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SOCIAL MEDIA USE, ADDICTION AND ACADEMIC PERFORMANCE AMONG MEDICAL STUDENTS: A PRELIMINARY EVIDENCE SYNTHESIS

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Abstract

Background: Single-institution surveys disagree on whether social media use is associated with poorer academic performance in medical students.

Objective: To summarise the available correlations between daily time spent on social media and academic performance in medical students, and to describe the evidence on addiction scores, perceived academic benefit, perceived distraction and online professional conduct.

Methods: This is a preliminary synthesis of 25 reports assembled by the authors, not a systematic search. Correlations between daily time spent and academic performance were pooled on the Fisher z scale with DerSimonian–Laird random effects and Hartung–Knapp–Sidik–Jonkman (HKSJ) intervals. Because two of the four coefficients were printed with a sign that contradicts their own reports, the analysis is presented with those coefficients corrected, as printed, and excluded. Outcomes with fewer than three comparable studies were presented study by study. Risk of bias was assessed with JBI checklists and certainty with GRADE.

Results: Seventeen studies were included. Whether daily time spent is associated with academic performance remains unresolved: four studies (n = 1,590) reported correlations, two of them printed with a sign that contradicts their own text. Entered as printed, the pooled correlation was r = −0.06 (95% CI −0.45 to 0.36); with those signs corrected, it was −0.16 (−0.28 to −0.03); with both studies excluded, two remained (r = −0.21 and −0.47) and no estimate was pooled. Two studies correlated addiction scores with performance (r = −0.47 and −0.22), one with an unverified value and one in a sample that was 11% medical students. Endorsement of benefit items ranged from 19.6% to 68.5%, with item formats differing between studies, and agreement that social media distracts from studying was 64.6% and 79.1%. Two studies of online professional conduct used outcomes that could not be compared. Certainty was very low for every outcome.

Conclusions: Whether time spent on social media is associated with academic performance in medical students cannot yet be determined from these data; the answer turns on two reporting errors. A registered systematic review with independent duplicate extraction is required.

Keywords: social media; addiction; academic performance; medical students; evidence synthesis

1. Introduction

Social media platforms are now part of undergraduate medical training. A survey from our own department, by two of the present authors, found that 65% of students accessed social media during clinical rounds[1]. Elsewhere use is near universal: 97% of medical students in Bengaluru used WhatsApp[2] and 97% of students in Multan used social media, most of them during lectures[3]. Students use these platforms for timetables, peer discussion, procedural videos and examination preparation, and also for entertainment that competes with study time.

Published studies disagree on the academic consequences. Some surveys have reported an inverse association between social media use or addiction and grades[4,5], although in at least two others the printed coefficient contradicts the text (Section 3.3). Others found that many students credit social media with improving their performance[6,7], or that time online had no direct effect on grade point average (GPA) once coping style was considered[8]. Previous systematic reviews of social media in medical education were narrative and focused on teaching interventions rather than routine use[9,10], and a recent meta-analysis of social media addiction addressed psychological rather than academic outcomes[11].

Exposure in this literature is measured in two conceptually different ways, as time spent and as addiction-like use, and the two may relate differently to performance. They are therefore analysed separately. The secondary objectives were to describe the proportions of students reporting academic benefit and distraction, and to summarise evidence on online professional conduct.

2. Methods

2.1 Design and registration

This is a preliminary evidence synthesis, reported with reference to the PRISMA 2020 statement[12] but not meeting its requirements for a systematic review, because no systematic search has yet been run. The protocol has not been registered.

2.2 Eligibility criteria

Studies were eligible if they enrolled undergraduate medical students; measured social media exposure as daily time, an addiction scale or a self-reported pattern of use; and reported academic performance (examination marks or GPA), perceived academic benefit, perceived distraction or online professional conduct. Cross-sectional and cohort studies were eligible if they reported a correlation coefficient, a proportion with a stated denominator, or another association measure suitable for narrative synthesis. Reviews, studies of postgraduate trainees, studies without medical students or without an academic outcome were excluded.

2.3 Information sources and selection

This synthesis is based on 25 full-text reports collected by the authors from their own reading and reference lists. It is not the product of a systematic search, and the selection of reports may be biased towards studies that are easy to find, recently published or known to the authors.

2.4 Data extraction and handling rules

Country, data-collection period, sampling, sample size, exposure instrument, academic outcome and effect estimates were extracted. All four coefficients in the pooled analysis were re-checked against the source tables (Bhandarkar 2021, Table 5; Alshanqiti 2023, Results text; Lone 2026, Table 2; Khanimov 2026, Table 4). The following rules were defined after initial extraction, when inconsistencies in the source reports became apparent:

1.One correlation per study and exposure type, against the stated academic outcome.

2.All correlations coded so that a negative value indicates lower performance with greater exposure.

3.Where a printed coefficient was positive but the text and conclusions of the same report described a negative association (Bhandarkar 2021; Alshanqiti 2023), the analysis was presented three ways: corrected, as printed and excluded.

4.Spearman coefficients were converted to Pearson equivalents by $r = 2 \sin(\pi\rho/6)$[13].

5.For five-point Likert items, agreement was counted as "agree" plus "strongly agree". Where the response format was not reported, the published proportion was used (Sanyamath 2024).

