhang et al., 2016). Women remain online for longer periods and possess more friends in social media, which can actually interfere with their fatigue (Xiao et al., 2019). Because they consider privacy in their thoughts more frequently than men do, women tend to be fatigued (Adhikari & Panda, 2020).

Sample Characteristics. Social media fatigue and discontinuance vary across ages. Due to the advanced technical ability of young people, they may be most unlikely to be annoyed and exhausted with technology (Tarafdar et al., 2011). They can adapt better to ongoing updates and new features. In contrast, growing networks are likely to cause general users to feel more social overload and communication overload (Hampton et al., 2011). Age also affects psychosocial stress. Younger people are more susceptible to feeling excluded or nervous as a result of FoMO (Barry & Wong, 2020).

Platform Type. Users show different patterns on various platforms due to system features and social ties. Granovetter (1973) categorizes social ties into strong-tie and weak-tie. According to Wykoff (2019), platforms like Facebook, where users typically connect with individuals with whom they share closer relationships, are considered strong-tie platforms. In contrast, platforms such as Twitter provide users with access to fresh and timely information shared by individuals with weaker connections, and are therefore categorized as weak-tie platforms. Strong-tie platforms facilitate more frequent interactions and closer relationships, making users more susceptible to fatigue during use (Song et al., 2017; Zhang et al., 2024). Conversely, weak-tie platforms tend to foster lower levels of emotional support and trust among users.

Period Background. In late 2019, COVID-19 began to spread worldwide. Many countries imposed lockdowns in 2020 to control the virus (Liu et al., 2021). These changes led people to work, study, and socialize online, causing more social and communication overload (Huynh, 2020). Throughout this period, social media emerged as the primary source of information regarding the pandemic (Laato et al., 2020). The amount of information grew, but users found it hard to consume. This also heightened anxiety and social media fatigue (Islam et al., 2022). Further, people were more wary of posting things online for fear of being negatively criticized, thereby adding to their fatigue (Kim et al., 2022).

METHODOLOGY

Structural equation modeling (SEM) has emerged as a conventional analysis method in the social sciences for testing theoretical models (Hershberger, 2003; Schumacker & Lomax, 2004). Nevertheless, SEM research results can be inconsistent, and confirmation bias can influence findings (Greenwald et al., 1986). Meta-analysis serves to synthesize outcomes from various studies to give improved conclusions and inform subsequent research (Glass, 1976). MASEM takes this further by merging correlation matrices and analyzing them using SEM (Cheung & Chan, 2005). This approach allows researchers to explore complex relationships and increases statistical power (Bergh et al., 2016; Jak, 2015). Therefore, this study uses MASEM to explore how social media overload, psychosocial stress, and fatigue affect discontinuous usage behavior.

Literature Search

This study was registered on PROSPERO (ID: CRD420251079070). A systematic search was conducted on February 28, 2025, using Web of Science, PubMed, Scopus and Google Scholar. Keywords included all possible combinations of terms related to social media (e.g., social network site, SNS, WeChat, Twitter, Facebook, DouYin, TikTok, Instagram, Qzone, Weibo) and discontinuous usage behaviors (e.g., negative use, discontinuance, fatigue, tired, exhausted, exhaustion, abstinence, lurking, disengagement, short break, opt out, switch, negative coping, reduced usage, abandoned usage). The search yielded 3,219 results. After removing duplicates, 2,573 titles and abstracts were screened. We kept studies that used quantitative methods to explore the effects of overload or stress on discontinuous use. A total of 232 full texts were reviewed using the inclusion and exclusion criteria listed in **Table 1**.

Table 1. Criteria for Study Selection

Criteria	Details
Inclusion	Written in English
	Focused on social media discontinuous usage behaviors
	Based on a quantitative research design
	Reported correlations or enough data to calculate effect sizes
Exclusion	Published in languages other than English
	Focused on general social media usage without reference to discontinuous behaviors
	Based on a qualitative research design
	Lacking empirical data (e.g., theoretical or review articles)
	Lacking sufficient statistical information to compute effect sizes

After full-text screening, 6 reports were not retrieved, 19 studies were not written in English, 78 were irrelevant, 13 were qualitative, and 9 lacked key data. Finally, 107 studies were included. **Figure 2** illustrates the selection process in accordance with the PRISMA guidelines.

