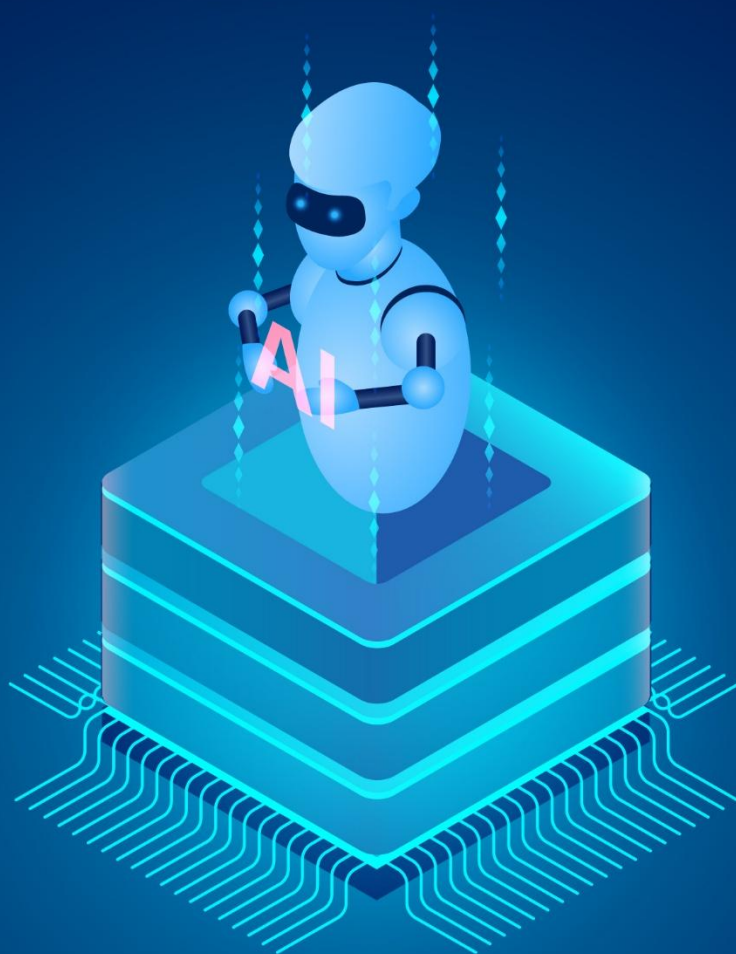


After Adoption: Use, Skill and Rules for Generative AI in Cambodian Higher Education

Evidence from Surveys of Students and Lecturers



Song Sopheak, Chunly Sereyvicheth,
Sak Sreynoch, Nou Sei Hak, and Ty Sokun Theary

Research Report
October 2026

After Adoption: Use, Skill and Rules for Generative AI in Cambodian Higher Education

Evidence from Surveys of Students and Lecturers

Song Sopheak, Chunly Sereyvicheth,
Sak Sreynoch, Nou Sei Hak, and Ty Sokun Theary



CDRI – Cambodia Development Resource Institute
Phnom Penh, October 2026

Editorial Committee:

Chief Editor: Eng Netra

Managing Editor: Khath Bunthorn

Associate Editor: Oum Chantha

© 2026 Cambodia Development Resource Institute (CDRI)

ISSN: 3136-327X (Print)

ISSN: 3136-3288 (Online)

DOI: <https://doi.org/10.64202/rr.202610>

Author(s) and affiliation(s):

Song Sopheak, Senior Director, Centre for Educational Research and Innovation, CDRI

Chunly Sereyvicheth, Director, Centre for Governance and Public Innovation, CDRI

Sak Sreynoch, Research Associate, Centre for Governance and Public Innovation, CDRI

Nou Sei Hak, Research Assistant, Centre for Educational Research and Innovation, CDRI

Ty Sokun Theary, Research Assistant, Centre for Educational Research and Innovation, CDRI

Disclaimer

The views expressed in this research report are those of the authors and do not necessarily reflect the views of the Cambodia Development Resource Institute. The authors are responsible for any unintentional errors or mistakes. Corresponding author: Song Sopheak, sopheak@cdri.org.kh.

Citation:

Song Sopheak, Chunly Sereyvicheth, Sak Sreynoch, Nou Sei Hak, and Ty Sokun Theary. 2026. *After Adoption: Use, Skill and Rules for Generative AI in Cambodian Higher Education: Evidence from Surveys of Students and Lecturers*. Research Report. Phnom Penh: CDRI.

CDRI

56 Street 315, Tuol Kork, Phnom Penh, Cambodia

+855 23 881 701/881 916/883 603

cdri@cdri.org.kh

www.cdri.org.kh

Table of contents

List of figures and tables.....	i
Acknowledgements	ii
List of acronyms and abbreviations.....	iii
Executive summary	iv
Key findings.....	iv
Policy recommendations	vi
1. Introduction	1
1.1. Research objectives	2
1.2. Research questions	2
1.3. Significance of the study	2
1.4. Key terms used in this paper	2
1.5. Organisation of the paper.....	4
2. Literature review and analytical framework	4
2.1. The Cambodian context	4
2.2. Use: from access to depth	5
2.3. Skill: AI literacy and the limits of self-report.....	6
2.4. Rules: academic integrity and institutional policy.....	7
2.5. The gap this study addresses.....	8
2.6. Analytical framework.....	8
3. Research methodology.....	10
3.1. Research design.....	10
3.2. Survey design and administration	10
3.3. What was measured and how.....	13
3.4. Analytical strategy	14
3.5. Ethics and data protection.....	14
3.6. Stakeholder validation.....	15
4. Key findings.....	15
4.1. How AI is used	15
4.1.1. Adoption, tools and plans	15
4.1.2. Frequency, devices and language.....	16
4.1.3. Purposes.....	17
4.1.4. Perceived benefits, outlook and barriers	18
4.2. Depth of use: who uses AI most	19
4.2.1. Differences between subgroups	19
4.2.2. Comparing like with like: what goes with frequent use	22
4.2.3. From occasional to intensive use	24
4.3. Skill: self-rated literacy and tested knowledge	24
4.3.1. How students and lecturers rate themselves	24
4.3.2. What students know.....	25
4.3.3. Self-rating and knowledge compared	26
4.3.4. Who rates themselves higher, and who knows more.....	27
4.4. Norms: where students and lecturers draw the line	27
4.4.1. Agreement on low-stakes uses, disagreement on assessed work	27
4.4.2. Views, perceived rules and behaviour	28
4.4.3. How lecturers are responding	28
4.5. Rules: how clear they appear.....	29
4.5.1. Awareness of a policy.....	29
4.5.2. Disagreement within institutions	29

4.5.3. Uncertainty about specific uses.....	30
4.5.4. What goes with clearer rules	31
4.6. The support students and lecturers ask for.....	32
4.7. Robustness analyses.....	33
5. Discussion	34
5.1. After access: differences in how AI is used	34
5.2. Moderate self-rated skills and a privacy gap	36
5.3. Lecturers: heavier users, uncertain rule-makers.....	36
5.4. Unwritten rules and unshared norms	37
5.5. Adoption ahead of institutions	38
5.6. Limitations and directions for future research.....	39
6. Conclusion and policy recommendations.....	40
6.1. Conclusions	40
6.2. Policy recommendations	42
References	44
Appendices	49
CDRI Working paper series	59

List of figures and tables

Figure 1: Analytical framework of the study	9
Figure 2: Selected indicators of AI use, students and lecturers (AI users).....	16
Figure 3: Frequency of AI use among students and lecturers (AI users).....	17
Figure 4: Purposes for which students use AI often or always (n = 1,485)	18
Figure 5: Biggest barriers to using AI, students and lecturers.....	19
Figure 6: Frequent AI use among students by subgroup (student AI users, n = 1,485)	20
Figure 7: Frequent AI use by field of study, and the access of students in each field (student AI users)	21
Figure 8: Frequent AI use among students by location, laptop ownership and prompt language (n = 1,485).....	22
Figure 9: Frequent AI use by number of disadvantages (student AI users)	22
Figure 10: Differences in the chance of frequent use among otherwise similar students (average marginal effects)	23
Figure 11: Predicted chance of frequent use for illustrative students.....	24
Figure 12: Agreement with the self-rated AI literacy items, students and lecturers (AI users) ...	25
Figure 13: Answers to the two knowledge questions (student AI users).....	26
Figure 14: Self-rated practice and tested knowledge on two matched topics (student AI users, n = 1,485).....	26
Figure 15: Share saying each use of AI by students is "not acceptable" (students n = 1,510; lecturers n = 285)	28
Figure 16: Whether the university has rules on AI use, as reported by students at twelve institutions.....	30
Figure 17: What respondents believe their university allows, for four uses of AI by students	31
Figure 18: Share of students seeing no clear rule on a contested use, by what they know of the rules	32
Figure 19: Training topics wanted by students and lecturers who did not reject training (students n = 1,332; lecturers n = 267)	33
Table 1: Profile of the analytical sample: students (n = 1,510)	11
Table 2: Profile of the analytical sample: lecturers (n = 285).....	12
Table A1: Survey items used in the analysis.....	49
Table B1: Binary logistic regression: frequent AI use (several times a week or daily)	51
Table B2: Multinomial logistic regression: intensity of use (reference: Occasional)	51
Table B3: Correlates of self-rated literacy and of two knowledge items (student AI users)	52
Table B4: Binary logistic regression: perceiving no clear rule on at least one contested scenario	52
Table B5: Headline results under alternative sample definitions	53
Table C1: AI use among students and lecturers	55
Table C2: Self-rated AI literacy items (AI users)	55
Table C3: Tested knowledge items (student AI users, n = 1,485).....	56
Table C4: Four uses of AI by students: own view and perceived university rule (students n = 1,510; lecturers n = 285)	57
Table C5: AI use and access by field of study (student AI users)	58

Acknowledgements

This study was carried out under *Building Regional Partnership for Higher Education Innovation*, a project funded by the Lancang-Mekong Cooperation Special Fund, as part of its programme *Leveraging AI for Research and Innovation*. We are grateful to the universities and institutes that shared the surveys with their students and staff, and to the students and lecturers who gave their time to answer them. The institutions are not named, to protect the confidentiality promised to respondents. We thank Touch Sou Hong and Meng Kimchhiv for their support in data collection. We also thank the 17 participants in the validation workshop of 16 October 2026, whose comments on the draft findings and recommendations improved this paper, and Matthew McCartney and Khath Bunthorn for reviewing an earlier version. The views expressed are those of the authors and do not necessarily reflect those of CDRI or the funder.

List of acronyms and abbreviations

Acronym	Meaning
AI	Artificial intelligence
AILS	Artificial Intelligence Literacy Scale
CADT	Cambodia Academy of Digital Technology
CDRI	Cambodia Development Resource Institute
GenAI	Generative artificial intelligence
HEPI	Higher Education Policy Institute (United Kingdom)
IT	Information technology
MOEYS	Ministry of Education, Youth and Sport
MoH	Ministry of Health
MPTC	Ministry of Post and Telecommunications
NIS	National Institute of Statistics
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
pp	Percentage points
RGC	Royal Government of Cambodia
STEM	Science, technology, engineering and mathematics
UNESCO	United Nations Educational, Scientific and Cultural Organization
UNITWIN	University Twinning and Networking Programme (UNESCO)

Executive summary

Generative artificial intelligence (AI) is now part of study and teaching in Cambodian universities. Within four years of the public release of ChatGPT, tools that draft, translate, summarise and explain have come into use among almost all of the students and lecturers surveyed for this paper. National government policy has begun to respond: the Education Strategic Plan 2024–2028 addresses digital education, and a national AI strategy is in draft. Some institutions have also begun to set their own rules. What has been missing is evidence on three questions: what students and lecturers actually do with these tools, how well equipped they are to use them, and what rules they believe apply.

This paper answers those questions with two matching online surveys that the Cambodia Development Resource Institute (CDRI) ran in September and October 2026, one of students and one of lecturers. After data cleaning, the analysis covers 1,510 students and 285 lecturers at more than 20 higher education institutions in Phnom Penh and six provinces. Many questions were asked of both groups, so their answers can be compared directly. Students also answered two questions that have a correct answer, so that what they know can be set beside how they rate their own skills. The analysis combines descriptive statistics with statistical models that compare students who are otherwise alike. The sample was not drawn at random: institutions were chosen on purpose and respondents decided for themselves whether to take part, so the results describe these respondents and are not national estimates. All answers are self-reported. The draft findings were reviewed with 17 participants at a stakeholder validation workshop in October 2026.

The starting point is that AI use is near-universal: 98.3 percent of students and 94.4 percent of lecturers have used AI for study or work. An online survey about AI is likely to attract users, so these figures are probably an upper bound, but earlier Cambodian studies also found that between 85 and 90 percent of students had used AI. The question for policy is therefore no longer whether AI will be used in Cambodian higher education, but whether students, lecturers and institutions are equipped for a practice that is already widespread. The findings below take up that question in turn: how AI is used, how well students can use it, what rules they and their lecturers believe apply, and what support both groups ask for.

Key findings

Use is near-universal, free and mobile. ChatGPT (89.4 percent of student users) and Google Gemini (83.6 percent) are the main tools. Three-quarters of students use AI mainly on a smartphone, and 95.1 percent rely on free versions. Lecturers use the same tools more often: 62.1 percent use AI several times a week or daily, compared with 46.2 percent of students. Some 30.9 percent of lecturers who use AI pay for a subscription, almost always from their own pocket.

Where students differ is in how much they use AI, and the heaviest use goes with the best access. Frequent use, meaning use several times a week or daily, is reported by 51.6 percent of students in Phnom Penh and 35.4 percent in the provinces. It is reported by 65.7 percent of those whose main device for AI is not a smartphone (mostly a laptop) and 39.9 percent of those who rely on a smartphone, and by 57.0 percent of those who prompt mostly in English against 33.5 percent of those who prompt mostly in Khmer. These gaps remain when students who are otherwise alike are compared: location, main device, length of experience and prompt language each stay linked to frequent use, as does a paid plan, although that link is less certain. Whether the institution is public or private makes no clear difference. The disadvantages also tend to fall on the same students. Among students with none of four disadvantages (a provincial campus, a smartphone as main device, prompting mostly in Khmer, no laptop), 70.5 percent are frequent users; among those with all four, 22.8 percent are, although this simple comparison does not

allow for differences in experience. Women are as likely as men to be frequent users despite weaker access to devices, and more likely among students with the same access.

Skills are rated as moderate, and data privacy appears to be a gap. On a five-point scale, the average self-rating is 3.61 for students and 3.74 for lecturers, and nine in ten students rate themselves between 3 and 4.5. Most students say they check, and most know what checking a reference involves: 82.2 percent say they check an AI answer before using it, and 75.1 percent know that the first step with a reference supplied by AI is to check that it exists. This knowledge differs little by location, device or language. Whether students act on it is a separate question: the survey observed checking only through students' own reports, and participants at the validation workshop doubted that many do it in practice. Privacy appears to be less well understood, although this rests on a single question. Only 45.9 percent know that the company running a tool can see text pasted into it, and 35.2 percent believe that only they can see it; half of the students who say they pay attention to privacy risks get this question wrong. Students are also unsure of their own judgement: only 40.4 percent agree that they can tell whether information from an AI tool is accurate, and 54.1 percent neither agree nor disagree.

Students and lecturers draw the line in different places. On low-stakes uses, such as explaining a concept or translating, the two groups agree. They differ on assessed work. Asked whether it is acceptable for a student to use AI to answer a take-home exam or online quiz, 47.4 percent of lecturers say it is not, compared with 24.5 percent of students; for writing large parts of an assignment, the figures are 41.8 and 29.5 percent. Lecturers judged students' use while students judged their own, so part of the gap may reflect the different wording.

The rules are unclear to the people they apply to. Only 21.5 percent of students and 17.2 percent of lecturers say their university has a formal written policy on AI. The survey recorded what respondents know of their university's rules; it did not check institutions' own policy documents. Students at the same university give different answers: in none of the twelve institutions with enough respondents is any single answer given by more than two-thirds of students. On the two contested uses, take-home exams and writing large parts of assignments, nearly half of students (47.4 percent) and more than half of lecturers (55.8 percent) see no clear rule for at least one. Uncertainty differs little between universities, but it is lower where lecturers explain the rules in class and where students know of a written policy. Both links rest on students' own reports, and the second is partly to be expected, since students who know of a policy are likely to find the rules clearer.

Lecturers appear to be adapting largely on their own. Some 85.9 percent of lecturers who use AI say colleagues or department heads encourage or expect them to use it, yet seven in ten are encouraged or expected to do so without knowing of a written policy. Their own use of AI also goes with their views on students' use: among lecturers who often use AI to mark or give feedback, 23.8 percent consider it acceptable for students to write substantial parts of an assignment with AI, against 4.4 percent of those who rarely or never do. This result rests on small groups and is tentative, but where rules are set course by course, the standard a student meets may depend partly on each lecturer's own views and practice.

Demand for support is high and specific. Some 80.4 percent of lecturers and 56.1 percent of students want training, and both groups rank writing effective prompts first and checking accuracy second. Half of the lecturers who are open to training are both willing and ready to train their colleagues. The cost of paid tools is the barrier mentioned most often (59.7 percent of students, 71.6 percent of lecturers), followed by tools that do not work well enough in Khmer (51.9 and 45.6 percent).

Policy recommendations

These findings point to a small set of measures, most of which build on what institutions and lecturers already do. Participants at the validation workshop judged a short written policy, a statement of permitted AI use in every course, and teaching data privacy and accuracy to be the most urgent.

Write the rules down and say them aloud. Each institution should adopt a short written policy that states what use of AI is allowed, restricted and prohibited in assessment, and should require lecturers to state the rule for each course and explain it in class. Students who know of a written policy, and those whose lecturers explain the rules in almost all classes, are clearly less likely to be uncertain.

Agree on what is acceptable before enforcing rules. Students and lecturers disagree most on take-home exams and on drafting large parts of assignments. Institutions should settle these two cases clearly, with students involved, before applying sanctions, and should review how such work is assessed where an agreed rule cannot be upheld. Sanctions should not rest on AI-detection scores alone, since independent tests have found such tools inaccurate and biased against writers of English as a foreign language (Liang et al. 2023; Weber-Wulff et al. 2023).

Teach data privacy and how to judge accuracy. Training should cover what happens to text pasted into a tool and how to judge whether an AI answer is accurate, the two points on which students are least informed or least sure. Lecturers need the same attention: one in seven have entered sensitive student data into an AI tool. Because few people ask for training on privacy, it is best built into training on prompting and checking accuracy, the topics both groups want first, and tested with questions that have right answers rather than by self-rating.

Design for the phone and for Khmer. Guidance, training and any institutional tools should work for students whose only device is a smartphone and who work mainly in Khmer, since these are the students who currently use AI least intensively.

Treat cost as a fairness issue. Paid plans are bought privately, and four in ten students say they cannot afford them. In the authors' judgement, access provided or negotiated by institutions could narrow the gap between those who can pay and those who cannot, if access for students is directed first at those with the weakest access. The link between a paid plan and frequent use is tentative and may partly reflect frequent users choosing to pay, and the cost of such access has not been estimated.

Build on lecturers' readiness. A programme that starts with lecturers who are willing and ready to train colleagues, prepares those who are willing but not yet ready, and uses the hands-on workshops lecturers prefer would build on capacity that already exists. Together, these measures would help institutions catch up with a practice that students and lecturers have already adopted on their own.

1. Introduction

The Royal Government of Cambodia has committed the country to a digital transformation of its economy and public institutions. The Digital Economy and Society Policy Framework 2021–2035 sets the direction (RGC 2021), and the Education Strategic Plan 2024–2028 applies it to education under the heading of digital education (MOEYS 2024). Artificial intelligence has moved quickly up this agenda. A draft National Artificial Intelligence Strategy 2025–2030, dated June 2025, puts human resource development first among its priorities (MPTC 2025).

These national policies respond to a change that has already happened on university campuses, in Cambodia and worldwide. Generative AI tools became freely available at the end of 2022 and spread among students within two academic years. In the United Kingdom, the share of undergraduates using AI rose from 66 percent in 2024 to 92 percent in 2025 (Freeman 2025). A survey of 3,839 students in 16 countries found that 86 percent used AI in their studies (Digital Education Council 2024). Institutions have been slower. A UNESCO survey of more than 450 schools and universities in May 2023 found that fewer than 10 percent had formal guidance on generative AI (UNESCO 2023). In a 2025 survey of respondents from UNESCO Chairs and UNITWIN Networks in 90 countries, 19 percent said their institution had a formal AI policy, and a further 42 percent said guidance was being developed (UNESCO 2025b).

Two wider debates give this change its weight. The first is about who gains from a new technology. Generative AI could narrow gaps: in a study of 5,172 customer-support agents, AI assistance raised productivity by 15 percent on average, with the largest gains for less experienced and lower-skilled workers (Brynjolfsson, Li, and Raymond 2025). But gains are shared only if adoption is. Among workers in Denmark, women were 16 percentage points less likely than men to have used ChatGPT for work, and those who adopted it already earned slightly more (Humlum and Vestergaard 2025). Who benefits from a new technology has historically depended on institutions and choices, not on the technology alone (Acemoglu and Johnson 2023). The second debate is about what AI does to learning. In a field experiment with nearly 1,000 high school students in Turkey, unrestricted access to a standard GPT-4 interface raised scores during practice, but once access was removed these students did worse than those who never had it; a version designed to tutor rather than give answers largely avoided this harm (Bastani et al. 2025). Both debates raise the same questions for universities: whether every student has the same chance to use AI well, and whether it is used under rules and with skills that build learning rather than replace it. Cambodia, a lower-middle-income country whose national language appears to be less well served by current models than English, is a useful setting in which to ask them.

For Cambodia, the evidence is thin. The published studies are recent and small. They include a survey of 370 undergraduates at three universities in Battambang (Hoeurng et al. 2024); two studies applying technology-acceptance models to 256 and 421 students (Be, Tep, and Long 2026; Lork et al. 2026); a survey of 301 students relating AI adoption to perceived learning outcomes (Huy et al. 2026); a qualitative study of English majors (Pum 2025); a review of 16 documents that called for empirical research and ethical guidelines (Pum and Sok 2024); and an online survey of 150 lecturers on their use of AI tools and the challenges and opportunities they see (Heng et al. 2026). A larger survey by the Cambodia Academy of Digital Technology (CADT) covered 476 lecturers and 921 students at 20 universities, but as far as we could find it has been published only as a short summary, in the national AI readiness assessment (UNESCO 2025a). None of the peer-reviewed studies we identified asks students and lecturers the same questions. None tests what students know, as distinct from what they say they can do, and none examines how institutional rules are perceived.

This paper addresses that gap and aims to provide evidence for institutional and national policy on AI in higher education. It reports two matching surveys, one of students and one of lecturers,

that CDRI ran in September and October 2026 at more than 20 higher education institutions in Phnom Penh and six provinces.

1.1. Research objectives

Earlier Cambodian studies found that most students already use AI (Hoeurng et al. 2024; Sol, Heng, and Sok 2025). The paper therefore does not set out to explain why people adopt AI. It asks whether students, lecturers and institutions are equipped for a practice that is already widespread. The paper has three objectives, one for each of the conditions on which beneficial use depends.

1. Use. To describe how students and lecturers use AI and to identify who uses it in depth.
2. Skill. To assess how students and lecturers rate their own AI skills, and to compare students' ratings with what they know on two points: verifying a reference and data privacy.
3. Rules. To establish where students and lecturers draw the line on acceptable use, and how clear institutional rules seem to them.

Throughout, students and lecturers are compared on questions asked of both groups. For lecturers, the paper also describes how they are adapting teaching and assessment and how ready they are to train colleagues. The support that both groups say they want is reported as the basis for the policy recommendations.

1.2. Research questions

1. How do students and lecturers in Cambodian higher education use AI, and which students use it most intensively?
2. How do students and lecturers rate their AI skills, and what do students know about checking AI output and about data privacy?
3. How do students and lecturers differ on what counts as acceptable use of AI, and how clear and consistent do institutional rules seem to them?
4. What do these patterns mean for institutional and national policy on AI in higher education?

1.3. Significance of the study

The study contributes to research in three ways. First, to our knowledge, it provides the largest body of survey evidence so far on generative AI in Cambodian higher education by number of respondents, covering institutions in both the capital and the provinces, and the first study in Cambodia to report in full a comparison of students and lecturers on matching questions. Second, it brings together three bodies of research that are usually separate: work on digital divides in use and skill, work on AI literacy, and work on academic integrity and institutional AI policy. Third, it adds two measurement features that are uncommon in the studies reviewed here. It pairs self-rated skill with knowledge questions that have a correct answer. It also asks students and lecturers about the same four scenarios twice: once for their own view and once for what they believe their university allows.

For policy, the timing matters. Institutions are drafting AI policies, and the national strategy is not yet final. Evidence on where students and lecturers already agree, where they do not, and what they do not know can make those documents more precise.

1.4. Key terms used in this paper

These terms are used throughout the paper.

Depth of use. How much a person uses AI: how often (frequency) and for how many purposes (breadth). The paper measures it in two ways, as frequent use and as the three intensity groups below.

Frequent use. Using AI several times a week or daily.

Intensity of use. Three groups of student users: occasional (monthly or less), focused (weekly or more, with at most two purposes used often or always) and intensive (weekly or more, with three or more purposes used often or always).

Digital divide. Differences between groups of people in how they relate to a digital technology. Research separates three levels: access (whether people have the technology), use and skills (what they do with it and how well), and outcomes (who benefits). This paper is mainly about the second level.

AI literacy. The knowledge and skills needed to use AI tools well and responsibly, including judging whether their output is correct. Here it is measured in two ways: by respondents' ratings of themselves and, for students, by two questions with a correct answer.

Prompt. The instruction or question that a user types into an AI tool. Prompt language is the language in which a student mostly writes prompts.

Data privacy. Control over personal or confidential information, including who can see, store or use the text that a person enters into an AI tool.

No clear rule. A respondent answers "there is no clear rule" or "don't know" when asked whether their university allows a given use of AI.

Comparing like with like. Many characteristics go together; for example, provincial students are also more likely to rely on a phone and to prompt in Khmer. The statistical models in this paper (regressions) compare students who are alike in all the other characteristics measured. In this way, a difference linked to one characteristic is not simply another characteristic in disguise. The models show associations, not causes.

Percentage points. The difference between two percentages. A rise from 40 to 50 percent is a rise of 10 percentage points.

Statistical significance. Stars in the tables (*, **, ***) mark differences that are unlikely to be due to chance in samples of this size. They say nothing about whether a difference is large or important.

Standard deviation. A measure of how widely answers are spread around the average. On the overall self-rating score for students, it is 0.44 points on a five-point scale.

Average marginal effect. The difference, in percentage points, in the chance of an outcome that goes with one characteristic among otherwise similar students. The percentage-point differences reported for otherwise similar students (for example in Section 4.2.2) are of this kind.

R² and pseudo R². The share of the differences between respondents that a model explains, from 0 (none) to 1 (all). Pseudo R² is a rough equivalent for yes-or-no outcomes. Low values mean that most of the differences lie in things the survey did not measure.

Intraclass correlation. The share of the differences between respondents that lies between institutions rather than within them. A value of 0.06 means that 6 percent of the differences are between institutions.

1.5. Organisation of the paper

The rest of the paper has five chapters. Chapter 2 introduces the Cambodian context, reviews the literature and sets out the analytical framework. Chapter 3 describes the surveys, the variables, how the data were analysed and how the draft findings were discussed with stakeholders at a validation workshop. Chapter 4 presents the findings in the order of the three objectives, followed by the support respondents ask for and a set of robustness checks. Chapter 5 discusses the findings, the limitations of the study and directions for future research. Chapter 6 concludes and sets out policy recommendations.

2. Literature review and analytical framework

2.1. The Cambodian context

Cambodian higher education has grown quickly from a small base. The number of higher education institutions rose from 8 in 1997 to 128 in 2021 (Bhatta et al. 2024) and to 194 in 2023–24, 79 public and 115 private, overseen by 17 ministries and institutions. In that year, 316,105 students were enrolled, 82 percent of them in bachelor's programmes, and the gross enrolment ratio for those aged 18 to 22 was 19.1 percent (MOEYS 2025). Enrolment is much lower in rural areas: in 2019, the ratio was 10 percent in rural areas against 30 percent in urban areas (Bhatta et al. 2024). Business and law account for almost half of associate and bachelor's students (46.9 percent), and only one in nine staff at institutions under the Ministry of Education, Youth and Sport (MOEYS) hold a doctorate (11.1 percent) (MOEYS 2025).