6.Perception items were grouped by similar wording and not combined across different wordings.

7.Studies whose samples were not confined to medical students (Azizi 2019, 11% medical students; Lahiry 2019, sample frame including nursing and paramedical students) were flagged as indirect.

Single-reviewer extraction is the main threat to the numbers in this report. An extraction error illustrates the risk: the Alshanqiti 2023 proportions were first taken from the "agree" column alone, omitting "strongly agree", and correcting this changed agreement that social media distracts from studying from 56.3% to 79.1% and agreement that it helped improve grades from 47.7% to 68.5%. Because two authors of this review are authors of Bansal 2025[1], its data are shown descriptively only and it was not appraised.

2.5 Risk of bias and certainty of evidence

Two JBI tools were used according to the outcome each study contributed[14,15]. Studies contributing correlations were assessed with the eight-item checklist for analytical cross-sectional studies, and studies contributing proportions with the nine-item checklist for prevalence studies; Alshanqiti 2023 was assessed with both. Each item was judged yes, no or unclear. In line with JBI guidance, items were not summed and no cut-off was applied. Certainty was graded per outcome with GRADE, starting at low for observational evidence[16].

2.6 Statistical analysis

Correlations were transformed to Fisher z with variance $1/(n - 3)$. Pooling was restricted to outcomes with at least three studies using a comparable exposure measure and outcome; with two studies, between-study variance cannot be estimated reliably and the DerSimonian–Laird interval is misleadingly narrow. Only the time-spent analysis met the threshold, and only when the disputed coefficients were retained (corrected or as printed).

Random-effects models used the DerSimonian–Laird estimator of τ^2[17] with HKSJ confidence intervals on $k - 1$ degrees of freedom[18], the scaling factor constrained to at least 1. REML estimation of τ^2[19] was a sensitivity analysis. Heterogeneity was summarised by Q, I^2 and τ^2[20], with Q-profile 95% confidence intervals for τ^2 and I^2, and a 95% prediction interval[21]. Leave-one-out analysis was performed. Single-study correlations carry Fisher z intervals and single-study proportions Wilson intervals[22]. Publication bias and small-study effects could not be assessed, because funnel plots and

regression tests are uninformative with fewer than ten studies. Analyses were run in Python 3.12 (NumPy, SciPy); DerSimonian–Laird estimates were reproduced in statsmodels.

3. Results

3.1 Report selection

Of 25 reports, three were duplicates. Three reviews were excluded at screening and two reports at full text (Figure 1; Table 1). Seventeen studies were included: four contributed to the time-spent analysis, five contributed study-level data on addiction or perceptions, Bansal 2025 is reported descriptively, and seven were synthesised narratively.

Identification	Reports assembled by the authors (no database search) n = 25	Duplicates removed n = 3
Screening	Unique reports screened n = 22	Reviews excluded n = 3
Eligibility	Full texts assessed n = 19	Excluded n = 2: postgraduate trainees (1); no academic outcome and not confined to medical students (1); see Table 1
Included	Studies included n = 17 Time-spent analysis 4 · study-level 5 · descriptive 1 · narrative 7	Pooled: time spent only. Study-level: addiction 2, benefit 4, distraction 2 (overlapping)

Figure 1. Flow of reports assembled by the authors, laid out after PRISMA 2020.

Table 1. Reports excluded at full text

Report	Population and design	Reason for exclusion
Guan 2026[23]	Resident physicians in standardised residency training, China; cross-sectional	Postgraduate trainees; no academic-performance outcome
Yucra-Mamani 2026[24]	828 university students of health sciences and social sciences, Peru; cross-sectional	Not confined to medical students; no academic-performance outcome

Three reviews excluded at screening (Guckian 2021, Sutherland 2017, Jing 2025) are cited in the Introduction.

3.2 Characteristics of included studies

The studies came from India (seven), Saudi Arabia (three), Iran (two), Pakistan (two), China (one), Jordan (one) and Aruba (one), with data collected between 2011 and 2026, and enrolled 6,934 students (range 25–1,100), of whom 6,256 were in samples confined to medical students; Azizi 2019 (n = 360, 11% medical students) and Lahiry 2019 (n = 318, sample frame including nursing and paramedical students)

were not. Three used a named, validated addiction scale. Only one obtained GPA from institutional records; all others relied on self-report (Table 2).

Table 2. Characteristics of included studies

Study	Country (city)	Data collection	Sampling	n	Exposure measure	Academic outcome	Analysis
Bansal 2025[1]	India (Faridkot)	Oct 2024–May 2025	Convenience	246	Structured questionnaire	Perceived benefit and distraction	Descriptive
Bhandarkar 2021[25]	India (Manipal)	Nov 2018–Jan 2019	NR	400	Hours/day; SMAS-SF	Self-reported university examination marks (%)	Time (pooled)
Monisha 2025[26]	India (Puducherry)	Oct 2024–Jan 2025	Multistage systematic random	620	BSMAS	Self-reported performance band	Addiction (study level)
Lahiry 2019[7]	India (Kolkata)	Nov 2017–Apr 2018	Online invitation (55% usable)	318 *	Online questionnaire	Perceived effect on performance	Benefit A (indirect population)
Sanyamath 2024[27]	India (Kolkata)	NR	Voluntary	275	KAP questionnaire	Perceived improvement	Benefit B
Arun 2025[2]	India (Bengaluru)	NR	NR	117	Platform use	Content relevance	Narrative
Ashraf 2021[28]	China (Jiangsu)	Jan 2021	Online survey	233	Social media use for open learning (TAM constructs)	Self-reported academic performance (latent construct)	Narrative
Gupta 2015[29]	India (Delhi)	2011–2012	All enrolled students	611	Facebook profile audit	Unprofessional content	Narrative

