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A Joint Examination of Social Media, Generative AI and Digital Marketing Exposure Among HEI Students in Jaipur, Rajasthan

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***Abstract*— Students today are pulled in several directions at once by social media, generative AI (GenAI) and digital marketing communications. Yet research has mostly looked at these influences in isolation, and it has leaned heavily on what students say about themselves rather than on what they actually do. This study takes a different approach and examines all three exposures together, drawing on established frameworks in digital competence, AI literacy and human–AI regulation. It highlights five gaps in the existing literature and tests statistically how these exposures relate to students' academic standing. Data for this study came from a cross-sectional online survey of 101 students. Responses were captured on areas including digital exposure, distractions and AI-dependence attitudes, self-regulation requirement, prior academic standing during school (Classes 10 and 12) as well as the academic attainment and satisfaction in the currently enrolled HEI. Analysis methods used include Spearman correlation, Mann–Whitney and Kruskal–Wallis tests, and ordinal and binary logistic regression. 51.5% reported distraction from social media notifications, 61.4% agreed that GenAI slows original thinking, and 56.4% believed digital marketing communications impact the productivity of their learning and study sessions. Most students (58.4%) judged the net impact of these technologies as positive, including 71.4% of those with a backlog or detention (not promoted) at their current institution and 65.6% of those reporting high social media distraction. Statistically, students' responses on the impact of the three digital exposures were weakly and inversely related to existing academic achievement ($\rho = -.23$) as well as the prior attainment ($\rho = -.26$). Among students who agreed that GenAI slows original thinking, 62.9% also agreed that they rely on it. Male students reported greater GenAI dependence concern than their female counterparts. Perceived digital burden and measured academic achievement appear to be only loosely connected, and prior academic attainment remains the dominant correlate. The results of this study suggest that academic institutions should target self-regulation and AI-literacy support to students whose academic attainment profile places them at risk because of digital exposure, rather than relying on their self-perceived impact. It is time that academic institutions design their academic assessment around explicit levels of permitted GenAI use.**

Keywords: **social media distractions, generative AI, cognitive offloading, digital marketing communications, academic achievement, self-regulation, digital competence, Higher Education Institutions (HEIs)**

I. INTRODUCTION

University students now study inside an attention economy. A single smartphone delivers social media notifications, instant answers from generative AI tools such as ChatGPT and Gemini, and a steady stream of marketing e-mails, in-app advertisements and promotional alerts to them. Each of these does have an academic upside, for example: WhatsApp messaging groups circulate class announcements and course material, GenAI offers on-demand explanations, and some digital marketing content may be relevant and important to a student's field. Each one of these, however, also competes for students' attention during sustained study sessions. Academic reviews covering digital distraction in education report that technology-related distractors are the most frequently cited cause of interrupted concentration during study sessions and that the consequences are primarily personal academic performance related problems [1], [2].

Research on these exposures has grown quickly but along separate lines. A significant number of academic studies link social media use to academic performance, with mixed results that depend on how, when and why platforms are used [3]–[5]. A newer strand of research, prompted by the arrival of GenAI platforms such as ChatGPT, asks whether these tools support higher-order thinking or quietly replace it [6], [7]. Digital marketing communications get far less attention as a source of academic distraction, even though students meet them constantly and some point to online advertising as a cause of their scattered focus [8].

Such fragmentation in the existing academic work leaves a practical question unanswered. When students face all three digital exposures at once, which one of them or which combination, is associated with how they actually perform academically, and does their own sense of the damage due to such exposures matches the existing records? This matters because academic institutions, especially in high-income countries such as France and Australia, are being asked to frame policies on notifications, AI use and digital communication

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exposure that are based on evidence that compares these exposures on common terms.

This study addresses that gap through a survey of 101 higher education students. It measures all three exposures together, records prior school attainment alongside current academic standing, and captures students' own judgement of the overall impact. The study makes five contributions. First, it models social media, GenAI and digital marketing exposure jointly rather than separately. Second, it tests associations with an existing measure of academic attainment while adjusting for Class 10 and Class 12 results, instead of relying only on how students perceive the academic impact. Third, it treats digital marketing communications as a distinct source of academic distraction and asks whether it holds together as a separate, coherent construct. Fourth, it documents a disconnect between perception and outcome, along with a paradox between GenAI use and academic behaviour, neither of which single-exposure studies could reveal. Fifth, it draws on recent digital-competence, AI-literacy and human-AI regulation frameworks to define the research gaps and to interpret the findings.

II. Literature Review and Hypotheses

A. Social Media and Academic Performance

The evidence linking social media to academic performance is substantial, but it does not point in one direction. A review of four studies from developing-country contexts found that heavier use goes with poorer grades, though its authors stress that how and when students use social media matters a great deal [4]. Problematic use, understood as addiction and measured with a validated scale, independently predicted a lower grade point average among students in the Middle East, and night-time use emerged as a particular concern [9].

A study done in Vietnam found that social media overuse was linked to psychological distress and weaker academic performance. The study identifies self-regulation as a moderating factor in this relationship [10]. Academic work shows benefits as well. For example, using social platforms for knowledge sharing and educational purposes related positively to academic performance of students in Pakistan and Ghana [3], [5], and a study done on students in Bangladesh identifies communication gains and better academic awareness due to readily available social media resources [11]. A study of students and educators in Pune in India reported that high social media use distracted students while purposeful academic use supported engagement. The students and educators differed in their perceptions [12].

Dynamics at the notification level are better established experimentally. Interestingly, notifications impaired academic performance on attention-heavy tasks regardless of phone ownership [13]. Notification-induced diversion of attention and involuntary vigilance on part of the students increased mental effort and harmed learning in a classroom experiment [14]. Most of this literature, however, relies on grade point average and self-reported impact. Few studies statistically adjust for what students had already achieved academically at school.