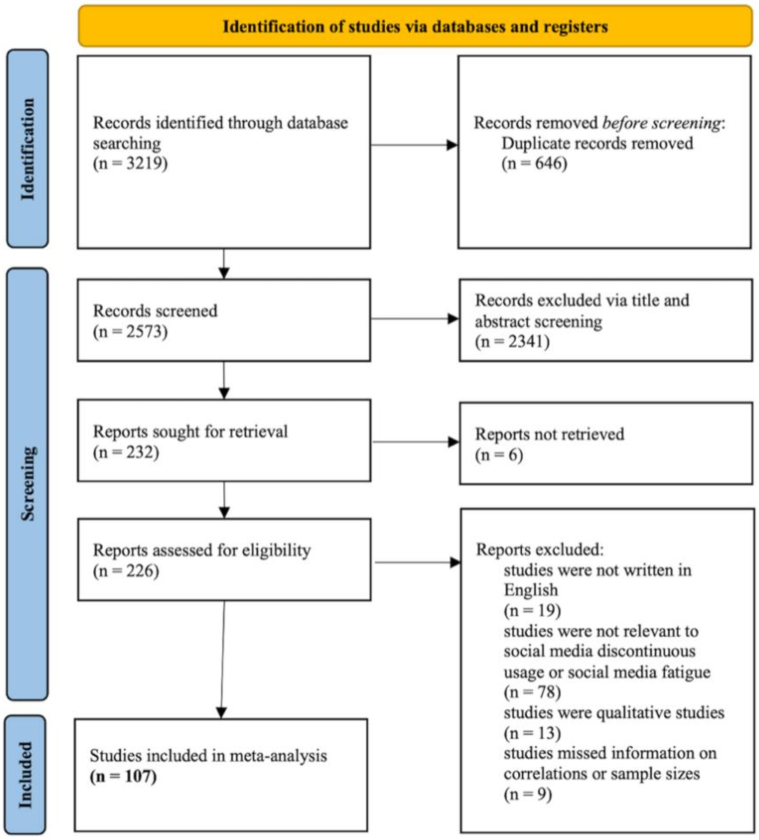

Figure 2. PRISMA Flowchart

In evaluating the methodological quality of the included studies, this meta-analysis followed the procedural standards propose by Kitchenham et al. (2009) and adopted the evaluation criteria developed by Lin et al. (2024). The specific quality assessment items and results are presented in Supplementary File 1.

Data Extraction and Coding

Information on (a) authors, (b) years, (c) country, (d) sample size, (e) percentage of young (age under 35), (f) gender, (g) social media platform, (h) reliability coefficient Cronbach's α, and (i) correlation coefficients were extracted. If reliability was missing, we used the weighted average from other studies (Lipsey, 2001). For studies reporting only regression coefficients, we converted β to r using Peterson and Brown (2005)'s method:

$$r = 0.98 * \beta + 0.05(\beta \geq 0), r = 0.98 * \beta - 0.05(\beta < 0), \beta \in (-0.5, 0.5)$$

To ensure precision and uniformity, full-text article extraction was independently verified by a second reviewer.

Following the procedures outlined by Brown et al. (2003), we first extracted and coded relevant information from all eligible studies. Gender was coded based on the percentage of female respondents. Sample characteristics were determined according to the proportion of young participants (those under 35 years of age), with were classified as (1) young group and (2) general group. The platform type was coded as (1) strong-tie platform, (2) weak-tie platform, or (3) general platform (studies that did not specify a particular platform). The period background was coded as (1) before COVID-19 and (2) after COVID-19. Following the steps proposed by Lipsey and Wilson (2001), three researchers independently carried out the initial coding. Inter-rater reliability, calculated using the percentage of agreement across all coded variables, reached 88.6%, which is considered acceptable in meta-analytic research. Any discrepancies were resolved through discussion until full consensus was achieved.

Correlation-Based Meta-Analysis

We used CMA 3.0 to conduct the meta-analysis and calculate effect sizes. Following the recommendation of Hedges and Olkin (2014), correlation coefficients (r) were transformed into Fisher's Z values. To assess publication bias, we utilized Egger's regression approach (Egger et al., 1997) and the fail-safe N technique (Rosenthal, 1979).

Heterogeneity was tested using Q and I^2 statistics. Heterogeneity was categorized as low (25%), moderate (50%), or high (75%) based on conventional thresholds for I^2 values, with 0 indicating no heterogeneity (Higgins et al., 2003). When significant heterogeneity was detected, a random-effects model was employed; in its absence, a fixed-effects model was adopted (Hedges & Vevea, 1998).

Moderator Analysis

Moderator analyses were performed to investigate possible causes of effect size heterogeneity using both meta-regression and subgroup analysis. Specifically, meta-regression assessed the role of gender. A significant z value showed a moderating effect (Borenstein et al., 2021). Subgroup analysis examined the potential moderating effects of sample characteristics, platform type, and period background. Moderation effects were evaluated through the Q-test for heterogeneity and the I^2 statistic. Following Hedges and Olkin (2014), a significant Q indicated differences across groups.

Meta-Analytic Structural Equation Modelling

Based on the meta-analysis results, we used SPSS Amos to run SEM and examine the multiple pathways among complex variables in our study model. Since meta-analysis combines studies with different sample sizes, we used the harmonic mean to estimate a balanced sample size for SEM, avoiding bias from large samples (Jiang et al., 2012). To find the best-fitting model, we compared two versions. The first was a fully mediated model, where social media fatigue fully mediated the effect of social media overload and psychosocial stress on discontinuous usage. The second was a partially mediated model, adding direct paths from overload and stress to discontinuous usage. The standardized root mean square residual (SRMR), root mean square error of approximation (RMSEA), goodness-of-fit index (GFI), comparative fit index (CFI), and non-normed fit index (NNFI, also known as the Tucker–Lewis index, TLI) are among the widely used fit indices used to assess the model fit (MacCallum et al., 1996). These indices offer a thorough evaluation of how well the proposed model replicates the observed data.

RESULTS

A total of 107 papers that were published between 2012 and 2025 were included. Participants in the various studies ranged from 60 to 6,002, for a total of 57,865 participants. Participants ranged in age from 12 to over 80. The list of included studies is provided in Supplementary File 2, and a description of their key characteristics is presented in Supplementary File 3.