Study	Country (city)	Data collection	Sampling	n	Exposure measure	Academic outcome	Analysis
Alshanqiti 2023[6]	Saudi Arabia (Medina)	NR	Convenience	842	Hours/day	Self-reported GPA; perceived benefit and distraction	Time (pooled); benefit B; distraction
Lone 2026[5]	Saudi Arabia (Al Ahsa)	Nov 2025–Feb 2026	Convenience	323	Hours/day; SNUQ motives	Self-reported GPA band	Time (pooled)
Alfaya 2023[30]	Saudi Arabia	NR	NR	326	Addiction score	Self-reported GPA	Narrative
Azizi 2019[4]	Iran (Kermanshah)	Jun–Aug 2018	Stratified random	360 †	BSMAS	Self-reported GPA	Addiction (study level; indirect population)
Shiraly 2024[8]	Iran (Shiraz)	Jul–Aug 2022	Convenience	400	Hours/day	Registry GPA	Narrative
Tufail 2025[3]	Pakistan (Multan)	Mar–Sep 2024	Convenience	309	Questionnaire	Use during lectures	Narrative
Imran 2024[31]	Pakistan (Lahore)	NR	NR	1,100	Questionnaire	E-professionalism	Narrative
Taha 2025[32]	Jordan (Zarqa)	NR	Random	429	Hours/day	Self-reported GPA; perceived effect and distraction	Benefit A; distraction (study level)
Khanimov 2026[33]	Aruba (Oranjestad)	Apr–Jul 2025	Convenience	25	Hours/day	Self-reported academic score	Time (pooled)

BSMAS, Bergen Social Media Addiction Scale; GPA, grade point average; KAP, knowledge, attitude and practice; NR, not reported; SMAS-SF, Social Media Addiction Scale–Student Form; SNUQ, Social Networking Usage Questionnaire. *Social media users among 359 usable respondents. †Medical students 11% of sample.

3.3 Daily time spent and academic performance

Four studies (1,590 students) correlated daily time on social media with academic performance (Table 3; Figure 2A). Two of the four coefficients were printed as positive in reports whose text describes a negative correlation. The result depends on how they are handled (Table 4; Figure 3):

•Signs corrected: r = −0.16 (95% CI −0.28 to −0.03); I^2 = 38% (95% CI 0%–99%); τ^2 = 0.002 (0–0.43); prediction interval −0.39 to 0.09. REML gave −0.15 (−0.25 to −0.05).

•As printed: r = −0.06 (−0.45 to 0.36); I^2 = 92% (81%–100%).

•Disputed coefficients excluded: two studies remain, Lone 2026 (r = −0.21, −0.31 to −0.10) and Khanimov 2026 (r = −0.47, −0.73 to −0.09); below the pooling threshold, so no estimate was calculated.

With the corrected signs, omitting any one of Bhandarkar 2021, Alshanqiti 2023 or Lone 2026 produced a confidence interval that included zero (Figure 4). The confidence intervals for I^2 and τ^2 span almost their full range, so the low point estimate of heterogeneity carries little information.

Table 3. Correlation data: time spent and addiction score

Study	Exposure	Printed r (type)	r analysed	n	Fisher z	SE	Weight (%)
A. Daily time spent — pooled							
Bhandarkar 2021	Hours/day	+0.108 (P)*	−0.108	400	−0.108	0.050	29.4
Alshanqiti 2023	Hours/day	+0.134 (S)*	−0.140	842	−0.141	0.035	41.9
Lone 2026	Hours/day	−0.21 (P)	−0.210	323	−0.213	0.056	25.9
Khanimov 2026	Hours/day	−0.47 (P)	−0.470	25	−0.510	0.213	2.8
Pooled, signs corrected†			−0.159	1,590	−0.160		100.0
B. Addiction score — not pooled							
Monisha 2025	BSMAS	−0.475 (NS)‡	−0.475	620	−0.517	0.040	—
Azizi 2019	BSMAS	−0.210 (S)	−0.219	360	−0.223	0.053	—

P, Pearson; S, Spearman (converted to Pearson equivalent); NS, type not stated; SE, standard error of Fisher z. †Random-effects estimate, 95% CI −0.28 to −0.03 (HKSJ); as printed, −0.06 (−0.45 to 0.36). All four time-spent coefficients re-checked against the source tables. Lone 2026 reported Pearson r against GPA bands, an ordinal measure; a rank correlation cannot be derived from the published data. *Printed with a positive sign; text and conclusions of the report describe a negative association (rule 3). ‡Value in the addiction column of the academic-performance row of Table 3 of the report; the depression column of the same row shows “-0475”.