Access to higher education and to digital technology is uneven along lines that matter for this study, though not always in the expected direction. Women now make up just over half of higher education students (52.5 percent in 2023–24), and their gross enrolment ratio is higher than men's (20.8 against 17.4 percent) (MOEYS 2025). Household survey data for 2019 still showed men ahead (16.5 against 13.8 percent; Bhatta et al. 2024). Women remain a minority in postgraduate study (36 percent of master's and 10 percent of doctoral students) and in science, technology, engineering and mathematics (STEM): 23.3 percent of women in associate and bachelor's programmes study a STEM major, against 47.9 percent of men (MOEYS 2025), so that about twice as many men as women choose one (Chea et al. 2026). Internet connections have grown quickly, but not evenly. By October 2025, there were an estimated 12.0 million internet users, 67.3 percent of the population, and mobile connections equal to 121 percent of the population (Kemp 2025). Yet only 10 percent of households own a computer, and men are more likely than women to own a mobile phone (91 against 85 percent) and to have used the internet (NIS, MoH, and ICF 2023).

Cambodia's digital policies are recent. The Digital Economy and Society Policy Framework 2021–2035 rests on two foundations, digital infrastructure and trust, and three pillars: digital citizens, digital government and digital businesses (RGC 2021). Policy on AI itself is still taking shape. Nationally, the draft National Artificial Intelligence Strategy 2025–2030 names education first among its priority sectors for adopting AI, but at the time of writing it had not been adopted (MPTC 2025). The ministry's review of the 2023–24 academic year reports progress on digital learning in higher education, including an online course network joined by 17 institutions and six new majors in digital technology, but does not mention guidance on the use of AI in teaching or assessment (MOEYS 2025). A national AI readiness assessment, led by CADT with UNESCO and MPTC, recommended investing in teacher training and bringing digital skills into the curriculum. It also reported that 12 of 18 public universities actively encouraged lecturers to use AI tools in their teaching (UNESCO 2025a). In public administration, a World Bank survey of 60 governments found that Cambodia was one of five economies whose self-reported AI adoption was above the sample median while their self-reported governance and institutional readiness was below it; the

study's authors present this grouping as approximate (Lundy et al. 2026). Internationally, UNESCO's Recommendation on the Ethics of Artificial Intelligence, adopted by its member states in 2021, asks governments to provide AI literacy education at all levels to reduce digital divides (UNESCO 2021). None of these documents sets rules for the use of AI in university teaching and assessment. They set priorities and principles and leave rules on teaching, assessment and academic integrity to each institution.

This context allows some expectations to be set out before the findings. If generative AI follows earlier technologies, its use should be lower in the provinces than in Phnom Penh, lower among students without a computer and, given the gender gaps in phone ownership, internet use and fields of study, lower among women. Students who work mainly in Khmer may also be at a disadvantage, since current models appear to serve Khmer less well than English (Section 2.2). Chapter 5 compares the findings with these expectations.

2.2. Use: from access to depth

Research on digital inequality separates several levels of divide. The first level concerns access to the technology itself (van Deursen and van Dijk 2019). The second, named by Hargittai (2002), concerns skills: among people who are all online, some are much better able than others to find what they need. Later work extended this second level to differences in what people do online. Evidence from the Netherlands showed that once nearly everyone was connected, differences reappeared in what people did online, following familiar lines of education and social position (van Deursen and van Dijk 2014). A third level concerns outcomes: who gains real benefits from use (van Deursen and Helsper 2015).

Two further points from this research matter directly for Cambodia. The first is about devices. Even where nearly everyone has access, material access remains unequal: the range of devices a person has shapes skills, uses and outcomes (van Deursen and van Dijk 2019). In Chile, people who go online only by mobile phone have lower skills and use the internet in fewer ways than those who also have a computer (Correa, Pavez, and Contreras 2020).

The second point is about language. Large language models work better in languages with plenty of training data. An evaluation of ChatGPT on seven tasks in 37 languages, from high-resource to extremely low-resource (languages with much or very little digital text), found that it generally did worse than models built for each task (Lai et al. 2023). Developers of a model for Southeast Asian languages reported that, under the system used by ChatGPT, Khmer text needed many times more tokens (the units in which models process text) than English. They also reported that their model did much better than ChatGPT-3.5 in Khmer, Lao and Burmese (Nguyen et al. 2023). This review found no dedicated test of chatbot quality in Khmer, so the size of the gap is uncertain. Still, a student who works mainly in Khmer is plausibly using a weaker tool than one who works in English.

Large surveys now show how widely students use generative AI. A study of 23,218 students in 109 countries and territories found that, between late 2023 and early 2024, they used ChatGPT mainly to brainstorm, summarise texts and find research articles (Ravšelj et al. 2025). A survey of more than 8,000 students at four Australian universities found that over 80 percent had used generative AI for study tasks and nearly half used it regularly. Most had learned to use it informally, not through their institution, and they had little trust in its factual accuracy (Chung et al. 2026).

Evidence from Southeast Asia is growing, but mostly models the intention to use AI rather than how much or how well it is used. In a survey of 1,117 students in Indonesia, facilitating conditions, such as access to resources and support, were the strongest determinant of the

intention to use ChatGPT, and intention in turn predicted use (Habibi et al. 2023). That emphasis on the conditions of access is close to the approach taken in this study.

Recent studies have begun to apply the idea of digital divides to generative AI. Beckman et al. (2025) describe a "GenAI divide" among university students and identify novice, cautious and enthusiastic users. Among 1,001 college students in the United States, gender, age, field of study and type of institution were linked to use. Non-native speakers of English were more likely than native speakers to use ChatGPT often for writing (Baek, Tate, and Warschauer 2024). There is less evidence on devices and language. In a convenience sample (people chosen because they were easy to reach) of 128 students in Uganda, those who used only a smartphone reported lower adoption of AI tools than those with a laptop. Internet access added little once device ownership was taken into account (Kakooza, Walugada, and Alege 2026). A plausible reason, discussed in Section 5.1, is that a phone is less suited than a laptop to sustained reading and writing. This review found no study that relates the language in which individual students write their prompts to how much they use AI.

Gender is a commonly reported line of difference, but the evidence is mixed. A survey of 1,041 undergraduates in the United Kingdom found that men and wealthier students used AI more often, and that STEM students were more familiar with AI than those in the arts and humanities (Freeman 2025). Among 2,692 students at a Norwegian university college, men reported more frequent use and a wider range of uses (Møgelvang et al. 2024). Among 5,894 students in Sweden, male students and those in technology and engineering reported higher use (Stöhr, Ou, and Malmström 2024). A systematic review of 30 studies concluded that male students generally report more frequent use and greater confidence, while female students approach the tools more cautiously. However, only a minority of the 30 studies measured how often students used AI (Matobobo 2026). The World Development Report 2026 cites a review of 76 studies that put the adoption of generative AI tools about 16 percent higher among men than among women in 2025. It also notes that in low- and middle-income countries, women are 13 percent less likely than men to own a smartphone (World Bank 2026).

Cambodian studies so far report widespread but not always intensive use. About 90 percent of 370 undergraduates in Battambang said they used AI tools for academic work, but only a third did so often (Hoeurng et al. 2024). About 90 percent of 328 university students of English had used AI tools, including translation and grammar tools, and some 70 percent had received no training in using them (Sol, Heng, and Sok 2025). A survey of 301 students found a moderate level of adoption (Huy et al. 2026). Other studies model students' intention to adopt AI and to keep using it. They measure this with agreement scales, not by how often or how widely students use AI (Be, Tep, and Long 2026; Lork et al. 2026).

For this study, the review suggests three choices. Because adoption is already high in Cambodia, use should be measured by its depth, combining frequency with breadth, rather than by whether students use AI at all. Because devices and language are the least studied lines of difference, both should be measured directly, including the language in which students write prompts. And because the evidence on gender is mixed and seldom allows for differences in access, gender should be examined both in the raw figures and among students with the same access.

2.3. Skill: AI literacy and the limits of self-report

Long and Magerko (2020) defined AI literacy as a set of competencies that lets people evaluate AI technologies critically, communicate and work effectively with AI, and use AI as a tool. Ng et al. (2021), reviewing 30 articles, proposed four aspects: know and understand, use and apply, evaluate and create, and ethical issues. International bodies have since issued frameworks. The Organisation for Economic Co-operation and Development (OECD) and the European Union published an AI literacy framework for schools in 2026, built around four domains: engaging with

AI, creating with AI, managing AI and shaping AI. One of its competences is to judge whether AI outputs should be accepted, revised or rejected (OECD and European Union 2026).

Measurement has lagged behind definition. A widely cited questionnaire is the Artificial Intelligence Literacy Scale (AILS) of Wang, Rau, and Yuan (2023). It is a twelve-item self-rating questionnaire covering four areas: awareness, usage, evaluation and ethics. Others followed, among them the Scale for the Assessment of Non-Experts' AI Literacy, with 31 items on technical understanding, critical appraisal and practical application (Laupichler et al. 2023). Most rely on self-report. A systematic review of 22 studies that tested 16 scales found thirteen self-report scales and only three performance-based ones, which test what people can do. None had been tested for validity across cultures (Lintner 2024). Performance tests now exist. One, a test of generative AI literacy, predicted performance on AI-supported tasks better than self-reported skill did (Jin et al. 2025).

Confidence and competence can therefore differ. In two samples of undergraduates in the United States, many students overestimated what chatbots can do, and those with more conceptual knowledge overestimated less (Rismanchian, Babar, and Doroudi 2026). Self-ratings also differ by gender: among 377 medical students in Germany, women rated their overall AI literacy lower than men did (Laupichler et al. 2024).

This gap matters in a particular way for generative AI. Chatbots produce fluent text that can be wrong. In one test, 55 percent of the citations generated by GPT-3.5 and 18 percent of those generated by GPT-4 were fabricated (Walters and Wilder 2023). A user who does not know this cannot guard against it, however confident they feel. Checking can be taught. In an experiment with 1,368 students in 65 course sections assigned at random, a 90-minute set of online modules improved knowledge of generative AI, of prompting and of checking facts and sources. It did not improve the evaluation of bias in output (Connell Pensky et al. 2026).

Two lessons follow for this study. Self-ratings alone cannot show what students know, so they should be paired with questions that have a correct answer, focused on errors that matter for generative AI, such as fabricated references and the handling of pasted text. And because many tested scales are long (31 items in one case) and none has been validated in Khmer, a short adapted scale is a practical choice, provided its limits are acknowledged.

2.4. Rules: academic integrity and institutional policy

Much of the early debate on generative AI in higher education was about academic integrity (Ying 2026). International guidance followed. UNESCO's guidance for generative AI in education and research called for a human-centred, age-appropriate approach and for the protection of data privacy (Miao and Holmes 2023). Practice in institutions has been uneven: a systematic review of 30 studies of university teachers found that general guidelines were lacking (Baggia, Tratnik, and Brezavšček 2026). By June 2023, 23 of the world's 50 top-ranking universities had published guidelines on generative AI and assessment. These covered academic integrity, the design of assessment and communication with students (Moorhouse, Yeo, and Wan 2023). Drawing on a survey of 457 students and 180 teachers and staff in Hong Kong, Chan (2023) proposed that an institutional AI policy should cover three dimensions: pedagogy (teaching and learning), governance (including privacy and accountability) and operations (including infrastructure and training).

Where policies exist, they are often not understood. Students at two universities in the United States recognised the policies set for their own classes but found institutional guidelines unclear (Jiang, Xie, and Cao 2025). In a survey of 200 students at a university in Singapore, those who understood the guidelines better were more likely to follow them and to declare their use honestly (Tan, Qu, and Wang 2025). A scoping review of 38 studies describes students as finding

their way through an ethical "grey zone", with notable gaps between their awareness of ethics and their actual practice (Ying 2026). The AI Assessment Scale was proposed precisely so that lecturers could state the permitted level of AI use for each task (Perkins et al. 2024).

Students and teachers do not necessarily share the same norms. Barrett and Pack (2023) compared 158 students at a university in the United States with 68 teachers from several countries. They found only minor disagreement overall, with students more accepting than teachers of submitting AI-generated work. About 94 percent of the teachers said their institution had no AI policy. A survey of 680 students and 87 educators at universities in Australia, Cyprus and the United States found that educators strongly preferred assessments adapted on the assumption that AI will be used, while students' reactions were mixed (Kizilcec et al. 2024). Lecturers themselves report being under-prepared. In a survey of 122 faculty members in Germany, lack of AI literacy among students and staff was named among the greatest challenges, and most wanted professional development (Mah and Groß 2024). A systematic review of 30 studies of university teachers found that they use generative AI mainly to prepare lessons, give feedback and carry out assessment used to support learning rather than to grade it (Baggia, Tratnik, and Brezavšček 2026). Technical enforcement offers no shortcut. In tests in 2023, tools that claim to detect AI-generated text were neither accurate nor reliable (Weber-Wulff et al. 2023). In another study, seven detectors wrongly classed essays by non-native English writers as AI-generated at an average rate of 61 percent (Liang et al. 2023). The second finding is a particular concern where students write in English as a foreign language, as many Cambodian students do.

For this study, the review points to measuring rules from both sides: what students and lecturers think is acceptable, and what they believe their institution allows. Asking both groups the same questions, as Barrett and Pack (2023) and Kizilcec et al. (2024) did, allows their norms to be compared directly.

2.5. The gap this study addresses

Three limitations run through the studies reviewed here. Most come from high-income settings, many of them English-speaking, and many rely on a single institution or a convenience sample. Most study one group, usually students. Most also rely on self-report to measure skill, and ask about attitudes to rules without asking what respondents believe the rules are. The Cambodian studies share these limits and are small.

Methods used elsewhere also suggest what to adopt and what to avoid. Studies built on technology-acceptance models explain the intention to use AI well but say little about how much or how well students use it, so this study measures reported behaviour rather than intention. Single-institution and convenience samples limit comparison, so this study draws on many institutions, while acknowledging that its sample, too, was not drawn at random.

The present study covers students and lecturers at more than 20 institutions in a country whose national language appears to be less well served by current models than English (Section 2.2). It measures use in enough detail to separate depth of use from simple adoption, and pairs self-rated literacy with tested knowledge. For the same scenarios, it records what both groups find acceptable and the rules as they understand them.

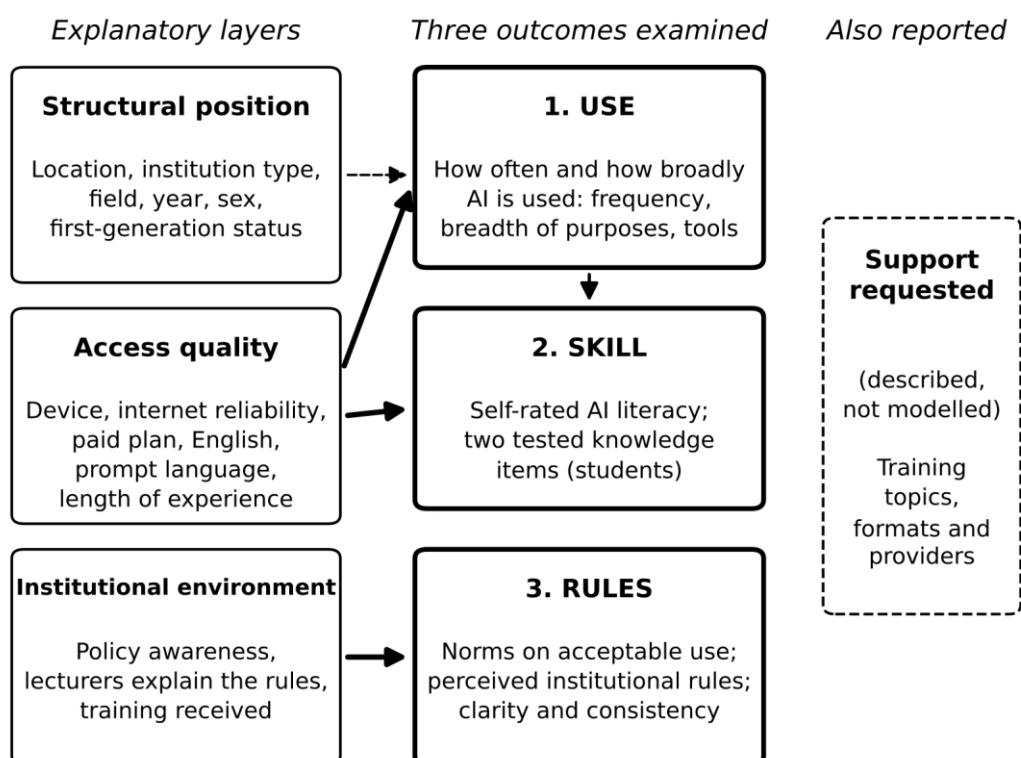
2.6. Analytical framework

The framework draws on the literature reviewed above and adapts it to the Cambodian context. It describes and organises: it shows where differences cluster, not what causes them. It groups the characteristics that might explain differences into three layers, each drawn from a strand of the review, and links them to three outcomes, one for each objective.

- **Structural position:** location (Phnom Penh or province), institution type, field of study, year of study, sex and whether the student is the first in the family to attend university. Research on digital divides links use to social position and, less consistently, to gender (Section 2.2); in Cambodia, gaps between urban and rural areas and between men and women (Section 2.1) make location and sex the first to examine.
- **Access quality:** the devices available and the main device used for AI, internet reliability, affordability and paid subscription, academic English, the language of prompts and the length of experience with AI (how long a student has been using it). These follow work on material access and mobile-only use (van Deursen and van Dijk 2019; Correa, Pavez, and Contreras 2020) and on how well models handle languages with little digital text, such as Khmer (Lai et al. 2023; Nguyen et al. 2023).
- **Institutional environment:** awareness of a university policy, whether lecturers explain the rules, and training received. These follow studies that link understanding of guidelines to following them (Tan, Qu, and Wang 2025) and that stress stating the permitted use of AI for each task (Perkins et al. 2024).

The three outcomes are intensity of use (how often and how widely AI is used), AI literacy (self-rated and tested) and views on acceptable use and the rules. They are treated as linked. Use is only as valuable as the skill behind it, and skill is used responsibly only within rules that users understand. The framework therefore expects access quality to matter most for use, both access quality and use to matter for literacy, and the institutional environment to matter most for clarity of rules. Figure 1 summarises the structure. The support that respondents ask for is reported alongside the three outcomes but is not analysed with statistical models.

Figure 1: Analytical framework of the study



Thick arrows: main expected associations (Section 2.6). Structural position is included in all models.

Students and lecturers compared on parallel items throughout.

Source: Authors.

3. Research methodology

3.1. Research design

The study is a cross-sectional survey (each person answered once, at one point in time) of two groups: students at higher education institutions in Cambodia, and lecturers who teach or have taught at such institutions in the past twelve months. The two questionnaires were built side by side so that core questions could be compared across groups. The design is quantitative, with no interviews. The findings were reviewed at a stakeholder validation workshop (Section 3.6). Open comments left at the end of each questionnaire are available but are not analysed in this paper.

3.2. Survey design and administration

The questionnaires were developed in English and Khmer and revised after two pilot rounds in August 2026. The pilots led to a reworded eligibility question for lecturers, symmetrical scales on the effects of AI, rephrased skill items, revised knowledge questions and checks on the quality of answers, such as a pledge to answer carefully and a fictitious tool in the list of tools; pilot answers are not analysed. Both questionnaires cover background, use of AI, skills, views on academic integrity, and support and barriers, and the lecturer questionnaire adds sections on teaching and assessment and on readiness to train colleagues.

Institutions were chosen on purpose (purposive selection) to cover public and private institutions in Phnom Penh and five provinces (Battambang, Siem Reap, Svay Rieng, Prey Veng and Kampong Cham); a few students from Tbong Khmum also responded. The surveys were run online through KoboToolbox, from 3 September to 6 October 2026 for students and from 4 September to 1 October 2026 for lecturers, using an open link sent out through contacts at each institution. Respondents may therefore be drawn more from students and staff who are engaged with their institution or with digital tools, which may raise the levels of use reported.

The student survey received 1,796 submissions and the lecturer survey 484. Cleaning removed those who did not consent, lecturer-survey respondents who did not teach in higher education, one duplicate and students under 18, leaving 1,707 students and 299 lecturers. The analytical sample also leaves out those who took under five minutes or gave the same answer to all fifteen skill items. It has 1,510 students and 285 lecturers, 93 and 71 percent of the study's targets, of whom 1,485 and 269 had used AI. Twenty-five lecturers resemble those removed as non-teachers but are kept; leaving them out changes no reported figure by more than about four percentage points.

Tables 1 and 2 describe the analytical samples. Students come from 22 institutions, 12 of which contribute 50 or more respondents, and lecturers from 17, 7 of which contribute 20 or more. Two-thirds of both samples are in Phnom Penh.

Table 1: Profile of the analytical sample: students (n = 1,510)

Characteristic	n	%
Sex		
Women	839	55.6
Men	636	42.1
Prefer not to say	35	2.3
Age		
19 or younger	450	29.8
20-21	708	46.9
22-23	236	15.6
24 or older	116	7.7
Year of study		
Year 1	156	10.3
Year 2	359	23.8
Year 3	440	29.1
Year 4	459	30.4
Year 5 or above	41	2.7
Postgraduate	55	3.6
Field (derived)		
STEM	760	50.3
Non-STEM	738	48.9
Not classifiable	12	0.8
Location		
Phnom Penh	1,011	67.0
Provinces	499	33.0
Institution type		
Public	1,220	80.8
Private	274	18.1
Not listed	16	1.1
First in family at university		
Yes	879	58.2
No	619	41.0
Unsure	12	0.8
Academic English		
Very limited or basic	398	26.4
Intermediate	929	61.5
Advanced or fluent	183	12.1
Devices available		
Own smartphone	1,406	93.1
Own laptop	935	61.9

Note: "Devices available" allows more than one answer. STEM is based on the reported field of study (IT, engineering, mathematics and science, health, agriculture).

Source: Authors' survey data, 2026.

Table 2: Profile of the analytical sample: lecturers (n = 285)

Characteristic	n	%
Sex		
Women	75	26.3
Men	209	73.3
Age		
Under 30	79	27.7
30-39	100	35.1
40-49	81	28.4
50 or older	25	8.8
Position		
Teaching assistant	28	9.8
Lecturer	225	78.9
Senior lecturer or professor	16	5.6
Other academic or management role	16	5.6
Highest qualification		
Bachelor's	52	18.2
Master's	203	71.2
PhD	30	10.5
Years teaching		
Less than 2	48	16.8
2-5	69	24.2
6-10	68	23.9
11-20	76	26.7
More than 20	24	8.4
Discipline (derived)		
STEM	173	60.7
Non-STEM	111	38.9
Location		
Phnom Penh	191	67.0
Provinces	94	33.0
Institution type		
Public	231	81.1
Private	47	16.5
Not listed	7	2.5
Employment		
Full-time	210	73.7
Part-time or hourly	75	26.3
Academic English		
Very limited or basic	21	7.4
Intermediate	177	62.1
Advanced or fluent	87	30.5

Source: Authors' survey data, 2026. Note: One lecturer who preferred not to state their sex and one whose discipline could not be classified are not shown in those rows.

The sample is not a probability (random) sample. Institutions were chosen, not drawn, and the number of people invited is unknown, so response rates cannot be calculated and no weights are applied. National figures for 2023–24 give a rough check. Women make up 55.6 percent of the students, close to their national share (52.5 percent), and 10.5 percent of the lecturers hold a doctorate, against 11.1 percent of staff at institutions under MOEYS. Students in STEM fields (50.3 against 33.8 percent, although definitions may differ) and full-time lecturers (73.7 percent, against about a third) are over-represented (MOEYS 2025).

3.3. What was measured and how

Appendix A gives the wording of the survey items (Appendix Table A1), and Appendix Table C3 gives the two knowledge items in full.

Three measurement decisions need explanation. First, the intensity grouping combines frequency of use with breadth (the number of purposes). The nine purposes of use rise and fall together closely (Cronbach's alpha 0.81, a measure of how consistently items move together), so their number serves as a summary of breadth. Differences in particular purposes, such as coding among IT students, are reported where relevant. Weekly use marks a habit, and three purposes is the first value above the median (middle) breadth of two. The grouping is a descriptive tool, and the models are also run on the simpler yes/no measure.

Second, the fifteen self-rated literacy items come from two sources. Ten were adapted from AILS (Wang, Rau, and Yuan 2023). This scale was chosen because it is short, written for general users rather than specialists, and covers four areas: awareness (D1–D3), usage (D4–D5), evaluation (D7–D8) and ethics (D9–D11). Two of the twelve AILS items were not used: one on using AI to work more efficiently (US_5) and one on choosing among the solutions offered by a smart agent (EV_3). The wording was adapted to study and teaching, and the response scale was shortened from seven points to five. After the pilots, the three negatively worded AILS items were rephrased positively in the student questionnaire. AILS was written before generative AI became widely available and has no items on checking output or on prompting. Five items were therefore written for this study: judging the accuracy of AI information (D6), checking AI answers against other sources and before use (D12, D13), giving an AI tool enough context and clear instructions (D14), and deciding when an answer should be accepted, improved or rejected (D15). They follow the competences on evaluating and guiding AI output in the OECD and European Union framework (OECD and European Union 2026). Among students, the ten adapted items and the five new ones each hang together well (alpha 0.82 and 0.78). The two sets are linked (correlation 0.62) and are combined in one index. In the lecturer questionnaire, two AILS items (D3, D5) and one new item (D13) were still negatively worded. Two of these are reverse-scored in the index, so that a higher score always means more skill. The third (accepting AI output that cannot be verified) was only weakly linked to the other items (item-rest correlation 0.13) and is left out. Neither AILS nor the adapted version has been validated in Khmer.

Third, two knowledge items were written for this study to test points that the self-rating items cover: checking a reference supplied by AI (D16) and knowing who can see text pasted into a tool (D18). Only students were asked them. The two items are almost unrelated to each other

(correlation 0.05), so they are reported one by one rather than added into a score. Two items cannot measure AI literacy as a whole; they show what students know on two specific points. D18 treats "me and the company that operates the AI tool" as the correct answer. Whether and how a company stores or reviews pasted text depends on the provider and on the user's settings. The item is therefore best read as a measure of awareness that pasted text leaves the user's control.

3.4. Analytical strategy

The analysis has four stages. The first describes use, skill, norms and perceived rules and compares students with lecturers on the questions asked of both (two-sample tests of proportions). The second asks which students are frequent and intensive users. It compares students who are alike in every other characteristic measured, using a logistic regression (a model for a yes/no outcome) for frequent use and a multinomial logistic regression for the three intensity groups. The third does the same for self-rated literacy (an ordinary least squares regression) and the two knowledge items. The fourth sets own views against perceived rules, measures agreement within institutions on whether a policy exists, and asks what goes with seeing no clear rule.

The models use the 1,193 student AI users who answered every question they include (Appendix Tables B1–B4). Most of those left out were unsure whether they had received training; treating "unsure" as a separate category leads to the same conclusions (Section 4.7). Standard errors are clustered by institution and were also recalculated leaving out one institution at a time. No conclusion about frequent use or the clarity of rules changes, but three other results lose statistical significance (private institution in Table B2; year 2 in the self-rating model and experience in the privacy-knowledge model in Table B3) and are treated as tentative, as are results significant only at the 5 percent level. Results describe associations among otherwise similar students, not causes. Lecturers are too few for such models and are reported descriptively. Analyses were run in Python.

3.5. Ethics and data protection

Taking part was voluntary. Each questionnaire began with information about the study, its purpose and how the data would be used, followed by a consent question. The introduction told respondents that taking part was voluntary and that they could stop at any time; that their answers were confidential and that their university, lecturers, colleagues or classmates would never see individual answers; and that results would be published only as group totals, with no individual named. The lecturer questionnaire added that no institution would be identified in the results. Respondents who did not consent were taken to the end of the form.

Names, telephone numbers, device identifiers, timestamps and "please specify" answers were removed before analysis. The analysis files are held by CDRI, and only the research team has access to them. Institutions are not named in this paper. Results for individual institutions are shown only for institutions with at least 50 student or 15 lecturer respondents, without the number of respondents at each. No result is shown for a subgroup of fewer than five lecturers.

3.6. Stakeholder validation

The draft findings and recommendations were reviewed at a validation workshop on 16 October 2026 with 17 participants from public and private universities and institutes. After a presentation of the findings, participants rated their agreement with each finding from 1 to 10 in an anonymous online poll, discussed the findings with the lowest or most divided scores, and chose the three recommendations they considered most urgent. The finding that drew most doubt was that most students know to check a reference supplied by AI (mean agreement 3.8 out of 10); demand for training and the barriers of cost and Khmer drew most agreement (8.4 and 8.2). The workshop was a check on how the findings read to people who work in the institutions concerned, not a test of them: where participants doubted a finding, the paper reports their view beside it, and no estimate was revised.

4. Key findings

The findings follow the three objectives. Section 4.1 describes how AI is used, and Section 4.2 examines who uses it in depth. Section 4.3 compares self-rated literacy with tested knowledge. Section 4.4 compares what students and lecturers find acceptable, and Section 4.5 examines how clear the rules appear. Section 4.6 reports the support that both groups ask for, and Section 4.7 the robustness checks.

