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DEVELOPMENT AND VALIDATION OF SOCIAL MEDIA CONTENT EXPOSURE SCALE

Ayesha Rafi[1], Syeda Raiha*[2]

[1, *2]*Department of Psychology, University of Jhang, Pakistan*

[*2]syedaraiha@hotmail.com

Corresponding Author: *
Syeda Raiha

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ABSTRACT

The current study aimed to develop and validate the Social Media Content Exposure Scale (SMCES) to measure multidimensional exposure to social media content. An exploratory sequential mixed methods design was used. Phase 1 involved qualitative interviews and literature search to generate an initial pool of 48 items that were then narrowed down during the expert evaluation. The second phase involved collecting data from 300 social media users aged 18-50 years. Exploratory factor analysis confirmed two factors: Content Exposure Risk and Susceptibility and Cognitive Engagement and Content Regulation. Confirmatory factor analysis further supported the two-factor model, demonstrating strong model fit, $\chi^2(43) = 49.802$, $\chi^2/df = 1.158$, CFI = 0.973, SRMR = 0.055, RMSEA = 0.030, and PClose = 0.836. The CERS had an acceptable composite reliability (CR = 0.709), while the CECR had a marginal composite reliability (CR = 0.646). However, AVE values were lower than the recommended values, which means there was limited convergent validity. There was moderate latent correlation between the constructs (r = 0.523), indicating related but distinct dimensions. External construct validity was confirmed with a high correlation with social media engagement and a weaker correlation with online information processing. Overall, the SMCES offers initial support for factorial validity as a multi-dimensional measure of exposure to social media content.

Keywords: *social media content exposure, scale development, psychometric validation, exploratory factor analysis, digital media, content exposure, social media engagement*

INTRODUCTION

Social media is a structurally embedded part of today's communication system and has changed the way people develop, access, and understand information. It can be generally described as online platforms that allow users to create, share and engage with user-generated content in networked environments (Kaplan & Haenlein, 2010; Carr & Hayes, 2015). The change is from mass communication to participatory digital communication, where users become content producers, distributors, and consumers.

Social media has become widespread and popular all over the world, with Facebook, Instagram, YouTube, TikTok, Snapchat, and X (formerly Twitter) reaching billions of users each day. Recent studies suggest that users spend multiple hours each day engaging with algorithmically curated environments (DataReportal, 2025). Social media has a strong impact on adolescent and young adult identity development, peer interaction, school involvement, and socio-political awareness (Boyd & Ellison, 2007; Ellison et al., 2007).

One of the most important changes in digital communication is algorithmic exposure. Social media platforms use machine-learning recommendation systems to tailor content to individual users based on their behavior and

engagement (Valkenburg et al., 2022), which differ from traditional media systems. This results in content being presented repeatedly in structured environments, with content being optimized for interaction rather than neutral information flows. In media effects research, exposure is defined as the encounter and cognitive processing of mediated stimuli (Potter, 2012; Bryant & Oliver, 2009). Exposure is defined as intentional selection and algorithmic exposure in digital environments. However, empirical evidence indicates that content characteristics are better predictors of psychological outcomes than usage-based measures, which suggests that usage-based measures have limitations (Orben & Przybylski, 2019; Valkenburg et al., 2022).

Social media content exposure is then understood as an organized encounter between users and algorithmically curated environments of content. This structure is formed in three interrelated dimensions: content type, emotional valence, and exposure modality. Content types range from educational, informational, entertainment, political/religious, to harmful, which are different cognitive and behavioral pathways. Educational and informational content facilitates knowledge acquisition and informal learning processes (Greenhow & Robelia, 2009; Pempek et al., 2009), while entertainment content is mainly used for affect regulation and can be used to fragment attention when used in excess (Vorderer et al., 2016; Wilmer et al., 2017). Violent or emotionally disturbing content has been shown to be associated with desensitization and aggressive cognition (Anderson & Bushman, 2001; Bandura, 2001), while political and religious content has been linked to identity formation and can be associated with ideological polarization in digitally mediated environments (Loader & Mercea, 2011). Exposure also occurs on a valence continuum, from positive (educational, prosocial), neutral (informational), to negative (disturbing or misleading) content. It has been demonstrated that valence plays a central role in psychological impact, and can even surpass the impact of exposure duration (Valkenburg, Meier, & Beyens, 2022). The second dimension of exposure is modality, in this case the difference between passive and active exposure. Passive exposure is when users are exposed to content via algorithmically-driven feeds without intentional selection, while active exposure is when users search for or engage with content. Research suggests that passive exposure is more linked to negative psychological consequences because of diminished cognitive control and greater algorithmic influence on content selection (Verduyn et al., 2017; Valkenburg et al., 2022).

