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Between the Prompt and the Case Study

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ABSTRACT

Generative AI tools have become part of daily study routines faster than most universities have written rules for them. This article reports a survey of students at Lagos Business School (LBS), the graduate management school of Pan-Atlantic University, about how they use AI in six everyday learning activities and how they feel about it. A questionnaire was shared with a target of 100 students and about 97 responded. The picture is one of heavy, habitual use: 88.8% of those answering said they always use AI to prepare for case discussions, 94.2% always use it for writing, and 86.7% always use it for revision. Every respondent who answered agreed that AI makes them less likely to do the full reading, and only 41.3% said they always form their own view before consulting a tool, even though all 63 who answered said their confidence in their own analysis had grown. At the same time, 91.5% said they understand the school's rules on AI, yet 77.6% said those rules are not applied fairly, and all 93 who answered the open question asked the institution for a better policy. Respondents were unanimous that access, cost and power supply create unequal advantages. The article sets out six structured problems drawn from these results and a matching set of recommendations. Because the sample was self-selected and the data are self-reported, the findings describe attitudes and stated habits, not measured learning outcomes.

Keywords: J. Sci. Technol. AI, Peer-Reviewed, Open Access, Case Study

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Between the Prompt and the Case Study

How Artificial Intelligence Is Reshaping the Learning Activities of University Students: A Survey-Based Case Study of Lagos Business School

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Abstract

Generative AI tools have become part of daily study routines faster than most universities have written rules for them. This article reports a survey of students at Lagos Business School (LBS), the graduate management school of Pan-Atlantic University, about how they use AI in six everyday learning activities and how they feel about it. A questionnaire was shared with a target of 100 students and about 97 responded. The picture is one of heavy, habitual use: 88.8% of those answering said they always use AI to prepare for case discussions, 94.2% always use it for writing, and 86.7% always use it for revision. Every respondent who answered agreed that AI makes them less likely to do the full reading, and only 41.3% said they always form their own view before consulting a tool, even though all 63 who answered said their confidence in their own analysis had grown. At the same time, 91.5% said they understand the school's rules on AI, yet 77.6% said those rules are not applied fairly, and all 93 who answered the open question asked the institution for a better policy. Respondents were unanimous that access, cost and power supply create unequal advantages. The article sets out six structured problems drawn from these results and a matching set of recommendations. Because the sample was self-selected and the data are self-reported, the findings describe attitudes and stated habits, not measured learning outcomes.

Keywords: generative AI; higher education; Nigeria; business school; case method; academic integrity; cognitive offloading

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1. INTRODUCTION

Picture a master's student in Lagos on a Sunday evening. Monday's strategy case runs to forty pages, the power has just gone off and the generator has taken over, mobile data is running low, and a chatbot is one tap away. What the student does next, whether that is summarising the case, arguing with it, or having the answer written, is the subject of this article.

Since late 2022, large language models have shifted from novelty to habit. Kasneci et al. (2023) set out the early promise clearly: personalised explanation, quick feedback, help with drafting, and relief for overstretched teachers. They also listed the costs, which included over-reliance, confident factual errors, and weaker independent thinking. That list has aged well. What early commentary could not say is how these tools settle into students' ordinary routines once the excitement fades, and whether that looks the same in Lagos as in the places where most of the research has been done.

Much of the empirical work so far comes from Europe, North America and East Asia (Zawacki-Richter et al., 2019). Nigeria deserves its own evidence. Lagos has a young, mobile-first, commercially minded student population, unreliable infrastructure, and expensive data. Lagos Business School is a useful place to look because it teaches through discussion-based cases, a method that depends on students arriving prepared, and because it has already engaged publicly with AI (Ogwo, 2026).

This article asks three questions. First, how often and for what do LBS students use AI in their studies? Second, how do they judge its effect on their learning, and how do they judge the rules around it? Third, what problems follow from those answers and what should the school, its staff and its students do about them? The analysis rests on a questionnaire completed by students, reported in Section 5.

2. CONTEXT: LAGOS BUSINESS SCHOOL AND NIGERIAN HIGHER EDUCATION

Lagos Business School is on the Lekki-Epe corridor in Lagos and belongs to Pan-Atlantic University. It offers MBA, Master in Management and doctoral programmes alongside executive education (CB Insights, n.d.). The school is generally associated with the case method, in which students read a real management situation beforehand and then defend a position in class. The method assumes that preparation is personal and that discussion exposes whether it was done.