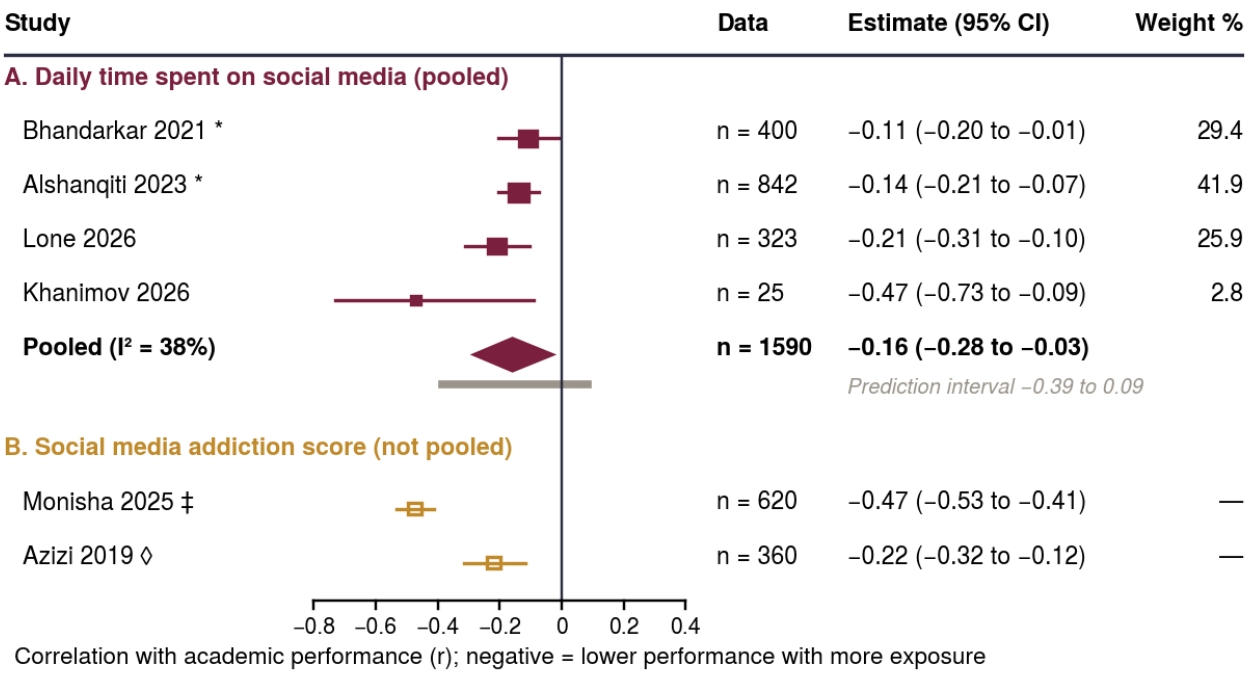


Figure 2. Correlation between social media exposure and academic performance. A, time spent, pooled with the two disputed signs corrected (as printed: r = −0.06, −0.45 to 0.36); B, addiction score (individual studies, not pooled).

HKSJ 95% CI for the pooled estimate; grey bar, 95% prediction interval. Open markers, not pooled. *Sign corrected. ‡Value unverified. ◊11% medical students.

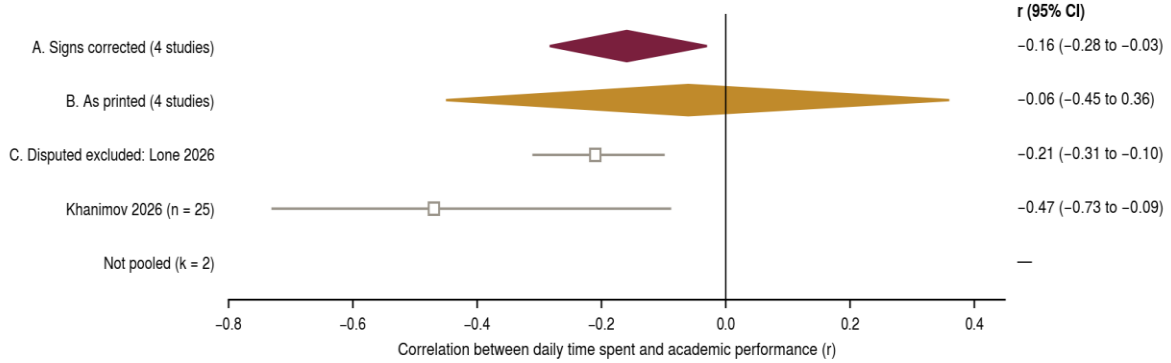


Figure 3. Time-spent analysis under three handlings of the two disputed coefficients.

A, Bhandarkar 2021 and Alshanqiti 2023 entered with the sign described in their text; B, entered as printed; C, both excluded, leaving two studies below the pooling threshold. Diamonds, pooled HKSJ 95% CI; open squares, single studies.