Correlation-Based Meta-Analysis

Table 2 shows the eight meta-analytic correlations in the SOR model. Egger's test found no significant bias ($p > 0.05$), indicating no publication bias. The results of fail-safe N test also showed significant results ($p < 0.05$), confirming the findings were stable. Forest plots in Supplementary File 4 display the effect sizes and study differences.

Table 2. Summary of Relationships Estimated by Random Effects Meta-Analysis

Pairwise Relationships	k	n	Effect Size (r)	95% CI		z	p	Egger's Intercept	Nfso.05	Q	I2
				Lower	Upper						
CO-SMF	21	7819	0.551	0.476	0.618	11.867	***	4.8973	4980***	415.104***	95.182
SO-SMF	40	23523	0.441	0.358	0.517	9.423	***	-1.01421	44779***	2101.878***	98.145
IO-SMF	57	23902	0.480	0.439	0.519	19.678	***	3.30952	36872***	914.218***	93.875
TO-SMF	27	12033	0.500	0.418	0.575	10.287	***	6.69421	21880***	858.456***	96.971
FoMO-SMF	24	21064	0.346	0.242	0.442	6.221	***	1.51282	3097***	1464.816***	98.430
PC-SMF	28	15574	0.345	0.298	0.390	13.610	***	-0.8184	3522***	277.375***	90.266
SC-SMF	12	6800	0.407	0.336	0.473	10.291	***	0.58195	3640***	124.792***	91.185
SMF-SMDU	75	28402	0.499	0.452	0.543	17.706	***	-1.37734	55903***	1963.918***	96.232

Note. *** $p < 0.001$.

Effect sizes were tested for heterogeneity using Q and I^2. **Table 2** shows that all Q values were significant ($p < 0.001$), ranging from 124.792 to 2101.878, suggesting clear heterogeneity. I^2 values ranged from 90.266% to 98.430%, well above the 75% threshold. Thus, a random-effects model was used.

As shown in **Table 2**, the correlation effect sizes were all significant, varying between 0.345 and 0.551 ($p < 0.001$). Specifically, the correlation of CO-SMF demonstrated the largest effect size at 0.551, reflecting a large effect. The remainder of the correlations exhibited effect sizes ranging from 0.30 to 0.50, reflecting medium effect sizes (Cohen, 2013).

Moderator Analysis

The meta-regression analysis results concerning the moderating variable of gender ratio are presented in **Table 3**. The results show that gender ratio had no significant effect on the correlations ($p > 0.05$). This suggests gender was not a key source of heterogeneity in the studies.

Table 3. Results of Meta-Regression Analysis (Gender)

Pairwise Relationships	k	n	coefficient	SE	95% CI		z	p
					Lower	Upper		
CO-SMF	21	7819	-0.0007	0.007	-0.015	0.014	-0.09	0.926
SO-SMF	40	23523	-0.0016	0.006	-0.015	0.012	-0.24	0.810
IO-SMF	57	23902	-0.0011	0.004	-0.008	0.006	-0.32	0.746
TO-SMF	27	12033	0.0025	0.010	-0.017	0.022	0.25	0.800
FoMO-SMF	24	21064	-0.0068	0.010	-0.003	0.012	-0.71	0.481
SC-SMF	12	6800	0.0021	0.006	-0.010	0.014	0.35	0.726
PC-SMF	28	15574	-0.0045	0.004	-0.012	0.003	-1.15	0.248
SMF-SMDU	75	28402	0.0013	0.005	-0.008	0.010	0.29	0.773

The results of the subgroup analysis examining the moderating effect of sample characteristics are shown in **Table 4**. The findings indicated that sample characteristics moderated the TO-SMF and SC-SMF correlations. The TO-SMF effect was stronger in general groups (0.555) than in youth (0.404; QBET = 4.056, $p < 0.05$). The SC-SMF effect was also larger in general groups (0.449) than in youth (0.315; QBET = 4.542, $p < 0.05$).

Table 4. Results of Subgroup Analysis (Sample Characteristics)

Pairwise Relationships	Sample	k	Estimate	95% CI		z	p	QBET
				Lower	Upper			
CO-SMF	youth	7	0.594	0.487	0.684	8.828	***	0.875
	general	14	0.528	0.423	0.618	8.477	***	
SO-SMF	youth	15	0.409	0.323	0.487	8.624	***	0.575
	general	23	0.464	0.342	0.571	6.724	***	
IO-SMF	youth	19	0.516	0.432	0.590	10.394	***	1.126
	general	35	0.465	0.419	0.510	16.987	***	
TO-SMF	youth	9	0.404	0.322	0.480	8.908	***	4.056*
	general	16	0.555	0.429	0.661	7.301	***	
FoMO-SMF	youth	7	0.325	0.175	0.460	4.125	***	0.086
	general	17	0.354	0.220	0.475	4.946	***	
SC-SMF	youth	4	0.315	0.215	0.409	5.909	***	4.542*
	general	8	0.449	0.370	0.523	9.890	***	
PC-SMF	youth	12	0.347	0.275	0.415	8.901	***	0.005
	general	16	0.343	0.279	0.405	9.778	***	
SMF-SMDU	youth	22	0.549	0.469	0.621	11.074	***	2.200
	general	50	0.475	0.413	0.532	13.192	***	

Note. *** $p < 0.001$, * $p < 0.05$.