B. Generative AI, Cognitive Offloading and Academic Performance

Academic literature on the impact of GenAI in academics points out the existence of conditionality rather than uniformity in relationships and effects. A review of 89 studies concluded that GenAI acts as a cognitive amplifier under structured pedagogical environment and as a cognitive substitute under unguided use. It identifies over-reliance as the most frequently reported risk [6]. A review of 67 studies reached a similar conclusion for critical thinking and creativity among students in academia [7]. A three-wave study linked ChatGPT use to procrastination, memory loss and lower performance, with workload and time pressure factors driving the usage [15]. In Zimbabwe, 32.7% of the students displayed addictive patterns of GenAI use. Interestingly, heavy users had a lower mean grade point average [16]. Selective usage of GenAI among students appears protective: first-year EFL students who relied heavily on AI tools wrote fluent but less original texts than those who used AI selectively [17]. A survey done on Chinese students found a paradox in which higher usage predicted greater loss of cognitive autonomy, while learning motivation among GenAI users predicted gains in critical thinking among the survey group [18]. A study done in Ghana found that ChatGPT use altered critical, creative and reflective thinking dimensions of the students [19], and small-sample work distinguished passive, AI-directed use from collaborative use [20].

C. Digital Marketing Communications as an Academic Distractor

Marketing messages are the least studied of the three exposures in an academic context. An eye-tracking experiment found that simple, static advertisements and social media notifications on screen did not impair reading comprehension among university students [21]. In contrast, in an academic study on prolonged smartphone screen time, student respondents attributed fragmented attention in part to marketing and advertising, alongside algorithmic feeds and short videos on social media platforms [8]. The two findings are not contradictory. This is because exposure to a single static advertisement differs from exposure to the cumulative volume of promotional e-mails, alerts and in-feed advertising that students encounter daily. Whether students experience marketing communications as a coherent academic burden has not, to the best of our knowledge, been examined with survey data alongside other exposures.

D. Self-Regulation

Academic reviews covering digital distractions have identified personal factors, including a limited capacity to self-regulate, as a major cause of digital distraction alongside technology-related factors [1]. For example, self-regulation moderated the stress-academic performance relationship in a study done on Vietnamese students [10]. Motivation to learn was the strongest predictor of critical thinking gains among the students using GenAI [18]. Whether a student's stated need for external help in regulating study time changes the link between exposure and outcome is largely untested in Indian management education.

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E. Recent Frameworks

Recently developed frameworks are used as interpretive lenses.

1) Digital Competence and Wellbeing: DigComp 3.0, the fifth edition of the European Digital Competence Framework, was published by the European Commission's Joint Research Centre in November 2025. DigComp 3.0 describes digital competence in terms of knowledge, skills and attitudes. It weaves AI competence through every competence area and gives priority to wellbeing in digital environments and to tackling misinformation [22]. Because it places social platforms, AI tools and online information flows within a single competence model, it offers a common footing for studying the three exposures together rather than separately. It also allows unsolicited marketing content to be read as a matter of digital wellbeing and critical evaluation of online content, not only as a nuisance.

2) AI Competence and Policy Context: The UNESCO AI competency framework for students sets out twelve competencies across four dimensions: a human-centred mindset, ethics of AI, AI techniques and applications, and AI system design. Each is described at three progression levels, namely understand, apply and create [23].

It was written for school students, but its human-centred dimension, which stresses critical judgement and humane application in relation to AI, offers a useful lens on the gap between what students believe about GenAI and how they use it. India's AI Governance Guidelines, issued by the Ministry of Electronics and Information Technology in November 2025, place a 'people first' principle and stress capacity building through education, skilling and training among their core elements [24].

3) Self-Regulation in Human–AI Learning: Hybrid human–AI regulation treats the regulation of learning as shared between learner and technology. It aims at gradually transferring regulation from the technology to the learner [25]. The risk of failing to make that transfer is illustrated by a randomised study of 117 university students, in which learners supported by ChatGPT improved their essay scores more than comparison groups, yet showed no significantly greater knowledge gain or transfer and displayed different self-regulated learning processes. The authors described this pattern as metacognitive laziness [26].

4) Assessment Design: The Artificial Intelligence Assessment Scale lets educators specify the level of GenAI use permitted in each assessment according to the learning outcomes being assessed [27].

F. Research Gaps Addressed

Table I summarises the gaps identified in this review (based on targeted, non-systematic searches of the recent literature), the framework lens applied to each, and how this study responds to each gap.

TABLE I
RESEARCH GAPS, FRAMEWORK LENSES AND HOW THE PRESENT STUDY ADDRESSES THEM

#	Gap in the Literature	Interpretive Lens	Response in This Study
G1	Social media, GenAI and marketing exposure are studied in isolation.	DigComp 3.0: one competence model spanning social platforms, AI and online information.	All three exposures are measured in one instrument and entered together in multivariable models.
G2	Exposure impact is typically self-reported, and prior academic attainment is rarely controlled.	Metacognitive laziness [26]: perceived benefit and actual learning can diverge.	Academic standing is analysed alongside perceived impact, adjusting for Class 10 and Class 12 attainment. The link between perceived impact and record is tested directly.
G3	Marketing communications are rarely treated as an academic distractor.	DigComp 3.0: covers wellbeing in digital environments and critical evaluation of online content.	Frequency of digital marketing notifications and the volume threshold are examined.
G4	The moderating role of self-regulation need is under-tested outside Western and East Asian regions.	Hybrid human–AI regulation [25] and self-regulated learning.	Self-regulation need is tested as a moderator of the effect of exposure on recorded standing and perceived impact.
G5	Management and commerce students of Jaipur are under-represented relative to other contexts.	India AI Governance Guidelines (2025): people-first principle and capacity building.	The sample is drawn from HEIs of Jaipur, with emphasis on early-year students.