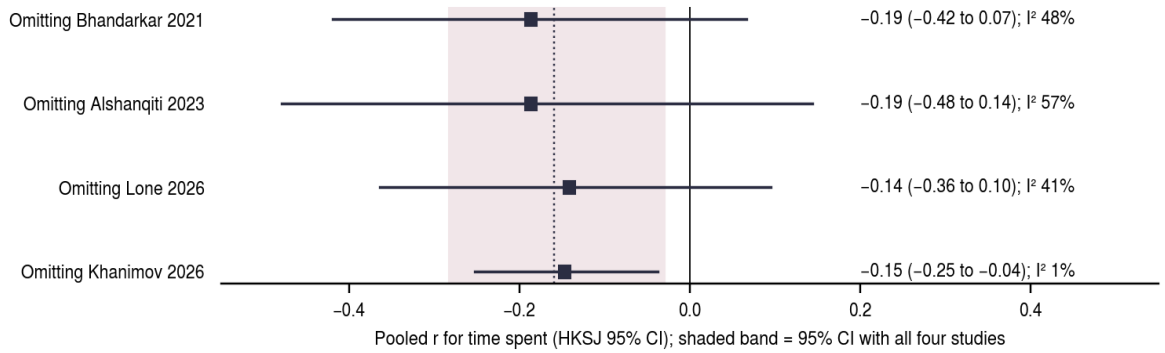


Figure 4. Leave-one-out analysis for the time-spent analysis, signs corrected (handling A).

Table 4. Time-spent analysis under three handlings of the disputed coefficients, and further sensitivity analyses

Analysis	Studies	Pooled r (95% CI)	I² (%)	CI includes zero
Handling of the two disputed coefficients				
Signs corrected (DerSimonian–Laird, HKSJ)	4	−0.16 (−0.28 to −0.03)	38	No
Entered as printed	4	−0.06 (−0.45 to 0.36)	92	Yes
Excluded (Lone 2026, Khanimov 2026 only)	2	Not pooled	—	—
Further analyses, signs corrected				
REML estimator (HKSJ)	4	−0.15 (−0.25 to −0.05)	38	No
Bhandarkar 2021 entered as printed (+0.108)	4	−0.13 (−0.44 to 0.21)	89	Yes
Alshanqiti 2023 entered as printed (+0.134)	4	−0.12 (−0.47 to 0.26)	93	Yes
Omitting Bhandarkar 2021	3	−0.19 (−0.42 to 0.07)	48	Yes
Omitting Alshanqiti 2023	3	−0.19 (−0.48 to 0.14)	57	Yes
Omitting Lone 2026	3	−0.14 (−0.36 to 0.10)	41	Yes
Omitting Khanimov 2026	3	−0.15 (−0.25 to −0.04)	1	No
Spearman coefficient not converted	4	−0.16 (−0.28 to −0.03)	40	No

Signs corrected: I^2 95% CI 0%–99%, τ^2 0.002 (95% CI 0–0.43), prediction interval −0.39 to 0.09. As printed: I^2 95% CI 81%–100%. Q-profile intervals.

3.4 Addiction score and academic performance

Two studies (980 students) correlated an addiction score with academic performance and are shown individually (Figure 2B). In Monisha 2025, −0.475 appears in the addiction column of the academic-performance row of the correlation matrix, but the depression column of the same row carries the identical value without a decimal point ("-0475"), the abstract prints the coefficient as r = 0.475 while describing the association as negative, and the regression model gives academic performance a non-significant standardised coefficient (−0.063). Azizi 2019 is internally consistent (r = −0.22, −0.32 to −0.12) but is an indirect population (11% medical students). Neither is a secure estimate for medical students. A third study, Alfaya 2023 (n = 326), found addiction scores fell as GPA rose in an adjusted regression but reported no correlation coefficient, so it could not be tabulated here[30].

3.5 Perceived academic benefit

Four studies asked about perceived academic benefit (Table 5; Figure 5). The two items rating the effect of social media on academic performance differed in format. Taha 2025 asked a single question with three options (negative, no effect, positive), and 19.6% of all 429 students chose positive. Lahiry 2019 first asked whether social networking had affected academic performance and then asked those who said yes whether it had improved or worsened; its 60.87% matches 140 of 230 students who reported any effect, rather than all 318 users, and its sample frame included nursing and paramedical students. The two figures therefore have different denominators and cannot be compared directly. For items stating that social media had helped improve performance or grades, endorsement was 42.5% in Sanyamath 2024 (response format not reported) and 68.5% in Alshanqiti 2023 (five-point scale). Bansal 2025 asked a narrower question about educational groups (86.6% agreed).

3.6 Perceived distraction

Two studies used items stating that social media distracts from studying; 79.1% (Alshanqiti 2023) and 64.6% (Taha 2025) agreed. Bansal 2025 asked about reduced concentration in studies (76.4%).

