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Artificial Intelligence Use, Workload, Productivity, and Job Satisfaction Among Lecturers in Phnom Penh Universities

Por Vutha[1]*, Paradise Ros[2]
[1]vuthabeltei2023@gmail.com, [2]paradiseros@gmail.com
BELTEI International University

*Corresponding Author: Por Vutha
E-mail: vuthabeltei2023@gmail.com

ABSTRACT

Universities are adopting artificial intelligence (AI) for teaching, assessment, research, and administration, yet little is known about how this adoption relates to the work experience of lecturers. This study examined the associations between AI use and lecturers' workload, productivity, and job satisfaction at five universities in Phnom Penh, Cambodia. A quantitative survey was conducted with 385 lecturers, drawn through an equal quota of 77 participants per university, using a questionnaire with 5-point Likert items. Descriptive statistics, Cronbach's alpha, Pearson correlation, and simple linear regression were applied. Lecturers rated all dimensions highly, with mean scores from 4.00 to 4.40. Greater AI use was positively associated with perceived workload and productivity, which supported the first two hypotheses, and with job satisfaction. Workload was also positively associated with job satisfaction, which did not support the expected negative relationship, while the mediation hypotheses were not tested. Correlation, regression, and reliability coefficients approached or reached 1.000, which pointed to overlap among the composite scores, so only the direction of the relationships was interpreted. The results suggest that AI use accompanies both higher productivity and higher perceived workload, and they do not show that AI simply reduces the burden on lecturers. Institutions should therefore pair AI adoption with clear protocols, training, and support, and future studies should verify the data and test mediation.

Keywords: *Academic Workload, Artificial Intelligence, Higher Education, Job Satisfaction, Lecturer Productivity*

INTRODUCTION

Artificial intelligence (AI) has become a routine part of academic work in universities, and generative systems in particular have altered how lecturers prepare teaching materials, design assessments, write feedback, and handle administrative correspondence (Ogunleye et al., 2024; Qian, 2025). A systematic review of early studies observed that the effects of AI on curriculum, instruction, and assessment practices had received much less attention than student-facing or administration-facing applications of the same technology (Liang et al., 2025). The studies in that review described the generation of new teaching material, the reduction of staff workload, and the automation of evaluation as the main benefits, and they also documented a set of challenges that accompanied these gains.

The expectation that such tools lighten the load of lecturers has not been confirmed in a simple way. A recent systematic review concluded that generative AI neither uniformly reduces nor uniformly increases faculty workload but transforms it (Su et al., 2026). Routine and procedural tasks such as preparing teaching materials and basic grading became more efficient, while new responsibilities emerged, including quality review of AI outputs, ethical judgment, and the monitoring of academic integrity (Ghorbani & Blankesteijn, 2026; Verboom et al., 2025). According to the same review, the direction and size of the change depended on individual conditions such as digital literacy and teaching experience and on conditions within the organization.

Evidence on the experience of lecturers is similarly mixed. A study of university faculty members found that ChatGPT adoption was associated with greater happiness and energy and with lower stress (Cambra-Fierro et al., 2025). A survey of 127 academic staff members, in contrast, showed that performance expectancy was positively related to the intention to continue using generative AI tools but was not positively related to satisfaction with those tools (Baig & Yadegaridehkordi, 2025). Taken together, these studies suggest that the perceived benefits of AI do not automatically produce favorable work experiences, and that outcomes such as well-being, satisfaction, and workload must be examined directly instead of being inferred from adoption.

The job demands-resources (JD-R) theory offers a coherent way to interpret these mixed findings. The theory classifies job characteristics as demands, which require sustained physical or psychological effort, and resources, which help workers reach their goals, reduce demands, and stimulate development, and it holds that resources can buffer the effect of demands on burnout (Bakker & Demerouti, 2017). Subsequent work extended the theory through person and situation approaches, multilevel perspectives, and proactive behaviors at work (Bakker et al., 2023). Within this framework, AI tools can function as a job resource when they accelerate routine tasks and free time for teaching, research, and student support, and they can generate additional demands when their output must be verified,

corrected, and ethically supervised. Workload and productivity therefore occupy a central position between AI use and job satisfaction, because they capture the demand side and the performance side of the same process.