The wider environment is moving. A BusinessDay review of twelve African business schools reported that they are drafting usage and ethics policies and leaning more on experiential learning, oral defences, presentations and field projects using local data to protect originality; LBS's director of learning innovation, Henry Ogundolire, was quoted as believing that AI can improve education if introduced carefully (Ogwo, 2026). The University of Lagos announced that it was preparing an ethical-use policy, with a senior official arguing that banning AI would be self-deception because students already use it (TheCable, 2025). The Lagos State government has also said it intends to train large numbers of students in state-owned tertiary institutions in AI and digital skills (ITWeb Africa, 2024). LBS has worked with Microsoft on AI leadership programmes for senior public servants, reportedly reaching 99 officials from 58 agencies (CB Insights, n.d.). Together these reports describe a sector that has stopped asking whether to engage and started asking how.

3. REVIEW OF THE LITERATURE

3.1 A FIELD THAT GREW AHEAD OF ITS THEORY

Zawacki-Richter et al. (2019) reviewed 146 studies of AI in higher education. Most were about profiling, prediction, assessment and tutoring systems, and few authors were educators. The field, in other words, was pushed by what the technology could do far more than by what learning needs. Holmes et al. (2019) made the same point from the teaching side, arguing that tools should be judged by whether they improve learning. Generative AI added fluent, general-purpose language on demand. Dwivedi et al. (2023) collected views from a large group of scholars and found enthusiasm for productivity and access alongside worry about bias, fabricated content, authorship and eroding skills.

3.2 LEARNING GAINS AND WHAT GETS OFFLOADED

The old dream in educational technology is one-to-one tutoring; Bloom (1984) reported that individually tutored students performed about two standard deviations better than conventionally taught peers. Generative AI looks like a way to give everyone a tutor. The better experiments are less comforting. In a field experiment with high-school mathematics students, Bastani et al. (2025) found that unrestricted access to a GPT-style assistant raised performance on practice problems but left students worse off on a later exam without the tool, while a version built with tutor-like guardrails largely avoided the harm. The design of the interaction, then, decides the outcome.

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Cognitive psychology gives us words for this. Risko and Gilbert (2016) define cognitive offloading as using external tools or actions to reduce mental demand. Offloading is often sensible; nobody needs to memorise a phone number. It becomes a problem when the thing offloaded is the skill the course exists to build. Cognitive load theory (Sweller, 1988) helps separate the cases: effort that is irrelevant to learning, such as fighting formatting, is fair game for automation, while effort that builds understanding, such as working out why a pricing strategy failed, is the part a student should keep. Bjork and Bjork (2011) argue that some difficulty during study is productive because it strengthens long-term learning, which is a caution against tools that remove all friction. Gerlich (2025) reported a negative association between frequent AI use and critical-thinking scores, though a survey correlation cannot show which way the effect runs. A 2025 preprint from the MIT Media Lab (Kosmyna et al., 2025) reported lower neural engagement in essay writers using an LLM; the sample was small and the paper had not completed peer review when it appeared, so it is a prompt for further study and not settled fact.

Not all AI use is offloading of the harmful kind. Self-testing is among the best-supported study techniques (Roediger & Karpicke, 2006), and an assistant that quizzes a student on course material could in principle support it. Whether students use it that way is an empirical question.

3.3 INTEGRITY, DETECTION AND FAIRNESS

Cotton et al. (2024) discuss how ChatGPT-type tools complicate academic integrity and argue for a combination of clear policy, redesigned assessment and staff training rather than reliance on detection software. There is a technical reason for the caution. Liang et al. (2023) showed that several popular detectors wrongly flagged a high share of essays by non-native English writers as machine-generated. An institution that treats a detector score as proof can therefore punish the wrong people.

3.4 ACCESS, COST AND CONTEXT

Much of the literature quietly assumes stable electricity, cheap bandwidth and personal devices. In Lagos those assumptions do not always hold, so two students in one cohort may have very different AI experiences. Davis's (1989) technology acceptance model reminds us that adoption depends on perceived usefulness and ease of use, and both are shaped by context. Models trained mostly on Western text can also handle Nigerian regulation and local market behaviour poorly, which is a risk for students who accept output uncritically (Dwivedi et al., 2023).