Table 5. Perception items: study-level data grouped by item wording (not pooled)

Study	Item (paraphrased) and response counted	Events / N	% (95% CI)
Benefit, item A — effect on academic performance rated positive (formats differ)			
Lahiry 2019	Two-step: any effect on academic performance, then improved or worsened; improved among those reporting an effect§	140 / 230	60.9 (54.4–66.9)
Taha 2025	Single question: effect on academic performance negative, no effect or positive; positive	84 / 429	19.6 (16.1–23.6)
Benefit, item B — social media has helped improve performance or grades			
Sanyamath 2024	Social media has helped improve academic performance (format not reported)¶	117 / 275	42.5 (36.8–48.5)
Alshanqiti 2023	Use of social media has helped improve my grades (agree + strongly agree)	577 / 842	68.5 (65.3–71.6)
Distraction — social media distracts from studying			

Study	Item (paraphrased) and response counted	Events / N	% (95% CI)
Alshanqiti 2023	Online social networks distract me from my studies (agree + strongly agree)	666 / 842	79.1 (76.2–81.7)
Taha 2025	Social media sites are distracting you from studying (agree + strongly agree)	277 / 429	64.6 (59.9–68.9)
Different items — shown descriptively (conflict of interest)			
Bansal 2025	Educational groups contributed positively to academic life	213 / 246	86.6 (81.8–90.3)
Bansal 2025	Social media decreased concentration in studies	188 / 246	76.4 (70.7–81.3)

Wilson 95% CI. §Lahiry 2019: 60.87% equals 140/230 exactly; 230 is taken as the number reporting any effect (questionnaire items Q24–Q25), so the denominator differs from Taha 2025. Sample frame included nursing and paramedical students. ¶Response options not reported; the abstract states that the remaining students disagreed, implying a two-option item. Khanimov 2026 asked matching items but its subgroup percentages are inconsistent with its subgroup sizes and were not used.

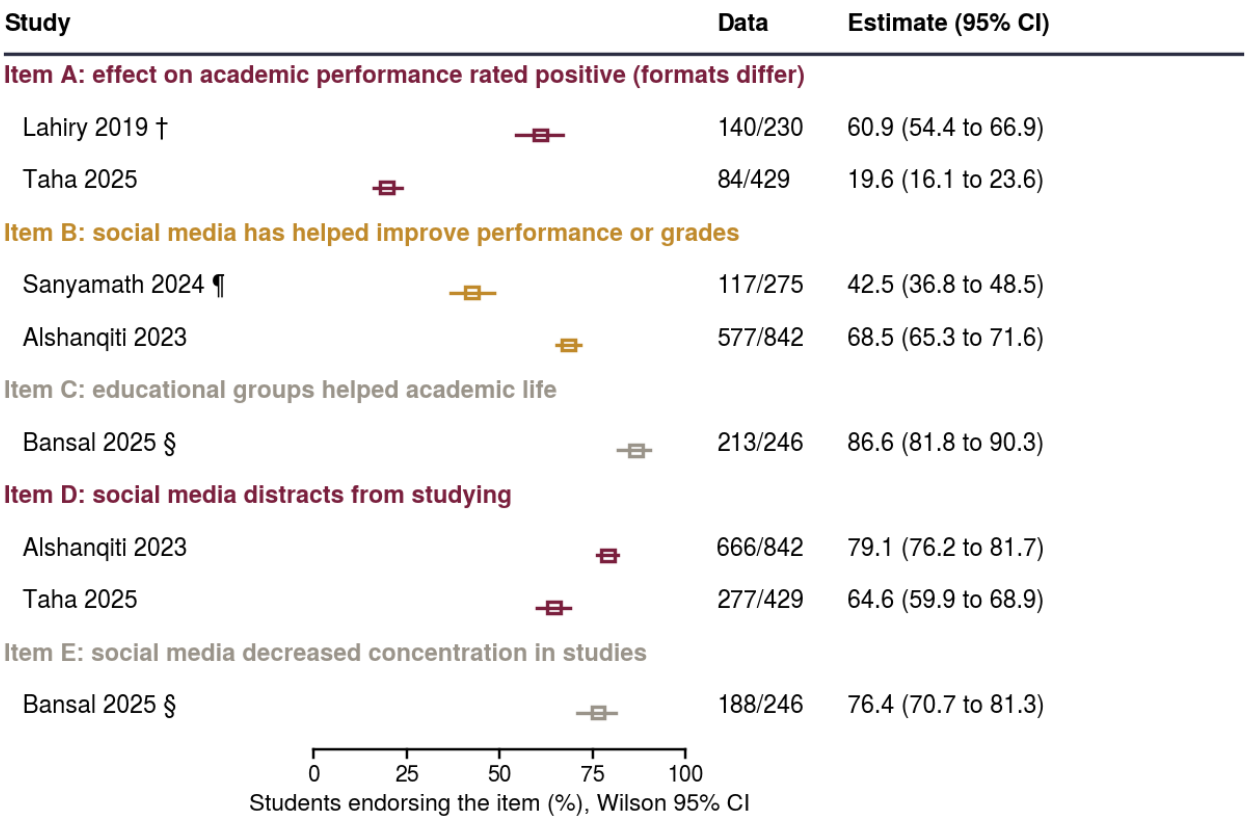


Figure 5. Perceived academic benefit and distraction: individual studies grouped by item wording (not pooled).

§ Shown descriptively (conflict of interest). ¶ Response format not reported. † Two-step item; denominator is students reporting any effect, so not comparable with Taha 2025.

3.7 Narrative synthesis

Seven studies contributed only to the narrative synthesis (Table 6). The only study using registry GPA found no significant correlation between daily time and GPA, but did not report the coefficient[8]. A study that separated motives for use found academic use positively ($r = +0.65$) and entertainment use negatively ($r = -0.47$) correlated with GPA[5]. A study of international medical students in China reported positive structural paths from social media-based open learning to self-reported academic performance[28]. Evidence on professional conduct came from two studies with non-comparable outcomes[29,31].

