

Online Mental-Health Content Exposure, Self-Identification of Depression and Depressive Symptoms Among Adolescents

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Abstract: Adolescents increasingly use social media to interpret their emotions, yet little is known about how exposure to online mental-health content relates to self-identification of depression and to standardised symptom scores. This cross-sectional study examined these links in 376 adolescents aged 15–19 years from schools and colleges in Kothanur, Bengaluru, India. Participants completed the Social Media Engagement Scale for Adolescents (SMES-A), the researcher-developed Online Mental Health Content Exposure Questionnaire (OMHCEQ) and Self-Identification of Depression Scale (SIDS), and the Patient Health Questionnaire-9 (PHQ-9). Self-identification correlated moderately with PHQ-9 scores ($r = .47, p < .001$), as did content exposure with self-identification ($r = .43, p < .001$). Content exposure explained an additional 12.9% of PHQ-9 variance beyond social-media use and engagement ($\Delta R^2 = .129, p < .001$), whereas daily use duration was unrelated to PHQ-9 scores ($p = .036, p = .485$). About one in three adolescents (33.2%) showed discordance between self-identification and PHQ-9 classification. Females scored higher than males on the PHQ-9 ($d = 0.37$). Findings are correlational; they support digital mental-health literacy and school screening with professional follow-up.

Keywords: Adolescents; Depressive symptoms; Self-identification; Online mental-health content; Social media engagement

1. Introduction

Adolescence is a period of rapid biological, emotional and social change, and many mental-health difficulties first appear during it. Half of all lifetime mental disorders begin by about age 14 [1], and the World Health Organization estimates that roughly one in seven adolescents aged 10–19 years lives with a mental disorder [2]. In India, the National Mental Health Survey reported a diagnosable mental disorder in 7.3% of 13–17-year-olds and a treatment gap above 70% [3]. Early recognition, including the adolescent's own ability to recognise difficulties, therefore matters for help-seeking [4].

Adolescents now grow up online. Many turn to the internet and social media to learn about their mental health [5]. This can reduce stigma and encourage help-seeking, but it also exposes them to distressing or inaccurate material [6]; one content analysis found much of the popular short-video material on attention-deficit/hyperactivity disorder to be misleading [7]. Such content may lead some adolescents to label ordinary distress as a disorder, an idea termed the prevalence inflation hypothesis [8], while others with elevated symptoms may not recognise themselves in the descriptions they meet.

This study separates two constructs that are often conflated. *Self-identification* is an adolescent's own belief that they are depressed. *Depressive symptom severity* is a standardised screening score, here the PHQ-9 [9], which is not a clinical diagnosis. The two can diverge: *over-identification* (identifying as depressed without elevated symptoms) and *under-recognition* (elevated symptoms without identifying as depressed) both matter for early support. Research on social media and adolescent depression has also relied mostly on time spent online, with small and inconsistent associations [10–12]. We therefore examined, among Indian adolescents

aged 15–19 years, how online mental-health content exposure, social-media engagement, self-identification and PHQ-9 symptom severity are related.

The setting matters. In India, social-media use is widespread and mental-health services are stretched [3], and the 15–19 age range, spanning school and early college, is rarely studied as one group even though it is a period of active identity exploration [13]. If self-labelling and symptom levels do not match, schools and counsellors need to know. This study contributes brief measures of content exposure and self-identification with reliability evidence, a joint analysis of self-identification and a standardised symptom score in one sample, and estimates of over-identification and under-recognition.

2. Literature Survey

Adolescent depression and recognition: Depression is among the major causes of illness and disability in adolescence [2]. In the National Mental Health Survey of India, depressive and recurrent depressive disorder were among the most common diagnoses recorded, alongside a treatment gap above 70% for mental disorders generally [3]. Because many adolescents with depression go unrecognised and untreated, the adolescent's own ability to recognise and name difficulties is itself of practical importance [4].

Social media use versus engagement: Time-based measures of social-media use show only small associations with adolescent well-being, explaining at most 0.4% of its variance in one large analysis [12]; a review of cohort and momentary-assessment research likewise found small associations without causal evidence [11]. A systematic review, however, linked several use domains (time, activity, investment and addiction) with depression, anxiety and distress [10], and in an Indian adolescent cohort social-media users had higher

odds of depressive symptoms than non-users, with no clear causal order [14]. Because duration captures only part of what adolescents do online, Ni et al. proposed a multidimensional view and developed the SMES-A, whose behavioural, cognitive and affective engagement factors explained 56% of the variance in 2,519 Chinese adolescents [15].