Table 5 shows that platform type significantly moderated the CO-SMF (QBET = 12.769, $p < 0.01$) and FoMO-SMF (QBET = 8.320, $p < 0.01$) correlations. The CO-SMF effect was strongest in general platforms (0.583), followed by strong-tie (0.500) and weak-tie platforms (0.372). The FoMO-SMF effect was also higher in general platforms (0.421) than in strong-tie platforms (0.209).

Table 5. Results of Subgroup Analysis (Platform Type)

Pairwise Relationships	platform	k	Estimate	95% CI		z	p	QBET
				Lower	Upper			
CO-SMF	general	14	0.583	0.481	0.670	9.102	***	12.769**
	strong-tie	6	0.500	0.389	0.597	7.731	***	
	weak-tie	1	0.372	0.305	0.435	10.174	***	
SO-SMF	general	15	0.437	0.247	0.595	4.237	***	0.283
	strong-tie	24	0.445	0.377	0.509	11.381	***	
	weak-tie	1	0.406	0.269	0.527	5.449	***	
IO-SMF	general	30	0.476	0.411	0.535	12.644	***	0.414
	strong-tie	22	0.493	0.436	0.546	14.587	***	
	weak-tie	5	0.448	0.293	0.580	5.245	***	
TO-SMF	general	12	0.566	0.403	0.694	5.868	***	2.568
	strong-tie	13	0.436	0.360	0.505	10.219	***	
	weak-tie	2	0.485	0.420	0.546	12.522	***	
FoMO-SMF	general	15	0.421	0.290	0.536	5.846	***	8.320**
	strong-tie	9	0.209	0.155	0.262	7.421	***	
SC-SMF	general	8	0.387	0.296	0.470	7.776	***	0.592
	strong-tie	4	0.444	0.322	0.551	6.555	***	
PC-SMF	general	12	0.324	0.240	0.402	7.278	***	5.443
	strong-tie	14	0.373	0.315	0.429	11.615	***	
	weak-tie	2	0.253	0.166	0.336	5.555	***	
SMF-SMDU	general	26	0.452	0.346	0.547	7.525	***	1.796
	strong-tie	42	0.526	0.474	0.574	16.520	***	
	weak-tie	7	0.498	0.410	0.576	9.680	***	

Note. *** $p < 0.001$, ** $p < 0.01$.

Table 6 shows that period background significantly moderated the FoMO-SMF (QBET = 5.430, $p < 0.05$) and PC-SMF (QBET = 21.079, $p < 0.001$) correlations. The FoMO-SMF effect was stronger after COVID-19 (0.361) than before (0.177), while the PC-SMF effect was stronger before the pandemic (0.460) than after (0.296).

Table 6. Results of Subgroup Analysis (Period Background)

Pairwise Relationships	Period (COVID-19)	k	Estimate	95% CI Lower	95% CI Upper	z	p	QBET
CO-SMF	after	17	0.557	0.471	0.632	10.513	***	0.164
	before	4	0.524	0.370	0.649	5.913	***	
SO-SMF	after	22	0.434	0.305	0.548	6.088	***	0.040
	before	18	0.450	0.354	0.537	8.262	***	
IO-SMF	after	40	0.486	0.433	0.536	15.386	***	0.386
	before	17	0.463	0.408	0.515	14.448	***	
TO-SMF	after	19	0.507	0.396	0.603	7.863	***	0.091
	before	8	0.489	0.432	0.542	14.442	***	
FoMO-SMF	after	22	0.361	0.247	0.464	5.912	***	5.430*
	before	2	0.177	0.067	0.282	3.141	**	
SC-SMF	after	29	0.475	0.400	0.544	10.848	***	0.050
	before	10	0.464	0.397	0.526	11.969	***	
PC-SMF	after	20	0.296	0.256	0.335	13.820	***	21.079***
	before	8	0.460	0.403	0.513	13.989	***	
SMF-SMDU	after	53	0.509	0.451	0.563	14.509	***	0.752
	before	22	0.469	0.395	0.538	10.933	***	

Note. *** *p* < 0.001, ** *p* < 0.01, * *p* < 0.05.

MASEM

Based on the meta-analysis results, we used SEM to explore multiple paths among variables. Two models were built: one for social media overload (external stimuli) and one for psychosocial stress (internal stimuli). This separation was due to limited prior research linking the two and the use of different data sources. Few studies covered both domains, making a combined model unreliable. Modeling them separately improved clarity and accuracy.

Table 7 presents the correlation matrix of social media overload stimuli utilized for conducting the MASEM. The partially mediated model fit better (SRMR = 0.004; RMSEA = 0.027; CFI = 0.999; GFI = 0.999; NNFI = 0.998) than the fully mediated one (SRMR = 0.032; RMSEA = 0.085; CFI = 0.981; GFI = 0.988; NNFI = 0.980). **Figure 3** illustrates the model results, while **Table 8** details the path analysis results. All paths were significant (p < 0.001), except CO-SMDU path (β = 0.03, p = 0.127).

Table 7. Correlations Matrix (Social Media Overload Stimuli)

Constructs	CO	SO	IO	TO	SMF	SMDU
CO	0.834					
SO	0.517	0.870				
IO	0.523	0.437	0.855			
TO	0.367	0.408	0.458	0.835		
SMF	0.551	0.441	0.480	0.500	0.893	
SMDU	0.355	0.267	0.394	0.372	0.499	0.848

Note. The diagonal value is the reliability coefficient, and the non-diagonal value is the average correlation coefficient weighted by the average sample size. Harmonic mean of N = 8,016.