Note. G = gap. Gap statements reflect the studies cited in Section II and are not the product of a systematic review. Framework lenses are interpretive and are not tested directly; DigComp 3.0 and the UNESCO framework were not developed for Indian higher-education cohorts.

G. Hypotheses and Research Questions

Drawing on the research gaps from above, the study tests the following hypotheses:

H1. Greater social media exposure and distraction are associated with lower recorded academic performance.

H2. Greater GenAI use frequency and dependence are associated with lower recorded academic achievement.

H3. Greater digital marketing communication exposure and interference are associated with lower recorded academic standing.

H4. Prior school performance is positively associated with

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existing academic standing. Three exploratory research questions are also asked. *RQ1:* Does self-regulation moderate the association between digital exposure and perceived academic impact? *RQ2:* Do exposure and attitude measures differ by gender, level of enrolment and year of study? *RQ3:* Does the perceived overall impact correspond to existing academic standing and prior attainment?

III. Method

A. Design and Participants

The study used a cross-sectional online survey questionnaire. Responses were collected from students enrolled at higher education institutions (HEIs) in Jaipur, Rajasthan. The final sample comprised 101 students (Table II). Most were undergraduates (72.3%), in their first year (61.4%), aged 18–22 (76.2%), and male (66.3%). Five respondents selected 'not applicable' for their result at the current institution and were excluded from analyses involving recorded academic standing (n = 96).

Table II
Sample Characteristics-Descriptive Statistics (N = 101)

Characteristic	n	%
Level: Undergraduate / Postgraduate / Doctoral / Other	73 / 22 / 2 / 4	72.3 / 21.8 / 2.0 / 4.0
Year: First / Second / Third / Fifth or other	62 / 30 / 8 / 1	61.4 / 29.7 / 7.9 / 1.0
Discipline: Management or Commerce / Humanities-Arts / Engineering or Technology / Sciences	91 / 7 / 2 / 1	90.1 / 6.9 / 2.0 / 1.0
Gender: Male / Female	67 / 34	66.3 / 33.7
Age: 18–22 / 22–26 / 26–30 / 30+	77 / 18 / 4 / 2	76.2 / 17.8 / 4.0 / 2.0
Standing: Detained / Promoted with backlog / Promoted without backlog	10 / 11 / 39	10.4 / 11.5 / 40.6
Standing: Top 10% / Top 5% / Top 1% of batch	23 / 9 / 4	24.0 / 9.4 / 4.2
Standing not applicable (excluded from standing analyses)	5	5.0

Note. Percentages are of N = 101, except the two recorded-standing rows, which are of the 96 respondents with a recorded academic standing. Percentages may not sum to 100 because of rounding.

B. Instrument and Measures

The questionnaire covered demographics, prior academic attainment in higher secondary and senior secondary levels, current academic standing, three digital exposure categories, behaviour and attitude statements and an overall impact question. Behaviour and attitude statements used a five-point Likert-type agreement scale (1 = strongly disagree to 5 = strongly agree).

1) Exposure: Social media exposure time was measured with two hour-band items (daily exposure time and average daily hours; Spearman r = .74), averaged into a single index. GenAI use frequency (rarely to almost always) and marketing communication exposure frequency (never to very often) were taken as individual items. A marketing notification volume threshold item asked at what daily volume students feel overwhelmed.

2) Attitudes: Social media distraction (SMD) was the mean of three items (distraction by notifications, compulsion to check, reduced motivation; α = .68). GenAI dependence concern (AID) was the mean of three items (GenAI slows original thinking, reliance on AI instead of own research, AI recommendations help short-term outcomes only; α = .73). Two marketing items (influence on learning output; preference not to engage during study) were uncorrelated (Spearman r = .06, α = .04) and were therefore analysed separately rather than in combination. The need for external regulation of study time and difficulty in filtering useful academic content amid digital distractions (distraction-filtering burden) were treated as individual items.

3) Outcomes and Controls: Prior academic attainment was the mean of Class 10 and Class 12 academic outcomes coded 0 (not promoted in first attempt), 1 (pass in first attempt), 2 (top 10%), 3 (top 5%) and 4 (top 1%). Recorded academic standing at the existing academic institution was coded 1 (detained or not promoted), 2 (promoted with backlog), 3 (promoted without backlog), 4 (top 10% of batch), 5 (top 5%) and 6 (top 1%). Respondents answering 'not applicable' had no recorded academic standing. Satisfaction with academic performance was coded on a scale of 1–4, and student perception on the overall impact of the three exposures was coded 1 (negative) to 4 (very positive). Respondents also chose, in forced-choice items, which exposure was the greater distraction and which the greater academic aid.

C. Analytic Strategy

Descriptive statistics and Spearman correlations were reported first. Group differences used Mann–Whitney and Kruskal–Wallis tests. Recorded standing and perceived academic impact were modelled with cumulative-link (ordinal logit) models, reporting odds ratios with 95% confidence intervals. Binary logit model for adverse standing (detained or promoted with backlog) served as a robustness check. Moderation was tested with mean-centred interaction terms. To limit the overfitting, models contained no more than six predictors. Because group comparisons were numerous, a Bonferroni threshold across eight comparisons ($p < .006$; gender on five measures, level of enrolment on two, and year of study on one) has been noted alongside conventional p values. All subgroup results are treated as exploratory. With N = 101 (n = 96 for analyses involving standing), the study had 80% power at α = .05 to detect only correlations of about $|r| \geq .28$. Smaller associations cannot be ruled out.