Online mental-health content and self-labelling: Mental-health content is highly visible on platforms adolescents use, is often produced by non-professionals, and is frequently incomplete or misleading [7]. Concept creep, the widening of psychological concepts to cover milder experiences [16], and its extension to awareness campaigns in the prevalence inflation hypothesis [8], suggest that greater exposure could raise self-labelling independently of symptom change. Haslam and Tse have argued that people who rely on social media for mental-health information may become less able to identify genuine cases [17]. A counter-view holds that accurate information improves mental-health literacy and help-seeking [18].

Measurement matters: Studies define social-media use in different ways, including time spent, activity, investment and addiction [10]. Measures based only on time online may capture a different construct from engagement, problematic use, emotional involvement or the type of content consumed. This motivated our separation of daily duration, engagement (SMES-A) and content exposure (OMHCEQ).

Direction of effects: Adolescents with depressive symptoms tend to spend more time on digital media than peers without symptoms [19,20], and the association between social-media use and depression appears bidirectional [21]. Duration alone therefore cannot show whether use leads to symptoms or symptoms lead to use. Quantitative work in India has likewise relied on use-frequency measures rather than content exposure [14].

Exposure, quality and misinformation: Personalised recommendation means adolescents may meet mental-health content without seeking it. Passive consumption is associated with greater susceptibility to false information [22], which spreads faster than accurate information online [23]. Most TikTok mental-health videos are not produced by professionals, and only about a tenth focus on coping skills [24].

Labels and identity: Self-labelling during identity formation can shape self-concept, and Hacking's looping effect describes how diagnostic labels and the people who adopt them come to redefine one another [25]. Online communities can strengthen belonging: marginalised youth may find welcoming communities, and online engagement strengthened group identification and resilience among LGB individuals in Hong Kong [26]. The same mechanisms can create identity bubbles that reinforce shared identities [27], and once an illness label becomes part of identity, over-identification with it may constrain change. We reasoned that over-identification may arise when limited emotional vocabulary and developmental immaturity meet generalised symptom content, and that under-recognition may reflect stigma, fear of social judgement or limited insight; either

would make self-report alone an inadequate basis for identifying depression.

Theoretical background: Erikson's account of adolescent identity formation [28], extended by Arnett into the late teens [13], suggests that adolescents may try on labels they meet online. The Common-Sense Model of Self-Regulation holds that people build an illness representation, including an identity label, partly from outside sources such as media and peers [29]; a label can thus diverge from a symptom score. Social comparison theory [30] adds that relatable posts and testimonials give adolescents many reference points for their own feelings.

Emotional awareness and interpretation: Emotional awareness is the ability to identify, differentiate and label emotional experiences accurately. Where it is limited, as it may be while it is still developing in adolescence, distress can be generalised and labelled as depression. Cognitive accounts add that people interpret emotions through the schemas and language available to them; as mental-health discourse grows, adolescents may adopt clinical terms without fully grasping their implications, opening a gap between subjective experience and clinical reality.

Research gap: We identified no study that measured online mental-health content exposure as a construct distinct from general engagement and compared it with both a standardised symptom score and adolescents' own self-identification in the same sample. Validated adolescent measures of exposure and self-identification are lacking, and evidence from Indian adolescents is limited, although the PHQ-9 has been validated for adolescents [31] including Indian adolescents [32].

3. Problem Definition

Aim

To examine self-identified depression and its association with social-media engagement, online mental-health content exposure and PHQ-9 symptom severity among adolescents aged 15–19 years. Secondary objectives were to identify discrepancies between self-identification and screening outcomes and to explore gender differences.

Rationale

Four gaps motivate the study: most research relies on time spent online rather than the content adolescents meet; work on self-diagnosis is largely conceptual or qualitative; evidence from Indian adolescents is limited; and no validated adolescent measures of content exposure or self-identification of depression exist. We therefore developed the OMHCEQ and SIDS and examined their reliability. The following hypotheses were tested.