4. RESEARCH DESIGN AND METHOD

The study is a single-case, descriptive survey. LBS was chosen as a bounded case because it combines a discussion-based pedagogy with a public record of engagement with AI. A single case cannot support statistical generalisation, but it can produce grounded findings that other institutions can compare with their own situations (Yin, 2018). A survey is a suitable instrument for describing the attitudes and stated behaviour of a population at one point in time (Creswell & Creswell, 2018).

Instrument. The questionnaire had 20 items in four sections: background (programme, mode of study, years of professional experience, first language); frequency of AI use across six activities, rated from never to always; attitudes to AI, learning and institutional rules, rated on a five-point agreement scale in the manner of Likert (1932); and barriers to use, ending with one open question on what the school should change. The full item list is in Appendix A.

Sampling and administration. A link to the questionnaire, hosted on Google's platform, was sent to a target of 100 LBS students, and about 97 responded. Participants were reached through a convenience approach, which is quick and practical but means the respondents are those who were reachable and willing (Etikan et al., 2016). The survey stayed open for one month.

Ethics. Ethical approval for this study was obtained from the relevant Research Ethics Committee at Lagos Business School, Pan-Atlantic University, Nigeria. The study was conducted in accordance with the applicable ethical principles and institutional guidelines for research involving human participants. Informed consent was obtained from all participants before data collection. Participants were informed of the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without penalty. Appropriate measures were taken to protect participants' privacy and ensure the confidentiality of their information. Data were handled securely and used solely for the purposes of the study, in accordance with the approved research protocol.

Analysis. Responses were tallied item by item and expressed as percentages of those who answered that item, not of the whole sample, because not every respondent answered every question. Counts per item ranged from 63 to 96. The number of answers is shown in each table. The open question was reported as a theme count.

Two data notes. First, item 17, on confidence in one's own analysis, was answered by only 63 respondents, about two thirds of the

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sample, so it may not represent those who skipped it. Second, all respondents reported 0 to 2 years of professional experience, including those who ticked an executive programme, which is an unusual combination and may reflect how the options were read. I discuss what both mean for interpretation in Section 8.

5. FINDINGS

5.1 WHO ANSWERED

Among the 90 who gave their programme, 67 (74.4%) were in the Master in Management, 22 (24.4%) in an executive programme and 1 in another. Of 85 who gave their mode of study, 75 (88.2%) studied full-time and 10 (11.8%) part-time. All 94 who answered the experience question reported 0 to 2 years of professional experience, and all 93 who answered the language question gave English as their first language. The sample is therefore mostly full-time, early-career Master in Management students. That differs from the picture of time-pressed senior managers that one might expect of a business school, and it shapes how the findings should be read.

Table 1. Respondent profile. Percentages are of those answering each item.

Item	Result (valid responses)
Programme (n = 90)	Master in Management 67 (74.4%); Executive 22 (24.4%); Other 1 (1.1%)
Mode of study (n = 85)	Full-time 75 (88.2%); Part-time 10 (11.8%)
Professional experience (n = 94)	0 to 2 years: 94 (100%)
First language (n = 93)	English: 93 (100%)

5.2 HOW STUDENTS USE AI

Use is heavy and, for the activities closest to assessed work, close to universal. Writing came first: 81 of 86 respondents (94.2%) said they always use AI to draft or edit written assignments. Case preparation followed at 71 of 80 (88.8% always, with another 7.5% often), then revision and self-study at 78 of 90 (86.7%). Summarising readings was somewhat lower, with 50.7% always and 41.3% sometimes. Group projects were the activity with the least constant use: 64 of 96 (66.7%) said sometimes and 32 (33.3%) always, and nobody chose rarely or never.

The most telling item is the last in this section. Asked whether they form their own view of a case before consulting an AI tool, 31 of 75 (41.3%) said always, 6 (8.0%) often, 33 (44.0%) sometimes and 5 (6.7%) rarely. Put differently, roughly half of those answering do not consistently think first. I cannot cross-tabulate this item with case preparation because I have counts and not individual records, so I cannot say whether the students who always use AI for case preparation are the same ones who do not always think first. The two figures are, however, uncomfortably close to each other.