Algorithmic exposure mechanisms continually fine-tune content delivery based on user activity such as “likes” and “shares” or “skips.” This creates repetition loops which make the cognitive content salient and reinforce the behavioral and attitudinal patterns over time (Bucher, 2018; Gillespie, 2014; Zuboff, 2019). Overall, these mechanisms show that exposure to social media content is not measured by static indicators of usage or screen time, but rather is a dynamic process that is shaped by the content itself, the valence of the emotion, the modality of exposure, and algorithmic feedback processes. Studies on social media also show that algorithmic systems affect the distribution and exposure inequality at the same time. Educational and informational content can be leveraged to foster learning and knowledge building and algorithmic filtering can also lead to more exposure to misinformation and less informational reliability in digital environments (Lazer et al., 2018; Vosoughi et al., 2018).

In addition to leisure, entertainment content is linked to affect regulation, and excessive consumption can lead to decreased sustained attention and increased habit formation, as a consequence of platform design, which is based on reinforcement (Vorderer et al., 2016). Exposure to negative or emotionally charged content, on the other hand, can have a detrimental impact on emotional control and lead to more aggressive thoughts (Anderson & Bushman, 2001). Political and religious discourses have a significant influence on the formation of ideologies and identities. Repeated exposure to different perspectives (Loader & Mercea, 2011) can be minimized in algorithmically curated

environments, leading to increased polarization and reinforcing echo chamber effects.

Although there has been a great deal of research on social media use, much of the current research is based on one-dimensional measures like hours spent on screen, how often one uses social media, or overall engagement. These measures do not capture the algorithmic exposure to content and the qualitative difference between content types. Furthermore, there is a lack of studies that have examined content-type variation in combination with exposure modality and reinforcement mechanisms, which led to inconsistent findings and operational definitions. To fill this gap, the present study aimed to develop a standardized scale to measure social media content exposure in various content domains such as educational, informational, entertainment, political/religious, and harmful content. On a theoretical level, it moves away from the usage-based approach to the structured exposure-based approach to media effects research. Methodologically, it offers a validated tool to measure multidimensional exposure patterns in algorithmically-driven environments. In practice, it allows for more accurate identification of exposure profiles related to psychological and behavioral outcomes, which will lead to better digital well-being research and intervention development.

Aims and Objectives

- To develop and validate the Social Media Content Exposure Scale (SMCES) for social media users.
- To assess the psychometric soundness of the SMCES.

Method

The present study employed an exploratory sequential mixed-methods design for the development and validation of the Social Media Content Exposure Scale (SMCES). The study was conducted in two distinct phases. Phase 1 involved qualitative data collection through in-depth interviews to explore participants' lived experiences of social media content exposure and to generate the initial scale items. Phase 2 involved quantitative survey administration to validate the psychometric properties of the developed scale.

Phase 1: Qualitative Study

The current study used an exploratory sequential mixed methods approach to develop and validate the Social Media Content Exposure Scale (SMCES). The study took place in two phases. The first phase was qualitative data collection using in-depth interviews to gain insights into the lived experiences of social media content exposure and to develop the initial scale items. The second phase was quantitative survey administration to validate the psychometric properties of the scale developed in phase 1.

Participants

The first phase was conducted with 15 male and female social media users. Convenience sampling was used to select the participants. The age range of participants was 18–50 years. The sample size was considered sufficient to obtain thematic saturation in phenomenological inquiry.

Materials

Interview Guide

The semi-structured interview guide was systematically developed by literature review and conceptual mapping of the content of social media exposure. The relevant literature on media exposure, digital behavior and psychological consequences of social media was examined to identify key areas of interest including exposure to educational, informational, entertainment, political/religious and harmful content. This framework was then used to develop open-ended questions to elicit participants' experiences of encountering, engaging with, and being influenced by different types of social media content. The guide included general probing questions and specific probes to get depth and context. Common types of content, emotional and cognitive responses to content, perceived influence of behavior, algorithmic recommendation experiences, and differential effects of intentional and incidental exposure were the key areas explored.

The interview guide was pretested before data collection for clarity, relevance and conceptual

consistency. Appropriate refinements were made to ensure consistency with the study's goals and construct domain to be measured.