Findings from other work settings are consistent with this reasoning. In a mixed-methods study of public sector organizations, digital transformation significantly predicted service delivery efficiency, but organizational culture and leadership also made significant contributions, and the authors concluded that technology implementation requires a supportive workplace and effective leadership (Sain et al., 2025). The link between satisfaction and performance is also less direct than often assumed. In a survey of 75 employees of one company, job satisfaction had no direct measurable effect on employee performance, although it contributed meaningfully to organizational citizenship behavior, which in turn had a favorable effect on performance (Budiyanto, 2025). These results indicate that efficiency gains, performance, and satisfaction depend on conditions in the work environment and cannot be treated as interchangeable outcomes.

Despite expectations that AI would relieve lecturers of repetitive tasks, strengthen instructional preparation, support assessment, and raise academic productivity, current evidence does not show that AI inherently reduces workload or improves productivity. Existing studies have commonly examined adoption, satisfaction with AI tools, or well-being as separate topics, and the evidence on how generative AI affects academic workload remains fragmented (Baig & Yadegaridehkordi, 2025; Cambra-Fierro et al., 2025; Su et al., 2026). The consequences of this gap are practical. University leaders in Phnom Penh, as elsewhere, must decide how much training, infrastructure, and policy support to provide, and these decisions depend on knowing whether AI lightens, redistributes, or intensifies the work of lecturers and how those changes relate to their satisfaction with their jobs.

This study therefore examined the influence of AI use on lecturers' workload, productivity, and job satisfaction at five universities in Phnom Penh, Cambodia, with the intention of informing a more effective and human-centered integration of AI in higher education. Three research questions guided the inquiry. The first asked how AI use affects the workload of lecturers, the second asked how it affects their productivity, and the third asked how it affects their job satisfaction. In this study, productivity referred to the capacity of lecturers to fulfill academic duties efficiently, produce high-quality work, use time effectively, and achieve teaching, research, and administrative objectives.

Guided by JD-R theory and by the mixed evidence reviewed above, the study tested seven hypotheses. Because the literature describes the effect of generative AI on workload as a transformation and not as a straightforward reduction (Su et al., 2026), the first hypothesis (H1) stated that AI use has a significant effect on lecturers' workload, without prescribing a direction. The second hypothesis (H2) stated that AI use has a significant positive effect on lecturers' productivity, since

AI tools accelerate routine academic tasks. The third hypothesis (H3) stated that workload has a significant negative effect on job satisfaction, and the fourth (H4) stated that productivity has a significant positive effect on job satisfaction, in line with the treatment of workload as a job demand and of productivity as a performance-related outcome. The remaining hypotheses addressed the mechanisms connecting these variables. H5 stated that workload significantly mediates the relationship between AI use and job satisfaction, H6 stated that productivity significantly mediates the same relationship, and H7 stated that AI use has a significant indirect effect on job satisfaction through workload and productivity.

LITERATURE REVIEW

Artificial Intelligence (AI) in Academic Work

Research on AI in academic work has grown quickly, but it has not developed evenly across the activities that make up the job of a lecturer. In a survey of 318 educators from different teaching levels and regions, most respondents expected generative AI to have a major or profound effect on teaching and assessment, and respondents with greater awareness of the technology predicted larger effects (Bower et al., 2024). The same educators were motivated to change their practices mainly by the expected improvement in performance for themselves and their students. At the level of research activity, a survey of 2,534 researchers at Danish universities evaluated 32 use cases of generative AI across five phases of the research process, which shows that the technology has reached well beyond the classroom (Andersen et al., 2025).

These studies share a limitation that matters for the present research. They describe perceptions, practices, and use cases, but they say little about what AI use costs or saves in terms of effort. Awareness and usage indicate that lecturers engage with AI, yet they do not show whether the engagement lightens work, shifts it to other tasks, or raises the standard that lecturers are expected to meet. This distinction between use and consequence explains why the present study described AI use through frequency, tool types, and purposes and then examined its associations with workload, productivity, and job satisfaction.

