The 'Spoil Syndrome': From Textbooks to Tabs – Exploring the Paradigm Shift from Textbook Learning to Internet Dependence among MBBS Undergraduates.

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ABSTRACT:

Objective: To evaluate the patterns and extent of internet and artificial intelligence (AI) use among MBBS students in private medical colleges of Punjab, Pakistan, with attention to gender-based differences, and to compare their perceived outcomes of textbook-based learning versus digital/AI-assisted learning. The study will reference the phenomenon of "spoil syndrome," defined as superficial, exam-oriented learning that arises from over-dependence on internet and AI resources.

Methodology: This cross-sectional, questionnaire-based study was conducted from September 2024 to February 2026 in three private medical colleges of Punjab, Pakistan, among students from first to final year. A pre-tested, semi-structured questionnaire assessed demographics, devices and access, preferred sources, learning activities, and perceived outcomes. Of 1615 students approached, 1336 met the inclusion criteria and responded. Gender differences were tested using chi-square (α=0.05).

Results: AI awareness was high among both female and male students (83.0% vs. 87.5%; p=0.082). However, males reported significantly greater daily use of AI tools (88.3% vs. 71.1%; p<0.001) and a stronger preference for AI over conventional internet resources (80.2% vs. 69.5%; p<0.001). The primary applications of AI included concept clarification (65%), quick revision summaries (60%), and MCQ/quiz generation (59.5%) (all p<0.001), whereas its use for research and methodology support remained low (11.5%). Learning preferences indicated a clear inclination toward blended approaches, with 38.5% favoring books plus internet/AI and 29.5% preferring slides plus internet/AI. Only 4.5% of students relied exclusively on internet/AI resources. Among AI platforms, ChatGPT emerged as the most frequently used tool (44.2%). Students perceived that internet/AI use enhanced their digital skills, motivation, and receptiveness to learning.

Conclusion: Students mainly use AI alongside conventional resources, but its concentration in exam-oriented tasks indicates a risk of superficial learning. The findings are self-reported, cross-sectional, and limited to private colleges, and are therefore exploratory. Curricular policies, faculty training, and assessment reform are needed to promote ethical, critical use of AI alongside textbooks and to prevent "spoil syndrome."

Keywords: Spoil syndrome; artificial intelligence; internet-based learning; medical education; MBBS students; Pakistan.

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Introduction:

Medical education has shifted from bulky textbooks toward mobile, internet-based platforms increasingly powered by artificial intelligence (AI). MBBS students now spend much of their study time on searchable databases, chatbots, AI text generators, multimedia modules, and interactive case libraries.[1]

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Adaptive learning systems and large language model chatbots personalize content and fill conceptual gaps instantly. Real-time access to exam-oriented handouts, quizzes, clinical scenarios, and virtual patient simulations also speeds the transition from theory to practical competence.[2] Collaborative cloud-based environments support peer tutoring and interdisciplinary dialogue,[3] and the COVID-19 pandemic accelerated the move toward flexible course delivery. Digital resources carry a risk of misinformation and false references, but AI can help identify such discrepancies and direct students to evidence-based sources. Medical curricula have therefore been restructured to integrate these technologies and build the digital literacy needed for lifelong learning.[4]

This shift, seen in both public and private sectors, moves learners from passive textbook reading toward more active, personalized learning.[5,6] It is driven by the rapid pace of medical advances and the need for flexible, concise resources.6 However, it has also given rise to the so-called "spoil syndrome," which describes superficial learning resulting from over-dependence on internet and AI resources.[7,8] The term is not an established diagnostic entity. A 2025 medical-education commentary described the phenomenon as superficial learning associated with information overload, rote memorization, and exam-focused preparation.[9] In this paper, "spoil syndrome" is used as a

descriptive, operationally defined construct (see Materials and Methods, Box 1) and not as a clinical diagnosis.