Procedure

Phase 1 was conducted in a qualitative phenomenological approach that focused on the lived experiences of social media content exposure among social media users. Prior to data collection, ethical approval and institutional permission were obtained from the relevant university authorities. Convenience sampling was used to recruit the participants. The participants were required to be active users of social media platforms and were required to be within the age group of 18-50 years. An information sheet was given to all participants outlining the purpose of the study and informed consent was obtained in writing before participating. Interviews were held in a controlled and quiet setting at the university to ensure there were no external distractions and an environment conducive to open discussion. The researcher used the semi-structured interview guide to conduct each interview face-to-face. A flexible interviewing style was used, with participants given the opportunity to provide their experiences in as much depth as they wished, but ensuring that all areas of the guide were addressed. Interviews were conducted for about 30-60 minutes, depending on the level of engagement and depth of response from the participants. All interviews were audio-recorded with the permission of the participants, to ensure accurate data capture. Field notes were also recorded to capture contextual observations and pertinent non-verbal cues. After data collection, the interviews were transcribed word for word. Transcripts were carefully read and checked against the audio recordings for accuracy. Thematic analysis, which included systematic coding, identification of patterns, and grouping of codes into higher order themes, was then applied to the data to identify dimensions of social media content exposure. The themes that emerged were used as the conceptual basis for the generation of items in Phase 2 of the study.

Phase 2: Quantitative Study

Participants

The second phase included 300 active users of social media platforms. The sample included 119 females (39.7%) and 181 males (60.3%), with an age range of 18–50 years. The subjects were chosen by convenience sampling from the University environment.

Measures

Demographic Information

Structured demographic form was used to collect background characteristics of the participants including age, gender, educational qualification, marital status, occupation, family system, socioeconomic status and self-reported history of physical and psychological illness. The variables were added to reflect characteristics of the sample and as a background for the variations in the exposure to social media content.

Social Media Engagement Scale (SMES)

The Social Media Engagement Scale (Stieglitz & Dang-Xuan, 2013) was used to assess patterns of user interaction with social media content. There are 18 items on the scale, with a 5-point Likert scale that ranges from strongly disagree to strongly agree. It includes active engagement behaviors (commenting, sharing, posting) as well as passive engagement behaviors (viewing and liking content). For the present study, the SMES was used as a convergent validity indicator to determine if there is a relationship between the intensity of behavioral engagement and the amount of social media content exposure measured by the SMCES. This enabled the evaluation of whether higher engagement is associated with higher exposure in content areas, which would help to establish construct validity of the newly developed scale. In previous studies, the scale has shown an acceptable internal consistency (α = 0.84–0.89).

Online Information Processing Scale (OIPS)

The Online Information Processing Scale (Sundar, 2008) was used to measure cognitive processing of online information. The scale is composed of 16 items that are measured on a 5-

point Likert scale and measures the depth, evaluation and interpretation of digital content. It reflects differences in user information processing and critical use of online information. The OIPS was added to this study to provide construct validation of the SMCES by testing for correlations between cognitive processing styles and differences in perceived content exposure. This gave evidence for convergent and discriminant validity because persons with different processing tendencies might experience and report exposure differently. The scale has been well validated in previous studies ($\alpha = 0.871$).

Social Media Content Exposure Scale (SMCES)

The Social Media Content Exposure Scale (SMCES) was developed using a systematic and theory-based scale construction process that was based on the well-documented procedures in scale construction. In order to conceptualize the concept of social media content exposure, a comprehensive literature review was carried out on the topics of media exposure, digital behavior and psychological impacts of social media consumption. This stage determined the size of the construct (e.g., exposure to educational, informational, entertainment, political/religious and harmful content). Secondly, items were inductively generated from the findings of the qualitative interviews carried out in Phase 1. The results of the thematic analysis were translated into an initial item pool of 48 statements that described the various aspects of social media content exposure. Third, content validity was obtained through the review of the items by experts who checked for clarity, representativeness of the domain of the construct and relevance. Based on expert feedback, redundant, unclear, or conceptually overlapping items were revised or removed. Fourth, the refined item pool was then given in a structured questionnaire, using a 5-point Likert response scale (strongly disagree = 1, strongly agree = 5). This scale was then validated in Phase 2 using 300 respondents. Exploratory factor analysis (EFA) was used to examine the factor structure of the items, to check construct validity, and Cronbach's alpha was used to check reliability.

Procedure

The quantitative phase adopted a structured data collection procedure which included a survey. After finishing the development of the items, the finalized 20-item SMCES was put together in a single questionnaire with demographic questions and additional scales (SMES and OIPS) on Google Forms. The survey was designed to take approximately 15–20 minutes. An introduction statement was given to the participants before the data was collected, describing the purpose of the study, its voluntary nature and the confidentiality and anonymity of the data. Informed consent was obtained electronically prior to completing the questionnaire. Data were collected using a convenience sampling technique from 300 social media users. The survey was sent to active social media users via online and institutional channels. Responses were then checked for completeness and consistency after data collection. Responses that were incomplete or incorrect were not included in the analysis. Data were analyzed using IBM SPSS Statistics (Version 29) for descriptive statistics, reliability analysis, and exploratory factor analysis. Confirmatory factor analysis was conducted using IBM SPSS AMOS (Version 29).