H1: Self-identification of depression is significantly associated with PHQ-9 symptom severity.

H2: Higher online mental-health content exposure is significantly associated with higher self-identification of depression.

H3: Higher online mental-health content exposure significantly predicts higher PHQ-9 severity after accounting for social-media use.

4. Methodology

4.1 Design and participants

A quantitative, cross-sectional design was used. Students were recruited by non-probability convenience and purposive sampling from schools and colleges in and around Kothanur, Bengaluru, Karnataka. The initial sample of 400 students was reduced to **376 adolescents** (mean age 16.65 years, $SD = 1.30$) after data cleaning in line with the exclusion criteria. Inclusion criteria were age 15–19 years, current enrolment, willingness to participate, informed consent or assent (with parental consent where applicable) and ability to understand the questionnaires. Students were excluded if they had a serious prior mental-health history, lacked the required consent, or returned substantially incomplete or invalid questionnaires.

4.2 Measures

Online mental-health content exposure (OMHCEQ), social-media engagement (SMES-A) and daily use duration were treated as predictors; self-identification (SIDS) and symptom severity (PHQ-9) were the outcomes. A background form recorded age, gender, class, daily social-media use (five categories: <1 h, 1–2 h, 2–4 h, 4–6 h, >6 h), prior mental-health contact and perceived family support. Four scales were used (Table 1):

SMES-A [15]: 11 items rated 1–5 (total 11–55; no reverse scoring) covering behavioural (habitual use, such as browsing whenever free), affective (emotional involvement) and cognitive engagement. The original 15-item pool was reduced to 11 items by factor analysis, with three factors explaining 56.01% of variance.

OMHCEQ (researcher-developed): 14 items rated from 1 (Never) to 5 (Very Often) for the previous month (total 14–70), covering passive exposure through feeds, active searching including AI tools, content types (personal stories, checklist or quiz content, professional information, memes) and responses to content.

SIDS (researcher-developed): four items rated 1–5 (total 4–20) on believing oneself depressed, willingness to describe oneself as having depression, resemblance of one's experiences to depression descriptions, and perceived need for help.

PHQ-9 [9]: nine items scored 0–3 over the previous two weeks (total 0–27); bands 0–4 minimal, 5–9 mild, 10–14 moderate, 15–19 moderately severe, 20–27 severe. A score ≥ 10 is a widely used screening threshold and defined *significant depressive symptoms* here; the PHQ-9 has been validated in adolescents [31,32].

Table 1: Study instruments

Scale	Construct	Items	Range	Response format
SMES-A	Social-media engagement	11	11–55	1–5 agreement
OMHCEQ	Online mental-health content exposure	14	14–70	1–5 frequency, past month
SIDS	Self-identification of depression	4	4–20	1–5 agreement
PHQ-9	Depressive symptom severity	9	0–27	0–3 frequency, past 2 weeks

SMES-A and PHQ-9 are established scales [9,15]; OMHCEQ and SIDS were developed for this study.

Table 2: Content of the researcher-developed scales

Scale	Content
OMHCEQ	Frequency of exposure to general mental-health and depression-symptom content; content from influencers, celebrities and creators; passive exposure through feeds and recommendations; active searching, including AI tools; searching to check whether one's feelings match online descriptions of depression; following mental-health accounts; content types (personal stories, checklist or quiz content, professional information, memes); responses (relating to content, liking or sharing, discussing with others).
SIDS	(1) "I think I am depressed." Remaining items, paraphrased: (2) would describe oneself as having depression; (3) emotional experiences resemble descriptions of depression; (4) needs help for depression even without having consulted a professional.

4.3 Operational definitions

Social-media engagement is behavioural, cognitive and affective involvement with social media, measured by the SMES-A. *Online mental-health content exposure* is the frequency with which adolescents encounter, view or engage with mental-health content on social media and other platforms, measured by the OMHCEQ. *Self-identification* is the adolescent's subjective perception that they are experiencing depression, measured by the SIDS; for discrepancy analysis SIDS totals were classified as high or low self-identification. A second, single-item classification used SIDS item 1 ("I think I am depressed"), where Agree or Strongly Agree meant self-identifying as depressed. *Significant depressive symptoms* were PHQ-9 scores ≥ 10 . *Over-identification* was self-identification with PHQ-9 <10; *under-recognition* was no self-identification with PHQ-9 ≥ 10 . These are research definitions, not diagnostic cut-offs.