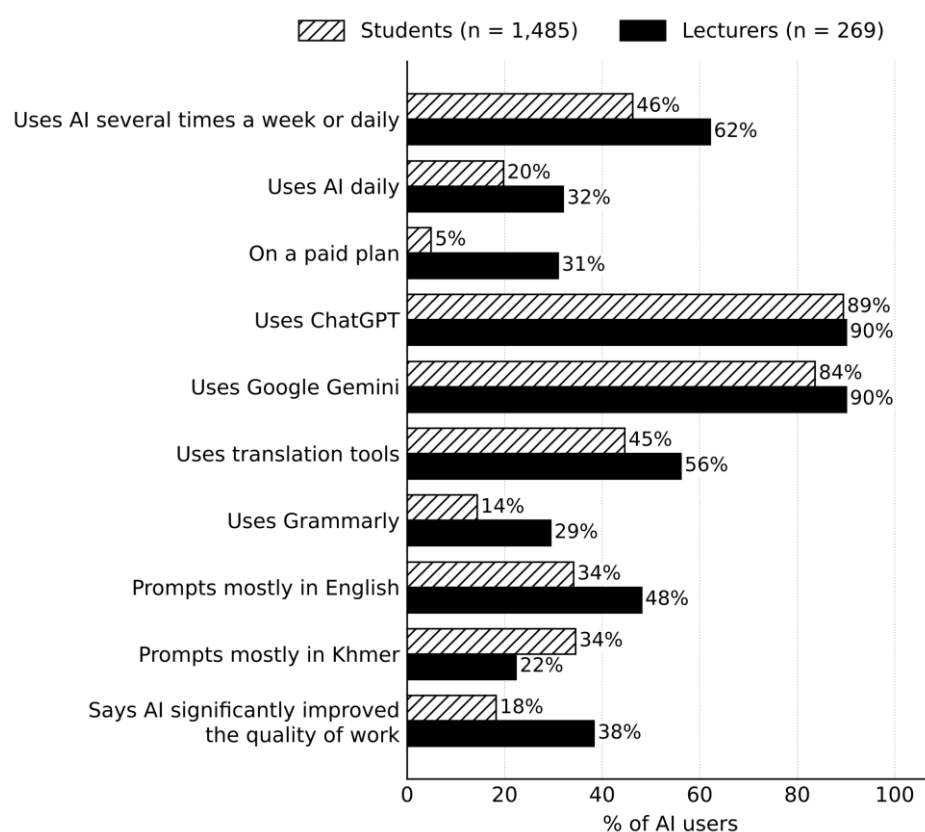
4.1. How AI is used

4.1.1. *Adoption, tools and plans*

Among respondents, almost everyone uses AI. Of the students in the analytical sample, 98.3 percent have used an AI tool for their studies. Of the lecturers, 94.4 percent have used one for academic or professional work. Only 25 students and 16 lecturers have not. More than half of student users (55.0 percent) have used AI for over a year, and 92.1 percent of them believe that most or almost all of their classmates use it.

Two products are used far more than any others (Figure 2; Appendix Table C1 gives the full comparison). ChatGPT is used by 89.4 percent of student users and 90.0 percent of lecturer users, and Google Gemini by 83.6 and 90.0 percent. Translation tools come third (44.6 and 56.1 percent). Lecturers use a wider range of tools: 3.94 on average, against 3.13 for students. They are also about twice as likely to use Microsoft Copilot or Grammarly.

Figure 2: Selected indicators of AI use, students and lecturers (AI users)

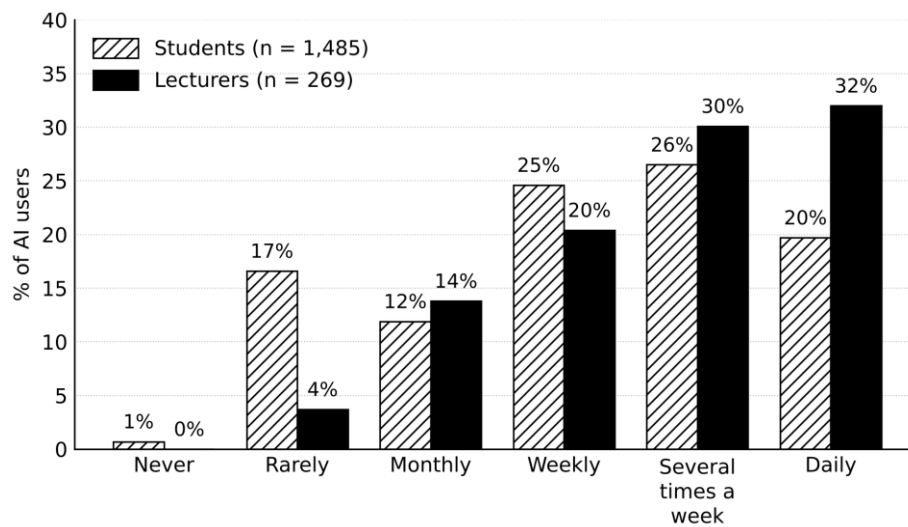


Source: Authors' survey data, 2026. Note: The quality item asked students about their academic work and lecturers about their teaching materials. Full comparison in Appendix Table C1.

The largest difference between the groups is in payment. Among students, 95.1 percent use free versions only. In addition, 41.6 percent say they cannot afford paid versions and a further 22.7 percent do not know what they cost. Among lecturers who use AI, 30.9 percent have a paid plan, and of those 83 lecturers, 95.2 percent pay from their own pocket. A quarter of students (24.8 percent) say the free versions are not enough for their study needs. Access has thus come largely through free tools and personal spending rather than through institutions.

4.1.2. Frequency, devices and language

Lecturers use AI more often than students (Figure 3). Among users, 32.0 percent of lecturers and 19.7 percent of students use it daily, and 62.1 and 46.2 percent use it several times a week or more. At the other end, 17.3 percent of students use it rarely or never, against 3.7 percent of lecturers.

Figure 3: Frequency of AI use among students and lecturers (AI users)

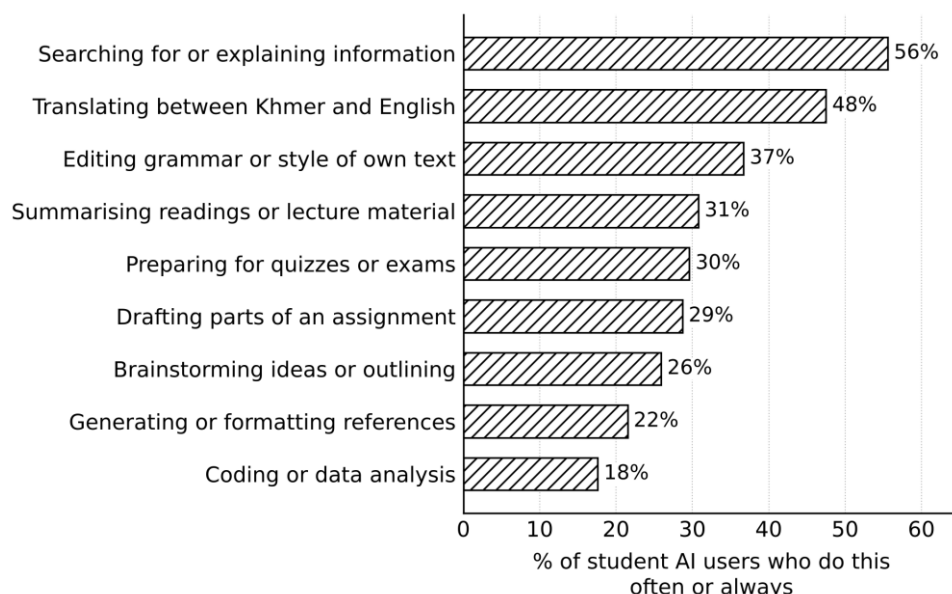
Source: Authors' survey data, 2026. Note: A few student users (0.7 percent) chose "never" for their current frequency of use.

For students, AI is used mainly on the phone. Of all 1,510 students in the sample, almost all own a smartphone (93.1 percent) and 61.9 percent own a laptop. Yet among student AI users, 75.5 percent name the smartphone as their main device for AI, and only 21.3 percent the laptop. Among all students, most connect through mobile data (83.7 percent); 54.4 percent use campus Wi-Fi and 37.2 percent home Wi-Fi. Just over half (54.4 percent) say their internet access is usually or very reliable.

Students divide almost evenly by language. About a third prompt mostly in Khmer (34.5 percent), a third mostly in English (34.1 percent) and a third in both (30.8 percent). Lecturers lean towards English: 48.0 percent prompt mostly in English and 22.3 percent mostly in Khmer. This matches English ability: 30.5 percent of lecturers and 12.1 percent of students rate their academic English as advanced or fluent. Because students rely so heavily on phones and many work in Khmer, what they can do with AI may depend on how well the tools work on a small screen and in Khmer.

4.1.3. Purposes

Students use AI mainly to understand and to translate (Figure 4). More than half (55.6 percent) often or always use it to search for or explain information, and 47.5 percent to translate between Khmer and English. Editing their own text comes next (36.7 percent). Uses that come closer to producing assessed work are less frequent but far from rare: 28.7 percent often or always use AI to draft parts of an assignment, and 29.6 percent to prepare for quizzes or exams. Coding or data analysis is the least common purpose (17.6 percent), and 30.9 percent never use AI for it. The drafting figure is students' own report of a use that bears on academic integrity, and it is likely to understate it. Participants at the validation workshop also described a practice that the survey did not ask about separately: pasting AI output into assignments with little change.

Figure 4: Purposes for which students use AI often or always (n = 1,485)

Source: Authors' survey data, 2026.

Lecturers were asked about five work tasks. Weekly or more often, 63.2 percent use AI for research or academic writing, 59.9 percent for preparing lectures or teaching materials, 50.2 percent for translation, 34.6 percent for administrative work and 23.8 percent for coding or data analysis. For both groups, most use supports understanding, preparation and translation; using AI to draft assessed work is less common but not rare, and it is where questions about rules arise (Section 4.4).

4.1.4. Perceived benefits, outlook and barriers

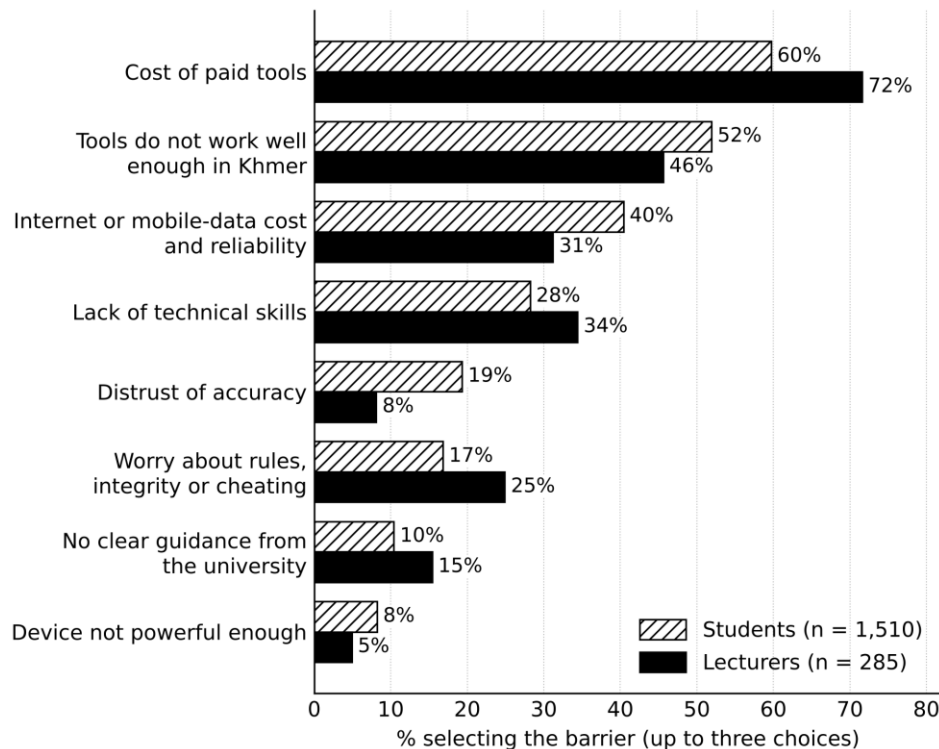
Both groups report clear benefits. Among student users, 94.1 percent say AI helps them finish coursework faster and 83.7 percent say it has improved the quality of their work. However, only 18.2 percent describe the improvement as "significant". Lecturers are more strongly positive: 92.6 percent say AI has reduced their workload and 38.3 percent that it has significantly improved their teaching materials. In each group, about seven in ten say that getting a useful result takes "some trial and error".

Lecturers are positive about AI but not relaxed. Asked how they feel about the pace of AI development, 43.5 percent say they are excited and well prepared, and 54.3 percent interested but overwhelmed. Six in ten (60.2 percent) expect AI to make teachers more valuable over the next five years, while 21.6 percent expect it to reduce the value of, or need for, human teachers. Asked whether AI is helping student learning more than harming it, lecturers divide between agreement (47.0 percent) and neutrality (47.7 percent). Most notice errors: 66.5 percent occasionally spot factual errors or hallucinations in AI output, and 23.8 percent do so frequently or almost always.

Asked to name up to three barriers, both groups put cost first and Khmer second (Figure 5). The cost of paid tools is named by 59.7 percent of students and 71.6 percent of lecturers, and tools that do not work well enough in Khmer by 51.9 and 45.6 percent. Third for students is the cost and reliability of the internet (40.4 percent), and third for lecturers is a lack of technical skills (34.4 percent). Few respondents see no need for AI (4.4 percent of students and 1.1 percent of lecturers). Few students name a device that is not powerful enough (8.2 percent) or a lack of clear university guidance (10.4 percent) as a barrier. Among students, cost is named most often by those who already use AI most: 76.3 percent of those whose main device for AI is a laptop and 67.6 percent of frequent users. For them, cost appears to limit how deeply they use AI rather than

whether they use it, although heavy users may also simply know more about what paid versions offer. Respondents thus see cost and the performance of tools in Khmer, more than devices or unclear rules, as what holds them back.

Figure 5: Biggest barriers to using AI, students and lecturers



Source: Authors' survey data, 2026. Note: Respondents could select up to three barriers. Wording differed slightly between the two questionnaires; lecturers were asked about barriers to using AI in teaching.

4.2. Depth of use: who uses AI most

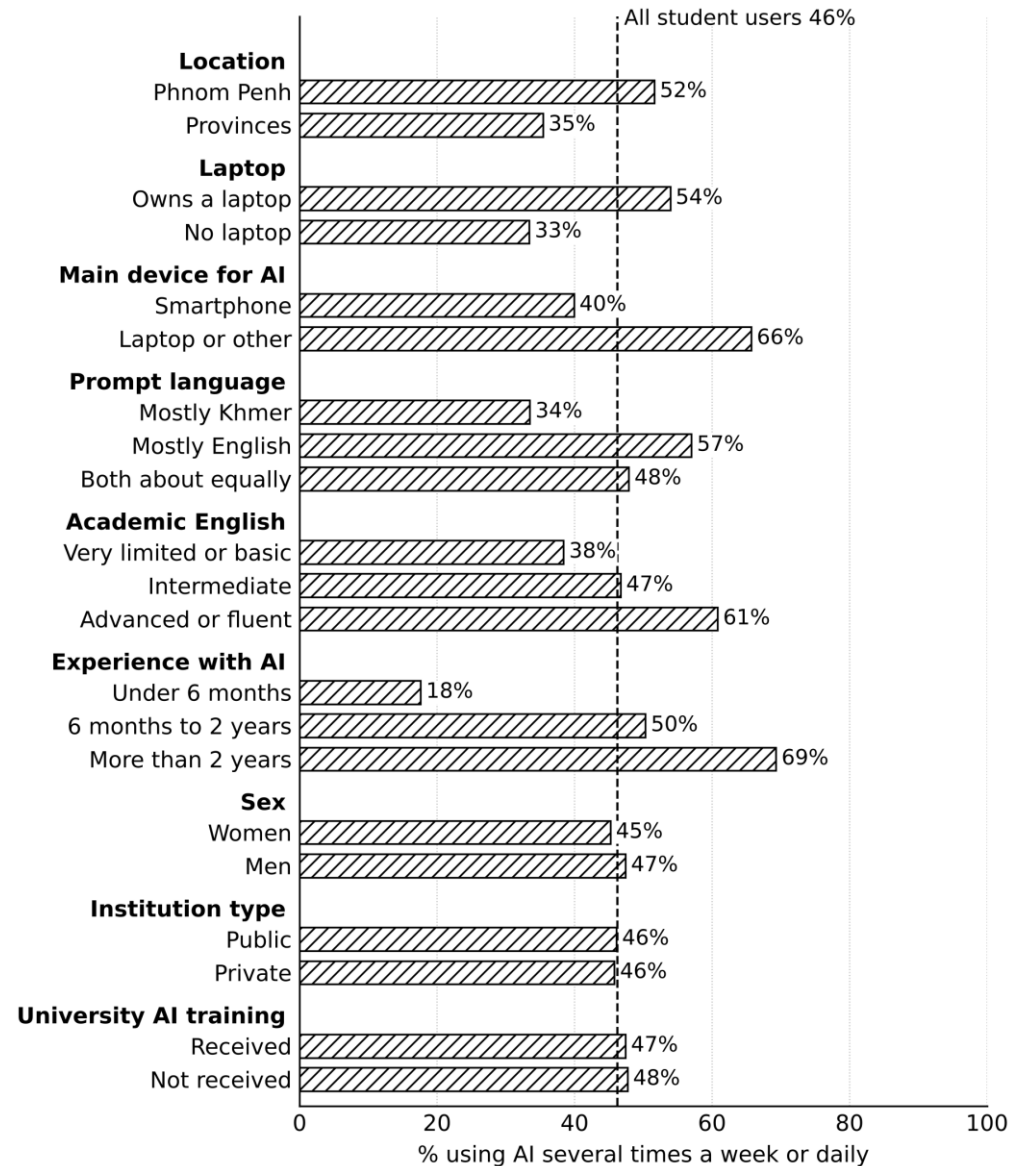
If nearly everyone uses AI, the differences that matter are in how much they use it. Using the groups defined in Sections 1.4 and 3.3, 29.2 percent of student users are occasional users, 27.3 percent focused and 43.5 percent intensive. The groups differ in what they bring to the tool. Among intensive users, 72.0 percent own a laptop and 23.1 percent prompt mostly in Khmer; among occasional users the figures are 51.2 and 46.5 percent. Intensive users are also the most likely to draft with AI: 51.1 percent often or always use it to draft parts of an assignment, against 14.7 percent of occasional users. This is partly built into the grouping, since drafting is one of the purposes counted. Frequent or intensive use is not in itself a good outcome, and the survey cannot show whether it improves learning. The concern in this section is that the chance to use AI intensively is unevenly spread.

4.2.1. Differences between subgroups

Figure 6 shows frequent use for different groups of students. Four patterns stand out. Frequent use differs by location: 51.6 percent of students in Phnom Penh are frequent users, against 35.4 percent in the provinces. It differs more by device: 65.7 percent of students whose main device for AI is not a smartphone (mostly a laptop) are frequent users, against 39.9 percent of those who rely on a smartphone. It differs by language: frequent use is 57.0 percent among students who prompt mostly in English, 47.9 percent among those who use both languages and 33.5 percent among those who prompt mostly in Khmer. And it differs most of all by experience: 17.6 percent of those who started within the past six months are frequent users, against 69.3 percent of those with more than two years of use.

Some expected differences do not appear. Students at public and private institutions use AI equally often (46.1 and 45.8 percent). Women and men differ little in the raw figures (45.2 and 47.4 percent). Lecturers show no gap by location: 62.1 percent of lecturer users in Phnom Penh and the same share in the provinces use AI several times a week or more, although the provincial group is small (87 lecturers who use AI).

Figure 6: Frequent AI use among students by subgroup (student AI users, n = 1,485)

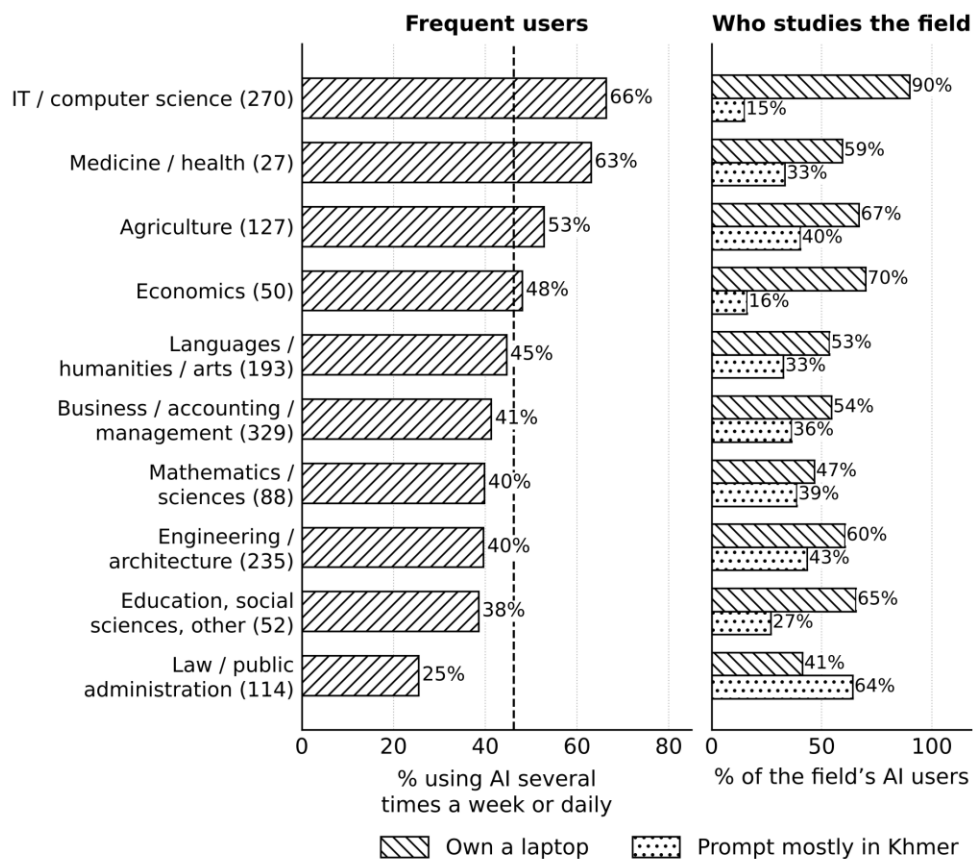


Source: Authors' survey data, 2026. Note: Frequent use = several times a week or daily. The vertical line marks the average for all student users.

Field of study shows the same pattern more sharply (Figure 7). Almost every student has used AI, whatever their field (96 to 100 percent). But frequent use ranges from 66.3 percent in IT and computer science to 25.4 percent in law and public administration. The figure for medicine and health (63.0 percent) is close to that for IT, but rests on 27 students and should be treated with caution. The usual split between STEM and other fields (52.3 against 40.0 percent) is largely due to IT. Students of engineering and architecture (39.6 percent) and of mathematics and the sciences (39.8 percent) are no more likely to be frequent users than students of business (41.3 percent) or of languages and the humanities (44.6 percent). Different kinds of students study different fields. Nine in ten IT students own a laptop, and 14.8 percent prompt mostly in Khmer.

Among law students, most of whom study outside Phnom Penh, 41.2 percent own a laptop and 64.0 percent prompt mostly in Khmer. When students who are alike in location, device, prompt language, experience and the other characteristics are compared, the differences between fields become smaller. IT's lead over business falls from 25 to about 9 points, and none of the differences can be clearly told apart from chance (Appendix Table C5). Device and prompt language may themselves partly follow from field, so this comparison may understate what field contributes. Field matters more for what students use AI for. Half of IT students (50.4 percent) often use it for coding or data analysis, against 26.1 percent in mathematics and the sciences and 12.3 percent or less in every other field.

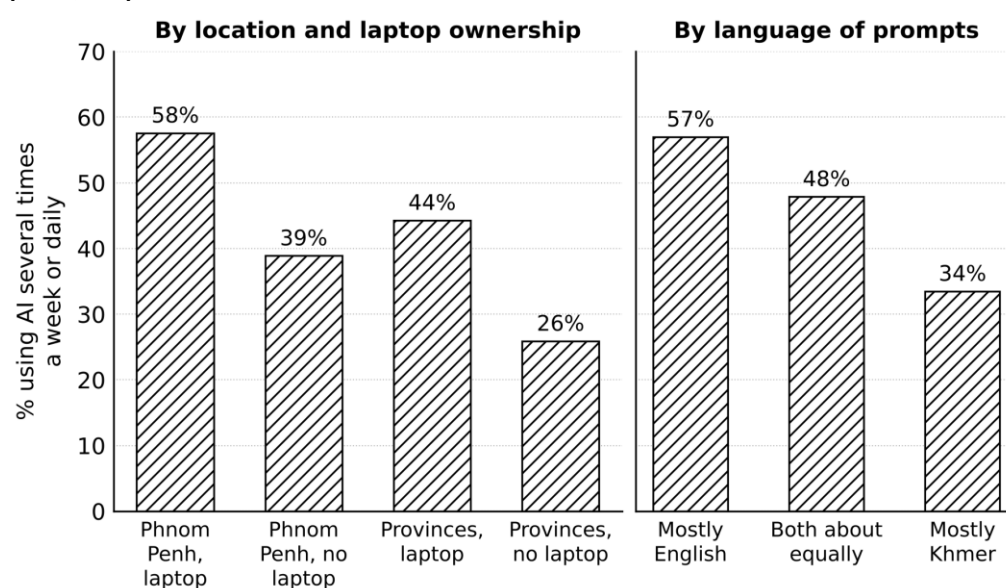
Figure 7: Frequent AI use by field of study, and the access of students in each field (student AI users)



Source: Authors' survey data, 2026. Note: Numbers of student AI users in brackets. The vertical line marks the average for all student users (46.2 percent). Education, social sciences and other fields are combined because each is small. See Appendix Table C5.

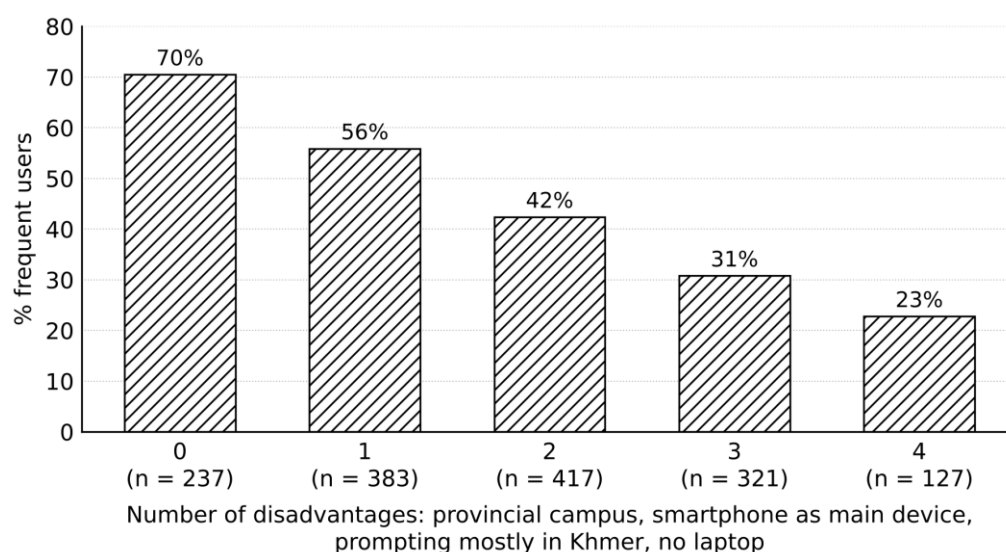
Location and device add to each other (Figure 8). Among students in Phnom Penh who own a laptop, 57.6 percent are frequent users. Among provincial students without one, the figure is 25.9 percent. The disadvantages also tend to occur together (Figure 9). Four of them were counted: a provincial campus, a smartphone as the main device for AI, prompting mostly in Khmer and no laptop. Of the 237 students with none, 70.5 percent are frequent users. The share falls to 55.9 percent with one ($n = 383$), 42.4 percent with two ($n = 417$), 30.8 percent with three ($n = 321$) and 22.8 percent with all four ($n = 127$). Three in ten students have three or four of these disadvantages. This count is a raw comparison: it does not take experience into account, and two of the four markers concern devices and overlap.

Figure 8: Frequent AI use among students by location, laptop ownership and prompt language (n = 1,485)



Source: Authors' survey data, 2026.

Figure 9: Frequent AI use by number of disadvantages (student AI users)



Source: Authors' survey data, 2026. Note: Disadvantages counted are a provincial campus, a smartphone as main device for AI, prompting mostly in Khmer and not owning a laptop. Two of the four concern devices and partly overlap.