Results

The findings from the statistical analysis to assess the psychometric properties of the Social Media Content Exposure Scale (SMCES) are presented in this section. Scale development started with a pool of 48 items, but after expert review, items were refined and a final 20 items were selected. A total of 300 social media users (181 males and 119 females) were selected for data collection. Data were analyzed with SPSS version 23. Exploratory factor analysis was conducted using Principal Axis Factoring with Varimax rotation to identify the underlying factor structure of the Social Media Content Exposure Scale (SMCES) while Confirmatory Factor Analysis (CFA) was conducted to validate the newly developed instrument.

Table 1
Demographic Variables of the Participants

Variable	Category	f	%
Age	18–50	300	100.0
Gender	Male	181	60.3
	Female	119	39.7
Education	Matric	31	10.3
	Intermediate	122	40.7
	Bachelor	115	38.3
	MPhil	25	8.3
	PhD	7	2.3
Occupational status	Student	84	28.0
	Professional	102	34.0
	Unemployed	67	22.3
	Part-time worker	47	15.7
Family system	Nuclear	149	49.7
	Joint	151	50.3
Marital status	Married	54	18.0
	Unmarried	246	82.0
Socioeconomic status	Lower	59	19.7
	Middle	204	68.0
	Upper	37	12.3
Physical illness history	Yes	21	7.0
	No	267	89.0
	Maybe	12	4.0
Psychological illness history	Yes	26	8.7
	No	274	91.3

Note: f = frequency; % = percentage.

A total of 300 individuals aged 18-50 years participated in the study. Most of the participants were males (60.3%) and females (39.7%). As far as educational level is concerned, most of the respondents were intermediate (40.7%) and bachelor's (38.3%) with MPhil (8.3%), matric (10.3%) and PhD (2.3%). Regarding the occupation, 34.0% of the participants were professionals, 28.0% students, 22.3% unemployed and 15.7% engaged in part-time work.

The distribution of family system was almost equal, with 49.7% being nuclear family system and 50.3% being a joint family system. The majority of the participants were unmarried (82.0%), and 18.0% were married. The majority of the respondents were from a middle class background (68.0%), with lower (19.7%) and upper class (12.3%).

As for health-related variables, the majority (89.0%) indicated that they had no physical illness, 7.0% indicated that they had a history of physical illness and 4.0% were unsure. Likewise, 91.3% said that they had no psychological disease and 8.7% said they had a history of psychological ailments.

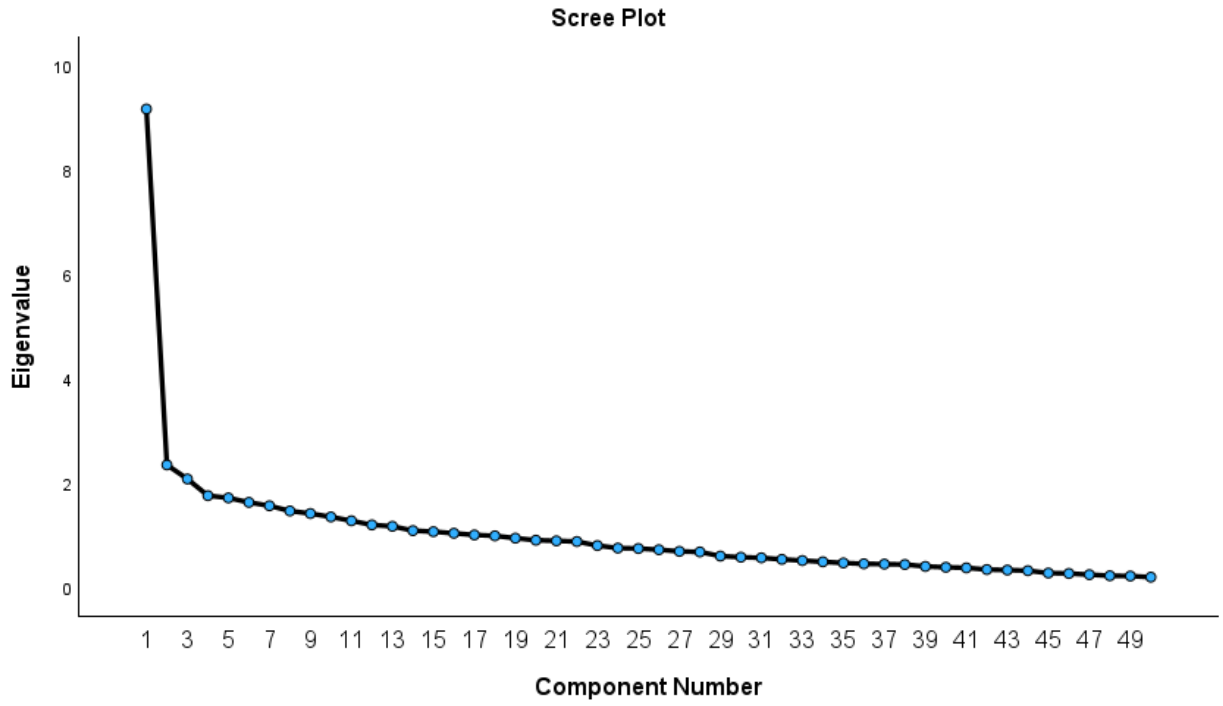
Table 2
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.788
Bartlett's Test of Sphericity	Approx. Chi-Square	2633.230
	df	1225
	Sig.	<.001