MBBS students increasingly prefer quick access to summarized material, quiz answers, and AI-generated explanations over reading comprehensive texts and building deep conceptual frameworks.[10] Although these tools make learning flexible and accessible, they may encourage fragmented knowledge, reduced critical thinking, and exam-driven habits, with weaker long-term retention and clinical reasoning.[11] Students may also accept information uncritically instead of evaluating it as they would a standard textbook.[12] They may consume content passively rather than construct an understanding of clinical situations, biological processes, and pathophysiology.[13] Spoil syndrome therefore threatens competency-based medical education, and a balanced policy for integrating digital and AI-driven learning is needed to preserve intellectual rigor and professional competence.[14]

Digital technology and AI are a disruptive force in medical education, reshaping how students learn and educators teach,[15] and they also connect faculty and students to new sources of knowledge.[16] E-books, audio, images, videos, and chatbots are now widely available, and the internet has become a central repository of learning materials that lets students progress at their own pace.[17,18] Despite this, students' perceptions of internet use for study-related activities remain relatively underexplored.[19]

Recent literature highlights the challenges of implementing AI in undergraduate medical education, although educators can use AI-assisted tools to engage students more effectively.[20] A recent Pakistani study reported widespread use of online platforms, with YouTube the most common. Students cited difficulty acquiring practical skills online and unreliable internet as barriers. Students are not simply replacing textbooks but assembling personalized exam-practice questions from various AI tools.[21] Digital resources excel in convenience, cost, and multimedia diversity, whereas textbooks retain value for structured, foundational learning, particularly in the early MBBS years and in low-resource settings with poor connectivity. Concerns persist that internet-based learning may reduce valuable student-teacher interaction, although most studies show that students do not expect AI to replace physicians. A 2026 study noted rising use of the internet and AI for assignments, presentations, and concise exam handouts.[22] Recent 2026 studies from Pakistan and India add that students' enthusiasm for AI-based learning often exceeds their measured understanding of it,[23] that AI use is lower in later training years and, paradoxically, lower among students with higher knowledge,[24] and that greater dependence on generative AI is inversely associated with critical thinking scores among medical students.[25]

A research gap remains regarding how internet-based learning and AI can be embedded in the undergraduate curriculum and how faculty can prepare for these changes. This study therefore explores the shift from textbook-based to internet- and AI-based learning among undergraduate medical students in three private medical colleges of Punjab and evaluates its perceived academic outcomes. Its primary objectives are to estimate the use of internet and AI learning tools by MBBS students and to compare traditional textbook-based and digital/AI-assisted learning styles. It also explores students' perceptions of the effects on conceptual understanding and critical thinking and determines preferences for AI tools versus recommended textbooks.

Methodology:

During September 2024 to February this cross-sectional, questionnaire-based study was conducted among undergraduate medical (MBBS) students from the 1st to the final year in three private medical colleges of Punjab, Pakistan; public-sector institutions were not included.

To capture the diverse aspects of internet usage comprehensively, we employed a pre-designed and semi-structured questionnaire as a primary study tool. The questionnaire aimed to delve into the multifaceted dimensions of internet-based learning among the participating students. For current study participants were eligible for inclusion if they were undergraduate medical students enrolled in three private medical colleges, ranging from first year to final year sessions. Individuals were excluded if they were students of allied health sciences, postgraduate medical students, recently graduated doctors, or those affiliated with public-sector institutions.

The initial pool comprised 1615 MBBS students, including all eligible students in private medical colleges, making it a complete enumeration rather than a random sample. Applying a rigorous inclusion and exclusion criteria process, the study sample was refined to 1336 participants utilizing a census method to represent the targeted population comprehensively.

Before disseminating the pre-tested questionnaire, it was ensured to conduct brief interactive orientation sessions with all the available participants. These interactive sessions were comprised of manual and online methods, catering for distant participants, and these sessions provided a comprehensive opportunity to elucidate the objectives of the current study and expected outcomes. Informed consent was necessarily obtained to establish amicable rapport with the included participants, underlining the importance of candid and authentic responses in this study. The comprehensive questionnaire covered a definite spectrum of demographic information, and the preferences related to internet search engines, devices, sources of internet access, and databases utilized in their learning modalities. Participation was entirely convenient and voluntary, and utmost efforts were executed to minimize the bias by conducting multiple follow-ups in the respective medical colleges.

Operational definition of "spoil syndrome" and its indicators: Because "spoil syndrome" is not an established diagnostic entity, we defined it a priori for this study as a pattern of superficial, examination-oriented learning that arises from habitual over-dependence on internet/AI resources, as a substitute for primary learning sources (textbooks and lecture material) and for independent critical appraisal. The definition has three components: (A) substitution of primary sources by internet/AI, (B) surface, examination-oriented use of AI, and (C) reduced critical appraisal of AI-generated content. Measurable indicators for each component are listed in Box 1. Indicators in components A and B were captured by the study questionnaire as behavioral proxies. Indicators in component C, and objective outcome measures, were not collected in this study; they are listed to provide a measurable framework for future validation. Frequency of AI use was treated as a risk marker and not as a diagnostic criterion, because high use alone does not establish maladaptive dependence.[24] The proxy indicators describe learning behavior at group level; no student was classified as having, or not having, "spoil syndrome.