D. Ethics

Student data were collected through an online Google Form, and consent was obtained from participants during data

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collection.

IV. Results

A. Exposure and Perceived Burden

About half of the respondents reported spending two or more hours daily on social media (48.5% on the daily-exposure item and 50.5% on the average-hours item in the survey questionnaire), and 59.4% used GenAI tools for academic work often or almost always (Table III). Marketing communications were received often or very often by 43.6%, and 84.2% (85 of 101) of the respondents and they reported feeling overwhelmed once the daily communication volume exceeded four messages (at one to two messages for 38.6%).

Table III
Exposure Profile (N = 101)

Item	Distribution, n (%)
Daily exposure to social media	<1 h: 10 (9.9%); 1–2 h: 42 (41.6%); 2–4 h: 34 (33.7%); 4+ h: 15 (14.9%)
Average hours per day on social media	<1 h: 11 (10.9%); 1–2 h: 39 (38.6%); 2–4 h: 44 (43.6%); 4+ h: 7 (6.9%)
Frequency of using AI tools for academic purposes	Rarely: 2 (2.0%); Sometimes: 39 (38.6%); Often: 31 (30.7%); Almost always: 29 (28.7%)
Daily uses of AI tools for academic tasks	1–2: 23 (22.8%); 5–10: 52 (51.5%); 20–25: 20 (19.8%); 25+: 6 (5.9%)
Frequency of receiving marketing communications	Never: 6 (5.9%); Rarely: 7 (6.9%); Sometimes: 44 (43.6%); Often: 35 (34.7%); Very often: 9 (8.9%)
Daily marketing communications received	1–2: 37 (36.6%); 5–10: 50 (49.5%); 15–20: 10 (9.9%); 20+: 4 (4.0%)
Daily volume after which marketing feels overwhelming	1–2: 39 (38.6%); 2–4: 46 (45.5%); 5–10: 14 (13.9%); 10+: 2 (2.0%)

Note. Percentages are of all respondents and may not sum to 100 because of rounding. Response bands are shown as per the options offered in the questionnaire.

Perceived burden due to the three categories of exposures was widespread among the respondents (Table IV). Distraction by social media notifications was identified by 51.5%, compulsive checking by 38.6%, reduced motivation from digital distractions by 49.5%, difficulty in filtering useful content by 45.5%, and a need for external help in regulating study time by 49.5%. On GenAI, 61.4% agreed that it slows their original thinking, 48.5% agreed that they rely on it instead of their own research, and 56.4% agreed that personalised GenAI recommendations help only in the short term. For digital marketing, 56.4% agreed that it influences their learning output and 62.4% preferred not to engage with it during study time. In contrast, 86.1% agreed that WhatsApp-type applications are useful for academic purposes.

Table IV
Agreement with Behaviour-Attitude Statements (N = 101)

Statement	Disagree n (%)	Neutral n (%)	Agree n (%)
Distracted from studying by social media notifications	13 (12.9)	36 (35.6)	52 (51.5)
Compulsive need to check social media during study time	20 (19.8)	42 (41.6)	39 (38.6)
WhatsApp-type applications are useful for academic purposes	1 (1.0)	13 (12.9)	87 (86.1)
Digital distractions reduce my motivation to study	18 (17.8)	33 (32.7)	50 (49.5)
Difficult to filter useful academic content amid distractions	16 (15.8)	39 (38.6)	46 (45.5)
Need external assistance to regulate study time	17 (16.8)	34 (33.7)	50 (49.5)
GenAI slows original thinking and mental ability	13 (12.9)	26 (25.7)	62 (61.4)
Rely on AI tools instead of own fact finding and research	19 (18.8)	33 (32.7)	49 (48.5)
AI personalised recommendations help short-term outcomes only	9 (8.9)	35 (34.7)	57 (56.4)
Marketing exposure influences my learning output	8 (7.9)	36 (35.6)	57 (56.4)
Prefer not to engage with marketing during study time	6 (5.9)	32 (31.7)	63 (62.4)

Note. Disagree = strongly disagree or disagree; agree = agree or strongly agree. Percentages are of all respondents and may not sum to 100 because of rounding.

B. Descriptive Statistics and Associations

Table V
Descriptive Statistics for Study Variables

Variable	Scoring	n	M	SD	α / r
Social media time index	1–4	101	2.50	0.77	r = .74
GenAI use frequency	1–4	101	2.86	0.86	single item
Marketing communication frequency	1–5	101	3.34	0.95	single item
Social media distraction (SMD)	1–5	101	3.35	0.72	α = .68
GenAI dependence concern (AID)	1–5	101	3.47	0.69	α = .73
Marketing influences learning output	1–5	101	3.50	0.76	r = .06 with next
Prefer not to engage with marketing	1–5	101	3.66	0.78	(α = .04)
Need for external regulation	1–5	101	3.36	0.90	single item
Distraction-filtering burden	1–5	101	3.35	0.84	single item

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Prior attainment (Classes 10, 12)	0–4	101	1.39	0.73	r = .62 (C10–C12)
Recorded standing	1–6	96	3.23	1.22	single item
Satisfaction with performance	1–4	101	2.96	0.65	single item
Perceived overall impact	1–4	101	2.59	0.84	single item

Note. Coefficients are Cronbach's alpha for multi-item scales and Spearman correlations where two items are involved. The correlation between Class 10 and Class 12 outcomes are in terms of Spearman coefficient. Recorded standing has n = 96 because five respondents reported 'not applicable' in their result in existing HEI.