4.4 Procedure and ethics

Permission was obtained from institutional authorities, with parental consent and student assent before participation. Questionnaires were administered offline in a classroom setting with clear instructions to ensure that students understood each section. Because the PHQ-9 contains an item on self-harm, names were recorded solely so that students endorsing it could be followed up with suitable intervention; confidentiality was maintained, participation was voluntary

with the right to withdraw, and referral information was given to students with high symptom levels.

4.5 Data screening and statistical analysis

Responses were checked against each instrument's permissible range. Out-of-range responses were treated as invalid and were not imputed; such cases were excluded only from analyses that required a valid total for the affected scale. Responses were scored by standard guidelines for the SMES-A and PHQ-9, assigned unique identification numbers, coded numerically and entered in Microsoft Excel. Data were screened in Microsoft Excel and analysed using SPSS, Jamovi and Python (SciPy, NumPy); significance was set at $p < .05$. Analyses comprised descriptive statistics, Cronbach's α , Pearson correlations, Spearman's ρ and a Kruskal–Wallis test for the ordinal duration variable, Pearson χ^2 with Cramér's V , Welch's t -tests for gender, and hierarchical multiple regression.

5. Results and Discussion

5.1 Sample, descriptives and reliability

The sample comprised 199 females (52.9%), 173 males (46.0%) and 4 students (1.1%) choosing other or prefer not to say (Table 3). Table 4 gives scale descriptives and reliability. The OMHCEQ ($\alpha = .84$) and SMES-A ($\alpha = .83$) were good and the SIDS acceptable ($\alpha = .71$), whereas the PHQ-9 showed modest internal consistency in this sample ($\alpha = .68$).

Table 3: Sample characteristics (N = 376)

Characteristic	n	%
Gender		
Female	199	52.9
Male	173	46
Other / prefer not to say	4	1.1
Class		
Grade 10	147	39.1
Grade 11 (PUC I)	63	16.8
Grade 12 (PUC II)	65	17.3
Degree	101	26.9

Mean age = 16.65 years (SD = 1.30).

Table 4: Descriptive statistics and internal consistency (N = 376)

Scale	Items	M	SD	Range	α
SMES-A	11	42.62	10.84	15–51	0.83
OMHCEQ	14	30.99	10.08	14–65	0.84
SIDS	4	9.41	3.8	4–20	0.71
PHQ-9	9	10.07	4.69	0–23	0.68

Range = observed minimum–maximum. PHQ-9 median = 10.

Relative to the possible score ranges, mean SMES-A engagement (42.62 of 11–55) was above the scale midpoint of 33, whereas mean OMHCEQ exposure (30.99 of 14–70) and SIDS self-identification (9.41 of 4–20) were below their midpoints of 42 and 12. The mean PHQ-9 score (10.07) sat at the moderate-severity threshold.

5.2 Depressive symptom severity

Table 5 shows that 203 of 376 adolescents (54.0%) scored ≥ 10 on the PHQ-9. This reflects screening scores in a non-probability sample and should not be read as the prevalence

of depressive disorder; the national survey, which used diagnostic assessment, found a diagnosable mental disorder in 7.3% of adolescents [3].

Table 5: Distribution of PHQ-9 severity categories (N = 376)

Severity band	Score	n	%
Minimal	0–4	44	11.7
Mild	5–9	129	34.3
Moderate	10–14	134	35.6
Moderately severe	15–19	64	17
Severe	20–27	5	1.3

5.3 Self-identification and symptom severity (H1)

SIDS and PHQ-9 scores were moderately and positively correlated, $r = .47$, $p < .001$ (Table 8), supporting H1. The categorical comparison revealed substantial discordance (Table 6). Using high versus low SIDS classification, 64 students (17.0%) showed over-identification and 61 (16.2%) showed under-recognition, so 125 (33.2%) were discordant (Figure 1).