4.2.2. Comparing like with like: what goes with frequent use

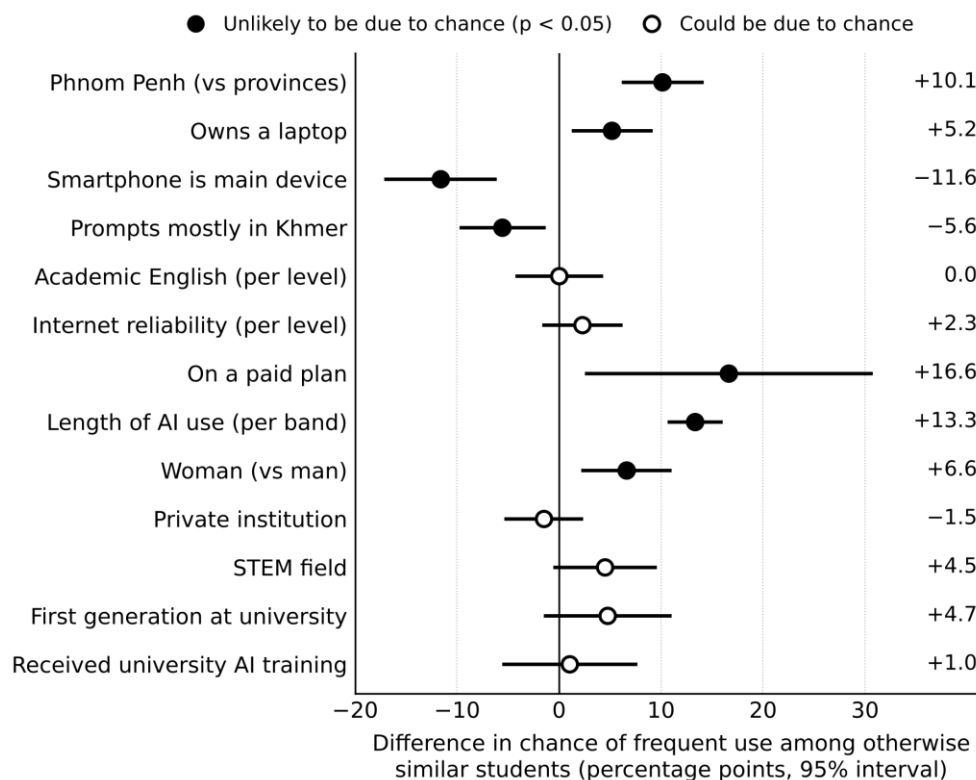
The characteristics in Figure 6 overlap. For example, students in the provinces are more likely than those in Phnom Penh to rely on a smartphone (85.8 against 70.3 percent) and to prompt mostly in Khmer (45.5 against 29.1 percent). Figure 10 therefore compares students who are alike in all the other characteristics measured. It uses a statistical model of the 1,193 students with complete answers (the full model is in Appendix Table B1). Among otherwise similar students, those studying in Phnom Penh are 10.1 percentage points more likely to be frequent users than those studying in a province. Relying on a smartphone as the main device for AI goes with a chance 11.6 points lower, and owning a laptop with a chance 5.2 points higher. Each step up the five bands of experience goes with a chance 13.3 points higher. A paid plan goes with a chance 16.6 points higher, although few students have one and this result is tentative. Prompting mostly in Khmer goes with a chance 5.6 points lower. Each of these differences remains after the others

are taken into account, although the laptop difference holds up least well in the checks (Section 4.7). Institutions account for only about 6 percent of the variation in frequent use (intraclass correlation 0.06).

Two results differ from the raw comparisons. In the raw figures, women are as likely as men to be frequent users, but women have weaker access. Among women, 82.3 percent mainly use a smartphone for AI, against 66.5 percent of men, and 58.4 percent own a laptop, against 67.9 percent of men. Among students who are alike in device, experience and the other characteristics, women are more likely than men to be frequent users, by 6.6 percentage points. This is a difference at equal access, not a higher rate of use among women overall. Nor is it explained by field of study. A smaller share of women than of men study a STEM field (39.5 against 65.6 percent), but within each group the shares of frequent users are close: 53.8 percent of women and 50.7 percent of men in STEM fields, and 39.6 and 41.5 percent in other fields. The difference at equal access remains (5.4 percentage points) when the ten field categories of Appendix Table C5 replace the STEM indicator. On daily use, men are ahead in the raw figures (23.2 against 16.7 percent). Among students with the same access, the difference is less than one percentage point (not shown in the tables).

Self-rated English is strongly linked to frequent use when looked at alone. Yet it makes no difference of its own once device, location, experience and prompt language are taken into account. The language of prompts explains part of this, and access and experience the rest. Institution type, field, year of study, being the first in the family at university, internet reliability and university training make no clear difference.

Figure 10: Differences in the chance of frequent use among otherwise similar students (average marginal effects)



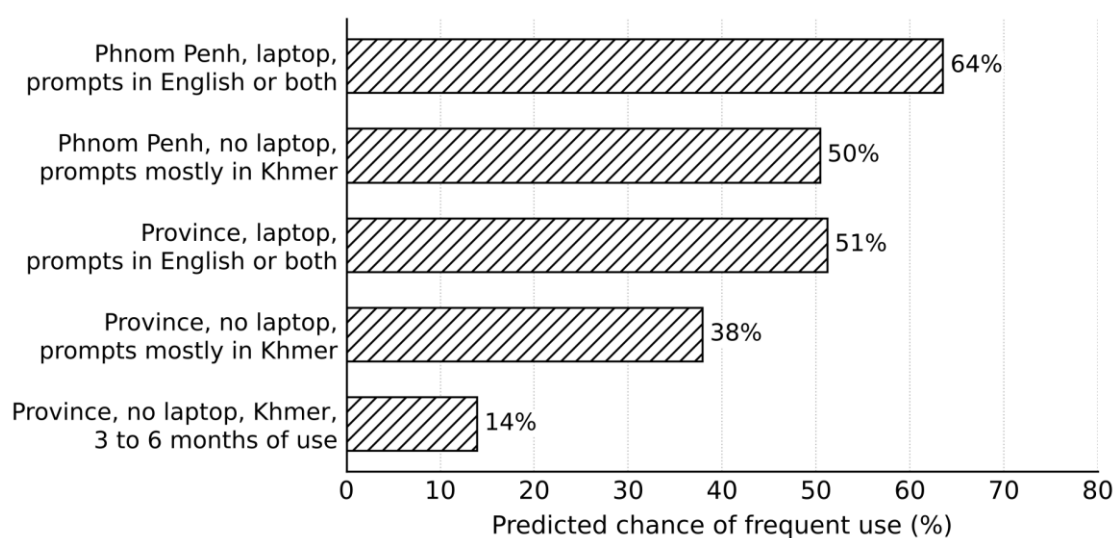
Source: Authors' calculation. Note: Logistic regression, N = 1,193; standard errors clustered by institution. Lines show 95 percent intervals; filled markers show differences unlikely to have arisen by chance. Year of study is included in the model but not shown. Full results in Appendix Table B1.

4.2.3. From occasional to intensive use

Appendix Table B2 applies the same comparison to the three intensity groups, using a model designed for more than two groups. It separates two steps: from occasional to focused use, and from occasional to intensive use. Length of experience matters for both. Relying on a smartphone and prompting mostly in Khmer go with a lower chance of intensive use, but make no clear difference to focused use. A paid plan and more reliable internet point towards intensive use, but these differences are small enough to have arisen by chance. Apart from experience, only institution type separates focused from occasional users: students at private institutions are less often focused users. This result rests on few private institutions and can no longer be clearly told apart from chance when the margins of error are recalculated leaving out one institution at a time, so it is given little weight here. Among students with the same experience, broad, intensive use goes with better access. Because the survey was conducted once, these are differences between students, not paths that individual students follow.

Figure 11 uses the models to give predicted chances for a few typical students. For an otherwise typical third-year student in Phnom Penh who has a laptop and prompts in English or both languages, the predicted chance of being a frequent user is 63.5 percent. For the same student in a province, without a laptop and prompting mostly in Khmer, it is 37.9 percent. If that student had also been using AI for only three to six months, it falls to 13.9 percent. All five profiles are women who use a smartphone as their main device for AI. For an otherwise identical man with the same access, the predicted chances are about 4 to 8 percentage points lower.

Figure 11: Predicted chance of frequent use for illustrative students



Source: Authors' calculation. Note: Third-year woman in a non-STEM field at a public institution, first generation at university, intermediate English, usually reliable internet, free plan, smartphone as main device for AI, one to two years of AI use and no university AI training, unless stated otherwise.

4.3. Skill: self-rated literacy and tested knowledge

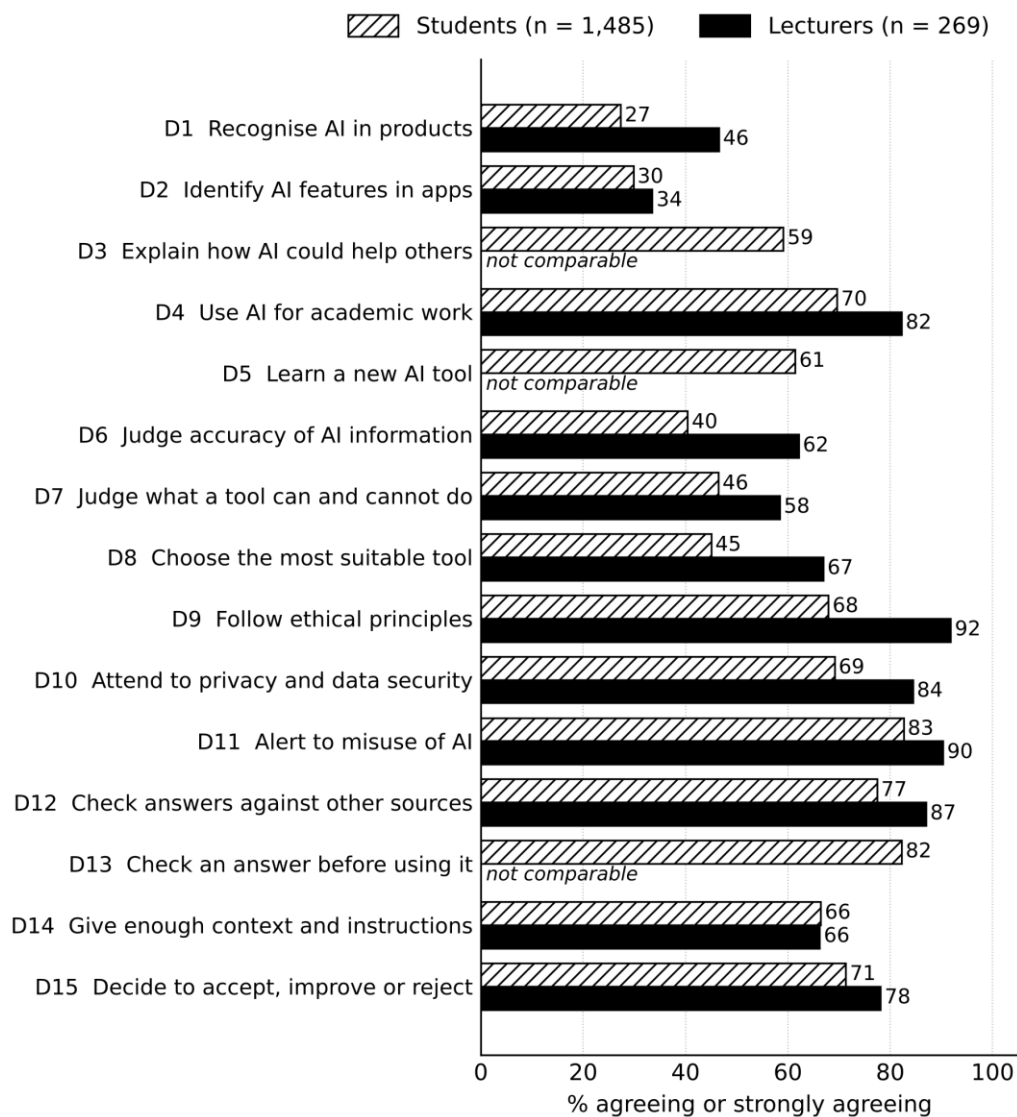
4.3.1. How students and lecturers rate themselves

Figure 12 shows the share agreeing with each item; Appendix Table C2 groups the items by what they measure and by source, and gives the average scores. On a five-point scale, students' average self-rated literacy is 3.61 (standard deviation 0.44) and lecturers' is 3.74 (0.39). Students rate themselves highest on checking and caution. Some 82.6 percent agree that they are alert to the misuse of AI, 82.2 percent that they check whether an AI answer is correct before using it, and 77.4 percent that they check answers against other sources. They are less sure of their own judgement: 40.4 percent agree that they can judge whether information from an AI tool is

accurate, and 54.1 percent neither agree nor disagree. Answers to the two items on recognising AI in products were mostly neutral, so they are not interpreted.

Lecturers rate themselves higher than students on almost every item that can be compared. The gap is clearest on following ethical principles (91.8 percent agree, against 67.9 percent of students) and on confidence in checking accuracy (62.1 percent of lecturers on a similarly worded item, against 40.4 percent of students). The two groups rate themselves equally on writing prompts that give enough context (66.2 and 66.4 percent).

Figure 12: Agreement with the self-rated AI literacy items, students and lecturers (AI users)



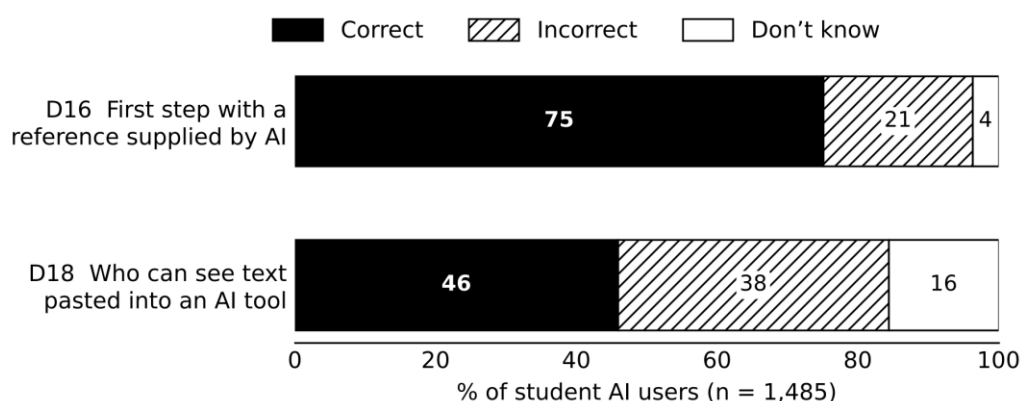
Source: Authors' survey data, 2026. Note: Lecturer items D3, D5 and D13 were negatively worded and are not comparable. Full wording and means in Appendix Table C2.

4.3.2. What students know

Students were then asked two questions that have a correct answer (Figure 13; Appendix Table C3). Three-quarters (75.1 percent) know that the first thing to do with a reference supplied by an AI tool is to check that it exists; 15.2 percent would ask the same AI tool whether it is correct. Fewer than half (45.9 percent) know that the company that runs an AI tool can see text pasted into it; 35.2 percent believe only they can see it.

Across the two items, 35.5 percent of students answer both correctly, 50.0 percent one and 14.5 percent neither. The contrast suggests that students are better informed about what they can see go wrong, such as a reference that does not exist, than about what stays hidden, such as where pasted text goes; the privacy result rests on a single question. Knowing the right first step is not the same as taking it: the reference question asked what students should do, not what they did (Section 5.2).

Figure 13: Answers to the two knowledge questions (student AI users)

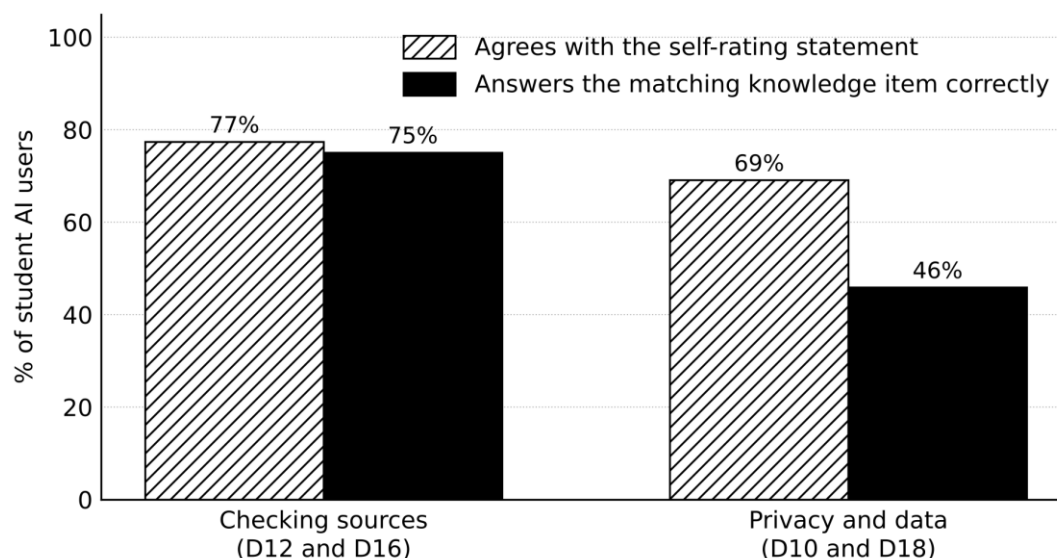


Source: Authors' survey data, 2026. Note: Incorrect combines the two wrong options for each question. Full distribution in Appendix Table C3.

4.3.3. Self-rating and knowledge compared

Figure 14 places two self-rating items beside the knowledge item on the same topic. On checking sources, the two measures agree: 77.4 percent say they check AI answers against other sources and 75.1 percent know that the first step with an AI-supplied reference is to check that it exists. On privacy, they do not: 69.1 percent say they pay attention to privacy and data-security risks, but 45.9 percent know who can see pasted text. Among those who say they pay attention, 50.3 percent answer correctly, against 35.9 percent of the others.

Figure 14: Self-rated practice and tested knowledge on two matched topics (student AI users, n = 1,485)



Source: Authors' survey data, 2026.

Self-ratings do carry real information. The share of students who answer both items correctly rises from 18.8 percent in the quarter with the lowest self-ratings to 49.3 percent in the quarter

with the highest. The share who know who can see pasted text rises from 30.6 to 56.7 percent. Even so, the link is modest. The correlation between the overall self-rating score and the number of correct answers is 0.21, and even in the highest quarter more than four in ten students do not know that the company running a tool can see what they paste.

Self-rated skill also goes with the benefits that students report. From the lowest to the highest quarter of self-ratings, the share who say AI helps them finish coursework much faster rises from 39.8 to 76.3 percent (57.2 percent of all student users), and the share who report a significant improvement in the quality of their work from 13.1 to 29.5 percent. The lowest quarter is also the most likely to say that AI has made their work worse (13.1 percent, against 3.9 to 5.3 percent in the other three quarters). Both measures are students' own reports, and the survey cannot say which comes first: students who gain more from AI may grow more confident, or more skilled students may gain more. These are not measures of learning, the third-level question of who benefits that the survey cannot answer (Section 2.2). They do suggest that, in students' own eyes, AI gives most to those who are most confident in using it.

4.3.4. Who rates themselves higher, and who knows more

Appendix Table B3 compares like with like for self-rated literacy and for each of the two knowledge items. Self-ratings are higher among students who use AI more often and for longer, who rate their academic English higher and who have reliable internet. They are lower among students who prompt mostly in Khmer. Together, these characteristics explain about a fifth of the differences between students ($R^2 = 0.222$). Women rate themselves 0.07 points lower than men on the five-point scale, although, as Section 4.2 showed, they are as likely as men to be frequent users. Students in years 3 and 4 rate themselves 0.11 to 0.14 points lower than first-year students (the year-2 difference is tentative).

Knowledge is much harder to explain from the characteristics measured, which account for almost none of the differences between students (pseudo R^2 of 0.028 and 0.049). For both items, there is a clear link with self-rating. A student whose self-rating is one standard deviation higher (0.44 points on the five-point scale) is about 4 percentage points more likely to answer the reference question correctly and about 7 points more likely to answer the privacy question correctly. Reliable internet goes with knowing to check a reference, and longer experience of AI goes with knowing who can see pasted text, although this last result is tentative (Section 3.4). Sex, location, institution type, field and English make no clear difference to either item. Nor does frequency of use, among students with the same self-rating. Knowing to check a reference varies little by location, device or language. Privacy knowledge is less even in the raw figures: 55.2 percent of students whose main device is not a smartphone answer correctly, against 42.8 percent of those who mainly use a phone. Among otherwise similar students, however, the difference is small enough to have arisen by chance. Students who report formal university training on AI do not rate their skills higher and are no more likely to answer either item correctly (Section 4.6).

4.4. Norms: where students and lecturers draw the line

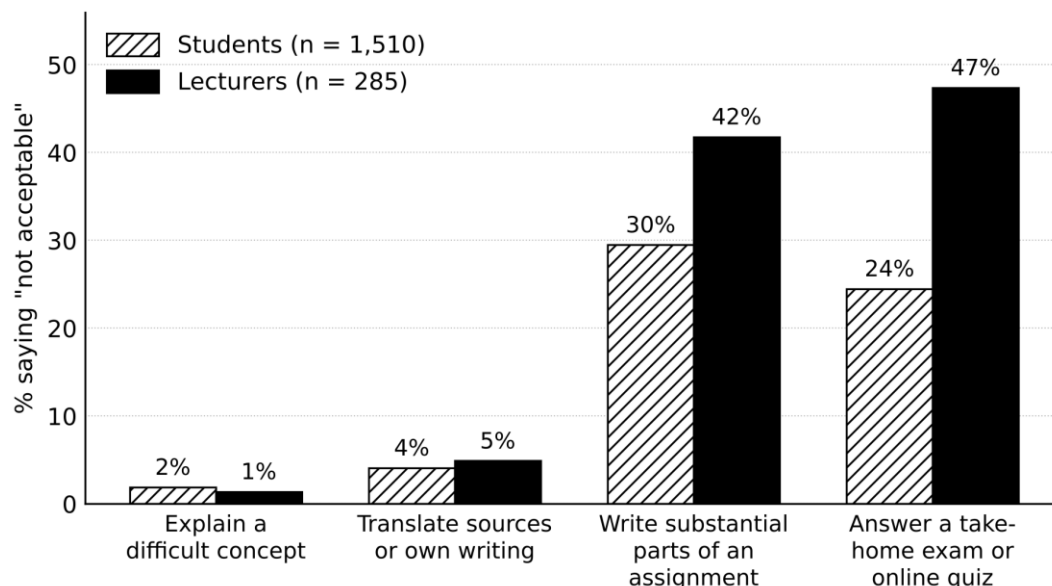
Both questionnaires described four uses of AI by a student. They asked, first, how acceptable each use is as academic practice and, second, whether the university currently allows it. Appendix Table C4 gives the full results for both groups. Students were asked about their own use and lecturers about use by students; this may explain part of the differences reported below.

4.4.1. Agreement on low-stakes uses, disagreement on assessed work

Two uses are not in dispute. Fewer than 5 percent of either group consider it "not acceptable" to use AI to explain a difficult concept, or to translate sources or one's own writing. Most respondents choose "acceptable" or "depends", and lecturers lean more towards "depends".

The groups differ on the two uses that involve assessed work (Figure 15). Using AI to write substantial parts of an assignment submitted as one's own is not acceptable to 41.8 percent of lecturers and 29.5 percent of students. Using AI to answer questions in a take-home exam or online quiz is not acceptable to 47.4 percent of lecturers and 24.5 percent of students, a gap of 23 percentage points. One in five students (20.5 percent) considers the exam use clearly acceptable, against 7.4 percent of lecturers.

Figure 15: Share saying each use of AI by students is "not acceptable" (students n = 1,510; lecturers n = 285)



Source: Authors' survey data, 2026.

Lecturers do not agree among themselves either. On both contested uses, about four in ten lecturers answer "depends". "Depends" is also the most common student answer for every scenario except translation. For the uses that matter most to academic integrity, neither group has a settled shared view. Disagreement is therefore concentrated on assessed work, which is where rules most need to be agreed rather than assumed.

4.4.2. Views, perceived rules and behaviour

Views on what is acceptable and beliefs about the rules are related, but far from identical. Among students who believe their university does not allow AI to write substantial parts of an assignment, 43.7 percent consider the practice not acceptable; among those who believe it is allowed, 8.2 percent do. At the same time, 21.6 percent of all students consider this practice acceptable, or acceptable depending on circumstances, while believing that their university forbids it. For take-home exams, the share is 27.2 percent. For these students, the rule as they understand it and their own view diverge.

Views are also linked to reported behaviour. Among students who consider AI-written assignments acceptable, 40.1 percent often or always use AI to draft parts of an assignment, compared with 21.2 percent of those who consider it not acceptable. The survey cannot show which way this link runs, but where many students do not share a rule, enforcement alone may be hard.

4.4.3. How lecturers are responding

Lecturers report that they have adapted. Among lecturers who use AI, 69.9 percent agree that they have set clear ground rules with their students, 85.5 percent that they encourage

appropriate use, and 50.6 percent that they have changed how they design assessments because of student AI use. What they allow varies: explaining concepts (72.5 percent), brainstorming or outlining (56.1 percent), translation (55.8 percent), drafting content (39.0 percent) and grammar or editing (38.3 percent); 15.6 percent have no set rule. Grammar or editing is allowed about as often as drafting, although it is the more limited use; some lecturers may see it as needing no permission. Two-thirds of all lecturers (66.0 percent) are confident that they can recognise AI-generated student work, and 49.4 percent of lecturers who use AI ($n = 269$) use AI-detection tools at least sometimes. Lecturers also use AI in assessment themselves: 75.5 percent use it at least sometimes to create assessments and 49.8 percent to help mark or give feedback. Some 14.9 percent have entered sensitive student data into an AI tool at least sometimes, and a few more say they did not realise this was a privacy risk.

Most lecturers also work under an expectation that they will use AI. Of lecturer users, 39.8 percent say colleagues or department heads officially encourage it and 46.1 percent that it is informally expected; 1.1 percent say it is discouraged. Seven in ten (70.3 percent) are encouraged or expected to use AI but know of no formal written policy on it, and even among those whose use is officially encouraged, only 28.0 percent know of one.

Lecturers' own use of AI goes with how they judge students' use. Among lecturers who often use AI to help mark or give feedback ($n = 42$), 23.8 percent consider it acceptable for a student to write substantial parts of an assignment with AI, against 4.4 percent of those who rarely or never do so ($n = 135$). Fewer of them consider AI use in a take-home exam not acceptable (31.0 against 53.3 percent). How often lecturers use AI overall makes no clear difference to whether they consider take-home exam use not acceptable (46.7 percent of frequent users and 48.0 percent of others). Lecturers who agree that they tend to accept AI output they cannot verify (20.1 percent; this item is left out of the literacy index, Section 3.3) are similarly more lenient: 31.5 percent of them consider AI use in a take-home exam not acceptable, against 57.8 percent of those who disagree. These differences are statistically significant, but the groups are small and the paper makes many comparisons, so they should be read as tentative. The survey also cannot show which comes first.

Students and lecturers agree on how common problematic use is. One in five in each group (20.0 percent of students, 20.7 percent of lecturers) say it is common or very common for students in their programme to use AI in ways lecturers would not approve of.

4.5. Rules: how clear they appear

4.5.1. Awareness of a policy

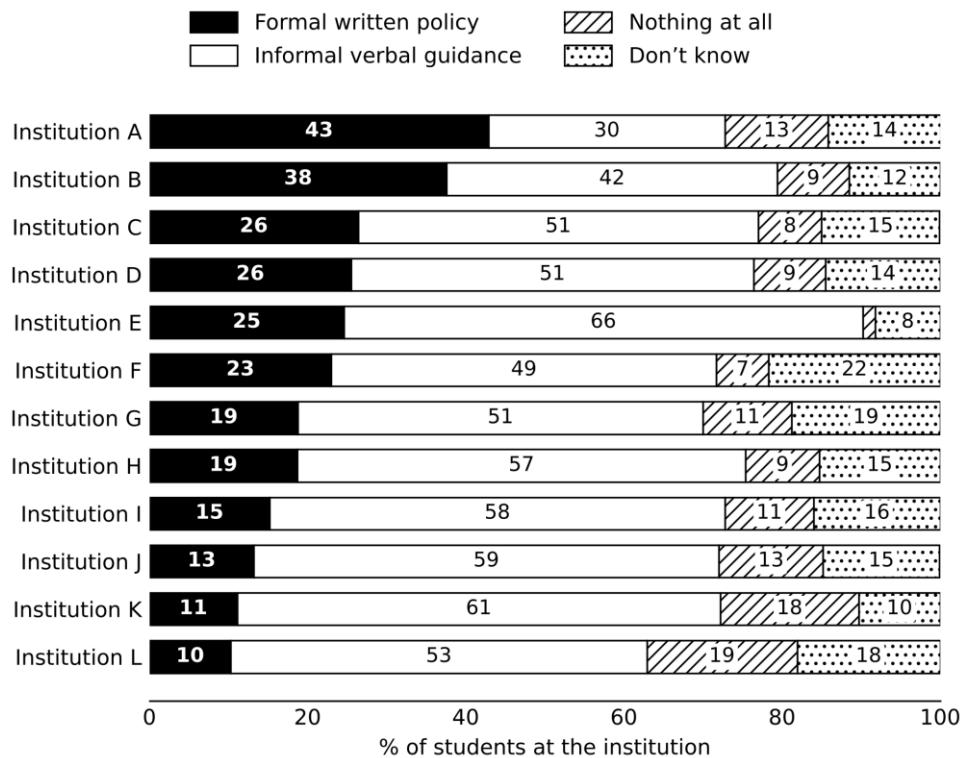
Few respondents know of a written policy. Asked whether their university has issued clear, official rules on student AI use, 21.5 percent of students say there is a formal written policy, 52.0 percent informal verbal guidance, 11.7 percent nothing at all, and 14.8 percent do not know. Lecturers answer in a similar way: 17.2 percent report a formal written policy, 41.1 percent informal guidance, 14.4 percent a policy in preparation, 11.2 percent nothing at all, and 16.1 percent do not know. In the classroom, 33.2 percent of students say lecturers have explained what is and is not acceptable in almost all their classes, 57.6 percent in only a few, and 9.1 percent rarely or never.