Table VI shows the main associations. Prior academic attainment, for instance, was strongly related to recorded existing academic standing (Spearman ρ = .52, p < .001). Social media time and social media distraction were weakly but positively related (ρ = .27, p = .006), and compulsive checking correlated positively with social media time (ρ = .29, p = .003). GenAI reliance and the belief that GenAI slows original thinking were positively correlated (ρ = .42, p < .001), and the need for external regulation was strongly related to SMD (ρ = .52, p < .001). Exposure and attitude measures correlated only weakly with existing academic standing: social media time ρ = −.16 (p = .114), SMD ρ = −.17 (p = .099), GenAI frequency ρ = .01 (p = .902) and marketing communications frequency ρ = .14 (p = .179). Difficulty in filtering useful content for academics was the one behaviour-attitude measure with a nominally significant but weak negative correlation with existing academic standing (ρ = −.21, p = .042). Perceived overall impact of exposure was uncorrelated with SMD (ρ = .01), AID (ρ = −.07) and the need for external regulation (ρ = .14). It was, however, related to perceived satisfaction (ρ = .37, p < .001) and, unexpectedly, inversely to existing academic standing (ρ = −.23, p = .027) and prior academic attainment (ρ = −.26, p = .007; Section IV-F).

TABLE VI
SELECTED SPEARMAN CORRELATIONS

Pair of Variables	ρ	p	n
Correlates of existing academic standing			
Prior academic attainment – existing academic standing	.52	< .001	96
Social media time – existing academic standing	−.16	.114	96
Social media distraction (SMD) – existing academic standing	−.17	.099	96
GenAI use frequency – existing academic standing	.01	.902	96
GenAI dependence concern (AID) – existing academic standing	−.06	.568	96
Marketing frequency – existing academic standing	.14	.179	96
Marketing influences learning – existing academic standing	−.10	.317	96
Distraction-filtering burden – existing academic standing	−.21	.042	96
Need for external regulation – existing academic standing	−.12	.251	96
Associations among exposures and behaviour-attitudes			
Social media time – SMD	.27	.006	101
Social media time – compulsive checking	.29	.003	101
Reliance on AI – GenAI slows original thinking	.42	< .001	101
Need for external regulation – SMD	.52	< .001	101
Perceived overall impact and satisfaction			
Perceived overall impact – SMD	.01	.887	101
Perceived overall impact – AID	−.07	.479	101
Perceived overall impact – need for external regulation	.14	.161	101
Perceived overall impact – satisfaction	.37	< .001	101
Perceived overall impact – existing academic standing	−.23	.027	96
Perceived overall impact – prior attainment	−.26	.007	101
Satisfaction – existing academic standing	.04	.672	96

Note. ρ = Spearman rank correlation. Standing correlations use the 96 respondses with existing academic standing in a HEI. Twenty correlations are shown, so only p-values below about .0025 would survive a Bonferroni correction across the table.

C. Group Differences

Male students reported greater GenAI dependence concern than their female counterparts (M = 3.61 vs 3.20, Mann–Whitney *p = .004; this difference survives the Bonferroni threshold). Female students reported more social media time (M = 2.76 vs 2.37, p = .015, not robust to Bonferroni correction), while male students' somewhat greater social media distraction (M = 3.44 vs 3.18, p = .100) was not significant. GenAI and marketing communications frequency did not differ by gender. Postgraduate respondents held higher academic standing than undergraduates (M = 3.81 vs 3.04, p = .014), but this difference did not survive Bonferroni correction, and the two groups did not differ on AID (M = 3.70 vs 3.43, p = .262). Year of study did not differ significantly on any of the five exposure or behaviour-attitude measures tested (all p > .27), although SMD declined numerically from first to third year (3.41, 3.27, 3.12; p = .274). Table VII gives the details.

TABLE VII
GROUP DIFFERENCES IN EXPOSURE, BEHAVIOUR-ATTITUDE AND STANDING MEASURES

Comparison and Measure	Group 1 M	Group 2 M	p
Gender: male (n = 67) vs female (n = 34)			
Social media time	2.37	2.76	.015

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GenAI use frequency	2.82	2.94	.453
Marketing communication frequency	3.33	3.35	.902
Social media distraction (SMD)	3.44	3.18	.100
GenAI dependence concern (AID)	3.61	3.20	.004*
Level: postgraduate (n = 22) vs undergraduate (n = 73)			
GenAI dependence concern (AID)	3.70	3.43	.262
Recorded standing (n = 21 vs 69)	3.81	3.04	.014
Year of study: first (n = 62) / second (n = 30) / third (n = 8)			
Social media distraction (SMD): 3.41 / 3.27 / 3.12	–	–	.274

Note. Mann–Whitney tests for two groups and a Kruskal–Wallis test for year of study. *Survives the Bonferroni threshold of p < .006 across the eight comparisons (gender on five measures, level on two, year on one). Year-of-study differences on social media time, GenAI frequency, marketing frequency and AID were also non-significant (all p > .27). Doctoral and 'other' respondents are excluded from comparison.

D. Prior Academic Attainment and Recorded Standing

Prior academic attainment was the clearest correlate of existing academic standing (Table VIII). Among the students with a prior mean of 1.5 or higher (n = 31), 74% (23) were in the top 10% of the batch or better and 6% (2) had been detained from further academic progression. Among the students with a lower prior mean (n = 65), 20% (13) were in the top 10% or better, 12% (8) were detained and 17% (11) were promoted with a backlog. Students in adverse academic standing (n = 21) had lower prior attainment than the rest (M = 1.05 vs 1.49; p = .009), but did not differ significantly on social media time, GenAI frequency, marketing exposure frequency, SMD, AID or distraction-filtering burden (all p > .13).