Table 6: High versus low SIDS classification by PHQ-9 category, n (row %)

SIDS	PHQ-9 <10	PHQ-9 ≥ 10	Total
Low	109 (64.1)	61 (35.9)	170
High	64 (31.1)	142 (68.9)	206
Total	173	203	376

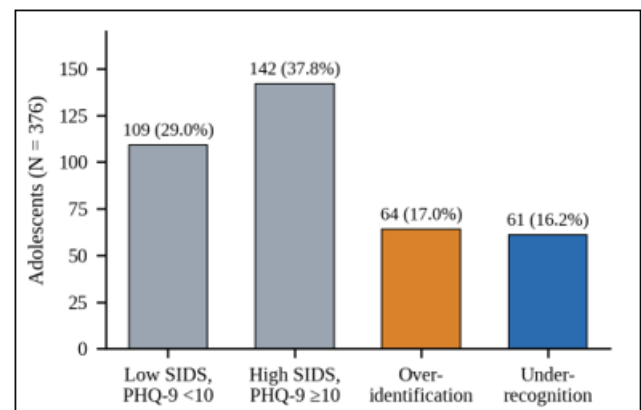


Figure 1: Concordant and discordant classifications by SIDS (high/low) and PHQ-9 (<10/≥10); n and % of N = 376

Using the single-item classification (Table 7), only 86 adolescents (22.9%) identified themselves as depressed, whereas 54.0% scored ≥ 10 . Of the 86, 72 (83.7%) had PHQ-9 ≥ 10 and 14 (16.3%) did not; of the 203 with PHQ-9 ≥ 10 , 131 (64.5%) did not identify as depressed. The association was significant, $\chi^2(1) = 39.68$, $p < .001$, Cramér's $V = .325$, a moderate effect. By conventional benchmarks this is a medium effect. Self-identification and symptom scores are therefore related but not interchangeable, and under-recognition was the dominant mismatch on the stricter single-item measure.

Table 7: Single-item self-identification (SIDS item 1) by PHQ-9 category (N = 376)

Self-identifies	PHQ-9 <10	PHQ-9 ≥ 10	Total
No	159	131	290
Yes	14	72	86

Total	173	203	376
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5.4 Content exposure, engagement and duration (H2)

Online mental-health content exposure correlated positively with self-identification ($r = .43$) and with PHQ-9 scores ($r = .40$), supporting H2 (Table 8). SMES-A engagement showed smaller correlations with PHQ-9 ($r = .23$), SIDS ($r = .25$) and OMHCEQ ($r = .31$). Self-identification ($r = .47$) and content exposure ($r = .40$) were thus the variables most strongly related to PHQ-9 scores, and all correlations were positive. In contrast, daily duration of social-media use was unrelated to PHQ-9 scores, $\rho = .036$, $p = .485$, and PHQ-9 did not differ across the five duration categories, $H(4) = 4.13$, $p = .389$ (Table 9). Duration of use, by itself, was not associated with symptom severity in this sample.

Table 8: Pearson correlations among study variables (N = 376)

	OMHCEQ	SMES-A	SIDS	PHQ-9
OMHCEQ	1	0.31	0.43	0.4
SMES-A		1	0.25	0.23
SIDS			1	0.47
PHQ-9				1

All correlations significant at $p < .01$.

Table 9: Daily social-media use and PHQ-9 scores (N = 376)

Test	Statistic	p
Spearman correlation	$\rho = .036$	0.485
Kruskal-Wallis (5 use categories)	$H(4) = 4.13$	0.389

5.5 Prediction of symptom severity (H3)

In the hierarchical regression, Model 1 (daily-use category and SMES-A) explained 4.9% of PHQ-9 variance. Adding OMHCEQ raised this to 17.8%, a significant increment of 12.9%, $\Delta F(1, 371) = 58.32$, $p < .001$, a medium effect ($f^2 = 0.16$) (Tables 10 and 11), supporting H3. In the final model OMHCEQ was the strongest predictor ($\beta = .378$, $p < .001$), SMES-A remained a significant but smaller predictor ($\beta = .149$, $p = .005$), and daily-use category did not reach significance ($p = .051$). Variance inflation factors (1.11–1.25) indicated no problematic multicollinearity. Figure 2 shows the OMHCEQ–PHQ-9 association.