4.5.2. Disagreement within institutions

Whether a university has a formal written policy is a matter of fact, so students at the same university should give the same answer. They do not (Figure 16). Across the 12 institutions with at least 50 student respondents, the share reporting a formal written policy ranges from 10.3 to 42.9 percent, and it does not reach half in any institution. In every one, a sizeable group says the guidance is only verbal and some say there is nothing at all; between 8 and 22 percent do not

know. The most common answer in each institution is given by between 42 and 66 percent of its students. The institution a student attends explains only about 6 percent of the variation in whether they report a formal policy (intraclass correlation 0.06).

Figure 16: Whether the university has rules on AI use, as reported by students at twelve institutions

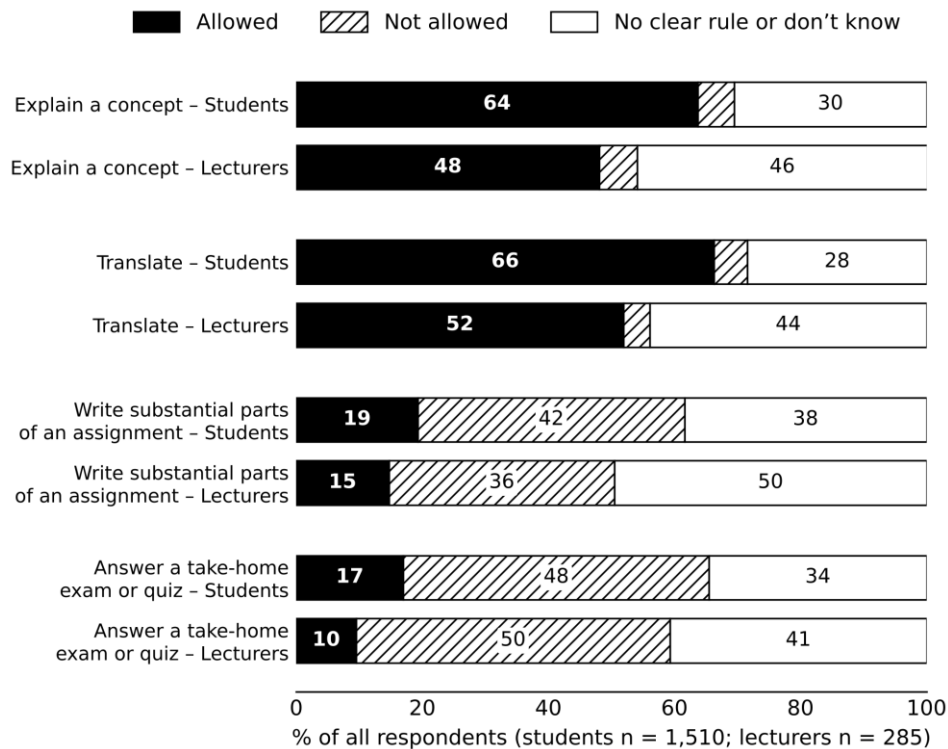


Source: Authors' survey data, 2026. Note: Institutions with 50 or more student respondents (between 55 and 165 each), ordered by the share reporting a formal written policy. Institutions are not named and their sizes are not shown.

Lecturers at the same institutions are no more consistent. In the institutions with at least 15 lecturer respondents, between none and 29 percent report a formal written policy. If a written policy exists at any of these universities, most of the people it applies to do not know about it. The survey cannot tell whether such policies exist but have not reached students and staff, or do not exist (Section 5.6).

4.5.3. Uncertainty about specific uses

The second set of scenario questions shows what this means in practice (Figure 17). For the two low-stakes uses, most students believe the university allows them (63.7 and 66.3 percent). For the two contested uses, beliefs split three ways. For writing substantial parts of an assignment, 42.3 percent of students think it is not allowed, 19.3 percent think it is allowed, and 38.4 percent say there is no clear rule or that they do not know. For take-home exams, the figures are 48.5, 17.0 and 34.5 percent. In all, 47.4 percent of students see no clear rule on at least one of the two contested uses, and 60.0 percent on at least one of the four.

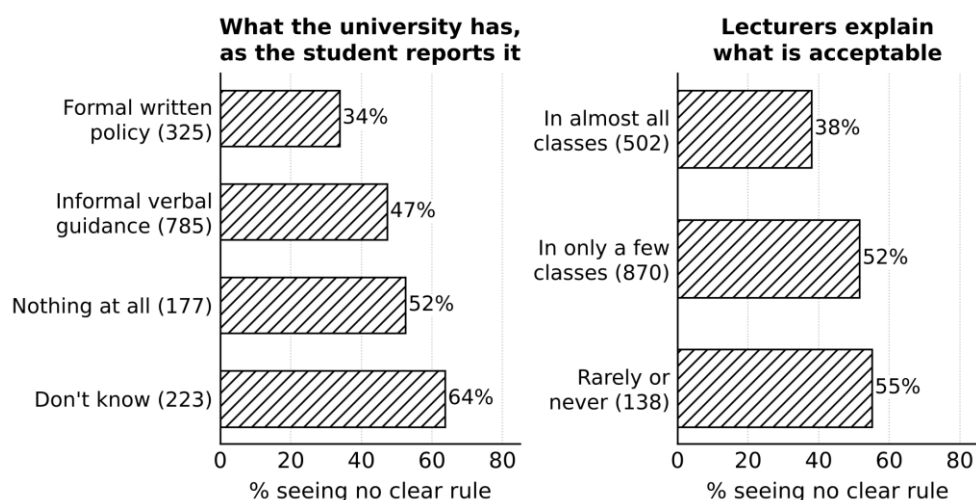
Figure 17: What respondents believe their university allows, for four uses of AI by students

Source: Authors' survey data, 2026. Note: Full results, including respondents' own views, in Appendix Table C4.

Lecturers are more uncertain than students. For every scenario, they are more likely to say that there is no clear rule or that they do not know, by between 6 and 15 percentage points. In all, 55.8 percent see no clear rule on at least one contested use. Lecturers are presumably better placed than students to know whether a rule exists; their answers may mean that in many cases it does not, or that the rules have not reached staff. The survey cannot tell these apart.

4.5.4. What goes with clearer rules

Appendix Table B4 compares otherwise similar students to see which characteristics go with seeing no clear rule on at least one contested use. Only two characteristics do, both institutional. Students who know of a formal written policy are 13.9 percentage points less likely to see no clear rule, and students whose lecturers explain the rules in almost all classes are 11.5 points less likely. In the raw figures (Figure 18), uncertainty is 33.8 percent among students who know of a written policy and 63.7 percent among those who do not know whether there is one. It is 38.0 percent where lecturers explain the rules in almost all classes and 55.1 percent where they rarely or never do. No personal characteristic (sex, field, year, location, device, language or experience) makes a clear difference. The institution a student attends explains almost none of it (intraclass correlation 0.01). Even the two institutional characteristics explain only a small part of who is uncertain.

Figure 18: Share of students seeing no clear rule on a contested use, by what they know of the rules

Source: Authors' survey data, 2026. Note: No clear rule = "no clear rule" or "don't know" for writing substantial parts of an assignment or for take-home exams. Numbers of students in brackets.

4.6. The support students and lecturers ask for

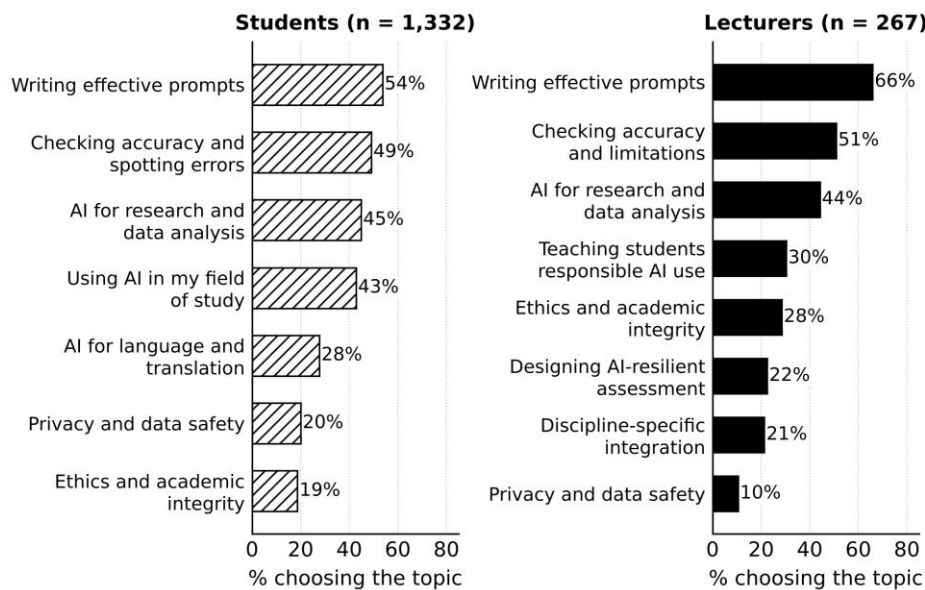
Training has reached some respondents. Among students, 43.3 percent say they have received formal training from their university on using AI for study, 40.6 percent have not, and 16.1 percent are unsure. Among lecturers, 64.2 percent say their university offered one or two optional sessions in the past academic year, 12.3 percent report regular or mandatory training, and 23.5 percent none. Training goes with awareness of the rules rather than with use or knowledge. Students who report training are more than twice as likely as those who do not to know of a formal written policy (31.8 against 13.4 percent), and much more likely to say that lecturers explain the rules in almost all classes (45.0 against 23.8 percent). They are no more likely to be frequent users (47.4 and 47.7 percent) or to answer either knowledge question correctly (74.2 and 76.9 percent for the reference question; 45.2 and 48.6 percent for privacy). Students who pay attention to rules may also be more likely to notice and report training, so the link may run either way. The survey did not record what the training covered, but these results are consistent with training that has dealt more with rules than with how to use and check AI tools.

Demand is still high, especially among lecturers: 80.4 percent agree that they are interested in training, against 56.1 percent of students. About half of students (48.7 percent) agree that knowing how to use AI will be important for their future career, and 40.5 percent are neutral. Both interest and perceived career value rise with use. Among students who use AI monthly or less, 38.2 percent want training and 28.6 percent think AI skills will matter for their career, against 67.8 and 62.7 percent of frequent users. Optional training may therefore reach mainly those who already use AI most.

Figure 19 shows the topics chosen by those who did not reject training. Both groups put writing effective prompts first, checking accuracy second, and AI for research and data analysis third. After that, students want AI applied to their own field, while lecturers want to learn how to teach students responsible use. Ethics and academic integrity is chosen by 18.7 percent of students and 28.5 percent of lecturers, and designing assessments that are resilient to AI by 22.5 percent of lecturers. Privacy and data safety is chosen by 20.0 percent of students and 10.5 percent of lecturers, the lowest share among the lecturers' options. Lecturers strongly prefer hands-on workshops (74.2 percent); students prefer short online modules (56.6 percent) and workshops (49.8 percent). About a fifth of students (18.8 percent) and a quarter of lecturers (27.7 percent) would use a printed or Khmer-language guide.

Students who want training would look first to a dedicated university unit (51.8 percent), then to their lecturers (36.9 percent), external experts (35.8 percent) and the government or ministry (31.0 percent). Lecturers are a resource not yet used. Of the 267 lecturers open to training (those who did not disagree that they want it), 65.5 percent would be willing to help train colleagues and 55.8 percent feel ready and confident to do so. Half (50.9 percent) are both willing and ready, and 14.6 percent are willing but do not yet feel ready. Women lecturers are less likely than men to feel ready to train others (43.1 percent of 72 women against 60.3 percent of 194 men), although their self-rated literacy is the same (3.73 and 3.75 on the five-point scale). Demand is practical, and the capacity for peer training appears to exist within institutions, although readiness here is self-reported.

Figure 19: Training topics wanted by students and lecturers who did not reject training (students n = 1,332; lecturers n = 267)



Source: Authors' survey data, 2026. Note: Up to three topics could be chosen.

4.7. Robustness analyses

Appendix B repeats the main results using three other definitions of the sample: a stricter rule that also requires a pledge to answer carefully and at least eight minutes spent on the survey (n = 1,408 students); only those who completed the form themselves; and all respondents in the cleaned file. In each, every main figure is within about two percentage points of the main result (Table B5).

Model results are also stable across samples (full results are available from the authors). The links between frequent use and location, main device and experience keep the same direction and about the same size in every model. Laptop ownership is the least stable result: it is statistically significant in only two of the four samples, and the paper gives it little weight. In the models of the two knowledge items, the self-rated index has a positive and statistically significant link with knowledge in every sample.

Two further checks support the results. First, keeping students who were unsure whether they had received training as a separate group, instead of leaving them out, raises the model sample to 1,416. The differences linked to studying in Phnom Penh (+9.1 points), a smartphone as main device (-12.0), a laptop (+6.1), prompting mostly in Khmer (-6.5), each band of experience (+13.0), a paid plan (+16.3) and being a woman (+5.3) are all close to the main results. The two institutional links with seeing no clear rule also remain (-12.7 and -9.8 points). Second, the gaps between students and lecturers hold within the ten institutions with at least 15 lecturer

respondents. When students are weighted to match the lecturers' mix of institutions, 50.7 percent of students and 58.7 percent of lecturers see no clear rule on a contested use, and 23.9 and 45.5 percent consider take-home exam use not acceptable.

5. Discussion

This chapter interprets the findings in light of the Cambodian context (Section 2.1), the framework in Section 2.6 and the wider literature. Three findings carry the argument. First, depth of use goes with the quality of access. Second, skills are rated as moderate, and a single knowledge question points to a gap on data privacy. Third, few respondents know of written rules for acceptable use, and views on what is acceptable are not shared. Lecturers are both the heaviest users and the people who, in practice, explain the rules in class, so Section 5.3 discusses them separately. Section 5.5 draws the findings together, and Section 5.6 sets out the limits of the study and directions for future research. One thread runs through all of them: adoption has rested on individuals' own resources, and the findings are consistent with the view that use has spread faster than the institutional rules and support that make it productive and safe.

5.1. After access: differences in how AI is used

The findings follow the pattern that research on the digital divide predicts. Once nearly everyone has access, the differences lie in what people do with it: the "second-level" divide. Among these respondents, access to generative AI is close to universal, and access has come mainly through free plans, mobile data and personal phones. What differs is the depth of use. It differs by the devices people have, as research on internet use has found (van Deursen and van Dijk 2019), and by where students study and the language they work in. That research stresses education and social position (van Deursen and van Dijk 2014). Here, by contrast, depth of use does not differ clearly by whether a student is the first in the family at university or by year of study. Lecturers offer a useful contrast. Those in the provinces use AI as often as those in Phnom Penh (Section 4.2.1), so the provincial gap among students does not appear to be a condition of provincial campuses that affects everyone alike. It may lie partly in students' own resources, including some that the survey did not measure, since studying in a province still goes with less frequent use among students with the same measured access (Section 4.2.2). Lecturers differ from students in many ways, however, not least in that almost all of them own a laptop (95.8 percent of all lecturers surveyed, against 61.9 percent of all students), and the provincial lecturer group is small (87 lecturers who use AI).

The share of these respondents who have used AI is as high as the highest figures reported elsewhere: 86 percent of students in a survey across 16 countries (Digital Education Council 2024) and 92 percent of undergraduates in the United Kingdom in 2025 (Freeman 2025). Earlier Cambodian studies found similar levels in single samples (Hoeurng et al. 2024; Sol, Heng, and Sok 2025). A survey by CADT reported lower shares: 85.3 percent of students had used generative AI for their studies and 74.5 percent of lecturers to assist their teaching (UNESCO 2025a). Its date and methods are not reported, so the difference may reflect when and how each survey was carried out and what it asked. In an online survey of 150 lecturers, 92.7 percent had used AI tools for teaching and learning, counting translation and grammar tools (Heng et al. 2026). In this survey, the level is similar across the public and private institutions and the provinces covered. An online survey about AI is likely to attract users, so the level is probably an upper bound.

The device finding is the clearest. Students who rely on a smartphone are less likely to be frequent and intensive users, even when compared with students who are alike in location, English and experience. This matches evidence that people who use the internet only on a mobile

phone use it in narrower ways and have lower skills (Correa, Pavez, and Contreras 2020), and it extends that evidence to generative AI. A small study in Uganda points the same way for AI tools (Kakooza, Walugada, and Alege 2026). One plausible reason, which the survey did not test, is that reading long documents, comparing sources and working with data are harder on a small screen. The finding concerns the main device used for AI, which is partly a matter of choice: two-thirds of laptop owners (66.3 percent) still use a phone as their main device for AI. The link may also run the other way, since heavier users may switch to a laptop.

Language is the finding most specific to Cambodia. Students who prompt mostly in Khmer use AI less intensively and rate their skills lower, and half of all students name poor performance in Khmer as a barrier. The data cannot show whether this reflects the tools, the students or both. However, computer science research gives reason to think that the tools are part of it (Lai et al. 2023; Nguyen et al. 2023). Consistent with this, prompting mostly in Khmer is still linked to less frequent use among students who are alike in English ability, device and experience. The direction of the link is uncertain, however: heavy users may also have switched to prompting in English. Governments report the same barrier. In a World Bank survey, most respondents from low- and lower-middle-income economies named limited AI support for local languages; the base is small, and the authors treat the result as indicative (Lundy et al. 2026). A divide that follows language would be hard to close through training alone.

Experience is more strongly linked to frequent use than any other single characteristic, which might suggest that the gaps will close with time. The data give reason for caution. Students with longer experience are more often focused or intensive users. But among students with the same experience, relying on a smartphone and prompting mostly in Khmer go with a lower chance of intensive use, though not of focused use. If this pattern reflects how students progress, which a single survey cannot show, students who study on a phone and in Khmer may become focused users without becoming intensive ones, and time alone would not close the gap.

Field of study tells the same story. At first sight, it is a major dividing line: frequent use ranges from two-thirds of IT students to a quarter of law students. But fields differ in who studies them. When students with the same location, device, language and experience are compared, the differences between fields narrow, and none can be clearly told apart from chance, although IT keeps a lead of about nine points over business. Much of what separates fields appears to be the resources their students bring. Because devices and language may themselves partly follow from field, this is an interpretation, not a finding. Field matters more for the purpose of use: half of IT students often use AI for coding or data analysis, against 26.1 percent in mathematics and the sciences and 12.3 percent or less elsewhere. In Sweden, students in technology and engineering have been found to use chatbots more (Stöhr, Ou, and Malmström 2024); here such differences appear to reflect access at least in part.

Two absences are worth noting. Public and private institutions do not differ, suggesting that institution type is not what separates frequent from occasional users among the institutions surveyed. And the gender gap reported elsewhere (Møgelvang et al. 2024; Stöhr, Ou, and Malmström 2024; Freeman 2025; Matobobo 2026; World Bank 2026) does not appear in frequent use. This is not what the Cambodian context would lead one to expect: women are less likely than men to own a mobile phone, to have used the internet and to study a STEM field (Section 2.1), and in this sample they are less likely to own a laptop. Women are as likely as men to be frequent users, even though more of them rely on a smartphone. Among students with the same access, they are more likely to be frequent users. Participants at the validation workshop were divided on this finding. Some recognised it from their own classes; one explanation offered was that women who are less willing to speak up in class may take their questions to AI, which would help explain why they use it as often as men despite weaker access. Others doubted it, pointing to the larger share of men in STEM fields and to differences in income and language. The field

explanation does not fit the data (Section 4.2.2), and the survey cannot test the others. None of this means higher use among women overall. Women nonetheless rate their own skills slightly lower (by 0.07 points on the five-point scale), a pattern also reported among medical students in Germany (Laupichler et al. 2024). Yet they are no less likely than men to answer the knowledge questions correctly, so the gap may lie partly in self-assessment rather than in knowledge of the two points tested.

5.2. Moderate self-rated skills and a privacy gap

The second finding concerns what students can do with the tools they use. They describe themselves as moderately skilled and careful: most say they check AI output, and three-quarters know that the first step with an AI-supplied reference is to check that it exists. Their self-ratings carry some meaning, since students who rate themselves higher are more likely to answer the knowledge questions correctly. But the link is modest. Elsewhere, a test of generative AI literacy predicted performance on tasks done with AI better than self-reported skill did (Jin et al. 2025). Undergraduates in the United States have been found to overestimate what chatbots can do (Rismanchian, Babar, and Doroudi 2026). With only two knowledge items, this study cannot measure overestimation, and it makes no claim about it.

The contrast between the two questions is informative. Knowing to check a reference may be common because made-up references are a widely reported failure of chatbots (Walters and Wilder 2023). This knowledge varies little across locations, devices and languages. Knowing it does not mean that students act on it. Participants at the validation workshop reported that many students copy AI output into their work without checking it, and some doubted that lecturers always check either. The survey cannot settle this, since it recorded what students know and report, not what they do. Far fewer know what happens to text they paste into a tool. A third believe that no one else can see it, and half of those who say they pay attention to privacy risks answer wrongly. On privacy, the care students report contrasts with what they know. This is a contrast between two different measures, not evidence of over-confidence.

The survey does not show how students learned these points. Knowing to check a reference is unrelated to how long a student has used AI, while privacy knowledge is modestly higher among students with longer experience (a tentative result). Even so, among the most confident quarter of students, more than four in ten do not know that the company running a tool can see what they paste. This suggests that the point needs to be taught explicitly.

Students are also least sure of a skill central to study. Only four in ten agree that they can judge whether information from an AI tool is accurate. Both students and lecturers place checking accuracy among the first things they want training on. Students who report university training on AI do not rate themselves higher or answer better, but the study cannot say what that training contained. One large experiment in the United States found that short, structured teaching improved the checking of facts and sources (Connell Pensky et al. 2026). This suggests that what training contains matters as much as whether it took place.

5.3. Lecturers: heavier users, uncertain rule-makers

Lecturers are in a double position. They are the heaviest users: they use AI more often than students, use more tools and rate their skills higher. At the same time, they are the people who, in practice, explain the rules in class, and in that role the data show strain. Lecturers are more uncertain than students about what their university allows, on every scenario. More than half (54.3 percent) describe themselves as interested but overwhelmed by the pace of AI development.

Their own practice raises questions that institutional policy may not yet have addressed. Three-quarters use AI at least sometimes to create assessments, and half use it to help mark or give feedback. A review of 30 studies found that university teachers elsewhere use generative AI mainly for lesson preparation, feedback and assessment used to support learning rather than to grade it, but keep traditional methods for assessing key student work (Baggia, Tratnik, and Brezavšek 2026). One in seven lecturers here has entered sensitive student data into an AI tool. As far as these data show, lecturers are making decisions about students' data and grades largely without written institutional guidance that they know of (only 17.2 percent report a formal written policy). Yet most work under an expectation to use AI (Section 4.4.3).

Lecturers' own habits may also be reflected in the rules that students meet. Those who often use AI to mark are more accepting of substantial AI drafting by students, and those who accept AI output they cannot verify are more lenient on take-home exams (Section 4.4.3). Lecturers as a group remain stricter than students on the contested uses, as Barrett and Pack (2023) also found. But where rules are set course by course, the standard a student meets may depend partly on each lecturer's own practice. These results are tentative and the direction of the link is unknown, but they add to the case for a shared institutional framework (Recommendation 1).

Lecturers have not stood still. Half have changed how they design assessments because of student AI use. This is in line with educators elsewhere, who prefer to adapt assessment on the assumption that AI will be used (Kizilcec et al. 2024). But these are individual responses. In a survey of 122 faculty members in Germany, lack of AI literacy among students and staff was named among the greatest challenges, and most wanted professional development (Mah and Groß 2024). Cambodian lecturers in another recent survey also named a lack of proper training and technical support among their concerns (Heng et al. 2026). Here, four in five lecturers want training, while most have been offered only one or two optional sessions. Their self-reported readiness to train colleagues (Section 4.6) suggests that an institutional framework could help turn individual adaptation into shared practice.

5.4. Unwritten rules and unshared norms

The third finding is that few respondents know of written rules on AI use, and views on what is acceptable are not shared. This is not unusual internationally. An early UNESCO survey found that fewer than 10 percent of schools and universities had formal guidance (UNESCO 2023), and students elsewhere report confusion about what is permitted (Ying 2026), even where policies exist (Jiang, Xie, and Cao 2025). What these data add is a view of the problem from inside institutions. Students at the same university do not agree on whether a policy exists. And the university a student attends makes almost no difference to how clear the rules seem. Guidance in these institutions appears to be largely oral and given classroom by classroom.

Universities are not alone in combining widespread use with few written rules. A World Bank survey of 60 governments found that nearly two-thirds give public servants access to generative AI tools. Yet only 39 percent have formal guidelines for the whole ministry, and a further 38 percent are drafting them. The authors warn of "shadow AI", meaning use without oversight (Lundy et al. 2026). The parallel is partial: those governments supply the tools, whereas students and lecturers here supply their own. But the institutions surveyed show a similar pattern: use is widespread, while the rules, as respondents report them, are mostly oral, local and unevenly known. Beckman et al. (2025) describe students elsewhere as working through a "policy vacuum"; for most respondents here, the description appears to fit.

The gap between students and lecturers on assessed work is of the kind Barrett and Pack (2023) reported. Here it is large on exactly the cases where integrity is at stake. It would be a mistake to read it only as students being permissive. Part of the gap may reflect the questions themselves: students judged their own use, while lecturers judged students' use. As Section 4.4.1 showed,

about four in ten lecturers also answer "depends"; and, as Section 4.4.2 showed, between a fifth and more than a quarter of students hold a view that differs from the rule as they understand it. The two groups agree on how common disapproved use is, about one in five. Seven in ten lecturers say they have set ground rules with their students, although only a third of students hear the rules explained in almost all their classes. These two figures come from different respondents and use different thresholds, so they cannot be compared directly. They leave open the possibility that the gap is partly one of communication as well as of values. The Cambodian setting may add to this. Higher education has expanded quickly and few academic staff hold a doctorate (Section 2.1); with national AI policy still in draft, institutions have had little time or guidance to agree rules, and individual lecturers may be filling the gap.

The distance between students' own views and the rules as they see them matters for whether rules are followed. Views go with behaviour: students who find AI-written assignments acceptable are almost twice as likely as those who do not to draft parts of assignments with AI often (40.1 against 21.2 percent). The survey did not measure compliance, the students whose view differs from the rule include those who answered "depends", and the direction of the link between views and behaviour is unknown. Even so, a rule that many students do not fully share may be hard to uphold by enforcement alone. This is one reason to settle the contested cases with students, and not only announce them.

Lecturers' confidence in their own enforcement deserves attention. Two-thirds of lecturers believe they can recognise AI-generated work, and half of those who use AI use detection tools. As Section 2.4 showed, such tools have been found neither accurate nor reliable, and biased against writers of English as a foreign language, as many Cambodian students are. Where there is no clear rule, enforcement that rests on detection risks unfair outcomes.

The more hopeful result is that clarity goes with simple measures. Among otherwise similar students, two things each go with uncertainty more than ten percentage points lower: knowing of a written policy, and having lecturers who explain the rules. Nothing else measured makes a clear difference. The link with a written policy is partly built in, since students who know of a policy are likely also to find the rules clear. The link with lecturers' explanations is the more telling of the two. Both links rest on students' own reports and may partly reflect how attentive a student is to rules. Together they explain only a small part of who is uncertain. Still, they point to the classroom as the place where rules become clear. This is the logic of stating the permitted level of AI use for each assessment (Perkins et al. 2024). It also matches evidence from Singapore that students who understand the guidelines are more likely to follow them (Tan, Qu, and Wang 2025). Participants at the validation workshop made a related point from experience: where an institution has no written policy, students take their lecturer's instructions as the rule, and they cannot be expected to know a policy better than their lecturers do.