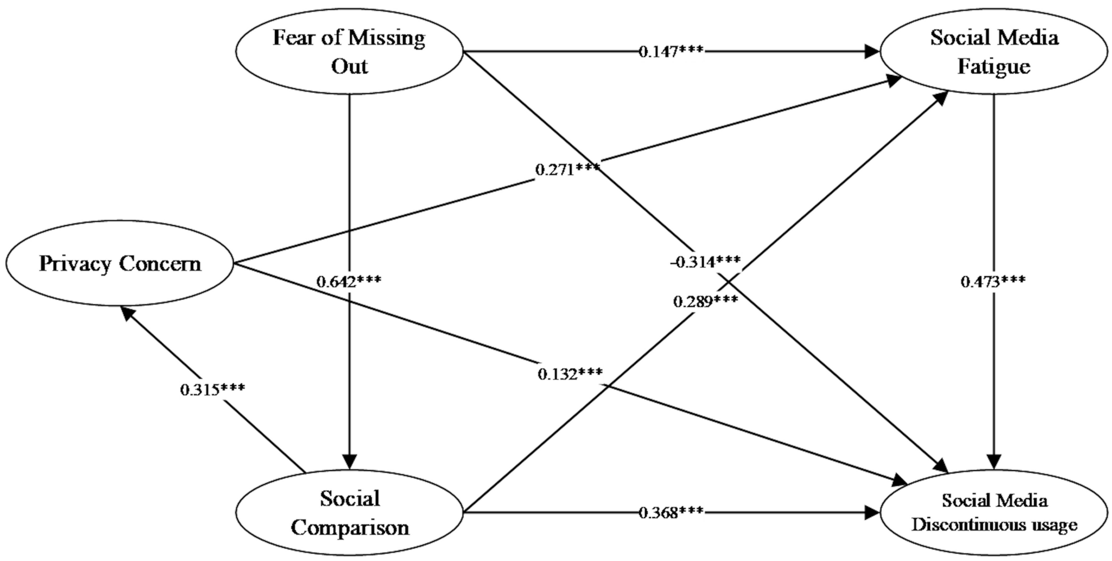

Figure 3. MASEM (Social Media Overload Stimuli)

Table 8. Results of Path Analysis (Social Media Overload Stimuli)

Path	Estimate	SE	CR	p
CO→SMF	0.409	0.016	26.004	***
SO→SMF	0.048	0.014	3.412	***
IO→SMF	0.094	0.015	6.183	***
TO→SMF	0.328	0.013	25.158	***
SMF→SMDU	0.416	0.017	23.891	***
CO→SMDU	0.030	0.02	1.528	0.127
SO→SMDU	-0.066	0.016	-4.143	***
IO→SMDU	0.185	0.017	10.741	***
TO→SMDU	0.119	0.016	7.274	***
TO→SO	0.480	0.012	39.909	***
SO→IO	0.318	0.013	24.417	***
TO→IO	0.391	0.013	29.402	***
SO→CO	0.395	0.013	31.358	***
IO→CO	0.421	0.013	33.172	***

Note. *** $p < 0.001$.

Specifically, CO (β = 0.409, p < 0.001) was the strongest predictor of SMF, followed by TO (β = 0.328), IO (β = 0.094), and SO (β = 0.048). SMF also positively predicted SMDU (β = 0.416). IO (β = 0.185), TO (β = 0.119), and SO (β = -0.066) had direct effects on SMDU, with SO showing a negative impact.

Additionally, SO exhibited significant positive associations with both CO (β = 0.395, p < 0.001) and IO (β = 0.318, p < 0.001). Likewise, TO demonstrated correlations with SO (β = 0.480, p < 0.001) and IO (β = 0.391, p < 0.001). In addition, IO was significantly associated with CO (β = 0.421, p < 0.001).Mediation analysis (**Table 9**) demonstrated that SMF significantly mediated the impacts of CO (Z = 0.170, p < 0.001), SO (Z = 0.020, p < 0.01), IO (Z = 0.039, p < 0.001) and TO (Z = 0.137, p < 0.001) on SMDU.

Table 9. Results of Mediating Effects (Social Media Overload Stimuli)

Parameter	Estimate	SE	95% CI		P
			Lower	Upper	
CO→SMF→SMDU	0.170	0.009	0.152	0.189	***
SO→SMF→SMDU	0.020	0.006	0.009	0.032	**
IO→SMF→SMDU	0.039	0.006	0.027	0.051	***
TO→SMF→SMDU	0.137	0.008	0.122	0.152	***

Note. *** $p < 0.001$, ** $p < 0.01$.

Table 10 presents the correlation matrix of psychosocial stress stimuli utilized in the MASEM. The partially mediated model fit better (SRMR = 0.015; RMSEA = 0.072; CFI = 0.995; GFI = 0.998; NNFI = 0.995) than the fully mediated one (SRMR = 0.048; RMSEA = 0.152; CFI = 0.916; GFI = 0.966; NNFI = 0.915). **Figure 4** and **Table 11** present the MASEM and path results. All paths were significant (p < 0.001).