Table 6. Studies synthesised narratively

Study	Reason not tabulated with the outcomes above	Principal finding
Shiraly 2024	Coefficient not reported numerically	No significant correlation between daily time and registry GPA; effect of social media use on distress mediated by maladaptive coping
Alfaya 2023	Regression coefficient only	Addiction score decreased with increasing GPA after adjustment for sex, depression and anxiety
Arun 2025	No matching outcome	YouTube (98.3%), WhatsApp (97.4%) and Instagram (83.8%) most used; 60.7% used social media 1–3 h/day
Tufail 2025	No matching outcome	97.4% used social media; 72.5% checked it during lectures
Imran 2024	Professionalism outcome	48.2% accepted faculty friend requests; 19.5% aware of professional guidelines
Ashraf 2021	Structural-equation path coefficients only	Social media-based open learning positively associated with self-reported academic performance and engagement (233 international medical students)
Gupta 2015	Professionalism outcome	477 of 611 students had visible profiles; 5 (1.05%) displayed unprofessional content

3.8 Risk of bias

Among the six studies contributing correlations, only Lone 2026 and Monisha 2025 identified and adjusted for confounders, and Lone 2026 met every item except a validated outcome measure; all six relied on self-reported grades (in Bhandarkar 2021 students wrote their university examination percentage on the questionnaire, and in Azizi 2019 GPA was an item on the personal information form), and four reported statistics that were internally inconsistent: Bhandarkar 2021, Alshanqiti 2023, Monisha 2025 and Khanimov 2026 (Table 7). Among the four studies contributing proportions, none used a validated instrument for the perception items, two used convenience or voluntary sampling, and a response rate was clear only for Lahiry 2019 (55%) (Table 8). Bansal 2025 was not appraised because of the authors' conflict of interest.

Table 7. Risk of bias in studies contributing correlations (JBI checklist for analytical cross-sectional studies)

Study	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Principal concerns
Lone 2026	Y	Y	Y	Y	Y	Y	N	Y	GPA self-reported in bands
Monisha 2025	Y	Y	Y	Y	Y	Y	N	N	Performance self-reported in three bands; correlation matrix inconsistent with abstract and regression
Bhandarkar 2021	Y	Y	Y	Y	N	N	N	N	Examination marks self-reported on the questionnaire; confounding not addressed; printed sign contradicts text; implausible SD for addiction total
Azizi 2019	Y	Y	Y	Y	U	U	N	Y	GPA self-reported on the personal information form; 11% medical students
Alshanqiti 2023	Y	Y	N	U	N	N	N	N	Self-reported time and GPA; confounding not addressed; printed sign contradicts text
Khanimov 2026	U	Y	N	U	N	N	N	N	n = 25; self-reported outcomes; internal percentage errors

Q1 inclusion criteria defined; Q2 subjects and setting described; Q3 exposure measured validly and reliably; Q4 objective, standard criteria for measurement; Q5 confounders identified; Q6 strategies to deal with confounders; Q7 outcome measured validly and reliably; Q8 appropriate statistical analysis. Y, yes; N, no; U, unclear. Items are not summed, following JBI guidance. Single-reviewer judgements.

Table 8. Risk of bias in studies contributing proportions (JBI checklist for prevalence studies)

Study	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Principal concerns
Lahiry 2019	N	U	U	Y	U	N	Y	Y	N	Frame included nursing and paramedical students; unvalidated item; 55% usable response
Taha 2025	Y	Y	U	Y	U	N	Y	Y	U	Unvalidated items; response rate unclear
Alshanqiti 2023	Y	N	U	Y	U	N	Y	Y	U	Convenience sample; unvalidated items; response rate unclear
Sanyamath 2024	U	N	U	N	U	N	Y	Y	U	Voluntary participation; minimal description; item response format not reported
Bansal 2025	—	—	—	—	—	—	—	—	—	Not appraised (conflict of interest)

Q1 sample frame appropriate to the target population; Q2 participants sampled appropriately; Q3 sample size adequate; Q4 subjects and setting described in detail; Q5 data analysis with sufficient coverage of

the identified sample; Q6 valid methods used to identify the condition; Q7 condition measured in a standard, reliable way for all participants; Q8 appropriate statistical analysis; Q9 adequate response rate, or low response managed appropriately. Items are not summed. Single-reviewer judgements.

3.9 Certainty of evidence

Certainty was very low for all outcomes (Table 9).