TABLE VIII
RECORDED ACADEMIC STANDING BY LEVEL OF PRIOR SCHOOL ATTAINMENT

Recorded Standing	Prior Mean < 1.5 (n = 65) n (%)	Prior Mean ≥ 1.5 (n = 31) n (%)
Detained / not promoted	8 (12.3)	2 (6.5)
Promoted with backlog	11 (16.9)	0 (0.0)
Promoted without backlog	33 (50.8)	6 (19.4)
Top 10% of batch or better	13 (20.0)	23 (74.2)

Note. Prior attainment is the mean of Class 10 and Class 12 outcomes (0–4). Percentages are column percentages and may not sum to 100 because of rounding. The 5 respondents with no applicable academic standing are excluded.

E. Multivariable Models

Table IX reports ordinal logit models for existing academic standing (n = 96). In Model 1, adjusted for gender and first-year status, prior academic attainment predicted higher existing academic standing (OR = 4.96, 95% CI 2.71–9.09, p < .001). Social media time (OR = 0.65, 95% CI 0.38–1.09, p = .104), GenAI frequency (OR = 0.80, p = .322) and marketing communications frequency (OR = 1.17, p = .424) were not significant. Male students had lower odds of higher academic standing than their female counterparts (OR = 0.41, 95% CI 0.18–0.94, p = .036). This was not significant in Model 2 (OR = 0.47, p = .079). The unadjusted difference in mean academic standing was not significant (M = 3.06 vs 3.55, p = .135). In Model 2, replacing exposure frequencies with behaviour-attitude factors and prior academic attainment again predicted their relationship with existing academic standing (OR = 5.01, p < .001), while SMD (OR = 1.14, p = .714), AID (OR = 1.32, p = .426) and distraction-filtering burden (OR = 0.59, p = .077) did not. A binary logit for adverse academic standing (detained or promoted with backlog; 21 of 96 students) gave a consistent pattern. Prior academic attainment was the only significant predictor (β = −1.39, p = .045 in the exposure model; β = −1.58, p = .028 in the behaviour-attitude model), with all exposure and behaviour-attitude terms at p > .24.

TABLE IX
ORDINAL LOGIT MODELS PREDICTING RECORDED ACADEMIC STANDING (N = 96)

Predictor	OR	95% CI	p
Model 1: exposures			
Prior attainment	4.96	2.71–9.09	< .001
Social media time	0.65	0.38–1.09	.104
GenAI use frequency	0.80	0.51–1.25	.322
Marketing frequency	1.17	0.79–1.73	.424
Male (vs female)	0.41	0.18–0.94	.036
First year (vs later)	0.80	0.38–1.70	.563
Model 2: behaviour-attitude			
Prior attainment	5.01	2.73–9.19	< .001
Social media distraction (SMD)	1.14	0.56–2.35	.714
GenAI dependence concern (AID)	1.32	0.67–2.59	.426
Distraction-filtering burden	0.59	0.33–1.06	.077
Male (vs female)	0.47	0.20–1.09	.079
First year (vs later)	0.88	0.41–1.90	.741

Note. OR = odds ratio per one-unit increase (cumulative-link logit; odds of higher standing category). Threshold parameters are not shown.

Neither perceived overall impact nor academic satisfaction was predicted jointly by exposure, need for regulation, prior academic attainment and existing standing (likelihood-ratio $\chi^2(6) = 10.12$, p = .120 for impact; $\chi^2(6) = 6.15$, p = .406 for satisfaction, with the single dissatisfied respondent combined with the neutral category). Moderation tests were also null. The interaction between social media time and need for regulation did not predict perceived impact on academics (OR = 0.95, 95% CI 0.56–1.60, p = .835). The interaction between GenAI use frequency and the need for external regulation did not predict existing academic standing (OR = 1.01, 95% CI 0.61–1.66, p = .971). RQ1 is therefore not supported in the given sample.

F. Perception–Outcome Disconnect

Despite the perceived burden, 58.4% of the student respondents (59) judged the combined impact of social media, AI tools and

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digital marketing on their academic performance as positive or very positive, 30.7% as neutral and 10.9% as negative (Table X). Positive judgements were as common or more common among students with high social media distraction (SMD ≥4; 65.6%, 21 of 32), high distraction- filtering burden (71.7%, 33 of 46) and adverse existing academic standing (71.4%, 15 of 21). Perceived impact was not associated with SMD or AID. Perceived impact was, however, weakly and inversely correlated with existing academic standing ($\rho = -.23$, $p = .027$) and prior academic attainment ($\rho = -.26$, $p = .007$). Students with weaker academic records judged the net impact more favourably. These exploratory correlations run against the expectation that perceived impact of exposure should at least be related to existing academic standing (RQ3).

TABLE X
PERCEIVED OVERALL IMPACT OF SOCIAL MEDIA, AI TOOLS AND MARKETING, BY SUBGROUP

Group	n	Positive n (%)	Neutral n (%)	Negative n (%)
All respondents	101	59 (58.4)	31 (30.7)	11 (10.9)
High social media distraction (SMD ≥4)	32	21 (65.6)	5 (15.6)	6 (18.8)
High distraction-filtering burden	46	33 (71.7)	6 (13.0)	7 (15.2)
High need for external regulation	50	36 (72.0)	8 (16.0)	6 (12.0)
Adverse standing (detained or backlog)	21	15 (71.4)	4 (19.0)	2 (9.5)

Note. Positive = positive or very positive; negative = negative. High = agree or strongly agree (SMD of 4 or more).