Table 10: Hierarchical regression models predicting PHQ-9 severity

Model	Predictors	R ²	Adj. R ²	ΔR^2	F
1	SM + SMES-A	0.049	0.044	—	9.63
2	+ OMHCEQ	0.178	0.174	0.129	26.85

SM = daily social-media-use category. All models $p < .001$.

Table 11: Coefficients of Model 2

Predictor	B	SE	β	t	p
SM	−0.357	0.183	−.101	−1.96	0.051
SMES-A	0.083	0.029	0.149	2.83	0.005
OMHCEQ	0.177	0.023	0.378	7.64	<.001

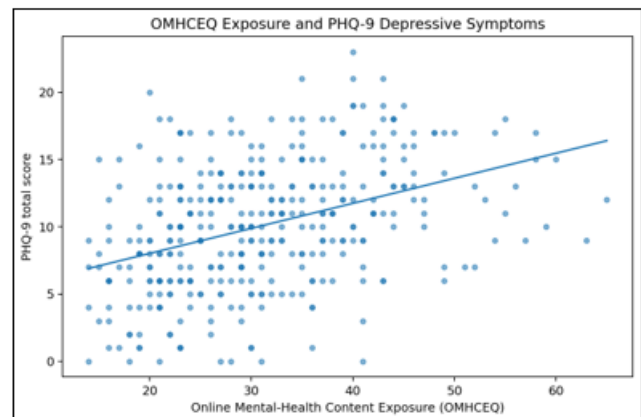


Figure 2: Scatterplot of OMHCEQ exposure and PHQ-9 total scores (N = 376) with fitted regression line

5.6 Gender differences

Females scored significantly higher than males on the PHQ-9 (Table 12), $t(370) = -3.50$, $p < .001$, $d = 0.37$, and a larger proportion of females met the ≥ 10 threshold (60.8% vs 46.8%), $\chi^2(1) = 6.74$, $p = .009$. Self-identification did not differ by gender, $t(370) = -1.23$, $p = .218$, $d = 0.13$, nor did the proportion of high self-identifiers, $\chi^2(1) = 1.77$, $p = .183$. The four students who chose other or prefer not to say were excluded from this comparison because of the small cell size.

Table 12: Gender comparison (males n = 173, females n = 199)

Measure	Male	Female	Test	p	d
PHQ-9	9.19 (4.78)	10.88 (4.50)	$t = -3.50$	<.001	0.37
SIDS	9.15 (3.89)	9.64 (3.70)	$t = -1.23$	0.218	0.13
PHQ-9 ≥ 10	46.8	60.8	$\chi^2 = 6.74$	0.009	—

Values are M (SD) except the last row (%). t -tests: $df = 370$; χ^2 : $df = 1$.

5.7 Summary of hypothesis tests

Table 13 summarises the outcome of the three hypothesis tests.

Table 13: Hypothesis testing results

	Test	Result	Decision
H1	Pearson: SIDS $\times$ PHQ-9	$r = .467$, $p < .001$	Supported
H2	Pearson: OMHCEQ $\times$ SIDS	$r = .431$, $p < .001$	Supported
H3	Regression: OMHCEQ added to use and engagement	$\Delta R^2 = .129$, $p < .001$	Supported

5.8 Discussion

Self-identification and symptoms: The moderate link between self-identification and PHQ-9 scores indicates that adolescents' own labels carry real information about their symptoms and should be taken seriously: a statement that one feels depressed may be an attempt to communicate distress or make sense of experience. Yet one-third of the sample was discordant on the composite classification, and nearly two-thirds of those with PHQ-9 ≥ 10 did not endorse the item "I think I am depressed". An elevated screening score warrants further evaluation but is not itself a diagnosis, and a self-label does not establish a depressive disorder. The label and the score measure related but distinct things, consistent with the

Common-Sense Model's view that illness identity is built from interpretation as well as bodily experience [29].

Over-identification and under-recognition: Over-identification (17.0% on the composite classification) is compatible with the concern that ready-made online descriptions may be adopted to explain ordinary distress [8,16]. Under-recognition (16.2% on the composite classification, and 64.5% of those with PHQ-9 ≥ 10 on the single item) may reflect stigma, limited emotional awareness, or not seeing one's own experience in the content one encounters. These explanations were not measured and remain hypotheses for future work.