Note. KMO=Kaiser-Meyer-Olkin, df=degree of freedom, Sig=Significance level

Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were used to test the suitability of the data for factor analysis. The KMO value was .788, which was considered good sampling adequacy, and appropriate data for structure detection and factor analysis. Bartlett's Test of Sphericity was statistically significant (χ^2 = 2633.230, df = 1225, $p < .001$), which indicated that the correlation matrix was not an identity matrix and that there were enough correlations between the items for Exploratory Factor Analysis (EFA) to proceed.

Figure 1
Scree Plot of the Eigenvalues



To identify the number of latent factors for Social Media Content Exposure Scale (SMCES), the scree plot was analyzed. The plot showed that there was a significant drop in the eigenvalues from the first component to the second, followed by a significant flattening of the curve after that. The highest point of inflection was located after the second component, indicating that the two first factors explain the substantive part of the common variance of the items. Other components had eigenvalues slightly above or near 1, but accounted for relatively little of the total variance and showed no obvious structural break. A two factor solution was therefore selected as the simplest and most meaningful solution to the data structure, according to the scree criterion by Cattell. This solution was kept for further confirmation.

Table 3
Factor Loadings of the Social Media Content Exposure Scale

	Factor	
	CERS	CECR
It is difficult to identify misleading information on social media.	.598	
The content available on social media is not always safe/secure.	.590	
Social media has content related to both love/affection and entertainment.	.547	
Social media content can influence the attitudes of young people.	.544	
Excessive use of social media affects my use of language/vocabulary.	.531	
The amount of negative content on social media is very high.	.525	
Social media affects my patience/actions.		.559
I look at social media content with a critical eye.		.556
I feel encouraged by seeing others' achievements on social media.		.544
I avoid unnecessary content on social media.		.509
I see content on social media because of advertisements.		.504

Extraction Method: Principal Axis Factoring; Rotation Method: Varimax with Kaiser Normalization. CERS = Content Exposure Risk and Susceptibility; CECR = Cognitive Engagement and Content Regulation

Exploratory factor analysis was conducted using Principal Axis Factoring with Varimax rotation and Kaiser normalization to identify the underlying factor structure of the SMCES. A stable two-factor solution was obtained after three iterations of the rotated solution. The two-factor solution was retained on the basis of theoretical interpretability and empirical clarity. All retained items demonstrated acceptable factor loadings, and no substantial cross-loadings were observed

The first factor, Content Exposure Risk and Susceptibility (CERS) included items that measured the perceived exposure to risky, misleading and potentially harmful social media content. Items with high loading were: difficulty finding false information, perceptions of unsafe or insecure content, perceived negative influence of social media on attitudes and language, and exposure to too much negative content. Content Exposure Risk and Susceptibility (CERS) reflects individuals' perceived exposure to harmful, misleading, and emotionally negative social media content, along with their perceived vulnerability to such exposure.

The second factor, Cognitive Engagement and Content Regulation (CECR) consisted of items related to cognitive assessment, emotional management and behavioral control with regard to social media content. Content, unnecessary information, emotional reactions to social comparison, advertisement-driven exposure, and self-regulatory behaviors were represented in items loading on this factor. Cognitive Engagement and Content Regulation (CECR) reflects users' cognitive evaluation of social media content and their behavioral strategies for regulating, filtering, and controlling content exposure.

The final solution adopted a parsimonious model of two factors related to social media content exposure. Factor 1 was content-related vulnerability and exposure risk, and Factor 2 was cognitive and behavioral regulation of content interaction. There were no significant cross-

loadings and the factors were conceptually coherent, thus supporting the construct validity of the SMCES.