Box 1: Operational framework for "spoil syndrome": components, measurable indicators, and status in this study.

Component	Measurable indicator	Data source / instrument	Status in this study
A. Substitution of primary sources	1. Internet/AI as the sole learning source (no books or lecture slides)	Questionnaire: preferred learning source (Table-3)	Measured
A	2. Preference for AI over conventional internet resources	Questionnaire (Table-1)	Measured
A	3. Daily (intensive) AI use	Questionnaire (Table-1)	Measured
B. Surface, exam-oriented use	4. Share of AI use directed to quick summaries, MCQ/quiz generation, and exam-recall tools	Questionnaire: learning activities (Table-2)	Measured
B	5. Low use of AI for detailed conceptual notes and for research/methodology work	Questionnaire (Table-2)	Measured
B	6. Surface versus deep approach to learning	Revised Study Process Questionnaire (R-SPQ-2F)[26]	Not measured; future work
C. Reduced critical appraisal	7. Habitual verification of AI output against textbooks or primary sources	Behavioral verification items or vignettes	Not measured; future work
C	8. Critical thinking disposition score	Validated scale, e.g., CTDAQ-20[25]	Not measured; future work
C	9. Objective academic performance (internal examinations, OSCE) and faculty evaluation of depth of understanding	Institutional assessment records; faculty rating	Not collected; future work

Chi-square tests were employed to examine differences across three categories: AI awareness, daily use, and preference for AI over conventional internet resources. All expected cell frequencies exceeded 5, thereby satisfying the assumptions of the test. A conventional significance threshold of $\alpha = 0.05$ was applied. Given the large sample size (n = 1336), the study possessed excellent statistical power to detect meaningful gender differences among undergraduate medical students. For AI-related items (awareness, daily use, and preference), responses were available from 746 participants (377 females and 369 males). Percentages for these variables were calculated based on this subgroup of respondents.

Table No1: Gender-wise distribution of preferences for learning and study (respondents to AI-related items, n = 746)

Category	Female (n=377)	Male (n=369)	χ^2 (df=1)	p-value	Interpretation
Awareness of AI	313 (83.0%)	323 (87.5%)	3.017	0.082	Nearly equal awareness between genders. Difference is not statistically significant ($p > 0.05$)
Frequent AI Use (overall)	80-83%	88-90%	-	-	High prevalence in both genders; slightly higher among males
Daily AI Use	268 (71.1%)	326 (88.3%)	34.239	4.87×10^{-9}	Males show significantly higher intensive (daily) usage ($p < 0.001$)
Diversity of internet/ AI tools utilized for learning	Comparable	Comparable	-	-	No significant gender difference
Perception / Attitude toward internet/AI-based learning	Similar	Similar	-	> 0.05 (given)	No significant difference between genders ($p > 0.05$)
AI Preference over Internet	262 (69.5%)	296 (80.2%)	11.37	0.00075	Male students show significantly higher preference for substituting AI over traditional internet resources ($p < 0.001$)

Note: Of the 1336 participants (677 females, 659 males), 746 (377 females, 369 males) answered the AI-related items; percentages are calculated among these respondents. χ^2 = Pearson chi-square test.

Results and Discussion:

Keeping in view the pattern of the study, we attempt to describe results along with relevant discussion. The gender wise preferences of study participants are shown in table 1. Awareness of AI, diversity of tools used, and overall attitudes/perceptions toward AI/internet-based learning are largely comparable between female and male students (no statistically significant differences). Male students demonstrate significantly higher engagement in intensive (daily) AI use and a stronger preference for AI over conventional internet resources.