G. GenAI Attitude–Behaviour Paradox and Forced-Choice Items

Of the 62 students who agreed that GenAI slows original thinking, 39 (62.9%) also agreed that they rely on it in place of their own research. In forced-choice items (Table XI), social media notifications were chosen as the greater distraction by 59.4% (60), advertisements shown on academic platforms by 22.8% (23), marketing alerts by 9.9% (10) and free or open access to AI platforms by 7.9% (8). GenAI was chosen as the greater academic aid by 80.2% (81) and academic material shared over digital media such as WhatsApp by 19.8% (20). Mean standing did not differ significantly across distraction choices (Kruskal–Wallis $p = .291$) or between students choosing WhatsApp-type material and those choosing GenAI as the greater aid ($M = 3.63$ vs 3.13, Mann–Whitney $p = .237$).

TABLE XI
FORCED-CHOICE ITEMS: GREATER DISTRACTION AND GREATER ACADEMIC AID

Option Chosen	n	%	Mean Standing (n)
Greater distraction in academics			
Social media notifications	60	59.4	3.07 (58)
Digital marketing or ads shown on academic platforms (e.g., YouTube)	23	22.8	3.68 (22)
Digital marketing alerts	10	9.9	3.12 (8)
Free or open access to AI platforms	8	7.9	3.25 (8)
Greater academic help or aid			
Academic information access using GenAI tools	81	80.2	3.13 (77)
Academic material received over digital media (e.g., WhatsApp groups)	20	19.8	3.63 (19)

Note. Percentages are of all respondents. Mean standing is on the 1–6 scale and is based on respondents with an existing academic standing.

V. DISCUSSION

A. Principal Findings

Three findings stand out. First, students overwhelmingly perceive a digital burden across all three exposures, yet none of the exposure or behaviour-attitude measures predicted existing academic standing once prior academic attainment was considered; H1, H2 and H3 were not supported, while H4 was. Second, students' overall judgement of the exposure impact was largely positive. It was unrelated to their own distraction ratings and, if anything, more favourable among those with weaker academic records. This points to a disconnect between perceived burden, perceived net effect and existing academic standing. Third, the findings reveal a GenAI attitude–behaviour paradox: most students who believe GenAI weakens original thinking also say they rely on it. Read alongside the frameworks in Section II-E, the second and third findings matter most. They suggest that the practical problem lies in calibration and regulation, not in how much exposure students have.

B. Why No Measurable Academic Loss/Penalty?

The null findings should not be taken as evidence that digital exposure is harmless. The odds ratio for social media time (0.65, 95% CI 0.38–1.09) is compatible with no effect, but it is equally compatible with a meaningful negative association. Observed correlations between academic standing and social media time and distraction ($\rho = -.16$ and $-.17$) are in the direction expected from earlier work [4], [9]. Difficulty in filtering useful academic content online offers a behaviour–attitude signal ($\rho = -.21$; adjusted OR = 0.59, $p = .077$) which is consistent with the digital-competence view that the ability to evaluate and select academic content online, rather than the volume of exposure, is what matters [22]. Prior academic attainment, which in this sample already carries strong predictive information, may also partially absorb the effects of long-standing study habits, including habits of digital use. Finally, students may use the same

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platforms productively: 86.1% regarded WhatsApp-type applications as academically useful, consistent with studies in which purposeful academic use of social platforms related positively to performance [3], [5].

C. A Perception–Outcome Disconnect

The finding that 71.4% of the respondents in adverse academic standing and 65.6% of those reporting high social media distraction still judged the net impact of the three digital exposures as positive suggests that self-perceived impact is a weak indicator of academic risk. The inverse correlations with existing academic standing ($\rho = -.23$) and prior academic attainment ($\rho = -.26$) suggest that it may even point the wrong way. One reading, offered as a hypothesis rather than a result, is the divergence between felt benefit and learning described in the metacognitive-laziness literature. Learners supported by ChatGPT improved their task performance without comparable gains in knowledge or transfer [26]. A tool can therefore feel helpful while contributing little to durable learning, and students with weaker academic records may have the most reason to feel helped. This matters for both research and practice. Studies that rely on perceived impact alone may be capturing students' general attitude toward technology rather than its consequences, a concern that fits with evidence that students and educators in India judge the effects of social media differently [12]. For institutions, surveys of student perception are unlikely to show who is struggling, where and why. Recorded academic performance indicators and prior attainment profiles are more informative.

D. The GenAI Attitude–Behaviour Paradox

That 62.9% of students who agree GenAI slows original thinking also report relying on it echoes the cognitive offloading literature, in which awareness of risk coexists with reliance [16], [17], and the finding that deeper offloading is linked to greater loss of autonomy [18]. In the language of hybrid human–AI regulation, these students appear to have handed regulation of their work to the tool without the planned transfer of regulation back to themselves [25]. In the language of the human-centred dimension of UNESCO's framework, students appear to hold the critical judgement without yet exercising the cognitive agency [23]. The gender difference in our data, with male students reporting greater concern about dependence than their female counterparts, contrasts with a Chinese study in which a high-depth, high-dependence subgroup was disproportionately female [18]. Because constructs, samples and settings differ, we treat the contrast as a prompt for replication rather than a conflict. GenAI was also the aid most students favoured (80.2%), which suggests they experience it mainly as a help even while doubting its effect on their thinking. The reviews point to pedagogical framing, not tool exposure alone, as what determines whether GenAI amplifies or substitutes for thinking [6], [7].