The perceived effect of AI is also not uniform across lecturers. In the survey by Bower et al. (2024), teaching level, experience, discipline, region, and gender all significantly influenced the perceived impact of generative AI on teaching and assessment. A survey of 711 faculty members in Chinese universities added a further dimension by examining stress, happiness, and energy as well-being outcomes of generative AI adoption (Liu et al., 2025). Because such differences are contextual, findings from one setting cannot be assumed to hold in another, and evidence from universities in Phnom Penh contributes to the comparative base on which institutions can draw.

Conceptual Framework of the Study

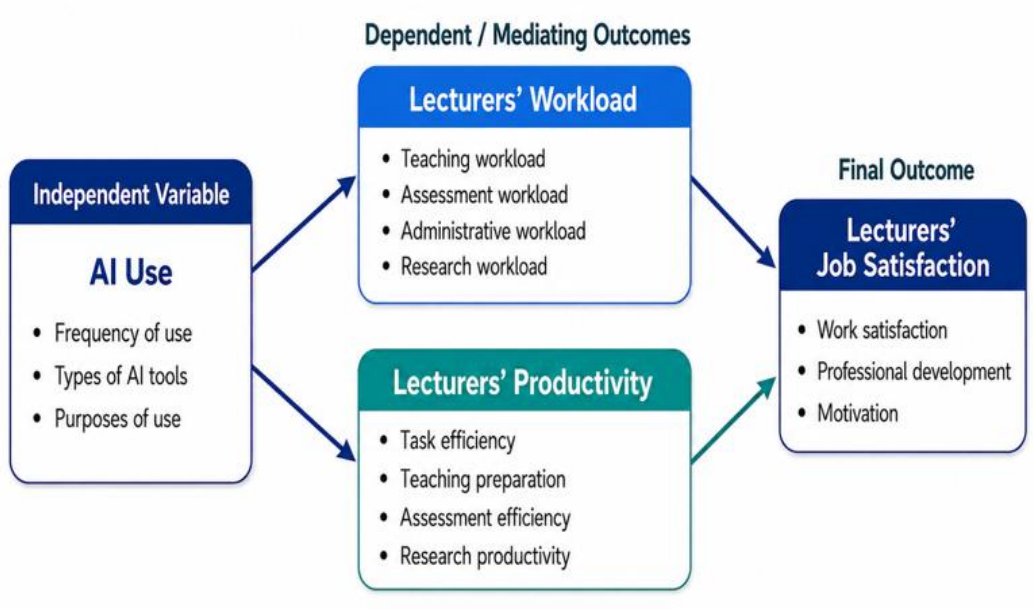


Figure 1 Conceptual Framework of the Study

Figure 1 presents the conceptual framework that guided the study. AI use is the independent variable and is described through three dimensions, namely frequency of use, types of AI tools, and purposes of use. Frequency denotes how regularly lecturers engage with AI. Types of tools cover the variety of applications used, including generative AI, writing aids, evaluation tools, and research assistance systems. Purposes of use cover lesson planning, evaluation, feedback, administrative tasks, communication, and research. Two intermediate outcomes receive the effect of AI use. Lecturers' workload refers to the physical, mental, and temporal effort needed to fulfill academic duties and is divided into teaching, assessment, administrative, and research workload. Lecturers' productivity refers to the capacity to complete academic duties efficiently and is divided into task efficiency, teaching preparation, assessment efficiency, and research productivity. Job satisfaction, composed of work satisfaction, professional development, and motivation, is the final outcome.

The arrows in Figure 1 correspond to the hypotheses stated in the Introduction. The paths from AI use to workload and to productivity represent H1 and H2, and the paths from workload and productivity to job satisfaction represent H3 and H4. The model contains no direct path from AI use to job satisfaction, so the effect of AI use on satisfaction is expected to operate through the two intermediate variables, which is the logic of the mediation hypotheses H5, H6, and H7. This structure reflects the distinction between job demands and performance-related outcomes in the JD-R perspective introduced earlier, with workload standing for the demand side and productivity for the performance side of the process.