Table No 2: Preferences for Use of Internet & AI Tools with Statistical Significance

Rank	Learning Activity	Preferred Tool Type	% Students Using (n=746)	p-value	Statistical Interpretation
1	Concept clarification of lengthy & difficult topics	AI tools	65%	<0.001	Highly significant preference over all other uses
2	Short notes & quick revision summaries	AI tools	60%	<0.001	Strong preference, slightly lower than concept clarification but still highly significant
3	MCQs practice & quiz generation	AI + Online Q-banks	59.5%	<0.001	Strong preference, reflects exam-oriented usage
4	Topic discussion / interactive learning	AI tools	52%	0.002	Statistically significant adoption for active learning
5	Lecture slides simplification / explanation	AI tools	50%	0.010	Moderately significant preference
6	Diagram explanation & visual learning	Internet + AI	48%	0.018	Significant but reduced reliance on AI alone
7	Detailed conceptual notes (deep learning)	Hybrid	45%	0.032	Borderline significance; reflects cautious use
8	Handouts & ready-made study material	Internet	42%	0.041	Marginally significant; traditional dominance persists
9	Exam-oriented recall tools	Apps + AI	38%	0.065	Not statistically significant
10	Peer discussion / collaborative learning	Internet forums	35%	0.081	Not significant; least preferred
11	Research and methodologies	AI + Google scholar	11.5%	0.91	Least preferred

This suggests male undergraduates in this medical cohort may be more inclined to integrate AI deeply into daily study routines. Both genders show high AI adoption (>80% frequent use), indicating broad readiness for AI-enhanced learning tools. Targeted interventions could focus on encouraging daily use among female students if equity in intensive adoption is desired, while leveraging the overall positive attitudes across genders.

There is a statistically significant shift toward AI-driven learning, especially for conceptual understanding, summarization and interactive learning. Traditional internet tools remain relevant but show declining statistical strength. The drop in significance after rank 7 suggests greater heterogeneity in student preferences and also lack of consensus for lower-order learning activities. Medical students demonstrated a clear, rank-ordered hierarchy of tool preferences for self-directed learning activities (Table-2). AI tools dominated the top five activities, accounting for 50-65% of reported usage and achieving highly significant statistical preference ($p \leq 0.010$). Concept clarification of lengthy/difficult topics ranked first (65% AI preference, $p<0.001$), followed closely by short notes/quick revision summaries (60% AI, $p<0.001$) and MCQ/quiz generation (59.5% AI + online Q-banks, $p<0.001$). These reflect strong, exam-oriented and cognitive-load-reducing utility of generative AI.

Interactive and visual learning activities showed moderate AI adoption (topic discussion 52%, $p=0.002$; lecture slides simplification 50%, $p=0.010$; diagram/visual explanation 48% Internet +AI, $p=0.018$), indicating transitional reliance on hybrid modalities. Traditional internet-based resources retained relevance only for lower-ranked tasks: handouts/ready-made material (42% Internet, $p=0.041$) and peer/collaborative discussion via forums (35%, $p=0.081$). Research and methodological exploration were least preferred (11.5% AI + Google Scholar, $p=0.91$), suggesting limited integration of AI into scholarly workflows.

These findings indicate a paradigm shift toward AI-augmented learning for high-cognitive-demand, time-sensitive tasks in undergraduate medical education, while conventional internet resources persist for passive or social activities. The data support targeted curricular integration of AI tools for concept mastery and exam preparation, with cautious adoption recommended for research training where traditional scholarly databases remain underutilized.

Table No 3: Preferences for learning and study among undergraduate medical students.

#	Preferred source	Number of students (n = 1335)	Percentage
1	Books and internet/ AI	514	38.5
2	Lecture slides and internet/AI	393	29.5
3	Books only	201	15
4	Lecture slides only	141	10.5
5	Internet/AI only	60	4.5
6	No response	26	2

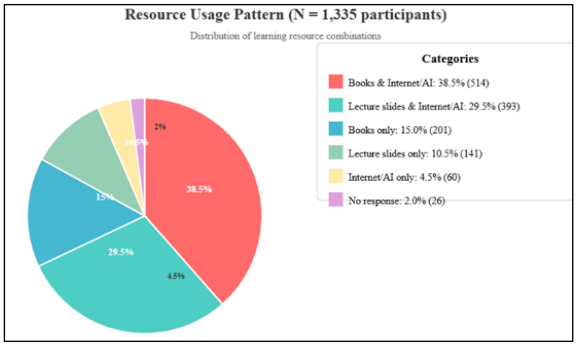
Table-3 clearly shows that most undergraduate medical students prefer a combination of traditional and digital learning resources. The highest proportion of students (38.5%) preferred using books together with internet/AI resources, followed by lecture slides combined with internet/AI (29.5%). In contrast, relatively fewer students relied solely on books (15%), lecture slides (10.5%), or internet/AI alone (4.5%). Overall, the findings suggest that students favor a blended learning approach integrating conventional study materials with modern digital and AI-based resources.