E. Marketing Communications

Students clearly found marketing communications irritating, but their responses did not form a coherent distraction construct. More than half agreed that marketing influences their learning (56.4%), and a larger share said they prefer not to engage with it while studying (62.4%). Yet these two items were essentially uncorrelated ($r = .06$). Volume also mattered: 84.2% reported feeling overwhelmed once they received more than four messages a day. Advertisements appearing while students accessed academic content on platforms such as YouTube were the second most common distraction (22.8%), ahead of marketing alerts. These patterns fit with students blaming advertising, at least in part, for their fragmented attention [8]. They also suggest that experimental findings showing little harm from static advertisements during reading [21] may miss the cumulative, in-context pressure that students describe. Framing digital marketing exposure as a digital-wellbeing and content-evaluation issue within DigComp 3.0 [22] offers a way to study it alongside the other exposures, though doing so requires measures that separate volume, relevance and interference. In adjusted models, marketing exposure was not associated with existing academic standing (OR = 1.17, $p = .424$). The two marketing items also showed weak internal consistency ($\alpha = .04$), so a purpose-built, validated scale is needed before firm conclusions can be drawn.

F. Implications

1) For Institutions: Prior academic attainment was the strongest signal of risk, with detention or backlog concentrated among students with lower Class 10 and 12 profiles (29.2% of those below a prior mean of 1.5 versus 6.5% of those at or above it). Early-warning and mentoring efforts could therefore combine academic attainment profiles with existing progress, instead of relying on students' reports of distraction. Because 49.5% of students said they need external help to regulate study time and this need was strongly linked to distraction ($\rho = .52$), structured self-regulation support, such as study-time planning and notification management, is required to be welcomed. In hybrid-regulation terms, such support should be designed to be withdrawn gradually so that regulation passes to the student [25]. Building the digital-wellbeing and AI components of DigComp 3.0, and the human-centred and ethical dimensions of UNESCO's framework, into induction and first-year skills courses would also be consistent with the capacity-building emphasis of India's AI Governance Guidelines [22]–[24].

2) For Faculty: Since students rely on GenAI while also doubting its effect on their thinking, an assessment design that makes the academic reasoning process more visible and apparent. Explicit guidance on selective, reflective GenAI use looks more promising than banning it outright. An "Allowed GenAI Usage Scale" could offer a practical way to provide that guidance, since it sets out, assessment by assessment, how much GenAI use is permitted given the learning outcomes [27]. Students' strong endorsement of messaging groups for academic purposes (86.1%) also suggests that institutional

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communication through channels they already use may help rather than harm.

3) For Students: The finding that perceived academic impact does not predict existing academic standing points to the value of evidence-based self-monitoring, such as tracking deadlines met and assessment results, rather than relying on how helpful technology feels.

G. Contribution to Theory

The study extends the literature in four ways. First, it shows, within a single sample, that students can perceive a digital burden from three distinct exposures and yet no association with existing academic standing is detectable once prior attainment is accounted for. Second, it introduces a perception-outcome disconnect, in which perceived impact does not track existing academic standing and may even run inversely to it. Third, it adds a GenAI attitude-behaviour paradox from a higher education institution (HEI) setting, complementing evidence from Africa, East Asia and Europe. Fourth, it shows how recent competence and regulation frameworks can be used to define and address research gaps within a single design, although here they remain interpretive lenses and will need direct operationalisation in future work.

VI. Limitations

The data are cross-sectional and self-reported, so the direction of causation cannot be established. Students with weaker prior academic records, for instance, may use technology differently because of those records. Exposure was captured through banded self-report items rather than device logs. Existing academic standing is a self-reported, six-category variable and not a verified grade point average, and for first-year students it reflects only a short assessment history. Four respondents had no applicable existing standing. Many exploratory tests were run, and only the gender difference in concern about GenAI dependence survives a conservative correction. The inverse association between perceived impact and academic standing, the gender difference in academic standing and the filtering-burden correlation should be treated as tentative findings that need replication. The frameworks discussed in Section II-E served as interpretive lenses and were not measured directly. Moreover, the UNESCO framework was written for school systems and DigComp 3.0 for European citizens, so neither was designed with Indian higher-education cohorts in mind. Finally, the literature review rested on targeted searches and was not a systematic review.

VII. Future Research

Future work could (a) replicate the design in larger, multi-state samples with adequate representation of later-year, postgraduate and medical students (b) use verified grades and prior attainment, ideally across multiple semesters, to separate cause from consequence (c) combine self-reporting with device or learning-management-system based logs; (d) develop and validate a scale for academic marketing interference (e) test GenAI use patterns (selective versus passive) and instructional support, as suggested by recent reviews [6], [7], including survey designs that vary the permitted level of GenAI use [27] and measure learning rather than task performance alone [26] (f) examine the gender differences in GenAI dependence and in academic standing, as well as the roles of urban–rural background and household income.

VIII. Conclusion

In a sample of 101 higher education students, perceived digital burden from social media, GenAI and marketing communications was widespread, but it was not associated with recorded academic standing once prior academic attainment was considered. But it was not a reliable guide to students' own judgement of net exposure impact, which, if anything, was more favourable among students with weaker academic records. Prior school attainment was the strongest correlate of current academic standing. Many students who doubted GenAI's effect on original thinking nonetheless relied on it. These findings point to a practical lesson. Student perceptions of digital harm can be a proxy for academic risk (overdependence on GenAI even while being aware that this could hamper original thinking), and the requirement of self-regulation and reflective AI use. Longitudinal studies with verifiable outcomes can help determine whether the absence of a detectable penalty in this study reflects genuine resilience among the students or is a highlight of limits of the design.

IX. Declarations

1) Ethics Approval and Consent: Student data were collected through an online Google Form. Proper consent was obtained from participants during data collection.

2) Funding: The authors received no external funding.

3) Conflict of Interest: The authors declare no conflict of interest.

4) Data Availability: Anonymised survey data may be shared on request or deposited in a repository.

5) Use of AI Assistance: Selective AI assistance was used in the preparation of this work.

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