Content, engagement and duration: The small positive association between engagement and symptoms ($r = .23$) is in line with reviews and cohort evidence linking engagement and use domains with depressive symptoms [10,14], and the null result for duration matches earlier work showing that time-based measures relate only weakly to adolescent mental health [11,12]. Here, daily duration was unrelated to PHQ-9 scores, engagement showed a small association, and content exposure was the strongest predictor, adding 12.9% of explained variance. This supports the argument that what adolescents encounter and how they engage matters more than hours online [15]. The association between exposure and self-identification is compatible with concern about prevalence inflation [8], but our design cannot test it: the same pattern would arise if adolescents with more symptoms seek out more mental-health content, and exposure may also help some adolescents recognise genuine difficulties [18]. A reciprocal relationship is plausible, and exposure should not be read as a cause of depressive symptoms.

Comparison with earlier research: Earlier studies link social-media use with internalising symptoms, but the strength of association varies with how use is defined, and time-only measures may capture a different construct from engagement, problematic use or content type [10,11]. Our results support this distinction. We identified no earlier study that reported content exposure, self-identification and a standardised symptom score together in Indian adolescents, so the discordance estimates cannot yet be compared directly with other samples.

Gender: Females reported more symptoms than males without reporting higher self-identification, which may suggest that their symptom burden is not matched by self-recognition. This is a tentative interpretation of a small-to-moderate effect and needs replication.

Theoretical implications: Adolescents in this sample were not simply passive consumers: their engagement with social media coexisted with exposure to symptom descriptions, terminology and personal stories that they may use to understand their own emotions, in line with identity-exploration [13,28] and social-comparison accounts [30]. The results do not show that online content produces inaccurate self-diagnosis; they show that exposure and self-identification are connected in this sample. Online content can also give adolescents vocabulary for feelings they struggle to express and encourage help-seeking. The central question is therefore whether information is accurate,

contextualised and accompanied by guidance towards professional assessment.

Practical implications: First, schools and colleges can run mental-health and digital-health literacy programmes that distinguish having symptoms, identifying with a condition and receiving a diagnosis, and teach critical evaluation of influencer content, symptom lists and anecdotes rather than discouraging information-seeking. Second, with 54.0% of students scoring ≥ 10 , accessible screening with referral and follow-up is needed, not screening alone. Third, mental-health professionals can use social media for accurate psychoeducation and early engagement. Finally, adolescents who label themselves depressed, and those with elevated scores who do not, both warrant assessment by a trained professional.

6. Conclusion

Among 376 adolescents aged 15–19 years, self-identification of depression, online mental-health content exposure, social-media engagement and PHQ-9 symptom severity were positively related, whereas daily duration of social-media use was not. Content exposure contributed most to explaining symptom severity beyond engagement and duration, and about one in three adolescents showed a mismatch between self-identification and screening results. Self-identification is a meaningful signal but not a substitute for standardised screening and professional assessment, and adolescent mental health in the digital age is better understood through the content and nature of online engagement than through screen time alone.

7. Future Scope

Strengths

The study used a sizeable sample, paired adolescents' self-identification with a standardised symptom measure in the same participants, and separated daily duration, engagement and content exposure, which are often conflated.

Limitations

The cross-sectional design precludes causal or directional inference. Sampling was non-probabilistic and limited to one locality, restricting generalisability. All measures were self-reported and open to recall and social-desirability bias. The PHQ-9 is a screening and severity measure, not a diagnosis, and its internal consistency here was modest. The OMHCEQ and SIDS were developed for this study and need further psychometric validation. Duration was recorded in broad categories, and platforms, content types and confounders such as academic pressure, family environment and sleep were not examined.

Future Research

- 1) Longitudinal designs should test the direction of the relationships between exposure, self-identification and symptoms.
- 2) Larger and more diverse samples from different regions and educational settings are needed.
- 3) The OMHCEQ and SIDS require factor-analytic and other psychometric validation, and specific content types (for example personal stories, checklist or quiz content,

professional information) should be analysed separately from overall exposure.

- 4) Intervention studies should test whether digital mental-health literacy programmes reduce inaccurate self-labelling while improving appropriate help-seeking.

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