Table No 4: Preferable patterns of internet/AI sources for learning and study.

Internet/AI source	N	Percentage
ChatGPT	591	44.2
Google chrome	278	20.8
Google scholar	266	19.9
Grok-β	59	4.4
PubMed	46	3.4
Quill Bot/Perplexity/Paper pal	11	0.8
Others	25	1.9
Note: Percentages are calculated on the total sample (n = 1336); 60 participants (4.5%) did not report a preferred source.		

Table-4 demonstrates that ChatGPT is the preferred internet/AI source for learning and study among undergraduate medical students, utilized by 44.2% of participants. Traditional online resources such as Google Chrome (20.8%) and Google Scholar (19.9%) were also commonly preferred. In comparison, relatively few students used Grok, PubMed, or other AI tools, indicating a strong inclination toward ChatGPT as the primary digital learning aid.

Figure 1: Distribution of preferred learning-resource combinations among participants (n = 1335).



Proxy indicators of "spoil syndrome" captured in this study

Table-5 reports the indicators from Box 1 that the questionnaire captured. Taken together, they describe students who use AI intensively and chiefly for efficiency-oriented, exam-relevant tasks, but who have not abandoned conventional resources: sole reliance on internet/AI was uncommon (4.5%), and about two-thirds of students combined internet/AI with books or lecture slides. The pattern is therefore best read as a risk of superficial learning rather than as evidence of established spoil syndrome. Two features deserve attention: the concentration of AI use in summaries, MCQ generation, and concept clarification, where fluent output can substitute for effortful processing, and the very low use of AI for research and methodological work (11.5%). Because verification behavior, critical thinking, and examination performance were not measured, component C of the framework could not be assessed, and the prevalence of spoil syndrome cannot be estimated from these data.

Table No 5: Proxy indicators of "spoil syndrome" measured in this study (see Box 1).

Component	Indicator	Finding	Reading
A. Substitution of primary sources	Internet/AI as sole learning source	60 of 1335 (4.5%)	Uncommon
A	Blended use of internet/AI with books or slides	907 of 1335 (about 68%)	Dominant pattern; conventional sources retained
A	Preference for AI over conventional internet resources	Females 69.5%; males 80.2% (p<0.001)	Higher in males
A	Daily AI use	Females 71.1%; males 88.3% (p<0.001)	High, especially in males; a risk marker, not diagnostic
B. Surface, exam-oriented use	AI use for quick revision summaries; MCQ/quiz generation; exam-recall tools	60%; 59.5%; 38% (of 746)	Exam-oriented uses are among the most frequent
B	AI use for detailed conceptual notes (deep learning)	45% (of 746; hybrid tools)	Lower than exam-oriented uses
B	AI use for research and methodology	11.5% (of 746)	Very low; limited scholarly use
C. Reduced critical appraisal	Verification behavior; critical thinking score; objective performance	Not measured	Cannot be assessed

Comparison with recent regional evidence:

Recent 2026 evidence from South Asia helps to place these findings in context. Our respondents reported high AI awareness (83.0% of females, 87.5% of males), whereas a multi-college survey in Khyber Pakhtunkhwa found favorable attitudes but only modest measured knowledge of AI-based learning,[23] which suggests that self-reported awareness may overstate competence. The lower daily AI use among female students in our data is consistent with the report that low AI use was more common among female students in Khyber Pakhtunkhwa,[24] and a study at a government medical college in Tamil Nadu, India, likewise found higher AI dependence among males.[25] The former study also found that higher knowledge was paradoxically associated with lower use and cautioned that frequency of use alone can misclassify critically literate students,[26] which supports our decision to treat use intensity as a risk marker rather than a diagnostic criterion.

Table No 6: Study findings and proposed curricular and policy actions.