Table 4
Reliability Statistics of the Social Media Content Exposure Scale

Scale/Subscale	Cronbach's Alpha	N of Items
Social Media Content Exposure Scale	.725	11
Content Exposure Risk and Susceptibility	.709	6
Cognitive Engagement and Content Regulation	.639	5

Cronbach's alpha was used to determine the internal consistency reliability of the Social Media Content Exposure Scale (SMCES) and its subscales. The Content Exposure Risk and Susceptibility dimension had acceptable reliability (α = .709) at the subscale level, indicating that the items measuring perceived vulnerability to social media content exposure were relatively homogeneous. The reliability analysis was conducted prior to CFA to assess internal consistency at the item level. The Cognitive Engagement and Content Regulation subscale showed lower reliability (α = 0.639), indicating moderate internal consistency and suggesting that the construct may be multidimensional at the item level. Therefore, this dimension should be interpreted as preliminary and may require refinement in future validation studies.

Table 5
Correlation Matrix for Convergent and Discriminant Validity

		SMCES	SMES	IPS
SMCES	Pearson Correlation	1		
	Sig. (2-tailed)			
	N	300		
SMES	Pearson Correlation	.661**	1	
	Sig. (2-tailed)	<.001		
	N	300	300	
IPS	Pearson Correlation	.205**	.538**	1
	Sig. (2-tailed)	<.001	<.001	
	N	300	300	300

**. Correlation is significant at the 0.01 level (2-tailed).

Convergent Validity

Pearson correlation analysis was used to examine external construct validity of the SMCES. Convergent validity was supported by a strong positive correlation between SMCES and the Social Media Engagement Scale (SMES), $r = .661$, $p < .001$, indicating that higher social media content exposure was associated with greater social media engagement. The weaker positive correlation between SMCES and the Online Information Processing Scale (OIPS), $r = .205$, $p < .001$, was interpreted as evidence of discriminant validity rather than convergent validity, as content exposure and cognitive information processing are theoretically related but distinct constructs.

Discriminant Validity

Discriminant validity was supported by the relatively weak association between SMCES and OIPS, suggesting that social media content

exposure is empirically distinguishable from cognitive processing of online information. Although SMES and OIPS were moderately correlated, r = .538, p < .001, the correlation remained below the commonly used redundancy threshold of .85, indicating that the constructs were not empirically interchangeable.

Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) was conducted to test the measurement model developed from the Exploratory Factor Analysis (EFA) and to examine the factorial validity of the Social Media Content Exposure Scale (SMCES). Specifically, CFA was used to test the hypothesized two factor structure to determine if it is sufficient to capture the underlying construct and to test the overall model fit to the observed data. This is a crucial step in scale development as it offers theory-based support for the factorial validity and adequacy of the measurement model (Byrne, 2016). The two factor model: Content Exposure Risk and Susceptibility, Cognitive Engagement and Content Regulation was confirmed by the CFA results. The model showed a good fit with several indices, $\chi^2(26) = 34.585$, $\chi^2/df = 1.33$, CFI = 0.959, SRMR = 0.057, RMSEA = 0.043, PClose = 0.591, indicating that the model structure is a good representation of the construct of social media content exposure. All 11 items retained were assessed for standardized loadings and model fit during CFA. There was no need to add any further items and the final model was the 11-item structure that was found in the EFA. The factor loadings for Factor 1 were in the range of .47 to .63, and for Factor 2 were in the range of .37 to .65, which indicated acceptable item representation of the latent constructs. The factor correlation (r = .523) also confirmed the discriminant validity of the two factors. Although the internal consistency of the items was low, the CFA results showed an acceptable two-factor structure at the latent level, suggesting that the construct is not a strictly homogeneous item set, but rather a latent multidimensional structure.

Figure 2

Path Diagram for Confirmatory Factor Analysis

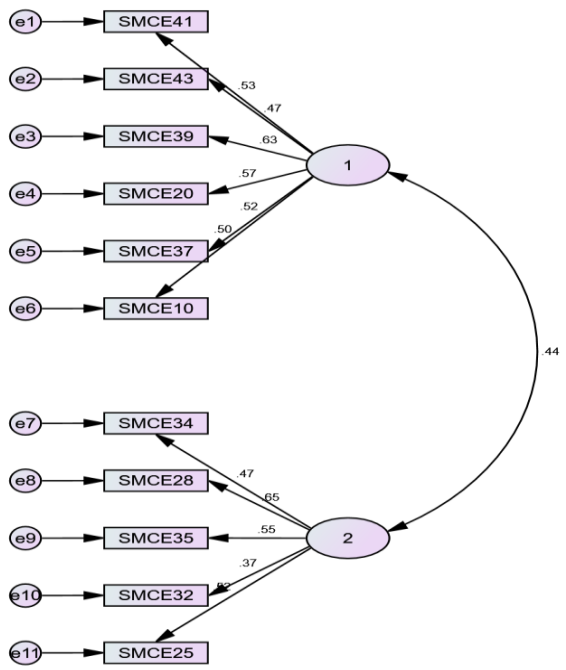


Table 6
Model Fit Indices for the Measurement Model

Fit Index	Estimate	Recommended Threshold	Interpretation
χ^2 (CMIN)	49.802	—	—
Df	43	—	—
χ^2/df	1.158	1.0–3.0	Good fit
CFI	0.973	≥ 0.95	Strong fit
SRMR	0.055	≤ 0.08	Good fit
RMSEA	0.030	≤ 0.06	Close fit
PClose	0.836	≥ 0.05	Close fit supported