5.5. Adoption ahead of institutions

The three findings are connected. Depth of use goes with the quality of access. Skill is rated as moderate, with a gap on privacy. And skill can be used responsibly only where the rules are known. On these data, a student in a provincial institution who works on a phone in Khmer is much less likely to use AI frequently, rates their own skill lower in the raw figures, and is often unsure of the rules: 50.2 percent of such students see no clear rule on a contested use. A student in Phnom Penh who has a laptop and works in English uses AI far more and with more confidence. Yet uncertainty about the rules is common among these students too: 40.5 percent see no clear rule on a contested use. Among otherwise similar students, personal characteristics make no clear difference once awareness of a written policy and lecturers' explanations are taken into account.

These results can be compared with the expectations in Section 2.6. As expected, access quality and structural position go with use: device, location, prompt language and experience go with frequent use, and device, prompt language and experience also go with intensive use. Among otherwise similar students, academic English, internet reliability, prompt language, frequency of use and experience also go with self-rated literacy; location and main device do not, once other characteristics are taken into account. These characteristics say little about tested knowledge, which is only weakly linked to any characteristic measured. The second expectation therefore holds for confidence but not for knowledge. Clarity about the rules goes with the institutional environment as students report it, but with none of their personal characteristics. Training received, the third institutional characteristic, shows no clear link of its own with use, self-rated literacy, knowledge or the clarity of rules among otherwise similar students.

A wider view may help to explain why the three findings go together. The World Development Report 2026 argues that AI works best where reliable infrastructure, good education systems and strong institutions are in place, and that adopting AI is not enough without these supporting conditions (World Bank 2026). A background paper to the report applies the same logic to governments (Lundy et al. 2026). A similar logic may apply to universities, although this study has no measure of the value of AI. Students and lecturers have supplied the tools themselves: on their own phones and, for lecturers on paid plans, at their own expense. What they cannot supply is what only institutions can provide: reliable access on campus, training that teaches points that can be checked, and rules that are written down and explained. In this sample, frequent use goes with private resources, such as a device other than a phone or a paid plan, and with working in English; whether institutional provision weakens this link was not studied. Without such provision, individuals must work out for themselves what is allowed and what is safe.

None of this means that use is going badly. Respondents see clear benefits, mainly in speed and workload, although few students report a significant gain in the quality of their work (Section 4.1.4). Lecturers are adapting their teaching, and many are ready to help colleagues. The task for institutions is to build on this practice.

Policy that addresses only one of the three is unlikely to be enough on its own, although the surveys cannot test this. Providing tools without teaching privacy and how to judge accuracy would leave users exposed to error. Teaching skills without settling the rules leaves students unsure whether they may use what they have learned. Rules enforced with detection tools may penalise those whom the tools misjudge most often, such as students writing in English as a foreign language. The surveys cannot show whether intensive use is improving learning, the third-level question of who benefits (van Deursen and Helsper 2015). They do show the conditions under which that question will be answered.

5.6. Limitations and directions for future research

The findings should be read with the limits of the study in mind. Several limits were noted earlier where they affect particular results; they are brought together here.

The sample is not representative. Institutions were chosen deliberately, not at random, and respondents decided for themselves whether to take part, through an open link. Students who use AI, who are comfortable with online forms or who are more engaged with their institution may be over-represented. Two-thirds of respondents are in Phnom Penh, and private institutions contribute fewer than one in five. Percentages describe respondents only.

The lecturer sample is small. There are 285 lecturers, three-quarters of them men and most in a handful of institutions. Lecturer results are therefore descriptive, and differences between groups of lecturers could not be examined.

The data are self-reported. Answers about academic integrity are likely to be shaped by a wish to give socially acceptable answers. Participants at the validation workshop judged the reported level of AI drafting to be low against what they see in submitted work. The surveys measure opinions and views on what is acceptable, not how common misconduct is. Whether a university actually has a policy was not checked against documents. Most characteristics and outcomes come from the same questionnaire, so some links may be inflated by the way individual respondents tend to answer questions in general.

The data come from a single point in time. Links, for example between device and frequent use or between a written policy and clarity, are associations, not causes.

Finally, some topics in the original study design were not measured: the use of AI in research beyond one question on how often lecturers use it for research or academic writing, the views of university administrators, and learning outcomes.

Several lines of research would address these limits and the questions this study leaves open:

- A random sample of students and lecturers, drawn from enrolment and staff lists, would allow national estimates and show whether the patterns found here hold more widely.
- Collecting and analysing the AI policies of the surveyed institutions would show whether students and lecturers are unaware of rules that exist or are correctly reporting that there are none.
- A fuller, validated test of AI literacy, given to both students and lecturers, would replace the items used here and allow self-rating and knowledge to be compared for lecturers as well.
- Studying how closely students and lecturers follow written rules where they exist, for example by comparing institutions' policies with practice in selected courses, would show whether clearer rules change behaviour.
- Examining why women in this sample are as likely as men to be frequent users despite weaker access, unlike in most studies elsewhere, for example by field, income and language, would test the explanations offered at the validation workshop.
- Tracing how students learn what happens to text they paste into AI tools, whether from lecturers, peers or the tools themselves, would show where teaching on privacy should start.
- Qualitative work with students, lecturers and administrators would explain how rules are communicated in class and why the two groups judge the contested cases differently.
- Linking AI use to assessed learning outcomes, ideally over time, would address the question this study cannot answer: who benefits, and whether heavy use weakens critical thinking, a concern raised at the validation workshop.

6. Conclusion and policy recommendations

6.1. Conclusions

This paper set out to assess whether students, lecturers and institutions in Cambodian higher education are equipped for a practice that, among those surveyed, is already almost universal. The answer is different for each of the three conditions examined.

On use, the question is no longer whether students and lecturers use AI but how much they use it. Lecturers use it more often than students: 62.1 percent use it several times a week or more, compared with 46.2 percent of students. Among students, how much they use AI goes with the

quality of their access: where they study, the device they rely on, the language they prompt in and how long they have used AI. These disadvantages tend to occur together. The share of frequent users falls from 70.5 percent among students with none of four disadvantages to 22.8 percent among those with all four (a raw comparison; see Section 4.2.1). Other expected differences are absent or small. Public and private institutions do not differ. Women are as likely as men to be frequent users despite weaker access, and more likely among students with the same access. Differences between fields narrow once location, device, language and experience are taken into account, which suggests that they partly reflect who studies each field.

On skill, students and lecturers rate themselves as moderately able. The two knowledge questions allow self-ratings to be set beside tested knowledge on two specific points; these are different measures, so a contrast between them is not by itself evidence of over-confidence. Three-quarters of students know to check a reference supplied by AI. But fewer than half (45.9 percent) know that text pasted into a tool can be seen by the company that runs it. Self-ratings carry some information, but they are only modestly related to knowledge (correlation 0.21). The university training that students report goes with knowing of a written policy but is linked to neither self-rated skill nor knowledge, although the survey did not record what the training covered.

On rules, students and lecturers agree on low-stakes uses but not on assessed work: 47.4 percent of lecturers and 24.5 percent of students say that using AI to answer a take-home exam is not acceptable. Few know of a written policy (21.5 percent of students and 17.2 percent of lecturers). Students at the same institution disagree about whether one exists, so any policy that does exist has not reached many of them, and lecturers are less sure than students about what is allowed. Clarity goes with two things that institutions control: students knowing of a written policy, and lecturers who explain the rules in class. Both links rest on students' own reports.

Taken together, the findings are consistent with the view that use has spread faster than institutional rules and support: adoption appears to be ahead of institutions. Students and lecturers have supplied the tools themselves. What remains for institutions and policy makers is what individuals cannot supply: rules that are written down and explained; training that teaches points that can be checked, starting with data privacy and judging accuracy; and access that does not depend on owning a laptop or working in English.

These results speak to the two wider debates set out in Chapter 1. On who gains, they give little support to the hope that a free tool will by itself level the field. Access to AI is near-universal among respondents, but depth of use follows devices, place and language, the lines along which earlier digital divides ran. Unlike in studies of workers and students elsewhere, however, women here are as likely as men to be frequent users despite weaker access, so the technology alone does not decide who uses it most. On learning, the study cannot show whether intensive use builds or replaces skill. It does show that many students lack two conditions for using AI to learn rather than to avoid learning: knowing what is allowed, and knowing how far to trust what AI tells them and where their data go. The findings that participants at the validation workshop questioned, and the limits of a single self-reported survey, set the next steps for research (Section 5.6): whether the patterns hold beyond these respondents, why women here do not lag behind men, how students learn about privacy, and how closely students and lecturers follow written rules.

The paper also adds to the evidence and to research methods. It is, to our knowledge, the largest survey so far of generative AI use in Cambodian higher education by number of respondents, and the first study in Cambodia to report in full a comparison of students and lecturers on matching questions. It pairs self-ratings with tested knowledge, and personal views with the rules as respondents understand them. This shows gaps that a single measure would hide. The scenario questions are short and can be reused in other settings and in later surveys. The knowledge items

show the value of the approach but should be extended and validated before reuse. The recommendations that follow address the needs identified in this chapter.

6.2. Policy recommendations

The recommendations follow from the findings in Chapter 4. Judgements about cost and about who should lead are the authors' suggestions. Together the recommendations broadly cover the three areas that Chan (2023) proposes for institutional AI policy: teaching and assessment (Recommendations 2 and 3); governance, including fair access (Recommendations 1 and 6); and operations, including infrastructure and training (Recommendations 4, 5 and 7). In the authors' judgement, the first two cost little and could start at once, while the others would take longer and involve the ministries; these costs have not been estimated. Participants at the validation workshop ranked a short written policy (Recommendation 1), teaching data privacy and accuracy (Recommendation 4) and a statement of permitted use in every course (Recommendation 2) as the three most urgent steps.

Recommendation 1: Give every institution a short written policy, and make sure it is seen.

Fewer than one in four respondents know of a written policy, and students at the same institution disagree about whether one exists. Uncertainty about the rules depends little on who the student is or which university they attend. It is lower among students who know of a written policy. Each institution should adopt a short policy in Khmer and English that sorts common uses of AI into allowed, allowed with acknowledgement, or prohibited. It should share the policy through channels that students actually use. The Ministry of Education, Youth and Sport could issue a model text, and the Accreditation Committee of Cambodia could ask institutions to show their policy during accreditation.

A model text would give institutions a shared starting point, and it need not be long. It could set out: the scope (students and staff; coursework, assessment and research); for each common use, whether it is allowed, allowed with acknowledgement or prohibited, with lecturers free to set a stricter rule for a given task; how to acknowledge use of AI; which student and institutional data must not be entered into AI tools; how assessment will be designed and checked; that a detection score is never the only evidence of misconduct; how the policy will be shared with students and staff; and a date for review.

Recommendation 2: Require a statement of permitted AI use in every course. Uncertainty is much lower where lecturers explain the rules in almost all classes, but only a third of students report this. What the survey measured is explanation in class. A short statement in each syllabus and assessment brief, saying what use of AI is allowed for that task and explained in class, is a simple way to put this into practice.

Recommendation 3: Settle the contested cases with students and lecturers together.

Students and lecturers agree on low-stakes uses, such as explaining a concept or translating, and institutions can allow these openly. They disagree most about take-home exams and substantial drafting, and neither group has a settled view. Institutions should decide these cases explicitly. They should agree the rules with student representatives before applying any sanctions, and review assessment formats where the agreed rule cannot be upheld in practice, for example by asking students to present or explain their work in person, as some institutions represented at the validation workshop have begun to do. Sanctions should not rest on AI-detection scores alone: the tools tested so far have been found inaccurate and biased against writers of English as a foreign language (Section 2.4), so a score should at most prompt a conversation with the student.

Recommendation 4: Teach data privacy and the judgement of accuracy, to students and lecturers. Fewer than half of students know that pasted text can be seen by the company that

runs a tool. Only four in ten feel able to judge whether information from AI is accurate, and more than half are unsure. Lecturers need the same attention: one in seven have entered sensitive student data into an AI tool. Training should cover both points, together with checking references, which most students already understand. It should be assessed with questions that have right answers, not by self-rating. Few of those open to training choose privacy as a topic (20.0 percent of students, 10.5 percent of lecturers). Privacy should therefore be built into training on prompting and checking accuracy rather than offered as a separate module. The same applies to ethics and academic integrity, chosen by only 18.7 percent of students and 28.5 percent of lecturers. Because students who use AI least are also the least interested in training, it should be built into existing courses, such as first-year study skills or research methods, rather than offered only as optional sessions. Institutional policies should state what student data may not be entered into AI tools. The OECD and European Union framework discussed in Section 2.3 provides a structure (OECD and European Union 2026).

Recommendation 5: Design for smartphones and for Khmer. Among respondents, access to AI is not the main problem; the quality of that access is. The students who use AI least intensively study in the provinces, work on phones, prompt in Khmer and have no laptop. Three in ten students combine three or four of these disadvantages. Guidance and training should work on a phone and be available in Khmer. Institutions could also consider wider access to shared computers and campus Wi-Fi: four in ten students name the cost or reliability of internet access as a barrier, although internet reliability is not clearly linked to frequency of use (Appendix Table B1). Among fields, law students have the weakest access in this sample: they most often study outside Phnom Penh, lack a laptop and prompt in Khmer. In the authors' view, IT students could be considered as peer helpers. National investment in Khmer-language AI resources could help address a barrier that half of respondents report.

Recommendation 6: Address cost. Cost is the barrier both groups name most often. Almost all lecturers who use paid tools pay for them personally, and among students, cost is named most often by those who already use AI most, for whom it appears to limit how deeply they use AI rather than whether they use it. Institutions and the ministry should explore institutional licences or negotiated educational access. They should start with lecturers, who use paid tools most, and extend access to students as resources allow, since four in ten students say they cannot afford paid versions. Access for students should be directed first at those with the weakest access, such as students who rely on a phone, so that it narrows gaps rather than widens them. The link between a paid plan and frequent use is tentative and may partly reflect heavy users choosing to pay. This paper has not estimated the cost of such access.

Recommendation 7: Use lecturers as trainers, and prepare them first. Four in five lecturers want training, and half of those open to training are both willing and ready to train colleagues; a further 14.6 percent are willing but do not yet feel ready. A train-the-trainer programme can start with those who are willing and ready, and should prepare the others before they teach. Training should begin with prompting and checking accuracy, the topics both groups ask for first. Hands-on workshops for lecturers and short online modules for students, supported by a dedicated unit in each institution, match the formats each group prefers. Because women lecturers are less likely than men to feel ready to train others, although they rate their skills the same, the programme should actively invite women rather than rely on volunteers.

References

- Acemoglu, Daron, and Simon Johnson. 2023. *Power and Progress: Our Thousand-Year Struggle over Technology and Prosperity*. New York: PublicAffairs.
- Baek, Clare, Tamara Tate, and Mark Warschauer. 2024. "'ChatGPT Seems Too Good to Be True': College Students' Use and Perceptions of Generative AI." *Computers and Education: Artificial Intelligence* 7: 100294. <https://doi.org/10.1016/j.caeai.2024.100294>.
- Baggia, Alenka, Alenka Tratnik, and Alenka Brezavšček. 2026. "University Teachers' Perceptions, Attitudes, and Practices with Generative AI: A Systematic Literature Review with a Meta-Analytic Component." *Quality & Quantity* 60: 14107–39. <https://doi.org/10.1007/s11135-026-02717-x>.
- Barrett, Alex, and Austin Pack. 2023. "Not Quite Eye to A.I.: Student and Teacher Perspectives on the Use of Generative Artificial Intelligence in the Writing Process." *International Journal of Educational Technology in Higher Education* 20: 59. <https://doi.org/10.1186/s41239-023-00427-0>.
- Bastani, Hamsa, Osbert Bastani, Alp Sungu, et al. 2025. "Generative AI without Guardrails Can Harm Learning: Evidence from High School Mathematics." *Proceedings of the National Academy of Sciences* 122 (26): e2422633122. <https://doi.org/10.1073/pnas.2422633122>.
- Be, Borey, Sopheng Tep, and Samnang Long. 2026. "Determinants of Artificial Intelligence Adoption in Higher Education: Evidence from Cambodian University Students." *Journal of Innovation in Academia* 5 (1): 1–22. <https://doi.org/10.32674/fq333m72>.
- Beckman, Karley, Tiffani Apps, Sarah K. Howard, Claire Rogerson, Ann Rogerson, and Jo Tondeur. 2025. "The GenAI Divide among University Students: A Call for Action." *The Internet and Higher Education* 67: 101036. <https://doi.org/10.1016/j.iheduc.2025.101036>.
- Bhatta, Saurav Dev, Jamil Salmi, Saurav Katwal, Lauri Pynnonen, and Somphosphreak Heng. 2024. *Reimagining Higher Education in Cambodia: Modernizing Governance for Improved Access and Relevance*. Report No. AUS0003389. Washington, DC: World Bank. <https://documents1.worldbank.org/curated/en/099031924051037712/pdf/P17929010668ee0461b4bc119eb01d77991.pdf>.
- Brynjolfsson, Erik, Danielle Li, and Lindsey Raymond. 2025. "Generative AI at Work." *Quarterly Journal of Economics* 140 (2): 889–942. <https://doi.org/10.1093/qje/qjae044>.
- Chan, Cecilia Ka Yuk. 2023. "A Comprehensive AI Policy Education Framework for University Teaching and Learning." *International Journal of Educational Technology in Higher Education* 20: 38. <https://doi.org/10.1186/s41239-023-00408-3>.
- Chea, Sathya, Veronica Mendizabal Joffre, Sopheak Song, and Boravin Tann. 2026. *Bridging the Gender Gap in Cambodia's STEM Education and Careers*. ADB Briefs 385. Mandaluyong City, Philippines: Asian Development Bank. <https://doi.org/10.22617/BRF260119-2>.
- Chung, Jennifer, Michael Henderson, Christine Slade, et al. 2026. "The Use and Usefulness of GenAI in Higher Education: Student Experience and Perspectives." *Computers and Education Open* 10: 100347. <https://doi.org/10.1016/j.caeo.2026.100347>.
- Connell Pensky, Allison E., Lydia E. Eckstein, Michael C. Melville, et al. 2026. "Can Asynchronous Learning Modules about Generative AI Increase Students' Knowledge, Skills, and Self-Efficacy for GenAI?" *Computers & Education* 250: 105640. <https://doi.org/10.1016/j.compedu.2026.105640>.
- Correa, Teresa, Isabel Pavez, and Javier Contreras. 2020. "Digital Inclusion through Mobile Phones? A Comparison between Mobile-Only and Computer Users in Internet Access, Skills and Use." *Information, Communication & Society* 23 (7): 1074–91. <https://doi.org/10.1080/1369118X.2018.1555270>.

- Digital Education Council. 2024. *AI or Not AI: What Students Want. Digital Education Council Global AI Student Survey 2024*. <https://www.digitaleducationcouncil.com/post/what-students-want-key-results-from-dec-global-ai-student-survey-2024>.
- Freeman, Josh. 2025. *Student Generative AI Survey 2025*. HEPI Policy Note 61. Oxford: Higher Education Policy Institute. <https://www.hepi.ac.uk/reports/student-generative-ai-survey-2025/>.
- Habibi, Akhmad, Muhaimin Muhaimin, Bernadus Kopong Danibao, et al. 2023. "ChatGPT in Higher Education Learning: Acceptance and Use." *Computers and Education: Artificial Intelligence* 5: 100190. <https://doi.org/10.1016/j.caeai.2023.100190>.
- Hargittai, Eszter. 2002. "Second-Level Digital Divide: Differences in People's Online Skills." *First Monday* 7 (4). <https://doi.org/10.5210/fm.v7i4.942>.
- Heng, Kimkong, Sarin Sok, Koemhong Sol, and Ratha Sor. 2026. "A Survey Study of Cambodian University Lecturers' Experiences and Perceptions of AI Use." *Discover Artificial Intelligence* 6: 1241. <https://doi.org/10.1007/s44163-026-02313-w>.
- Hoeurng, Heak, Phearun Phorn, Sopharath Kheav, and Rany Sam. 2024. "Integrating Artificial Intelligence in Higher Education: A Case Study of Cambodian Universities." *European Journal of Theoretical and Applied Sciences* 2 (5): 462–73. [https://doi.org/10.59324/ejtas.2024.2\(5\).47](https://doi.org/10.59324/ejtas.2024.2(5).47).
- Humlum, Anders, and Emilie Vestergaard. 2025. "The Unequal Adoption of ChatGPT Exacerbates Existing Inequalities among Workers." *Proceedings of the National Academy of Sciences* 122 (1): e2414972121. <https://doi.org/10.1073/pnas.2414972121>.
- Huy, Sopheaktra, Phinavuth Chhay, Sokroern Ang, Mony Ho, and Piseth Soeng. 2026. "AI Tool Adoption and Its Impact on Perceived Learning Outcomes among University Students in Cambodia." *AUB Research Series* 5: 1–27. <https://doi.org/10.71215/ars.202651>.
- Jiang, Yingying, Lindai Xie, and Xiaoyu Cao. 2025. "Exploring the Effectiveness of Institutional Policies and Regulations for Generative AI Usage in Higher Education." *Higher Education Quarterly* 79 (4): e70054. <https://doi.org/10.1111/hequ.70054>.
- Jin, Yueqiao, Roberto Martinez-Maldonado, Dragan Gašević, and Lixiang Yan. 2025. "GLAT: The Generative AI Literacy Assessment Test." *Computers and Education: Artificial Intelligence* 9: 100436. <https://doi.org/10.1016/j.caeai.2025.100436>.
- Kakooza, Tobias, Derrick Walugada, and John Alege. 2026. "Digital Device Access as a Predictor of Artificial Intelligence Tool Adoption among University Students in Uganda." *East African Journal of Information Technology* 9 (2): 310–30. <https://doi.org/10.37284/eajit.9.2.5786>.
- Kemp, Simon. 2025. "Digital 2026: Cambodia." *DataReportal*, November 8, 2025. <https://datareportal.com/reports/digital-2026-cambodia>.
- Kizilcec, René F., Elaine Huber, Elena C. Papanastasiou, Andrew Cram, Christos A. Makridis, Adele Smolansky, Sandris Zeivots, and Corina Radulescu. 2024. "Perceived Impact of Generative AI on Assessments: Comparing Educator and Student Perspectives in Australia, Cyprus, and the United States." *Computers and Education: Artificial Intelligence* 7: 100269. <https://doi.org/10.1016/j.caeai.2024.100269>.
- Lai, Viet Dac, Nghia Trung Ngo, Amir Pouran Ben Veyseh, Hieu Man, Franck Dernoncourt, Trung Bui, and Thien Huu Nguyen. 2023. "ChatGPT beyond English: Towards a Comprehensive Evaluation of Large Language Models in Multilingual Learning." In *Findings of the Association for Computational Linguistics: EMNLP 2023*, 13171–89. <https://doi.org/10.18653/v1/2023.findings-emnlp.878>.
- Laupichler, Matthias Carl, Alexandra Aster, Nicolas Haverkamp, and Tobias Raupach. 2023. "Development of the 'Scale for the Assessment of Non-Experts' AI Literacy': An Exploratory Factor Analysis." *Computers in Human Behavior Reports* 12: 100338. <https://doi.org/10.1016/j.chbr.2023.100338>.

- Laupichler, Matthias Carl, Alexandra Aster, Marcel Meyerheim, Tobias Raupach, and Marvin Mergen. 2024. "Medical Students' AI Literacy and Attitudes towards AI: A Cross-Sectional Two-Center Study Using Pre-Validated Assessment Instruments." *BMC Medical Education* 24: 401. <https://doi.org/10.1186/s12909-024-05400-7>.
- Liang, Weixin, Mert Yuksekgonul, Yining Mao, Eric Wu, and James Zou. 2023. "GPT Detectors Are Biased against Non-Native English Writers." *Patterns* 4 (7): 100779. <https://doi.org/10.1016/j.patter.2023.100779>.
- Lintner, Tomáš. 2024. "A Systematic Review of AI Literacy Scales." *npj Science of Learning* 9: 50. <https://doi.org/10.1038/s41539-024-00264-4>.
- Long, Duri, and Brian Magerko. 2020. "What Is AI Literacy? Competencies and Design Considerations." In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, Paper 598, 1–16. Honolulu, HI, April 25–30, 2020. New York: ACM. <https://doi.org/10.1145/3313831.3376727>.
- Lork, Chumneanh, Piseth Holl, Chanbopheak Nguon, Dymo Sun, Chen Rous, and Vichheka So. 2026. "An Integrated Model of ChatGPT Acceptance and Continuance in Cambodian Higher Education." *International Journal of Special Education* 41 (7s): 61–81.
- Lundy, Timothy, Manuel Ramos-Maqueda, Shyam Jayanti Patel, Daniel Rogger, Flavia Sacco Capurro, and Josefina Silva Fuentealba. 2026. "How Is Government Using Artificial Intelligence?" Background paper for *World Development Report 2026: The Promise of Artificial Intelligence*. Washington, DC: World Bank. <https://www.worldbank.org/en/publication/wdr2026/brief/world-development-report-2026-background-papers>.
- Mah, Dana-Kristin, and Nele Groß. 2024. "Artificial Intelligence in Higher Education: Exploring Faculty Use, Self-Efficacy, Distinct Profiles, and Professional Development Needs." *International Journal of Educational Technology in Higher Education* 21: 58. <https://doi.org/10.1186/s41239-024-00490-1>.
- Matobobo, Courage. 2026. "A Systematic Review of Gender Differences in Students' Use of AI Tools for Learning in Higher Education." *Discover Education* 5: 90. <https://doi.org/10.1007/s44217-026-01116-6>.
- Miao, Fengchun, and Wayne Holmes. 2023. *Guidance for Generative AI in Education and Research*. Paris: UNESCO. <https://doi.org/10.54675/EWZM9535>.
- MOEYS (Ministry of Education, Youth and Sport). 2024. *Education Strategic Plan 2024–2028*. Phnom Penh: MOEYS.
- MOEYS (Ministry of Education, Youth and Sport). 2025. *Education Congress: The Education, Youth and Sport Performance in the Academic Year 2023–2024 and Goals for the Academic Year 2024–2025*. Report to the Education Congress, 24–26 February 2025. Unofficial translation. Phnom Penh: MOEYS.
- Møgelvang, Anja, Camilla Bjelland, Simone Grassini, and Kristine Ludvigsen. 2024. "Gender Differences in the Use of Generative Artificial Intelligence Chatbots in Higher Education: Characteristics and Consequences." *Education Sciences* 14 (12): 1363. <https://doi.org/10.3390/educsci14121363>.
- Moorhouse, Benjamin Luke, Marie Alina Yeo, and Yuwei Wan. 2023. "Generative AI Tools and Assessment: Guidelines of the World's Top-Ranking Universities." *Computers and Education Open* 5: 100151. <https://doi.org/10.1016/j.caeo.2023.100151>.
- MPTC (Ministry of Post and Telecommunications). 2025. *Draft National Artificial Intelligence Strategy 2025–2030*. June 2025. Phnom Penh: MPTC.