Table 10. Correlations Matrix (Psychosocial Stress Overload Stimuli)

Constructs	FOMO	SC	PC	SMF	SMDU
FOMO	0.842				
SC	0.546	0.867			
PC	0.226	0.264	0.852		
SMF	0.346	0.407	0.345	0.879	
SMDU	0.125	0.370	0.307	0.499	0.863

Note. the diagonal value is the reliability coefficient, and the non-diagonal value is the average correlation coefficient weighted by the average sample size. Harmonic mean of N = 5,465.

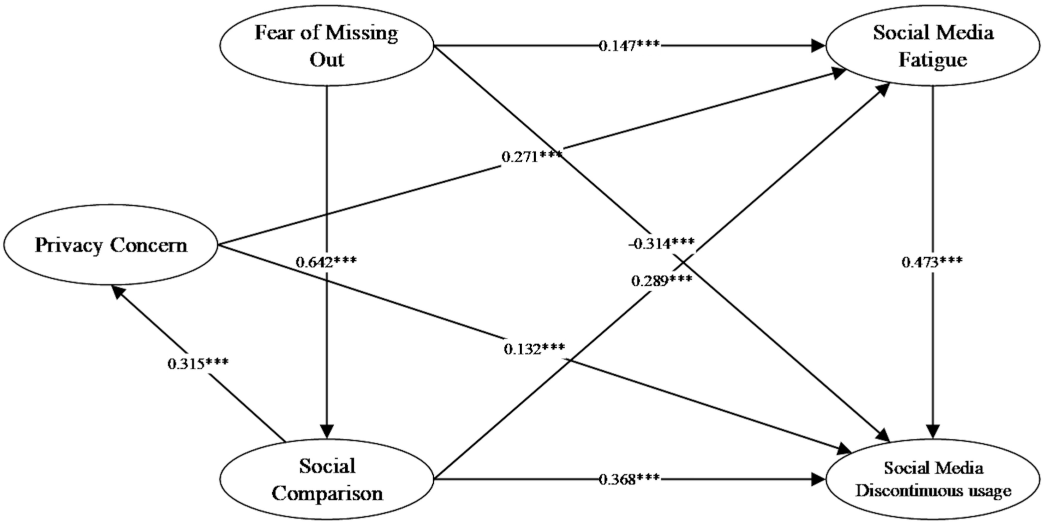

Figure 4. MASEM (Psychosocial Stress Stimuli)

Table 11. Results of Path Analysis (Psychosocial Stress Overload Stimuli)

Path	Estimate	SE	CR	P
FoMO→SMF	0.147	0.02	7.511	***
PC→SMF	0.271	0.015	18.527	***
SC→SMF	0.289	0.02	14.317	***
SMF→SMDU	0.473	0.016	29.259	***
FoMO→SMDU	-0.314	0.019	-16.382	***
PC→SMDU	0.132	0.015	8.948	***
SC→SMDU	0.368	0.02	18.286	***
FoMO→SC	0.642	0.013	47.828	***
SC→PC	0.315	0.015	20.863	***

Note. *** $p < 0.001$.

Specifically, SC (β = 0.289, p < 0.001) was the strongest predictor of SMF, followed by PC (β = 0.271) and FoMO (β = 0.147). SMF also positively affected SMDU (β = 0.473). SC (β = 0.368) and PC (β = 0.132) were positively linked to SMDU, while FoMO had a negative effect (β = -0.314).

Moreover, FoMO was positively related with SC (β = 0.642, p < 0.001), and SC was positively correlated to PC (β = 0.315, p < 0.001). Mediation tests (**Table 12**) further demonstrated that SMF significantly mediated the effects of FoMO (Z = 0.070, p < 0.001), PC (Z = 0.128, p < 0.001) and SC (Z = 0.136, p < 0.001) on SMDU.

Table 12. Results of Mediating Effects (Psychosocial Stress Overload Stimuli)

Parameter	Estimate	SE	95% CI Lower	95% CI Upper	P
FoMO→SMF→SMDU	0.070	0.010	0.050	0.089	***
PC→SMF→SMDU	0.128	0.008	0.113	0.143	***
SC→SMF→SMDU	0.136	0.010	0.117	0.155	***

Note. *** *p < 0.001.*

DISCUSSION

This study used MASEM to combine effect sizes from 107 studies on factors influencing fatigue and discontinuous use. Guided by SOR theory and meta-analysis results, we built SEM models to examine the pathways between key variables.

Effects of Different Stimuli on Social Media Fatigue (S-O)

The meta-analysis showed that four extrinsic stimuli (communication, social, information, and technological overload) were significantly linked to social media fatigue. Communication and technological overload had strong correlations, while social and information overload had moderate ones. These results support past studies (Fakhfakh & Bouaziz, 2022; Teng et al., 2022; Zhang et al., 2024). Firstly, online communication heightens pressure to remain connected and to respond in time (Mahmud et al., 2023; Pang & Liu, 2024). Inability to cope with these pressures successfully creates fatigue (Zhang et al., 2016). Secondly, individuals are subjected to excessive information on a daily basis that requires time and energy to process and may even surpass cognitive ability (Kim et al., 2019). The COVID-19 pandemic has worsened this issue, bombarding users with stress-causing information (Liu et al., 2021; Mertens et al., 2020). Further, individuals fatigue when they are managing complicated and multi-dimensional online relationships (Liu & He, 2021). Finally, additional features such as payments and games being incorporated into platforms (Su & Xiao, 2021). Usage of these technologies can have psychological and cognitive impacts on users (Ngien & Jiang, 2022).