Note. χ^2 = chi-square statistic; df = degrees of freedom; CFI = comparative fit index; SRMR = standardized root mean square residual; RMSEA = root mean square error of approximation; PClose = p-value for test of close fit.

The measurement model showed good and stable fit on the various indices, with no evidence of model misspecification. The chi-square test was not significant, $\chi^2(43) = 49.802$, $p = .121$, indicating that there was no significant difference between the hypothesized and observed covariance matrices. The incremental fit is good, CFI = 0.973, indicating that the proposed factor structure fits significantly better than the null (independence) model. This value is within the range of acceptable thresholds for good model fit in SEM applications. Absolute fit indices also contribute to model adequacy. The average standardized residuals (SRMR) value of 0.055 is low and below the conventional threshold of 0.08, suggesting that the observed and predicted correlations are not far from each other on average. Likewise, the RMSEA = 0.030 is close to the approximate fit in the population, and the error of approximation is small. The PClose value of 0.836 implies that the hypothesis of close fit cannot be rejected further supporting the adequacy of the model specification. In summary, the overall fit of the hypothesised factor structure is adequate, and is supported by both incremental and absolute fit indices.

Table 7
Construct Reliability and Validity Estimates

Construct	CR	AVE	MaxR(H)	CERS	CECR
CERS	0.709	0.291	0.716	—	0.523
CECR	0.646	0.273	0.668	0.523	—

Note. CR = composite reliability; AVE = average variance extracted; MaxR(H) = maximal reliability; diagonal elements represent constructs; off-diagonal values represent latent correlations.

The results indicate mixed evidence for construct validity of the Social Media Content Exposure Scale (SMCES). Composite reliability values showed acceptable internal consistency for CERS (CR = 0.709), while CECR demonstrated marginal reliability (CR = 0.646), suggesting moderate internal consistency for one construct and weaker stability for the second.

Convergent validity was not completely confirmed because the average variance extracted (AVE) for both constructs (CERS = 0.291; CECR = 0.273) were below the threshold of 0.50. This suggests that the observed indicators account for less than 50% of the variance in the respective latent constructs, indicating that convergent validity at the item level is somewhat limited. Inter-construct correlation was used to test the discriminant

validity. The latent correlation between CERS and CECR is 0.523, which shows moderate positive correlation between CERS and CECR. This value is lower than the traditional criterion for construct redundancy, but it indicates that there is some conceptual similarity between exposure-related risk perceptions and cognitive regulation processes, and that constructs are still empirically distinct. In general, the measurement model has a satisfactory factorial structure with good model fit at the CFA level; however, the convergent validity is not satisfactory and the reliability of CECR is not high, suggesting that this dimension needs to be further theoretically developed in future research.

Discussion

The current study used an exploratory sequential mixed methods design to develop and validate the Social Media Content Exposure Scale (SMCES). The results offer empirical evidence for a multidimensional conceptualization of social media content exposure, which is not a unidimensional usage-based phenomenon, but a structured psychological construct that is influenced by content characteristics and user-level psychological responses.

The exploratory factor analysis resulted in a stable two-factor solution: Content Exposure Risk and Susceptibility, Cognitive Engagement and Content Regulation. Theoretically, this structure aligns with the current framework of media effects, which focuses on the characteristics of the environmental exposure and the cognitive processing mechanisms at the individual level (Valkenburg, Meier, & Beyens, 2022; Orben & Przybylski, 2019). The introduction of a risk-based dimension comes in line with the previous evidence that suggests that users who are exposed to algorithmically curated content are more likely to be vulnerable to misinformation, emotional manipulation and negative affective states (Bakshy, Messing, & Adamic, 2015; Bucher, 2018). The results presented here align with the idea of social media environments as algorithmically designed exposure systems, not as neutral information channels.

The second factor, Cognitive Engagement and Content Regulation, is the active participation of users in the interpretation, filtering and regulation of content exposure. This is in line with the theoretical framework of Uses and Gratifications Theory, which considers the media user as an active agent who chooses the media content depending on his/her cognitive and psychological needs (Katz, Blumler, & Gurevitch, 1973). It is also consistent with Social Cognitive Theory, which proposes that people observe, evaluate, and regulate their reactions to mediated experiences (Bandura, 2001). The presence of cognitive regulation behaviors like critical evaluation and content avoidance emphasizes the adaptive strategies that users adopt to cope with information overload and algorithmic influence in digital spaces.