Table 2. Frequency of AI use by learning activity. Percentages are of valid responses to each item. No respondent chose "never" on any

Activity	n	Always	Often	Sometimes	Rarely
Summarising readings (Q5)	75	38 (50.7%)	6 (8.0%)	31 (41.3%)	0
Preparing case answers (Q6)	80	71 (88.8%)	6 (7.5%)	0	3 (3.8%)
Drafting or editing writing (Q7)	86	81 (94.2%)	0	1 (1.2%)	4 (4.7%)
Group projects (Q8)	96	32 (33.3%)	0	64 (66.7%)	0
Quizzing and revision (Q9)	90	78 (86.7%)	0	12 (13.3%)	0
Forming own view first (Q10)	75	31 (41.3%)	6 (8.0%)	33 (44.0%)	5 (6.7%)

5.3 WHAT STUDENTS THINK

Students rate AI as useful: 82 of 87 (94.3%) agreed or strongly agreed that it helps them understand difficult material, and 5 disagreed. They are also candid about a cost. All 93 who answered item 12 agreed that AI makes them less likely to do the full reading, 82 agreeing and 11 strongly. All 91 who answered item 13 agreed that they verify AI output against course materials or

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other sources, with 96.7% strongly agreeing. On confidence, all 63 who answered item 17 said their confidence in their own analysis had increased since they started using AI tools; no other response was recorded, though only about two thirds of respondents answered that item.

The institutional questions produced the sharpest split. Most respondents, 86 of 94 (91.5%), said they understand the school's rules on AI use. Yet of 85 who answered the item on fairness, 66 (77.6%) disagreed that the rules are applied fairly and 19 (22.4%) agreed. On equity, all 94 respondents agreed that students with better access to AI tools have an advantage (92.6% agree, 7.4% strongly agree).

Table 3. Attitudes and barriers. Item 17 (confidence in own analysis) is reported in the text: all 63 respondents who answered said it had

Statement	n	Strongly agree	Agree	Disagree
AI helps me understand difficult material (Q11)	87	51 (58.6%)	31 (35.6%)	5 (5.7%)
AI makes me less likely to do the full reading (Q12)	93	11 (11.8%)	82 (88.2%)	0
I verify AI output against other sources (Q13)	91	88 (96.7%)	3 (3.3%)	0
I understand the school's rules on AI (Q14)	94	55 (58.5%)	31 (33.0%)	8 (8.5%)
The rules are applied fairly (Q15)	85	0	19 (22.4%)	66 (77.6%)
Better access gives some students an advantage (Q16)	94	7 (7.4%)	87 (92.6%)	0
Cost of data or subscriptions limits my use (Q18)	93	0	93 (100%)	0
Power or connectivity limits my use (Q19)	96	91 (94.8%)	5 (5.2%)	0

5.4 WHAT STUDENTS WANT

The open question (item 20) was answered by 93 respondents, and all 93 gave the same theme: the institution should provide a better policy on AI use. No other theme was recorded. That is a remarkable level of agreement for an open-ended question, though it also means the data cannot tell us what a better policy should contain.

6. STRUCTURED ANALYSIS OF THE PROBLEMS

The results point to six problems. For each I set out what the data show, why it matters in light of the literature, and how far the survey supports the claim. Problems 1 to 5 rest directly on survey responses. Problem 6 is an inference from them and should be treated as a hypothesis for the school to test.

PROBLEM 1: NEAR-UNIVERSAL, HABITUAL USE IN THE ACTIVITIES THAT ARE ASSESSED

Evidence. Always-use rates of 94.2% for writing, 88.8% for case preparation and 86.7% for revision (Table 2). Why it matters. When a tool sits inside nearly every assessed task, what a submitted piece of work shows about the student becomes unclear. Cotton et al. (2024) make the same point about integrity in the age of ChatGPT. Use itself is not the problem; Bastani et al. (2025) show that the same tool can help or harm depending on how it is set up, and this survey tells us how often students use AI, not how well.

PROBLEM 2: INDEPENDENT PREPARATION IS BEING DISPLACED

Evidence. All respondents agreed that AI makes them less likely to do the full reading, and only 41.3% always form their own view before using a tool. Why it matters. The case method depends on students arriving with a position they can defend. If the reading is skipped and the view is borrowed, the class loses the disagreement that gives the method its value. This is cognitive offloading (Risko & Gilbert, 2016) of the costly kind, because the effort being skipped is the effort that builds judgement (Sweller, 1988; Bjork & Bjork, 2011). The students themselves recognise the trade-off, which is encouraging, since they say they use the tool anyway.