There were three intrinsic stimuli (FoMO, social comparison and privacy concern) which were associated with social media fatigue on medium level. This supports previous research (Jabeen et al., 2023; Malik et al., 2020; Qin et al., 2024). Viewing idealized content online can make individuals feel insufficient, anxious, and exhausted. Social comparison also makes users to keep updating and processing information, which causes cognitive and emotional overload (Kaur et al., 2021). Further, FoMO causes users to stay online, resulting in compulsive use and mental fatigue (Cao & Sun, 2018; Khan et al., 2024; Seko & Lewis, 2018). Privacy concern is the other stimulus. As data breach threats increase, users are becoming more concerned about safeguarding their personal data (Choi, 2023). This constant fear can lead to emotional exhaustion and tension (Barati & Yankson, 2022).

Effect of Social Media Fatigue on Discontinuous Usage Behaviors (O-R)

The findings indicate a positive correlation between fatigue and discontinuous usage behaviors, which support previous research conclusions (Faisal et al., 2024; Fan et al., 2021; Zhang et al., 2016). Discontinuous usage behaviors can be understood as adaptive responses to the negative feelings associated with fatigue. Based on the uses and gratifications theory (Katz et al., 1973), individuals use media to fulfill specific psychological needs. When social media fails to meet these demands or creates additional pressure, it loses its value of gratifications and prompts discontinuance behaviors. According to the negative state mitigation model (Weyant, 1978), people reduce unpleasant emotional states by changing their behavior. Fatigue from overload or stress may lead to coping actions such as opting out (Kang et al., 2020), lurking (Liu et al., 2024), taking breaks (Schoenebeck, 2014), switching (Al-Jallad & Radwan, 2021), or reducing usage (Tran & Chen, 2024). Collectively, these behaviors represent forms of intermittent discontinuous usage. Most users stay on social media but reduce activity rather than quit completely (Shokouhyar et al., 2018). Therefore, while social media users actively respond to feelings of fatigue, this does not equate to a complete withdrawal from social media platforms.

Moderators

First, moderator analysis showed that sample characteristics affected the links between technological overload, social comparison, and social media fatigue. The general population was more affected by technological overload than younger users. This may be because younger people adapt more easily to new media (Bolin & Skogerbø, 2013) and feel less stress from tech changes. In contrast, older users often feel more overwhelmed. Moreover, the general population also showed more fatigue from social comparison. As people age, their social ties grow and may become more distant (Lucas, 2006), leading to more comparisons online. Older users often interact with a wider range of people on social media, which increases social comparison and related fatigue.

Second, the type of platform moderated the relationships between communication overload, FoMO, and fatigue. Communication overload had the strongest impact on fatigue in general platforms, followed by strong-tie and weak-tie platforms. Today's diverse platforms increase communication demands, making users more prone to overload. And we also found communication overload caused more fatigue on strong-tie platforms than weak-tie ones. This may be because strong-tie platforms include close contacts like family and friends, while weak-tie platforms involve more strangers (Croes & Antheunis, 2021). Ignoring messages from close contacts can hurt relationships and social standing, thereby making users of strong-tie platforms more vulnerable to fatigue related to social media overload. Additionally, FoMO also had a stronger link to fatigue on general platforms than on strong-tie platforms. One potential explanation for this trend is that General platforms often push frequent updates and wide content streams, which may increase users' FoMO and cause more fatigue.

Third, period background also emerged as a moderator in the relationships between FoMO, privacy concern and fatigue. Specifically, after COVID-19, FoMO caused more fatigue than before. Lockdowns and distancing made people rely more on social media, increasing their FoMO and leading to fatigue (Ashiru et al., 2023). This heightened FoMO on crucial information resulted in a marked increase in social media usage, further intensifying feelings of fatigue. Moreover, before the pandemic, privacy concerns caused more fatigue than in the post-COVID period. The pandemic fostered an urgent need for social connections and access to information, leading users to prioritize social interaction and information-seeking over privacy considerations. In emergencies, people tend to overlook privacy risks due to their dependence on social media (Saroj & Pal, 2020).

Findings from MASEM (S-O-R)

The MASEM results clarify how social media overload and psychosocial stress (stimuli) lead to social media fatigue (organism) and then to discontinuous usage (response), in line with the SOR model. This pathway is further illuminated when situated within the framework of media ecology theory (Postman, 2000), which emphasizes how technological environments shape human behavior and perception. In this case, social media platforms act as complex media environments that overload users, disrupting cognitive equilibrium and prompting behavioral adaptations such as discontinuance. In addition, social overload, information overload, technological overload, FoMO, privacy concern, and social comparison affect discontinuous usage both directly and through fatigue. In contrast, communication overload influences usage only through fatigue. This means users will not reduce use due to communication overload alone unless it causes fatigue. This phenomenon may be attributed to the essential nature of social connections for individuals. Social ties are essential, and users may stay active despite overload to maintain these connections (Whiting & Williams, 2013). While confronted with excessive information, users often experience anxiety and stress, resulting in significant time and energy spent on social media interactions (AlHeneidi & Smith, 2021; Srinivasan, 2020), users may still value social updates and not disengage. However, when overload leads to fatigue, it often results in reduced usage (Dai et al., 2020; Shokouhyar et al., 2018). Thus, fatigue is a key factor linking most stimuli to discontinuous behavior.