The framework rests on two distinctions drawn from the literature reviewed in this chapter. The first separates the effort that lecturers invest from the output they achieve, because AI assistance can raise grading productivity, as shown in a randomized trial, which is an outcome conceptually distinct from the overall effort a task demands (Heinrich et al., 2025). The second places job satisfaction at the end of the model, because studies of faculty samples show that influences on satisfaction often operate through intermediate states such as work-life balance and burnout. Huang and Zhao (2025) found this pattern for AI literacy, and Kim and Yeo (2024) found it for workload. These distinctions justify modeling workload and productivity as parallel intermediate variables and not as a single combined outcome.

Workload and Productivity Under AI Use

The workload of lecturers is broad and typically covers instruction, assessment, administrative duties, research, student support, and contributions to the university. In this study it was represented by four dimensions, namely teaching, assessment, administrative, and research workload, because these are the domains in which AI tools are most often applied. The importance of workload lies in its consequences for well-being. In a structural equation study of 450 Thai lecturers, workload and work-family conflict significantly raised stress, and stress, workload, and work-family conflict were the main predictors of burnout, which in turn influenced work satisfaction (Kim & Yeo, 2024). An earlier study of Thai university lecturers reached a similar conclusion, with workload increasing stress and stress mediating the relationship between workload and work satisfaction (Kim et al., 2023).

Two competing accounts describe how AI could change this burden. The automation account holds that AI takes over routine production tasks and returns time to lecturers (Osadcha et al., 2025). The technostress account holds that the effort of learning, supervising, and correcting digital tools becomes a new demand. Studies of higher education teachers show that technology-related stress is not uniformly harmful, since techno-eustress, the positive form of the response, was positively related to job satisfaction and work performance and was predicted by perceived usefulness, literacy, IT mindfulness, and coping flexibility, although with small effects (Nascimento et al., 2024, 2025; Saleem & Malik, 2023). The survey of Chinese faculty by Liu et al. (2025) concluded that universities should strengthen training, usability design, and workload management policies to balance innovation with well-being. Taken together, the two accounts imply that the direction of the relationship between AI and workload cannot be set in advance and depends on whether lecturers experience the technology as a resource or as a demand. This reasoning supports the decision to state H1 without a direction.

Teaching is the dimension in which both accounts are most plausible at once. The teaching workload encompasses the time and energy that lecturers allocate to

course design, lesson preparation, instructional material development, class delivery, student engagement, and the updating of resources, and it extends well beyond scheduled class hours (Morris et al., 2026). Generative AI can assist with several of these tasks, such as drafting lesson plans, generating examples and explanations, preparing presentation material, summarizing sources, and adapting content for students at different levels (Giannakos et al., 2025). The same technology also adds teaching tasks. The educators surveyed by Bower et al. (2024) believed that teaching should move toward learning with AI, higher-order thinking, ethical values, a focus on learning processes, and face-to-face relational learning, and each of these shifts implies additional design work for lecturers.

Assessment offers the clearest evidence of efficiency gains. A randomized controlled trial across four undergraduate courses with almost 300 students found that large language model assistance increased the productivity of instructors who graded short-answer questions, which allowed personalized feedback in large classes without prohibitive time costs (Heinrich et al., 2025). The authors also noted that long-term studies would be needed to establish whether such feedback improves learning, so the evidence concerns the effort of instructors and not yet the quality of outcomes. In research work, respondents in the Danish survey assessed the research integrity of generative AI use cases as well as their use, which suggests that using AI in research carries obligations of verification and judgment alongside any gain in speed (Andersen et al., 2025). Administrative workload, which covers correspondence, scheduling, and reporting, has received little direct attention in the studies reviewed here, and the present study therefore treated it as an empirical question.

Productivity and workload are related but distinct. A lecturer can produce more in the same time, for example by giving more detailed feedback to more students, without any reduction in the effort invested, and the trial by Heinrich et al. (2025) illustrates this point because instructors working with AI assistance could deliver personalized grading in classes where it would otherwise have been impractical. The study of higher education teachers by Nascimento et al. (2024) links the favorable experience of technology to work performance, which indicates that productivity depends on how lecturers experience the tools they use. For this reason, the framework treats productivity as a separate pathway from workload, and it was assessed through task efficiency, teaching preparation, assessment efficiency, and research productivity.