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PROBLEM 3: VERIFICATION AND RISING CONFIDENCE ARE CLAIMED BUT NOT DEMONSTRATED

Evidence. All 91 who answered item 13 agreed that they verify AI output, and 96.7% strongly agreed. All 63 who answered item 17 said their confidence in their own analysis had increased. Why it matters. The same group said they read less and mostly do not always think first. Both can be true, but the strength of the verification claim deserves caution, and so does the rise in confidence: this survey measures how sure students feel, not whether their understanding has grown. Bastani et al. (2025) reported that students using the unrestricted assistant did not perceive any loss in learning even though their later unaided performance fell, so felt confidence is a weak guide to what was learned. Self-reports on socially approved behaviour tend to be inflated (Nederhof, 1985; Podsakoff et al., 2003), and a school that accepts the claim at face value will not teach or check the skill. Language models can produce confident errors and fabricated references (Dwivedi et al., 2023; Kasneci et al., 2023), so verification is a practical skill that has to be taught and observed, not assumed.

PROBLEM 4: A POLICY GAP IN CLARITY, FAIRNESS AND TRUST

Evidence. 91.5% say they understand the rules, 77.6% say the rules are not applied fairly, and all 93 who answered the open question asked for a better policy. Why it matters. Knowing the rules and trusting them are different things. The pattern suggests that the problem is less ignorance of the policy than doubt about how it is enforced, though the survey did not ask why students think enforcement is unfair. One plausible source is over-reliance on detection software, which the literature shows can misclassify honest writers (Liang et al., 2023). I flag that as a possibility, not a finding, because nothing in the data speaks to what students had in mind.

PROBLEM 5: UNEQUAL ACCESS AND INFRASTRUCTURE

Evidence. All respondents agreed that better access gives some students an advantage, all agreed that cost limits their use, and 94.8% strongly agreed that power or connectivity does. Why it matters. The literature on AI in education mostly assumes stable electricity and affordable data (Section 3.4). Here, students in the same programme describe themselves as constrained in the same way, which suggests a shared structural problem. It also raises a fairness question for any rule: a policy that permits AI use while ignoring who can afford it creates uneven ground. Technology acceptance depends on perceived ease of use (Davis, 1989), and cost and power directly affect ease.

PROBLEM 6 (INFERRED): ASSESSMENT MAY NO LONGER TELL THE SCHOOL WHAT STUDENTS CAN DO

Evidence. This follows from Problems 1 and 2 and was not asked directly. Reasoning. If most take-home work is produced with AI and many students do not form their own view first, then written outputs say less about individual understanding. The pattern in the BusinessDay review, a move towards oral defences, presentations and local-data projects (Ogwo, 2026), is a reasonable response. Group projects add a further wrinkle. Only a third said they always use AI there, which may reflect more caution or more coordination cost, but the survey does not say. The risk in any group task is that visible polish hides uneven contribution, a familiar free-rider problem (Kerr & Bruun, 1983). A direct question on assessment and on group dynamics would turn this hypothesis into evidence.

7. RECOMMENDATIONS

Each recommendation below is tied to one of the problems above. They are suggestions for the school's consideration, and the evidence for them is the survey results combined with the cited literature, not a trial of the measures themselves.

Table 4. Problems, recommendations, suggested owners and timing.

Problem	Recommendation	Owner	Timing
1 Habitual use	Publish an activity-by-activity guide that lists what is permitted (for example glossing a term, practice quizzes), restricted (drafting with disclosure) and prohibited (submitting generated analysis as one's own).	School leadership with faculty	Before next intake
2 Displaced preparation	Use a commit-first routine: students write a short position on the case, by hand or in class, before using any tool. Open class with cold calls and follow-up questions. Ask for brief annotated reading notes.	Faculty	Next term
3 Unproven verification	Set "audit the AI" tasks in which students check a generated answer against the case and course sources and report the errors they found. Include source checks in marking.	Faculty	Next term