The results of reliability analysis indicated that the overall scale and the first subscale had good internal consistency, and the second subscale had moderate internal consistency. This is not unusual in the early stages of scale development, especially if the constructs being measured are multidimensional (higher-order cognitive and behavioral processes) (DeVellis, 2016). The low reliability of the Cognitive Engagement and Content Regulation dimension suggests that this dimension should be further developed, particularly in terms of the differentiation of cognitive evaluation, emotional response and behavioral control. The items in this dimension could be made more specific and the conceptual overlap between items reduced in future research to improve the internal consistency of this dimension.

The results of the convergent validity showed that there was a strong positive relationship between SMCES and social media engagement, meaning that the more exposed to social media, the more interaction with social media. This is consistent with prior research, which has shown that engagement behaviors are closely related to exposure intensity in algorithmically-driven digital environments (Valkenburg et al., 2022).

The relatively low correlation between SMCES and online information processing was used to test the discriminant validity, which showed that

exposure to content does not necessarily mean cognitive interpretation or evaluation of the content. Theoretically, this distinction is crucial as it separates exposure as a structural and environmental factor from cognitive processing as an individual difference factor. Digital media research has also tended to focus on the distinction between exposure and engagement and processing, viewing these as separate but related constructs (Potter, 2012; Bryant & Oliver, 2009).

The results also help to provide cultivation-based explanations of the effects of digital media. According to cultivation theory, over time, repeated exposure to media content will influence one's perception of social reality (Gerbner et al., 1986). Algorithms, which may be reinforced by social media, can also facilitate this process by continuously presenting them with content that is thematically similar, which can affect their perceptions, attitudes and behavioral norms. The present results contribute to this framework by demonstrating a structural differentiation of exposure along risk and regulatory dimensions, which suggests a more complex mechanism of digital cultivation.

The results of the confirmatory factor analysis (CFA) are empirical evidence of the measurement properties of the Social Media Content Exposure Scale (SMCES). The model was consistent with the established procedures in construct validation with structural equation modeling (Byrne, 2016; Kline, 2016) and showed a two factor structure: Content Exposure Risk and Susceptibility (CERS), and Cognitive Engagement and Content Regulation (CECR).

The construct reliability results showed acceptable internal consistency for CERS (CR = 0.709) and marginal reliability for CECR (CR = 0.646). This indicates that CERS items are more homogeneous, whereas CECR is more heterogeneous and broader conceptually. These patterns are typical for behavior and cognitive constructs that are multidimensional, not strictly unidimensional (Hair et al., 2019; Kline, 2016).

Convergent validity was not fully supported, as the average variance extracted (AVE) of both constructs were below the recommended value of 0.50. Fornell and Larcker (1981) suggest that AVE values < 0.50 suggest that the variance of the measurement is larger than the variance of the latent construct. In the early stages of scale development, however, a slight reduction in AVE can be acceptable if there is theoretical support for the breadth of the construct (Hair et al., 2019).

Latent construct correlation was used to evaluate the discriminant validity. The correlation between CERS and CECR is moderate (r = 0.523), indicating a relationship between the constructs but also an empirical difference. This aligns with the theoretical prediction that the risk perception and cognitive regulation processes related to exposure are not mutually redundant aspects of social media content exposure (Brown, 2015; Kline, 2016).

In general, the CFA results show that the conceptualization of SMCES is multidimensional, with the model having an acceptable factorial structure and model fit. The relatively low AVE values and the low reliability for the CECR, however, indicate that this dimension needs to be further developed to increase convergent validity and measurement precision in future studies.

Conclusion

The present study created and tested the Social Media Content Exposure Scale (SMCES), which has a two factor structure of Content Exposure Risk and Susceptibility, and Cognitive Engagement and Content Regulation. The CFA results showed good model fit, suggesting that the proposed two factor structure was a good representation of the observed data. Reliability evidence was satisfactory for CERS and only marginally satisfactory for CECR, indicating that the cognitive engagement and content regulation dimension might represent a more general and more heterogeneous group of cognitive and behavioral processes. But the convergent validity was not achieved since the AVE values for both constructs were lower than the recommended value. The moderate correlation between the two factors indicates that the dimensions are theoretically connected but empirically distinguishable. Overall, SMCES is a preliminary, but promising multi-dimensional measure of social media content exposure. The scale needs to be further validated in independent and more

diverse samples and the CECR dimension needs to be further developed to improve the reliability and convergent validity.

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