- Ng, Davy Tsz Kit, Jac Ka Lok Leung, Samuel Kai Wah Chu, and Maggie Shen Qiao. 2021. "Conceptualizing AI Literacy: An Exploratory Review." *Computers and Education: Artificial Intelligence* 2: 100041. <https://doi.org/10.1016/j.caeai.2021.100041>.
- Nguyen, Xuan-Phi, Wenxuan Zhang, Xin Li, et al. 2023. "SeaLLMs: Large Language Models for Southeast Asia." arXiv:2312.00738v2. Version 2, July 2024. <https://arxiv.org/abs/2312.00738>.
- NIS (National Institute of Statistics), MoH (Ministry of Health), and ICF. 2023. *Cambodia Demographic and Health Survey 2021–22: Summary Report*. Phnom Penh: NIS and MoH; Rockville, MD: ICF. <https://dhsprogram.com/pubs/pdf/SR281/SR281.pdf>.
- OECD and European Union. 2026. *Empowering Learners for the Age of AI: An AI Literacy Framework for Primary and Secondary Education*. Paris: OECD Publishing. <https://doi.org/10.1787/65cd27d4-en>.
- Perkins, Mike, Leon Furze, Jasper Roe, and Jason MacVaugh. 2024. "The Artificial Intelligence Assessment Scale (AIAS): A Framework for Ethical Integration of Generative AI in Educational Assessment." *Journal of University Teaching and Learning Practice* 21 (6). <https://doi.org/10.53761/q3azde36>.
- Pum, Mengkorn. 2025. "The Paradox of Augmentation and Erosion: Navigating Utility, Critical Agency, and Trust Deficit in AI Writing Tools among Cambodian English Major Undergraduates." *Interdisciplinary Educational Technology* 1 (1): e105. <https://doi.org/10.71176/interedtech/17573>.
- Pum, Mengkorn, and Sarin Sok. 2024. "Leveraging AI in Education in Cambodia: A Review of Perceived Concerns and Associated Benefits." *Asian Journal of Distance Education* 19 (2): 157–67. <https://doi.org/10.5281/zenodo.13354998>.
- Ravšelj, Dejan, Damijana Keržič, Nina Tomažević, et al. 2025. "Higher Education Students' Perceptions of ChatGPT: A Global Study of Early Reactions." *PLOS ONE* 20 (2): e0315011. <https://doi.org/10.1371/journal.pone.0315011>.
- RGC (Royal Government of Cambodia). 2021. *Cambodia Digital Economy and Society Policy Framework 2021–2035*. Phnom Penh: RGC.
- Rismanchian, Sina, Eesha Tur Razia Babar, and Shayan Doroudi. 2026. "What Undergraduate Students Need to Know and Actually Know about Generative AI." *Computers and Education: Artificial Intelligence* 10: 100554. <https://doi.org/10.1016/j.caeai.2026.100554>.
- Sol, Koemhong, Kimkong Heng, and Sarin Sok. 2025. "Using AI in English Language Learning: An Exploration of Cambodian EFL University Students' Experiences and Perceptions." *Journal of Science of Learning and Innovations* 2 (2): 113–44. <https://doi.org/10.1163/29497736-bja00015>.
- Stöhr, Christian, Amy Wanyu Ou, and Hans Malmström. 2024. "Perceptions and Usage of AI Chatbots among Students in Higher Education across Genders, Academic Levels and Fields of Study." *Computers and Education: Artificial Intelligence* 7: 100259. <https://doi.org/10.1016/j.caeai.2024.100259>.
- Tan, Michelle Xin Yi, Yao Qu, and Jue Wang. 2025. "Student Perceptions of Generative Artificial Intelligence Regulations: A Mixed-Methods Study of Higher Education in Singapore." *Higher Education Quarterly* 79 (3): e70038. <https://doi.org/10.1111/hequ.70038>.
- UNESCO. 2021. *Recommendation on the Ethics of Artificial Intelligence*. Paris: UNESCO. <https://www.unesco.org/en/legal-affairs/recommendation-ethics-artificial-intelligence>.
- UNESCO. 2023. "UNESCO Survey: Less than 10% of Schools and Universities Have Formal Guidance on AI." June 1, 2023. <https://www.unesco.org/en/articles/unesco-survey-less-10-schools-and-universities-have-formal-guidance-ai>.
- UNESCO. 2025a. *Cambodia: Artificial Intelligence Readiness Assessment Report*. Phnom Penh: UNESCO.

- UNESCO. 2025b. "UNESCO Survey: Two-Thirds of Higher Education Institutions Have or Are Developing Guidance on AI Use." September 2, 2025. <https://www.unesco.org/en/articles/unesco-survey-two-thirds-higher-education-institutions-have-or-are-developing-guidance-ai-use>.
- van Deursen, Alexander J. A. M., and Ellen J. Helsper. 2015. "The Third-Level Digital Divide: Who Benefits Most from Being Online?" In *Communication and Information Technologies Annual: Digital Distinctions and Inequalities*, edited by Laura Robinson, Shelia R. Cotten, Jeremy Schulz, Timothy M. Hale, and Apryl Williams, 29–52. Studies in Media and Communications 10. Bingley: Emerald. <https://doi.org/10.1108/S2050-206020150000010002>.
- van Deursen, Alexander J. A. M., and Jan A. G. M. van Dijk. 2014. "The Digital Divide Shifts to Differences in Usage." *New Media & Society* 16 (3): 507–26. <https://doi.org/10.1177/1461444813487959>.
- van Deursen, Alexander J. A. M., and Jan A. G. M. van Dijk. 2019. "The First-Level Digital Divide Shifts from Inequalities in Physical Access to Inequalities in Material Access." *New Media & Society* 21 (2): 354–75. <https://doi.org/10.1177/1461444818797082>.
- Walters, William H., and Esther Isabelle Wilder. 2023. "Fabrication and Errors in the Bibliographic Citations Generated by ChatGPT." *Scientific Reports* 13: 14045. <https://doi.org/10.1038/s41598-023-41032-5>.
- Wang, Bingcheng, Pei-Luen Patrick Rau, and Tianyi Yuan. 2023. "Measuring User Competence in Using Artificial Intelligence: Validity and Reliability of Artificial Intelligence Literacy Scale." *Behaviour & Information Technology* 42 (9): 1324–37. <https://doi.org/10.1080/0144929X.2022.2072768>.
- Weber-Wulff, Debora, Alla Anohina-Naumeca, Sonja Bjelobaba, Tomáš Foltýnek, Jean Guerrero-Dib, Olumide Popoola, Petr Šigut, and Lorna Waddington. 2023. "Testing of Detection Tools for AI-Generated Text." *International Journal for Educational Integrity* 19: 26. <https://doi.org/10.1007/s40979-023-00146-z>.
- World Bank. 2026. *World Development Report 2026: The Promise of Artificial Intelligence*. Washington, DC: World Bank. <https://doi.org/10.1596/978-1-4648-2331-2>.
- Ying, Ji. 2026. "Academic Integrity in the Age of Generative AI: A Scoping Review of Research on Higher Education Student Voices." *Journal of Academic Ethics* 24 (3): 78. <https://doi.org/10.1007/s10805-026-09752-1>.

Appendices

Appendix A: Survey items and measurement

Table A1: Survey items used in the analysis

Construct	Survey item (English)	Response scale and source
Ever used AI	Have you ever used an AI tool for your studies, coursework, or learning activities? (Lecturers: for your academic or professional work?)	Yes / No. Developed by the authors
Tools used	Which AI tools have you used for your studies? (Lecturers: for your work?)	Multiple response, 13 options including one fictitious tool. Developed by the authors
Plan	What AI subscription plan do you use?	Free / Paid. Lecturers on a paid plan: who pays
Frequency of use	Overall, how often do you use AI tools for your studies? (Lecturers: for your work?)	Never, rarely, monthly, weekly, several times a week, daily
Length of use	How long have you been using AI tools for study?	Five bands from under 3 months to over 2 years. Students only
Purposes (students)	How often do you use AI for each of the following? Nine purposes, from searching for or explaining information to generating or formatting references	Never, rarely, sometimes, often, always
Purposes (lecturers)	How often do you use AI for each of the following? Five tasks: preparing lectures, research or academic writing, administration, translation, coding or data analysis	Never to daily
Prompt language; main device	Which language do you mainly use when prompting AI tools? Which device do you mainly use for AI tools?	Mostly Khmer, mostly English, both, other; device asked of students only
Self-rated AI literacy: awareness	D1 I can recognise when a product or service I use relies on AI. D2 I can identify which AI features are used in the apps and products I use. D3 I can explain to someone else how AI tools could help with their studies (lecturers: I do not really understand how AI can be useful to me, reversed)	Five-point agreement. Adapted from AILS items AW_1, AW_9 and AW_8 (Wang, Rau, and Yuan 2023)
Self-rated AI literacy: usage	D4 I can use AI applications to help me with my academic work. D5 I can work out how to use an AI tool I have never used before (lecturers: I find it hard to learn how to use a new AI tool, reversed)	Adapted from AILS items US_1 and US_3
Self-rated AI literacy: evaluation	D6 I can judge whether the information an AI tool gives me is accurate. D7 After using an AI tool for a while, I can judge what it is good and bad at. D8 When several AI tools could do a task, I can choose the most suitable one	D6 developed by the authors; D7 and D8 adapted from AILS items EV_2 and EV_6
Self-rated AI literacy: ethics	D9 I try to follow ethical principles when I use AI tools. D10 I pay attention to privacy and data-	Adapted from AILS items ET_1, ET_2 (reworded positively) and ET_5

Construct	Survey item (English)	Response scale and source
Self-rated AI literacy: verification and prompting	security risks when I use AI tools. D11 I am alert to the misuse of AI D12 I check AI answers against other sources before I use them. D13 Before I use an AI answer, I check whether it is correct (lecturers: I tend to accept AI outputs even when I cannot verify whether they are correct, reversed; excluded). D14 I can give an AI tool enough context and clear instructions to get a useful result. D15 I can decide when an AI's answer should be accepted, improved, or rejected	Developed by the authors, following the competences on evaluating and guiding AI output in OECD and European Union (2026)
Tested knowledge	D16 (checking an AI-supplied reference), D18 (who can see pasted text)	Multiple choice with one correct answer and "don't know". Developed by the authors. Students only
Perceived benefits	How has using AI tools affected the speed at which you complete your coursework? How has AI impacted the overall quality of your academic work or grades? (Lecturers: daily workload; quality of teaching materials)	Five-point scales from strong improvement to strong worsening
Own view on four uses	In your opinion, how acceptable is each of the following as academic practice? Explaining a concept; translating; writing substantial parts of an assignment submitted as one's own; answering questions in a take-home exam or online quiz	Acceptable, depends, not acceptable, unsure. Developed by the authors
Perceived rule on four uses	For each of the same situations, does your university currently allow it?	Yes, allowed; no, not allowed; there is no clear rule; don't know
Policy awareness	Has your university issued clear, official rules regarding student AI use? (Lecturers: official rules or guidance for lecturers and students?)	Formal written policy; informal verbal guidance; (lecturers: being worked on); nothing at all; don't know
Lecturers explain	Have your lecturers explicitly explained what is and is not acceptable AI use in their classes?	Almost all classes; only a few; rarely or never. Students only
Barriers	Which of these are the biggest barriers limiting your use of AI for study? (Lecturers: in teaching?)	Select up to three from 10 (students) or 11 (lecturers) options
Training	Training received; interest in training; topics wanted (up to three); preferred format; preferred provider (students); willingness and readiness to train peers (lecturers)	Mixed formats. Developed by the authors
Lecturer practice and outlook	Use of AI to create assessments, mark and detect; changes to assessment; ground rules; what students are permitted; feeling about the pace of AI; expected impact on the profession	Frequency and agreement scales. Lecturers only

Note: Both questionnaires were administered in Khmer with English available. The complete instruments are available from the authors.

Source: Authors.

Appendix B: Robustness analyses and full model results

Table B1: Binary logistic regression: frequent AI use (several times a week or daily)

Predictor	Coefficient	Std. error	p-value	Marginal effect
Woman (ref: man)	0.329	0.107	0.002 **	+6.6 pp
Phnom Penh (ref: provinces)	0.507	0.098	<0.001 ***	+10.1 pp
Private institution (ref: public)	-0.075	0.093	0.419	-1.5 pp
STEM field (ref: non-STEM)	0.226	0.125	0.071	+4.5 pp
Year 2 (ref: Year 1)	-0.160	0.202	0.429	-3.2 pp
Year 3	-0.273	0.214	0.202	-5.5 pp
Year 4	-0.409	0.216	0.058	-8.2 pp
Year 5 or above, postgraduate	-0.199	0.282	0.481	-4.0 pp
First generation at university	0.237	0.155	0.127	+4.7 pp
Academic English (1-5)	-0.001	0.106	0.994	-0.0 pp
Owns a laptop	0.259	0.099	0.009 **	+5.2 pp
Smartphone is main device for AI	-0.582	0.137	<0.001 ***	-11.6 pp
Internet reliability (1-5)	0.113	0.096	0.241	+2.3 pp
On a paid plan	0.832	0.357	0.020 *	+16.6 pp
Prompts mostly in Khmer	-0.279	0.104	0.007 **	-5.6 pp
Length of AI use (1-5)	0.666	0.075	<0.001 ***	+13.3 pp
Received university AI training	0.052	0.165	0.752	+1.0 pp

Note: N = 1,193; McFadden pseudo R^2 = 0.157; log-likelihood = -696.4. Standard errors clustered by institution. Marginal effects are average marginal effects in percentage points. *** p<0.001; ** p<0.01; * p<0.05.

Source: Authors' calculation.

Table B2: Multinomial logistic regression: intensity of use (reference: Occasional)

Predictor	Focused vs. Occasional			Intensive vs. Occasional		
	Coef.	Std. error	p	Coef.	Std. error	p
Woman (ref: man)	0.072	0.148	0.627	0.182	0.125	0.145
Phnom Penh (ref: provinces)	-0.029	0.217	0.894	0.331	0.177	0.062
Private institution (ref: public)	-0.414	0.123	<0.001 ***	-0.255	0.312	0.413
STEM field (ref: non-STEM)	0.094	0.182	0.605	0.003	0.189	0.989
Year 2 (ref: Year 1)	-0.444	0.321	0.166	-0.280	0.322	0.385
Year 3	-0.381	0.368	0.300	-0.020	0.409	0.960
Year 4	-0.575	0.386	0.136	-0.319	0.396	0.420
Year 5 or above, postgraduate	-0.526	0.462	0.255	-0.749	0.513	0.144
First generation at university	-0.304	0.203	0.135	-0.093	0.196	0.634
Academic English (1-5)	0.017	0.131	0.897	0.183	0.123	0.137
Owns a laptop	0.047	0.161	0.772	0.089	0.178	0.617
Smartphone is main device for AI	-0.092	0.272	0.734	-0.796	0.223	<0.001 ***
Internet reliability (1-5)	0.170	0.111	0.124	0.205	0.169	0.227
On a paid plan	0.010	0.456	0.983	0.937	0.504	0.063

Predictor	Focused vs. Occasional			Intensive vs. Occasional		
	Coef.	Std. error	p	Coef.	Std. error	p
Prompts mostly in Khmer	0.026	0.236	0.913	-0.379	0.161	0.018 *
Length of AI use (1-5)	0.439	0.081	<0.001 ***	0.883	0.097	<0.001 ***
Received university AI training	0.021	0.156	0.892	0.266	0.211	0.208

Note: N = 1,193; McFadden pseudo R^2 = 0.128. Standard errors clustered by institution (22 institutions). *** p<0.001; ** p<0.01; * p<0.05.

Source: Authors' calculation.

Table B3: Correlates of self-rated literacy and of two knowledge items (student AI users)

Predictor	Self-rated literacy index (OLS)	D16 correct: checking a reference (logit)	D18 correct: who can see pasted text (logit)
Woman (ref: man)	-0.065*** (0.011)	0.054 (0.148)	0.196 (0.118)
Phnom Penh (ref: provinces)	-0.047 (0.031)	0.027 (0.216)	-0.028 (0.173)
Private institution (ref: public)	-0.006 (0.023)	-0.186 (0.224)	-0.280 (0.169)
STEM field (ref: non-STEM)	-0.008 (0.018)	0.017 (0.128)	0.151 (0.083)
Year 2 (ref: Year 1)	-0.092* (0.041)	-0.293 (0.442)	-0.173 (0.247)
Year 3	-0.139*** (0.039)	-0.281 (0.391)	-0.107 (0.233)
Year 4	-0.106** (0.037)	-0.273 (0.333)	-0.343 (0.231)
Year 5 or above, postgraduate	0.002 (0.041)	0.081 (0.484)	-0.202 (0.323)
First generation at university	0.060 (0.034)	-0.033 (0.107)	-0.093 (0.121)
Academic English (1-5)	0.086*** (0.016)	-0.074 (0.069)	0.043 (0.083)
Owns a laptop	0.025 (0.018)	0.086 (0.194)	0.106 (0.130)
Smartphone is main device for AI	-0.036 (0.032)	-0.130 (0.150)	-0.216 (0.117)
Internet reliability (1-5)	0.047*** (0.013)	0.298** (0.107)	0.140 (0.076)
On a paid plan	0.039 (0.044)	-0.133 (0.345)	-0.118 (0.319)
Prompts mostly in Khmer	-0.083** (0.029)	-0.179 (0.157)	-0.160 (0.158)
Length of AI use (1-5)	0.065*** (0.012)	-0.075 (0.058)	0.131* (0.060)
Received university AI training	-0.022 (0.026)	-0.119 (0.135)	-0.111 (0.106)
Frequency of AI use (1-6)	0.056*** (0.008)	-0.051 (0.054)	0.004 (0.041)
Self-rated AI literacy index	-	0.551** (0.172)	0.726*** (0.168)
N	1,193	1,193	1,193
R² / pseudo R²	0.222	0.028	0.049

Note: Column 1 reports OLS coefficients and columns 2 and 3 logit coefficients, with standard errors in parentheses, clustered by institution. D16 = knows that the first step with a reference supplied by AI is to check that it exists; D18 = knows that pasted text can be seen by the company operating the tool. *** p<0.001; ** p<0.01; * p<0.05.

Source: Authors' calculation.

Table B4: Binary logistic regression: perceiving no clear rule on at least one contested scenario

Predictor	Coefficient	Std. error	p-value	Marginal effect
Woman (ref: man)	0.127	0.144	0.379	+3.0 pp
Phnom Penh (ref: provinces)	-0.061	0.193	0.750	-1.4 pp
Private institution (ref: public)	-0.049	0.188	0.794	-1.2 pp

Predictor	Coefficient	Std. error	p-value	Marginal effect
STEM field (ref: non-STEM)	-0.023	0.266	0.930	-0.6 pp
Year 2 (ref: Year 1)	-0.053	0.206	0.796	-1.3 pp
Year 3	-0.001	0.204	0.997	-0.0 pp
Year 4	-0.013	0.217	0.954	-0.3 pp
Year 5 or above, postgraduate	-0.243	0.327	0.457	-5.7 pp
First generation at university	0.067	0.143	0.641	+1.6 pp
Academic English (1-5)	-0.051	0.094	0.587	-1.2 pp
Owns a laptop	-0.051	0.097	0.600	-1.2 pp
Smartphone is main device for AI	-0.067	0.160	0.674	-1.6 pp
Internet reliability (1-5)	0.038	0.084	0.647	+0.9 pp
On a paid plan	-0.493	0.276	0.074	-11.7 pp
Prompts mostly in Khmer	-0.173	0.096	0.071	-4.1 pp
Length of AI use (1-5)	0.002	0.042	0.964	+0.0 pp
Received university AI training	-0.125	0.130	0.337	-2.9 pp
Reports a formal written policy	-0.588	0.123	<0.001 ***	-13.9 pp
Lecturers explain rules in almost all classes	-0.486	0.124	<0.001 ***	-11.5 pp

Note: N = 1,193; McFadden pseudo R² = 0.031. Outcome = answers "there is no clear rule" or "don't know" for writing substantial parts of an assignment or for take-home exams. Standard errors clustered by institution. *** p<0.001; ** p<0.01; * p<0.05.

Source: Authors' calculation.

Table B5: Headline results under alternative sample definitions

Indicator	Main	Stricter	Self-completed	All in file
Students (n)	1,510	1,408	1,471	1,707
Lecturers (n)	285	279	279	299
Students using AI several times a week or daily (%)	46.2	47.0	46.7	45.4
Lecturers using AI several times a week or daily (%)	62.1	62.4	62.0	60.6
Frequent use, Phnom Penh students (%)	51.6	52.7	52.0	50.7
Frequent use, provincial students (%)	35.4	35.0	36.1	35.2
Frequent use, students with a laptop (%)	53.9	54.7	54.1	53.7
Frequent use, students without a laptop (%)	33.4	33.8	34.2	32.4
Student self-rated literacy index (mean)	3.61	3.63	3.62	3.58
D16 correct (%)	75.1	76.1	75.9	73.0
D18 correct (%)	45.9	46.3	45.8	44.6
D16 and D18 both correct (%)	35.5	36.4	35.8	33.7
Correlation of self-rating and number correct (D16, D18)	0.21	0.21	0.21	0.20
Students reporting a formal written policy (%)	21.5	20.8	20.9	23.4
Lecturers reporting a formal written policy (%)	17.2	17.2	17.2	17.1

Indicator	Main	Stricter	Self-completed	All in file
Students: writing substantial parts not acceptable (%)	29.5	30.2	29.7	27.5
Lecturers: writing substantial parts not acceptable (%)	41.8	42.3	42.3	40.8
Students: take-home exam use not acceptable (%)	24.5	24.9	24.3	23.3
Lecturers: take-home exam use not acceptable (%)	47.4	47.3	47.7	45.8
Students seeing no clear rule on a contested scenario (%)	47.4	47.2	47.0	46.1
Students on a paid plan (%)	4.9	5.1	4.9	5.1
Lecturers on a paid plan (%)	30.9	30.4	30.4	30.1
Students wanting training (%)	56.1	57.5	56.8	54.3
Lecturers wanting training (%)	80.4	81.0	81.0	79.9

Note: Main = 5 minutes or more and Section D not answered with a single value. Stricter = careful-answer pledge given, 8 minutes or more, Section D not flat. Self-completed excludes respondents who said someone else completed the form or that it was completed in a group. All in file = all consenting, eligible respondents after removal of duplicates, under-18s and non-teachers.

Source: Authors' calculation.

Appendix C: Detailed tables

These tables give the full figures behind the charts in Chapter 4.

Table C1: AI use among students and lecturers

Indicator	Students (%)	Lecturers (%)	Difference (pp)
All respondents (students n = 1,510; lecturers n = 285)			
Has ever used AI	98.3	94.4	+4.0***
Cannot afford paid versions	41.6	21.1	+20.5***
Advanced or fluent academic English	12.1	30.5	-18.4***
AI users (students n = 1,485; lecturers n = 269)			
Uses AI several times a week or daily	46.2	62.1	-15.9***
Uses AI daily	19.7	32.0	-12.2***
On a paid plan	4.9	30.9	-25.9***
Uses ChatGPT	89.4	90.0	-0.5
Uses Google Gemini	83.6	90.0	-6.4**
Uses translation tools	44.6	56.1	-11.6***
Uses Claude	24.1	30.5	-6.4*
Uses DeepSeek	18.0	27.1	-9.2***
Uses Microsoft Copilot	14.3	26.0	-11.7***
Uses Grammarly	14.3	29.4	-15.1***
Prompts mostly in Khmer	34.5	22.3	+12.2***
Prompts mostly in English	34.1	48.0	-13.8***
AI significantly improved quality of work	18.2	38.3	-20.0***
Needs very little effort to get a useful result	15.8	17.5	-1.6

Note: Difference is students minus lecturers in percentage points. Two-sample test of proportions: *** p<0.001; ** p<0.01; * p<0.05. The quality item refers to academic work or grades for students and to teaching materials for lecturers.

Source: Authors' survey data, 2026.

Table C2: Self-rated AI literacy items (AI users)

Item (student wording)	Students			Lecturers	
	Mean	Agree (%)	Neither (%)	Mean	Agree (%)
Awareness (D1-D3; adapted from AILS)					
D1. I can recognise when a product or service I use relies on AI.	3.09	27.3	58.2	3.45	46.5
D2. I can identify which AI features are used in the apps and products I use.	3.12	29.8	55.6	3.22	33.5
D3. I can explain to someone else how AI tools could help with their studies.	3.54	59.1	34.3	-	-
Usage (D4-D5; adapted from AILS)					
D4. I can use AI applications to help me with my academic work.	3.73	69.6	26.7	3.97	82.2
D5. I can work out how to use an AI tool I have never used before.	3.58	61.4	32.2	-	-

Item (student wording)	Students			Lecturers	
	Mean	Agree (%)	Neither (%)	Mean	Agree (%)
<i>Evaluation (D6 by the authors; D7-D8 adapted from AILS)</i>					
D6. I can judge whether the information an AI tool gives me is accurate.	3.36	40.4	54.1	3.63	62.1
D7. After using an AI tool for a while, I can judge what it is good and bad at.	3.40	46.4	45.7	3.58	58.4
D8. When several AI tools could do a task, I can choose the most suitable one.	3.37	45.0	46.5	3.64	66.9
<i>Ethics (D9-D11; adapted from AILS)</i>					
D9. I try to follow ethical principles when I use AI tools.	3.71	67.9	26.6	4.12	91.8
D10. I pay attention to privacy and data-security risks when I use AI tools.	3.75	69.1	26.1	4.01	84.4
D11. I am alert to the misuse of AI.	4.00	82.6	12.4	4.22	90.3
<i>Verification and prompting (D12-D15; by the authors, after the OECD and European Union AI literacy framework)</i>					
D12. I check AI answers against other sources before I use them.	3.94	77.4	19.7	4.19	87.0
D13. Before I use an AI answer, I check whether it is correct.	4.02	82.2	15.8	-	-
D14. I can give an AI tool enough context and clear instructions to get a useful result.	3.71	66.4	30.8	3.70	66.2
D15. I can decide when an AI's answer should be accepted, improved, or rejected.	3.79	71.3	26.3	3.90	78.1
Index (mean of items)	3.61			3.74	

Note: Five-point agreement scale. Agree = agree or strongly agree. AILS = Artificial Intelligence Literacy Scale (Wang, Rau, and Yuan 2023). Lecturer items D3, D5 and D13 were negatively worded and are not comparable item by item; D3 and D5 are reverse-scored in the lecturer index and D13 is excluded. Cronbach's alpha: students 0.87 (15 items); lecturers 0.81 (14 items). Students n = 1,485; lecturers n = 269.

Source: Authors' survey data, 2026.

Table C3: Tested knowledge items (student AI users, n = 1,485)

Item and response	%
<i>D16. An AI tool gives you the reference of a journal for an essay. What is the first thing you should do?</i>	
Check whether the reference actually exists (correct)	75.1
Ask the same AI tool whether it is correct	15.2
Cite it in the essay as the AI wrote it	6.0
Don't know	3.7
<i>D18. You paste a classmate's draft into an AI tool to check the grammar. Who can see the text you pasted?</i>	
Me and the company that operates the AI tool (correct)	45.9
Only me	35.2
Nobody - it is deleted immediately	3.3
Don't know	15.6

Item and response	%
Number of the two items (D16, D18) answered correctly	
Neither	14.5
One	50.0
Both	35.5

Source: Authors' survey data, 2026.

Table C4: Four uses of AI by students: own view and perceived university rule (students n = 1,510; lecturers n = 285)

Scenario and response	Students (%)	Lecturers (%)	Difference (pp)
<i>Explain a difficult concept</i>			
Own view: acceptable	44.3	33.3	+11.0***
Own view: depends	52.8	63.5	-10.7***
Own view: not acceptable	1.9	1.4	+0.5
University: allowed	63.7	48.1	+15.6***
University: not allowed	5.8	6.0	-0.2
University: no clear rule or don't know	30.5	46.0	-15.4***
<i>Translate sources or own writing</i>			
Own view: acceptable	47.7	42.8	+4.9
Own view: depends	45.7	50.5	-4.8
Own view: not acceptable	4.1	4.9	-0.8
University: allowed	66.3	51.9	+14.4***
University: not allowed	5.3	4.2	+1.1
University: no clear rule or don't know	28.4	43.9	-15.4***
<i>Write substantial parts of an assignment</i>			
Own view: acceptable	14.8	9.8	+4.9*
Own view: depends	49.8	44.6	+5.2
Own view: not acceptable	29.5	41.8	-12.2***
University: allowed	19.3	14.7	+4.5
University: not allowed	42.3	35.8	+6.5*
University: no clear rule or don't know	38.4	49.5	-11.1***
<i>Answer questions in a take-home exam or online quiz</i>			
Own view: acceptable	20.5	7.4	+13.2***
Own view: depends	48.9	40.7	+8.2*
Own view: not acceptable	24.5	47.4	-22.9***
University: allowed	17.0	9.5	+7.5**
University: not allowed	48.5	49.8	-1.3
University: no clear rule or don't know	34.5	40.7	-6.2*

Note: Students were asked about their own use; lecturers about use by students. "Unsure" responses on own view (1-6 percent) are not shown. Difference is students minus lecturers. *** p<0.001; ** p<0.01; * p<0.05.

Source: Authors' survey data, 2026.

Table C5: AI use and access by field of study (student AI users)

Field of study	n	Frequent use (%)	Coding or data analysis often (%)	Owns a laptop (%)	Prompts mostly in Khmer (%)
IT / computer science	270	66.3	50.4	90.0	14.8
Medicine / health	27	63.0	7.4	59.3	33.3
Agriculture	127	52.8	5.5	66.9	40.2
Economics	50	48.0	12.0	70.0	16.0
Languages / humanities / arts	193	44.6	6.7	53.4	32.6
Business / accounting / management	329	41.3	10.6	54.4	36.2
Mathematics / sciences	88	39.8	26.1	46.6	38.6
Engineering / architecture	235	39.6	12.3	60.4	43.4
Education, social sciences, other	52	38.5	3.8	65.4	26.9
Law / public administration	114	25.4	7.0	41.2	64.0
All student AI users	1,485	46.2	17.6	62.3	34.5

Note: Frequent use = several times a week or daily. Field is the cleaned field of study; education, social sciences and other fields are combined. Differences in the chance of frequent use relative to business, among students alike in sex, location, institution type, year, academic English, laptop, main device, internet reliability, first generation, paid plan, prompt language, experience and training (logistic regression, N = 1,199, slightly more than in the other models because field replaces the STEM indicator, which is missing for a few students; standard errors clustered by institution), in percentage points: IT +9.3, agriculture +8.2, medicine and health +16.2, languages and humanities +6.1, mathematics and sciences +2.0, law -2.8, engineering -3.7, economics -5.5, education, social sciences and other -6.2. None is statistically significant at the 5 percent level.