Finding	Implication	Proposed action
High daily AI use (71.1% of females, 88.3% of males); ChatGPT the leading tool (44.2%)	Widespread use in the absence of clear institutional rules	Adopt an institutional AI-use policy that states permitted uses (concept clarification, self-testing, language support), prohibited uses (submitting AI output as one's own assessed work), disclosure norms, and consequences for breaches; review it annually as tools change.
Most students blend AI with books (38.5%) or slides (29.5%); only 4.5% use internet/AI alone	Blending is already the norm and can be reinforced	Make a "textbook-anchored, AI-supplemented" model the default: give each module a core reading list and expect AI-assisted study to be cross-checked against it, particularly in the early years when foundational concepts are formed.
AI used mainly for concept clarification (65%), quick summaries (60%), and MCQ generation (59.5%)	Fluent AI output can replace effortful processing and may contain errors	Teach critical appraisal explicitly: embed short exercises in which students identify errors, unsupported statements, and fabricated references in AI-generated summaries,[24,27] and verify claims against textbooks and guidelines.
Exam-oriented uses prominent; research use only 11.5%	Assessment formats may reward recall rather than reasoning	Rebalance assessment toward reasoning: add case-based questions, structured viva, OSCE stations, and short justified answers alongside MCQs; include process-based tasks such as oral defense of a written answer.
Positive attitudes toward internet/AI learning here; modest AI knowledge in a 2026 regional survey[23]	Enthusiasm may exceed competence	Provide faculty development and student AI-literacy workshops (limits of large language models, referencing, ethics), and have faculty model responsible AI use in teaching.
Male-female differences in daily AI use	Need for monitoring and equitable access without over-reading use frequency	Monitor the Box 1 indicators annually, ideally linked to objective performance data; support equitable access (campus connectivity, licensed tools); avoid using frequency of use alone as a metric.[24]

The most direct evidence on the cognitive dimension of spoil syndrome comes from the Tamil Nadu study, in which greater AI dependence was inversely associated with critical thinking scores,[25] and from an online survey of early-career medical researchers across Pakistan (a preprint) in which 59.2% typically did not verify AI outputs before use.[27] Neither behavior was measured in our survey, and this is the principal gap that the indicator framework in Box 1 is intended to address in future work. On the outcomes side, a randomized crossover trial in Pakistan compared ChatGPT-4-supported personalized learning with conventional resources using pre- and post-tests,[28] and a 2026 cohort study of emergency interns reported higher odds of accurate diagnostic decisions with blended learning than with textbook-based learning alone.[29] The latter finding is consistent with the blended preference of most of our respondents, although our own data cannot show that blending improves learning.

Policy and curricular implications:

The findings suggest that the priority is not to restrict AI use, which is already widespread and largely combined with conventional resources, but to steer it toward deeper learning. Table-6 links each principal finding to a proposed curricular or policy action.

Implementation should be phased and evaluated: for example, piloting the measures for one academic year under the curriculum committee, tracking the Box 1 indicators before and after, and adjusting accordingly. Regulators and affiliating universities could also consider incorporating AI-literacy and critical-appraisal competencies into MBBS curriculum guidance so that institutional policies are consistent across the country.

Limitations and directions for future research:

This study has several limitations. First, only three private medical colleges in Punjab were included, so the findings cannot be generalized to public-sector institutions, which may differ in resources, connectivity, admission profile, and institutional AI policy. Future work should sample public and private institutions across provinces, using stratified or cluster designs that allow comparison between sectors. Second, the cross-sectional design captures a single time point; it cannot show how learning behavior changes as students progress, whether AI-driven learning habits are sustained, or whether AI use causes any change in learning. A longitudinal cohort that follows students from the first to the final year, with repeated measurement at fixed intervals, is needed to address this.

Third, all data were self-reported. Perceived improvements in digital skills, motivation, and receptiveness were not verified against examination scores, OSCE performance, or faculty evaluations, and social desirability may have inflated positive responses; future studies should link questionnaire data, with consent and de-identification, to objective performance records. Fourth, "spoil syndrome" was assessed only through behavioral proxies. Critical thinking, verification of AI output, and learning approach were not measured, so we could not estimate prevalence or test associations with cognitive outcomes; validated instruments (Box 1) should be used for this purpose. Finally, AI tools evolved rapidly during the study period, which may limit the durability of tool-specific findings.

Conclusions:

Across the three private medical colleges surveyed, MBBS students reported extensive use of internet and AI resources, primarily for concept clarification, rapid revision, and MCQ practice. These tools were generally employed in combination with textbooks and lecture slides rather than as substitutes. Male students indicated more intensive daily AI use and a stronger preference for AI compared to conventional internet sources. Students perceived internet-based learning positively, citing improvements in digital skills, motivation, and receptiveness. However, given that the data are self-reported, cross-sectional, and limited to

private institutions, the findings cannot establish whether learning outcomes have objectively improved or whether spoil syndrome (superficial, exam-oriented learning) is present or absent.

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