The MASEM results show that, unlike the SOR model's assumption, six stimuli have direct effects on discontinuous usage. Information overload, technological overload, privacy concerns, and social comparison increase users' discontinuous usage. This indicates that users may adopt avoidance strategies when overwhelmed (Chen et al., 2019). For instance, when faced with overwhelming amounts of information, individuals often resort to avoidance behaviors (Sweeny et al., 2010). However, FoMO and social overload directly reduce discontinuous usage. Social media is essential for work, study, and communication (Kaplan & Haenlein, 2010). So, even when feeling social overloaded, users often stay active due to social obligations. FoMO also keeps them engaged, as they fear missing out on important updates (Alutaybi et al., 2019), making it challenging users to completely withdraw from social media. Thus, users are unlikely to cut back unless these pressures lead to fatigue.

MASEM analysis also revealed several key links among stimuli. Social overload increased both communication and information overload. This may be because more social interactions bring more messages and content, leading to communication and information overload (Fakhfakh & Bouaziz, 2022). Further, technological overload also raised social and information overload. Using multiple platforms expands social networks and speeds up information exchange, adding to the burden (Rheingold, 2012). Moreover, information overload further increased communication overload, as users may feel the need to clarify or respond to excess content. Additionally, FoMO positively influences social comparison. FoMO drives users to monitor others' activities on social media in real time, compensating for their own perceived lack of experiences (Tandon et al., 2021). As users engage in this process of understanding others' actions and experiences, they inevitably make social comparisons. Finally, social comparison was positively correlated with privacy concerns. Seeing others' successes can cause negative emotions, prompting users to protect their personal information more carefully (Nisar et al., 2019).

Theoretical Implications

This meta-analysis offers key theoretical insights. First, it uses MASEM to combine existing data on social media fatigue and discontinuous usage. The results show that both external (social media overload) and internal (psychosocial stress) factors lead to fatigue, which then affects usage behavior. MASEM helps overcome the limits of small sample studies and provides a broad view of these effects. Second, the findings extend the SOR model. While the traditional model suggests that stimuli influence behavior only through fatigue, this study shows that some stimuli also have direct effects. This adds depth to our understanding of users' discontinuous usage behavior. Lastly, this study also highlights the presence of significant moderators shaping the correlation between various stimuli and fatigue. The results suggest that sample characteristics, social media platform type, and period background emerge as key sources of heterogeneity in the observed correlations.

This study also provides beneficial implications for future research in the field of communication. By empirically validating a structured pathway linking social media overload, psychological stress, emotional fatigue, and behavioral discontinuance, it encourages communication scholars to go beyond surface-level analysis of social media usage. Future research can generalize this model to examine how platform design features function as stress-evoking stimuli. Moreover, the integration of MASEM with the SOR model also offers an extensible theoretical framework for examining user experience and behavioral reactions in rapidly evolving digital environments. Thus, this study lays a theoretical foundation for further exploration of technology–emotion–behavior linkages in digital media contexts.

Practical Implications

Extensive social media use has amplified fatigue from information overload and stress, leading to discontinuous usage. Understanding the causes of this fatigue helps both users and platform developers. For users, addressing overload can begin with reducing unnecessary connections in their friend lists. Additionally, adjusting one's mindset during social media use can help mitigate psychosocial stress; for instance, users should strive to manage their FoMO and limit online social comparisons. For platform developers, it is important to design simple and user-friendly platforms while taking users' habits into account. Using big data to recommend relevant content can reduce overload. For example, DouYin, a prominent social media platform in China, reduces information overload by recommending content based on users' search histories (Dwivedi et al., 2018). Furthermore, governments can also help by promoting healthy usage, such as encouraging people to limit screen time. Through collaborative efforts from users, platforms, and governments, social media fatigue and its effects can be reduced.

CONCLUSIONS

This study conducted a quantitative review of stimuli associated with social media fatigue and discontinuous usage behaviors through MASEM. Grounded in the SOR model, we examined how the organism (social media fatigue) is influenced by stimuli (social media overload and psychosocial stress) and how this, in turn, affects the response (social media discontinuous usage behaviors). Our findings indicated that both social media overload and psychosocial stress are positively related to social media fatigue, which subsequently has a positive relationship with discontinuous usage behaviors. Notably, we also discovered that some aspects of social media overload and psychosocial stress have direct relationships with discontinuous usage behaviors. Moreover, the results suggest that factors such as sample characteristics, platform type, and period background impact the correlations between various stimuli and fatigue. These findings offer practical implications and scientific recommendations for social media users, platform developers and governments. Additionally, we propose ideas and directions for future research to further explore these dynamics.

Despite its contributions, this study has several limitations that suggest important avenues for future research. First, most included studies are quantitative, while many qualitative studies also explore these topics (Calancie et al., 2017; Cho, 2015; Nıcola, 2022). Future reviews should combine both types of evidence. Second, we focused on seven stimuli due to limited data; other possible factors, like behavioral or environmental ones, were excluded. Future research should include a broader range of stimuli. Third, only four moderators (gender, sample characteristics, platform types, and period background) were tested. Future work could examine more moderators, such as culture or education. Finally, this study treated discontinuous usage as a single category. For more insights, subsequent investigations should distinguish between latent, deletion, reduction and other discontinuance behaviors.

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