Source: Authors' survey data and calculation, 2026.

CDRI Working paper series

- WP 159) Sao Davy, Ang Raksmei, Karthikeyan Matheswaran, Avintha Senavirathne, Sean Vichet, Sok Sao, Mak Sithirith, and De Silva Sanjiv (August 2026). *Hydrological Dynamics and Implications for Integrated Water Resources Management of Boeng Sneh Lake, Cambodia*.
- WP 158) Chunly Sereyvicheth, Khath Bunthorn, and Sak Sreynoch (July 2026). *Autonomists, Delegators, and Traditionalists: How Cambodian Citizens Engage with Digital Government Services*.
- WP 157) Mak Sithirith and Khath Bunthorn (May 2026). *The Transnational Geo-Body of the Cambodian–Thai Border Conflicts: Symbolic Geopolitics, Nationalism and Externalisation of Domestic Securities*.
- WP 156) Mak Sithirith and Chhaing Marong (February 2026). *The Role of Community Fish Refuges (CFRs) in Promoting the Integration of Water, Land, and Aquatic Food Systems: A Case Study of the CFRs in the Mekong Delta and the Tonle Sap Lake*.
- WP 155) Mak Sithirith, Sanjiv de Silva, Sok Sao, Chhaing Marong, Sean Vichet, Ang Raksmei, Mam Kosal, and Deepa Joshi (January 2026). *Decentralised Food System Governance at the District Level in Cambodia: Studying the Performance of District Technical Working Groups in Boeng Sneh (Mekong Delta) and Boeng Ream (Tonle Sap)*.
- WP 154) Nhem Davut, Chea Sathya, and Heng Sok Mean (December 2025). *STEM Teachers' Continuous Professional Development: Opportunities, Challenges, and Policy Implications in Cambodia*.
- WP 153) Mak Sithirith (December 2025). *Community-Based Water Management in Cambodia: A Comparative Study of Farmer Water User Communities (FWUCs) and the Indigenous Metuk System*.
- WP 152) I Younan An and Chhorn Dina (December 2025). *Firm-Level Performance in Cambodia: An Economic Census-Based Diagnostics*.
- WP 151) Chhorn Dina, Muth Sumontheany and Houy Sivly (October 2025). *Building Resilience in the Geoeconomic Fragmentation: The Role of Transitioning MFIs to Banks in Cambodia's Financial Development*.
- WP 150) Veung Naron. (November 2024). *Enhancing the Collaboration between TVET Institutions and the Private Sector in Cambodia: Implications for Skills Provision*.
- WP 149) Simona Iammarino, Muth Sumontheany, and Nith Kosal. (October 2024). *20 Years of FDI in Cambodia: Towards Upper Middle-Income Status and Beyond*.
- WP 148) Ang Raksmei, Ananya Cumming-Bruce, Chhaing Marong, Bunnath Zoe Sidana, So Lyhong and Ngin Chanrith. (September 2024). *Barriers to Nutritious Food Production and Consumption: Insights from Two Case Studies*.
- WP 147) Derek Richardson. (August 2024). *A Bourdieusian Analysis of How Citizen-led Aid Organisations Provide Health Care Transnationally*.
- WP 146) Jessica Garber (August 2024). *Negotiating Family and Personal Aspirations: Four Young Cambodian Women Reflecting on Choosing a Major*.
- WP 145) Chea Phal, Nhem Davut, Chea Sathya, and Bo Chankouluka (June 2024). *The Reversal of Gender Gap in Learning: Why Boys Are Falling Behind in Upper Secondary Schools*.
- WP 144) Roth Vathana, Keo Socheat and Sim Sokcheng (May 2024). *Profitability and Technical Efficiency of Chilli Farms in Cambodia*.
- WP 143) Saing Chan Hang, Chea Phal and Song Sopheak. (November 2023). *Assessing Technology Readiness of Students and Teachers in Cambodian Higher Education during COVID-19*.
- WP 142) Joakim Öjendal, Nong Monin, Sean Chanmony, Bunnath Zoe Sidana and Ngin Chanrith. (November 2023). *The Political Economy of Land-Water Resource Governance in the Context of Food Security in Cambodia*.

- WP 141) Chea Phal, Tek Muytieng, and Nok Sorseseckha. (July 2023). *Gender Gap Reversal in Learning and Gender-Responsive Teaching in Cambodia*.
- WP 140) Roth Vathana and Benghong Siela Bossba. (June 2023). *Impacts on the Lives and Livelihoods of Factory Workers during COVID-19: A Gender-sensitive Analysis*.
- WP 139) Hing Vutha. (May 2023). *The Effects of COVID-19 on the Export Industry and Comparative Advantage of Cambodia*.
- WP 138) Heng Kimkong. (May 2023). *Cambodia's Aspirations to Become a Knowledge-Based Society: Perspectives of Cambodian University Students*.
- WP 137) Thy Savrin, Ly Tong and Ean Sokunthy. (May 2023). *Cambodian Upper Secondary School Education amid COVID-19 Pandemic: Challenges and Opportunities*.
- WP 136) You Saokeo Khantey, Alvin Leung, In Leavsovath, and Song Sopheak. (January 2023). *A Quantitative Study on Entrepreneurial Intention of University Students in Cambodia*.
- WP 135) Tek Muytieng, Nok Sorseseckha and Chea Phal (December 2022). *Faculty Engagement in Cambodian Higher Education Internationalisation*.
- WP 134) Chea Phal, Bo Chankouluka and Minami Ryuto (May 2022). *Cambodian Secondary School Teachers' Readiness for Online Teaching During the Covid-19 Pandemic*.
- WP 133) Kao Sovansopha, Chea Phal and Song Sopheak (March 2022). *Upper Secondary School Tracking and Major Choices in Higher Education: To Switch or Not to Switch*.
- WP 132) Ang Len and Young Sokphea (October 2021). *Civil Society Organisations and Youth Civic Engagement in Cambodia*.
- WP 131) Veung Naron and Ven Seyhah (October 2021). *Exploring Insights into Vocational Skills Development and Industrial Transformation in Cambodia*.
- WP 130) Chea Phal, Hun Seyhakunthy and Song Sopheak (September 2021). *Permeability in Cambodian Post-secondary Education and Training: A Growing Convergence*.
- WP 129) Sry Bopharath, Hiev Hockheang, and Benghong Siela Bossba (August 2021). *Vending in the city: unprotected yet better off*.
- WP 128) Sim Sokcheng, Keo Socheat, Sarom Molideth (August 2021). *Pesticide Use Practices in Cambodia's Vegetable Farming*.
- WP 127) Leng Phirom, Khieng Sothy, Chhem Rethy and Gregory Smith (May 2021) *De-framing STEM discourses in Cambodia*.
- WP 126) Chea Vatana, You Saokeo Khantey and Song Sopheak (May 2021) *What Skills Training Do Cambodian Garment Workers Need?*
- WP 125) Nong Monin (March 2021). *The Impacts of Climate Change on Agriculture and Water Resources in Cambodia: From Local Communities' Perspectives*.
- WP 124) Chea Sathya, Song Sopheak and Hun Seyhakunthy (December 2020). *Competency-Based TVET in Cambodia: Promise and Reality*.
- WP 123) Eam Phyrom, Heng Sambath, Ravy Sophearth, Tim Bunly, Song Sopheak (July 2020). *Characteristics and Issues of Internship at Cambodian Private Firms: A Scoping Study*.
- WP 122) Ven Seyhah and Veung Naron (July 2020). *The Contribution Vocational Skills Development to Cambodia's Economy*.
- WP 121) Eam Phyrom, Ros Vutha, Heng Sambath and Ravy Sophearth (July 2020). *Understanding Cambodian Dean's Conceptions and Approaches to University Accountability*.
- WP 120) Ros Vutha, Eam Phyrom, Heng Sambath and Ravy Sophearth (January 2020). *Cambodian Academics: Identities and Roles*.
- WP 119) Ven Seyhah and Hing Vutha (October 2019). *Cambodia in the Electronic and Electrical Global Value Chains*.
- WP 118) Sothy Khieng, Sidney Mason and Seakleng Lim (October 2019). *Innovation and Entrepreneurship Ecosystem in Cambodia: The Roles of Academic Institutions*.

- WP 117) Un Leang, Saphon Somolireasmey and Sok Serey (September 2019). *Gender Analysis of Survey on Cambodia's Young and Older Generation: Family, Community, Political Knowledge and Attitudes, and Future Expectations*.
- WP 116) Eng Netra, Ang Len, So Hengvotey, Hav Gechhong, Chhom Theavy (March 2019). *Cambodia's Young and Older Generation: Views on Generational Relations and Key Social and Political Issues*.
- WP 115) Mak Ngoy, Sok Say, Un Leang with Bunry Rinna, Chheng Sokunthy and Kao Sovansopha (May 2019). *Finance in Public Higher Education in Cambodia*.
- WP 114) Mak Ngoy, Sok Say, Un Leang with Bunry Rinna, Chheng Sokunthy and Kao Sovansopha (Apr 2019). *Governance in Public Higher Education in Cambodia*.
- WP 113) Ear Sothy, Sim Sokcheng, Chhim Chhun and Khiev Pirom (Dec 2017). *Rice Policy Study: Implications of Rice Policy Changes in Vietnam for Cambodia's Rice Policy and Rice Producers in South-Eastern Cambodia*.
- WP 112) Roth Vathana, Abdelkrim Araar, Sry Bopharath and Phann Dalis (March 2017). *The Dynamics of Microcredit Borrowings in Cambodia*.
- WP 111) Ear Sothy, Sim Sokcheng and Khiev Pirom (March 2016). *Cambodia Macroeconomic Impacts of Public Consumption on Education – A Computable General Equilibrium Approach*.
- WP 110) Vong Mun (December 2016). *Progress and Challenges of Deconcentration in Cambodia: The Case of Urban Solid Waste Management*.
- WP 109) Sam Sreymom, Ky Channimol, Keum Kyungwoo, Sarom Molideth and Sok Raksa. (December 2016). *Common Pool Resources and Climate Change Adaptation: Community-based Natural Resource Management in Cambodia*.
- WP 108) Ly Tem (January 2016). *Leadership Pathways for Local Women: Case Studies of Three Communes in Cambodia*.
- WP 107) Chhim Chhun, Buth Bora and Ear Sothy (September 2015). *Effect of Labour Movement on Agricultural Mechanisation in Cambodia*.
- WP 106) Chhim Chhun, Tong Kimsun, Ge Yu, Timothy Ensor and Barbara McPake (September 2015). *Impact of Health Financing Policies on Household Spending: Evidence from Cambodia Socio-Economic Surveys 2004 and 2009*.
- WP 105) Roth Vathana and Lun Pide (August 2015). *Health and Education in the Greater Mekong Subregion: Policies, Institutions and Practices – the Case of Cambodia in Khmer*.
- WP 104) Sum Sreymom and Khiev Pirom (August 2015). *Contract Farming in Cambodia: Different Models, Policy and Practice*.
- WP 103) Chhim Chhun, Tong Kimsun, Ge Yu, Timothy Ensor and Barbara McPake (June 2015). *Catastrophic Payments and Poverty in Cambodia: Evidence from Cambodia Socio-Economic Surveys 2004, 2007, 2009, 2010 and 2011*.
- WP 102) Eng Netra, Vong Mun and Hort Navy (June 2015). *Social Accountability in Service Delivery in Cambodia*.
- WP 101) Ou Sivhouch (April 2015). *A Right-Based Approach to Development: A Cambodian Perspective*.
- WP 100) Sam Sreymom with Ouch Chhuong (March 2015). *Agricultural Technological Practices and Gaps for Climate Change Adaptation*.
- WP 99) Phay Sokcheng and Tong Kimsun (December 2014). *Public Spending on Education, Health and Infrastructure and Its Inclusiveness in Cambodia: Benefit Incidence Analysis*.
- WP 98) Srinivasa Madhur (August 2014). *Cambodia's Skill Gap: An Anatomy of Issues and Policy Options*.
- WP 97) Kim Sour, Dr Chem Phalla, So Sovannarith, Dr Kim Sean Somatra and Dr Pech Sokhem (August 2014). *Methods and Tools Applied for Climate Change Vulnerability and Adaptation Assessment in Cambodia's Tonle Sap Basin*.

- WP 96) Kim Sean Somatra and Hort Navy (August 2014). *Cambodian State: Developmental, Neoliberal? A Case Study of the Rubber Sector.*
- WP 95) Theng Vuthy, Keo Socheat, Nou Keosothea, Sum Sreymom and Khiev Pirom (August 2014). *Impact of Farmer Organisations on Food Security: The Case of Rural Cambodia.*
- WP 94) Heng Seiha, Vong Mun and Chheat Sreang with the assistance of Chhuon Nareth (July 2014). *The Enduring Gap: Decentralisation Reform and Youth Participation in Local Rural Governance.*
- WP 93) Nang Phirun, Sam Sreymom, Lonn Pichdara and Ouch Chhuong (June 2014). *Adaptation Capacity of Rural People in the Main Agro-Ecological Zones in Cambodia.*
- WP 92) Phann Dalis (June 2014). *Links between Employment and Poverty in Cambodia.*
- WP 91) Theng Vuthy, Khiev Pirom and Phon Dary (April 2014). *Development of the Fertiliser Industry in Cambodia: Structure of the Market, Challenges in the Demand and Supply Sides and the Way Forward.*
- WP 90) CDRI Publication (January 2014). *ASEAN 2030: Growing Together for Economic Prosperity—the Challenges (Cambodia Background Paper).*
- WP 89) Nang Phirun and Ouch Chhuong (January 2014). *Gender and Water Governance: Women's Role in Irrigation Management and Development in the Context of Climate Change.*
- WP 88) Chheat Sreang (December 2013). *Impact of Decentralisation on Cambodia's Urban Governance.*
- WP 87) Kim Sedara and Joakim Öjendal with the assistance of Chhoun Nareth (November 2013). *Gatekeepers in Local Politics: Political Parties in Cambodia and their Gender Policy.*
- WP 86) Sen Vicheth and Ros Soveacha with the assistance of Hieng Thiraphumry (October 2013). *Anatomy of Higher Education Governance in Cambodia.*
- WP 85) Ou Sivhuoch and Kim Sedara (August 2013). *20 Years' Strengthening of Cambodian Civil Society: Time for Reflection.*
- WP 84) Ou Sivhuoch (August 2013). *Sub-National Civil Society in Cambodia: A Gramscian Perspective.*
- WP 83) Tong Kimsun, Lun Pide and Sry Bopharath with the assistance of Pon Dorina (August 2013). *Levels and Sources of Household Income in Rural Cambodia 2012.*
- WP 82) Nang Phirun (July 2013). *Climate Change Adaptation and Livelihoods in Inclusive Growth: A Review of Climate Change Impacts and Adaptive Capacity in Cambodia.*
- WP 81) Hing Vutha (June 2013). *Leveraging Trade for Economic Growth in Cambodia*
- WP 80) Saing Chan Hang (March 2013). *Binding Constraints on Economic Growth in Cambodia: A Growth Diagnostic Approach.*
- WP 79) Lun Pidé (March 2013). *The Role of Rural Credit during the Global Financial Crisis: Evidence From Nine Villages in Cambodia.*
- WP 78) Tong Kimsun and Phay Sokcheng (March 2013). *The Role of Income Diversification during the Global Financial Crisis: Evidence from Nine Villages in Cambodia.*
- WP 77) Saing Chan Hang (March 2013). *Household Vulnerability to Global Financial Crisis and Their Risk Coping Strategies: Evidence from Nine Rural Villages in Cambodia.*
- WP 76) Hing Vutha (March 2013). *Impact of the Global Financial Crisis on the Rural Labour Market: Evidence from Nine Villages in Cambodia.*
- WP 75) Tong Kimsun (March 2013). *Impact of the Global Financial Crisis on Poverty: Evidence from Nine Villages in Cambodia.*
- WP 74) Ngin Chanrith (March 2013). *Impact of the Global Financial Crisis on Employment in SMEs in Cambodia.*
- WP 73) Hay Sovuthea (March 2013). *Government Response to Inflation Crisis and Global Financial Crisis.*

- WP 72) Hem Socheth (March 2013). *Impact of the Global Financial Crisis on Cambodian Economy at Macro and Sectoral Levels.*
- WP 71) Kim Sedara and Joakim Öjendal with Chhoun Nareth and Ly Tem (December 2012). *A Gendered Analysis of Decentralisation Reform in Cambodia.*
- WP 70) Hing Vutha, Saing Chan Hang and Khieng Sothy (August 2012). *Baseline Survey for Socioeconomic Impact Assessment: Greater Mekong Sub-region Transmission Project.*
- WP 69) CDRI Publication (March 2012). *Understanding Poverty Dynamics: Evidence from Nine Villages in Cambodia.*
- WP 68) Roth Vathana (March 2012). *Sectoral Composition of China's Economic Growth, Poverty Reduction and Inequality: Development and Policy Implications for Cambodia.*
- WP 67) Keith Carpenter with assistance from PON Dorina (February 2012). *A Basic Consumer Price Index for Cambodia 1993–2009.*
- WP 66) Tong Kimsun (February 2012). *Analysing Chronic Poverty in Rural Cambodia Evidence from Panel Data.*
- WP 65) Ros Bansok, Nang Phirun and Chhim Chhun (December 2011). *Agricultural Development and Climate Change: The Case of Cambodia.*
- WP 64) Tong Kimsun, Sry Bopharath (November 2011). *Poverty and Environment Links: The Case of Rural Cambodia.*
- WP 63) Heng Seiha, Kim Sedara and So Sokbunthoeun (October 2011). *Decentralised Governance in Hybrid Polity: Localisation of Decentralisation Reform in Cambodia.*
- WP 62) Chea Chou, Nang Phirun, Isabelle Whitehead, Phillip Hirsch and Anna Thompson (October 2011). *Decentralised Governance of Irrigation Water in Cambodia: Matching Principles to Local Realities.*
- WP 61) Ros Bandeth, Ly Tem and Anna Thompson (September 2011). *Catchment Governance and Cooperation Dilemmas: A Case Study from Cambodia.*
- WP 60) Saing Chan Hang, Hem Socheth and Ouch Chandarany with Phann Dalish and Pon Dorina (November 2011). *Foreign Investment in Agriculture in Cambodia.*
- WP 59) Chem Phalla, Philip Hirsch and Someth Paradis (September 2011). *Hydrological Analysis in Support of Irrigation Management: A Case Study of Stung Chrey Bak Catchment, Cambodia.*
- WP 58) Hing Vutha, Lun Pide and Phann Dalis (August 2011). *Irregular Migration from Cambodia: Characteristics, Challenges and Regulatory Approach.*
- WP 57) Tong Kimsun, Hem Socheth and Paulos Santos (August 2011). *The Impact of Irrigation on Household Assets.*
- WP 56) Tong Kimsun, Hem Socheth and Paulos Santos (July 2011). *What Limits Agricultural Intensification in Cambodia? The role of emigration, agricultural extension services and credit constraints.*
- WP 55) Kem Sothorn, Chhim Chhun, Theng Vuthy and So Sovannarith (July 2011). *Policy Coherence in Agricultural and Rural Development: Cambodia.*
- WP 54) Nang Phirun, Khiev Daravy, Philip Hirsch and Isabelle Whitehead (June). *Improving the Governance of Water Resources in Cambodia: A Stakeholder Analysis.*
- WP 53) Chann Sopheak, Nathan Wales and Tim Frewer (August 2011). *An Investigation of Land Cover and Land Use Change in Stung Chrey Bak Catchment, Cambodia.*
- WP 52) Ouch Chandarany, Saing Chanhang and Phann Dalis (June 2011). *Assessing China's Impact on Poverty Reduction In the Greater Mekong Sub-region: The Case of Cambodia.*
- WP 51) Christopher Wokker, Paulo Santos, Ros Bansok and Kate Griffiths (June 2011). *Irrigation Water Productivity in Cambodian Rice System.*
- WP 50) Pak Kimchoeun (May 2011). *Fiscal Decentralisation in Cambodia: A Review of Progress and Challenges.*

- WP 49) Chem Phalla and Someth Paradis (March 2011). *Use of Hydrological Knowledge and Community Participation for Improving Decision-making on Irrigation Water Allocation.*
- WP 48) CDRI Publication (August 2010). *Empirical Evidence of Irrigation Management in the Tonle Sap Basin: Issues and Challenges.*
- WP 47) Chea Chou (August 2010). *The Local Governance of Common Pool Resources: The Case of Irrigation Water in Cambodia.*
- WP 46) CDRI Publication (December 2009). *Agricultural Trade in the Greater Mekong Sub-region: Synthesis of the Case Studies on Cassava and Rubber Production and Trade in GMS Countries.*
- WP 45) CDRI Publication (December 2009). *Costs and Benefits of Cross-country Labour Migration in the GMS: Synthesis of the Case Studies in Thailand, Cambodia, Laos and Vietnam.*
- WP 44) Chan Sophal (December 2009). *Costs and Benefits of Cross-border Labour Migration in the GMS: Cambodia Country Study.*
- WP 43) Hing Vutha and Thun Vathana (December 2009). *Agricultural Trade in the Greater Mekong Sub-region: The Case of Cassava and Rubber in Cambodia.*
- WP 42) Thon Vimealea, Ou Sivhuoch, Eng Netra and Ly Tem (October 2009). *Leadership in Local Politics of Cambodia: A Study of Leaders in Three Communes of Three Provinces.*
- WP 41) Hing Vutha and Hossein Jalilian (April 2009). *The Environmental Impacts of the ASEAN-China Free Trade Agreement for Countries in the Greater Mekong Sub-region.*
- WP 40) Eng Netra and David Craig (March 2009). *Accountability and Human Resource Management in Decentralised Cambodia.*
- WP 39) Horng Vuthy and David Craig (July 2008). *Accountability and Planning in Decentralised Cambodia.*
- WP 38) Pak Kimchoeun and David Craig (July 2008). *Accountability and Public Expenditure Management in Decentralised Cambodia.*
- WP 37) Chem Phalla et al. (May 2008). *Framing Research on Water Resources Management and Governance in Cambodia: A Literature Review.*
- WP 36) Lim Sovannara (November 2007). *Youth Migration and Urbanisation in Cambodia.*
- WP 35) Kim Sedara and Joakim Öjendal with the assistance of Ann Sovatha (May 2007). *Where Decentralisation Meets Democracy: Civil Society, Local Government, and Accountability in Cambodia.*
- WP 34) Pak Kimchoeun, Horng Vuthy, Eng Netra, Ann Sovatha, Kim Sedara, Jenny Knowles and David Craig (March 2007). *Accountability and Neo-patrimonialism in Cambodia: A Critical Literature Review.*
- WP 33) Hansen, Kasper K. and Neth Top (December 2006). *Natural Forest Benefits and Economic Analysis of Natural Forest Conversion in Cambodia.*
- WP 32) Murshid, K.A.S. and Tuot Sokphally (April 2005). *The Cross Border Economy of Cambodia: An Exploratory Study.*
- WP 31) Oberndorf, Robert B. (May 2004). *Law Harmonisation in Relation to the Decentralisation Process in Cambodia.*
- WP 30) Hughes, Caroline and Kim Sedara with the assistance of Ann Sovatha (February 2004). *The Evolution of Democratic Process and Conflict Management in Cambodia: A Comparative Study of Three Cambodian Elections.*
- WP 29) Yim Chea and Bruce McKenney (November 2003). *Domestic Fish Trade: A Case Study of Fish Marketing from the Great Lake to Phnom Penh.*
- WP 28) Prom Tola and Bruce McKenney (November 2003). *Trading Forest Products in Cambodia: Challenges, Threats, and Opportunities for Resin.*
- WP 27) Yim Chea and Bruce McKenney (October 2003). *Fish Exports from the Great Lake to Thailand: An Analysis of Trade Constraints, Governance, and the Climate for Growth.*

- WP 26) Sarthi Acharya, Kim Sedara, Chap Sotharith and Meach Yady (February 2003). *Off-farm and Non-farm Employment: A Perspective on Job Creation in Cambodia*.
- WP 25) Chan Sophal and Sarthi Acharya (December 2002). *Facing the Challenge of Rural Livelihoods: A Perspective from Nine Villages in Cambodia*.
- WP 24) Kim Sedara, Chan Sophal and Sarthi Acharya (July 2002). *Land, Rural Livelihoods and Food Security in Cambodia*.
- WP 23) McKenney, Bruce, Prom Tola. (July 2002). *Natural Resources and Rural Livelihoods in Cambodia*.
- WP 22) Chan Sophal and Sarthi Acharya (July 2002). *Land Transactions in Cambodia: An Analysis of Transfers and Transaction Records*.
- WP 21) Bhargavi Ramamurthy, Sik Boreak, Per Ronnås and Sok Hach (December 2001). *Cambodia 1999-2000: Land, Labour and Rural Livelihood in Focus*.
- WP 20) So Sovannarith, Real Sopheap, Uch Utey, Sy Rathmony, Brett Ballard and Sarthi Acharya (November 2001). *Social Assessment of Land in Cambodia: A Field Study*.
- WP 19) Chan Sophal, Tep Saravy and Sarthi Acharya (October 2001). *Land Tenure in Cambodia: a Data Update*.
- WP 18) Godfrey, Martin, So Sovannarith, Tep Saravy, Pon Dorina, Claude Katz, Sarthi Acharya, Sisowath D. Chanto and Hing Thoraxy (August 2001). *A Study of the Cambodian Labour Market: Reference to Poverty Reduction, Growth and Adjustment to Crisis*.
- WP 17) Chan Sophal and So Sovannarith with Pon Dorina (December 2000). *Technical Assistance and Capacity Development at the School of Agriculture Prek Leap*.
- WP 16) Sik Boreak (September 2000). *Land Ownership, Sales and Concentration in Cambodia*.
- WP 15) Godfrey, Martin, Chan Sophal, Toshiyasu Kato, Long Vou Piseth, Pon Dorina, Tep Saravy, Tia Savara and So Sovannarith (August 2000). *Technical Assistance and Capacity Development in an Aid-dependent Economy: The Experience of Cambodia*.
- WP 14) Toshiyasu Kato, Jeffrey A. Kaplan, Chan Sophal and Real Sopheap (May 2000). *Enhancing Governance for Sustainable Development*.
- WP 13) Ung Bunleng (January 2000). *Seasonality in the Cambodian Consumer Price Index*.
- WP 12) Chan Sophal, Toshiyasu Kato, Long Vou Piseth, So Sovannarith, Tia Savara, Hang Chuon Naron, Kao Kim Hourn and Chea Vuthna (September 1999). *Impact of the Asian Financial Crisis on the SEATEs: The Cambodian Perspective*.
- WP 11) Chan Sophal and So Sovannarith (June 1999). *Cambodian Labour Migration to Thailand: A Preliminary Assessment*.
- WP 10) Gorman, Siobhan, with Pon Dorina and Sok Kheng (June 1999). *Gender and Development in Cambodia: An Overview*.
- WP 9) Teng You Ky, Pon Dorina, So Sovannarith and John McAndrew (April 1999). *The UNICEF/Community Action for Social Development Experience—Learning from Rural Development Programmes in Cambodia*.
- WP 8) Chan Sophal, Martin Godfrey, Toshiyasu Kato, Long Vou Piseth, Nina Orlova, Per Ronnås and Tia Savara (January 1999). *Cambodia: The Challenge of Productive Employment Creation*.
- WP 7) McAndrew, John P. (December 1998). *Interdependence in Household Livelihood Strategies in Two Cambodian Villages*.
- WP 6) Murshid, K.A.S. (December 1998). *Food Security in an Asian Transitional Economy: The Cambodian Experience*.
- WP 5) Kato, Toshiyasu, Chan Sophal and Long Vou Piseth (September 1998). *Regional Economic Integration for Sustainable Development in Cambodia*.
- WP 4) Chim Charya, Srun Pithou, So Sovannarith, John McAndrew, Nguon Sokunthea, Pon Dorina and Robin Biddulph (June 1998). *Learning from Rural Development Programmes in Cambodia*.

- WP 3) Kannan, K.P. (January 1997). *Economic Reform, Structural Adjustment and Development in Cambodia*.
- WP 2) McAndrew, John P. (January 1996). *Aid Infusions, Aid Illusions: Bilateral and Multilateral Emergency and Development Assistance in Cambodia. 1992-1995*.
- WP 1) Kannan, K.P. (November 1995). *Construction of a Consumer Price Index for Cambodia: A Review of Current Practices and Suggestions for Improvement*.

Cambodia Development Resource Institute

📍 56 Street 315, Tuol Kork, Phnom Penh, Cambodia

☎ +855 23 881 701/881 916/883 603

✉ cdri@cdri.org.kh

🌐 www.cdri.org.kh