Table 9. Summary of findings and certainty of evidence (GRADE)

Outcome	Studies (participants)	Estimate	Certainty	Reasons for downgrading (from low)
Time spent and academic performance (r)	4 (1,590)	−0.16 (−0.28 to −0.03) corrected; −0.06 (−0.45 to 0.36) as printed	Very low	Risk of bias: self-reported grades in all four studies; two sign-corrected coefficients. Inconsistency: prediction interval includes zero; direction depends on handling of two coefficients. Imprecision: four studies; leave-one-out intervals include zero. Publication bias: not assessable
Addiction score and academic performance (r)	2 (980)	Not pooled; −0.47 and −0.22	Very low	Risk of bias: unverified matrix value. Inconsistency. Indirectness: 11% medical students in one study
Perceived benefit (%)	4 (1,776)	Not pooled; 19.6 and 60.9 (item A, different denominators), 42.5 and 68.5 (item B)	Very low	Risk of bias: unvalidated items, non-random samples. Indirectness: item formats and denominators differ. Inconsistency
Perceived distraction (%)	2 (1,271)	Not pooled; 64.6 and 79.1	Very low	Risk of bias: unvalidated items, convenience sample in one study. Only two studies

Very low certainty: the true effect is likely to be substantially different from the estimate.

3.10 Reporting inconsistencies

Eleven inconsistencies were identified in seven reports (Table 10). Three bear directly on the correlation analyses: the two sign contradictions and the Monisha 2025 correlation matrix.

Table 10. Reporting inconsistencies identified during data extraction

Report	Inconsistency	Handling
Bansal 2025	Sex distribution reported as 55.3% female and 55.7% male (111%)	Erratum required
Bansal 2025	87.6% reported for two different items	Noted
Bansal 2025	Ethics approval number incomplete ("GGS/IEC//22")	Erratum required
Bhandarkar 2021	Correlation printed as +0.108 but described as negative in abstract and discussion	Entered as −0.108
Bhandarkar 2021	SD of total addiction score (1.72) smaller than SD of each domain (3.98–6.7)	Addiction correlation not used
Alshanqiti 2023	Spearman coefficient printed as 0.134 and described as negative	Entered as −0.140
Monisha 2025	Table 3: −0.475 (addiction) and "-0475" (depression) in the academic-performance row	Not pooled
Monisha 2025	Abstract reports r = 0.475 as negative; regression β = −0.063 (p = 0.066)	Not pooled
Khanimov 2026	Heavy users n = 16, but percentages (61.1%, 66.7%, 55.6%) imply n = 18	Perception items not used
Lahiry 2019	Funding attributed to an Iranian university for a study conducted in Kolkata	No effect on data
Sanyamath 2024	Benefit given as 42.5% (abstract) and 42.6% (discussion); response options not reported	42.5% used

4. Discussion

4.1 Principal findings

This preliminary synthesis cannot establish whether time spent on social media is associated with academic performance in medical students. With two printed signs corrected, the pooled correlation is small and inverse (r = −0.16); as printed, it is close to zero with a wide interval; and without those two studies there are too few to pool. The direction of the result therefore depends on two reporting errors that only the original authors can resolve. For addiction scores, the only study confined to medical students contains an unverified value, and no estimate is offered. Perceived benefit varied too widely between similarly worded items for a summary value to be meaningful.

4.2 Interpretation

Time spent combines academic and recreational use, and one study found these motives correlated with GPA in opposite directions[5]. If that pattern holds elsewhere, aggregate time would be expected to show at most a small net association; this is a hypothesis from a single study, not a finding of this synthesis. All four studies in the time-spent analysis used self-reported grades, and the one study with registry GPA found no significant association[8]. Because that study did not report its coefficient, its precision and

power cannot be assessed, so it neither supports nor refutes the possibility that self-report inflates the association. The only study measuring social media use for open learning, in international medical students in China, reported positive associations with academic performance, using structural paths to self-reported performance[28]. It is not directly comparable with the correlation studies, but it is consistent with the view that purpose of use matters, and it cautions against reading the time-spent data as evidence of a uniformly harmful effect. Differences in item format, particularly whether students were first asked if social media had any effect, may account for much of the variation in perceived benefit. Two studies of distraction are too few to judge its consistency.

4.3 Strengths and limitations

The synthesis separates exposure types, declines to pool where two discordant studies would produce a falsely precise estimate, shows how the main result depends on disputed data, and documents every source inconsistency. Its limitations are serious. The reports were assembled by the authors rather than identified by a systematic search, so selection bias is likely. The protocol was not registered, and the handling rules, pooling threshold and three-way presentation were set after extraction began. Screening, extraction and appraisal were performed by one reviewer, and the Alshanqiti 2023 correction shows that single extraction can shift outcomes by about 20 percentage points. Two authors wrote one included study, which is shown descriptively only. All studies are cross-sectional, and all but one relied on self-reported grades. Publication bias could not be assessed.

4.4 Implications

No practical recommendation for educators follows from evidence of this certainty. For researchers, primary studies should report full correlation matrices with consistent signs, obtain GPA from institutional records, use validated addiction scales, distinguish academic from recreational use, and report response formats for attitude items.

5. Conclusions

These data do not yet show whether time spent on social media is associated with academic performance in medical students, and they do not permit an estimate for social media addiction or perceived academic benefit. Certainty is very low for every outcome. A registered systematic review with a full database search and independent duplicate extraction is needed before any conclusion is drawn.

Declarations

Competing interests: Dr Nagma Bansal and Dr Raj Kumar are authors of an included study (Bansal 2025), which is shown descriptively only and was not appraised.

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Ethics approval: Not required; this is a secondary analysis of published, aggregate data with no access to individual participant information.

Data availability: The extraction sheet and analysis code are available from the corresponding author on reasonable request.

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