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4 Policy gap	Co-write the policy with students, since 93 of them asked for one. Require a short disclosure of tools used on submitted work. Base integrity decisions on drafts, notes and a conversation, never on a detector score alone. Publish how cases are handled.	School leadership, student reps	Within one semester
5 Unequal access	Provide a vetted, institution-supported tool for every student, and name acceptable free alternatives. Make sure study spaces have reliable power and connectivity.	School leadership, IT	Within one academic year
6 Assessment validity	Shift a meaningful share of assessment to oral defences, live cases, supervised components and projects using local data. Use peer evaluation and a short oral check on group work.	Faculty, programme directors	Phased over a year
All	Train staff in AI-aware course design, and repeat this survey each year with added items on assessment, group work, tool types and reasons for the fairness rating.	Learning innovation unit	Ongoing

For students. A single question before each use can help: is this removing effort that does not matter for what I need to learn, or effort that does? Form a view first. Check every fact and every reference. Keep your drafts. The person who has to defend the analysis in class on Monday morning is you.

For researchers. The next step is to move beyond self-reported frequency towards comparisons of outcomes, such as performance on later unaided tasks under different AI conditions, in the way Bastani et al. (2025) did. African institutions are under-represented in this literature, and a well-designed study at a single school is a real contribution.

8. LIMITATIONS

Several limits should be kept in mind. The sample was reached by convenience and respondents chose to take part, so it may over-represent students who are comfortable with AI or keen to see a policy (Etikan et al., 2016). The data are self-reported and, on questions about socially approved behaviour such as verification, may be flattering (Nederhof, 1985; Podsakoff et al., 2003). Item-level answer counts varied from 63 to 96, and item 17 was answered by only 63 people, so it may not represent the third of the sample who skipped it. I worked from tallies, not individual records, so I could not cross-tabulate, for instance, programme by AI use.

The sample is also unusual. Everyone reported 0 to 2 years of experience and English as a first language, and three quarters were in one programme. Findings may not transfer to part-time executive students with long careers, and the argument that AI helps second-language writers could not be tested here because respondents were all first-language English speakers. Finally, one school at one moment cannot speak for Nigerian universities in general, and tools and habits are changing quickly.

9. CONCLUSION

LBS students use AI constantly, mostly for the tasks closest to assessment, and they know it costs them some of the reading, even as their confidence in their own analysis has risen. They also believe the school's rules are unfairly applied and that access is uneven, and they overwhelmingly want a better policy. None of that is a call to ban the tools. Students find them useful, and the better evidence says that outcomes depend on how the interaction is designed (Bastani et al., 2025).

Generative AI has made it cheap to produce something that looks like learning. It has not made it cheap to learn. The problems identified here sit within the school's own control: how preparation is structured, how assessment is designed, how clearly and fairly the rules work, and who can afford to take part. The next piece of evidence the school needs is not another survey of how often students use AI. It is evidence on what happens to their understanding when they do.

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APPENDIX A. QUESTIONNAIRE ITEMS

Respondents were told the survey was anonymous and voluntary. Items 5 to 10 used a frequency scale (never, rarely, sometimes, often, always); items 11 to 19 used a five-point agreement scale (strongly disagree to strongly agree).

1. Programme: MBA / Master in Management / Doctoral / Executive programme / Other

2. Mode of study: Full-time / Part-time / Modular

3. Years of professional experience: 0-2 / 3-5 / 6-10 / 11+

4. First language: English / Other

5. I use AI tools to summarise readings or cases.

6. I use AI tools to prepare answers for case discussions.

7. I use AI tools to draft or edit written assignments.

8. I use AI tools in group projects.

9. I use AI tools to quiz myself or revise.

10. I form my own view of a case before consulting an AI tool.

11. AI tools help me understand difficult material better.

12. AI tools make me less likely to do the full reading.

13. I verify AI output against course materials or other sources.

14. I understand the school's rules on AI use.

15. The rules on AI use are applied fairly.

16. Students with better access to AI tools have an advantage.

17. My confidence in my own analysis has increased / stayed the same / decreased since I started using AI tools.

18. Cost of data or subscriptions limits my use of AI tools.

19. Power or connectivity problems limit my use of AI tools.

20. Open question: What one change to teaching or assessment would make AI use more helpful for your learning?

STATEMENTS & DECLARATIONS

Conflict of Interest:

The authors declare that they have no competing financial or non-financial interests.

Data Availability:

All experimental scripts, model architectures, and benchmark configurations are openly available as cited in the paper.

Ethical Approval & Consent:

Not applicable. No human participants or vertebrate animals were involved in this computational study.

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