Job Satisfaction of Lecturers

Job satisfaction among lecturers pertains to the extent to which academic personnel hold favorable attitudes toward their duties, work environment, career advancement, and accomplishments. In higher education it is closely associated with turnover, lecturer retention, institutional cohesion, well-being, professional teaching improvement, and research and publication performance (Kim & Yeo,

2024). Satisfaction therefore matters to universities for reasons that extend beyond the comfort of individual lecturers, and any technology that alters the conditions of academic work can be expected to influence it, whether favorably or unfavorably.

Evidence on how work conditions and technology relate to satisfaction points to indirect pathways. Among 511 university faculty members, AI literacy enhanced the satisfaction of the needs for autonomy, competence, and relatedness, which promoted work-life balance, and only autonomy predicted job satisfaction directly while competence and relatedness operated through work-life balance (Huang & Zhao, 2025). In the Thai studies, work satisfaction was significantly influenced by burnout, and the relationship between stress and satisfaction was mediated by burnout (Kim & Yeo, 2024). The earlier study of Thai lecturers reported that stress mediated the relationship between workload and satisfaction, and that satisfaction rose as stress and work-family conflict diminished, with workload as the exception (Kim et al., 2023). The direct effect of workload on satisfaction may therefore be weak once stress is taken into account, which means that H3 requires careful testing and that the mediation hypotheses carry real weight in the model.

Evidence on productivity and satisfaction is thinner, and it is thinner still for AI specifically. Among higher education teachers, the positive form of technology-related stress was positively related to both job satisfaction and work performance, which suggests that lecturers who experience a tool as useful and manageable tend to report better work outcomes and higher satisfaction together (Nascimento et al., 2024, 2025). This pattern is consistent with H4, although it does not establish a causal path from productivity to satisfaction. The literature as a whole supports an expectation of mixed and indirect effects, and it is this expectation that the framework and the seven hypotheses were designed to test.

RESEARCH METHODOLOGY

This study used a quantitative survey design to examine how the use of artificial intelligence (AI) relates to the workload, productivity, and job satisfaction of lecturers at universities in Phnom Penh, Cambodia. The design followed the conceptual framework in Figure 1, in which AI use is the independent variable, workload and productivity are intermediate variables, and job satisfaction is the final outcome. A structured questionnaire was chosen as the data collection tool because it produces comparable responses from a large number of participants and allows statistical examination of the relationships among variables (Creswell & Creswell, 2023). The study relied exclusively on quantitative data and did not include interviews, observations, or other qualitative procedures, so the findings describe patterns of association and perception and do not explain the reasons behind individual experiences.

The target population comprised full-time lecturers at five universities in Phnom Penh, four private and one public. The universities are identified as Private University 1 to 4 and Public University 1 in Table 2 to protect institutional

anonymity. The required sample size was calculated with the formula of Cochran (1963) for large populations, which is shown below.

$$n_0 = \frac{Z^2 \cdot p(1-p)}{e^2}$$

In this equation, n_0 is the required sample size, Z is the value for the confidence level and was 1.96 for a 95% confidence level, p is the estimated proportion in the population and was set at .50 to reflect maximum variability, q equals 1 − p, and e is the margin of error and was .05. Substituting these values gives the following result.

$$n_0 = \frac{(1.96)^2 \cdot 0.5 \cdot 0.5}{0.05^2} = 384.16 \approx 385$$

The result was rounded up to a target of 385 lecturers. The target was then divided equally among the five universities, so each university contributed 77 lecturers. Because the allocation was equal and not proportional to the number of lecturers at each university, the procedure is best described as quota sampling. It should not be described as proportionate stratified random sampling, which would have required larger universities to supply more participants. A consequence of this choice is that the results describe the lecturers who took part and cannot be generalized statistically to all lecturers in Phnom Penh.

A total of 400 questionnaires were returned, and 15 of them (3.8%) were removed because the responses were incomplete. The remaining 385 valid cases (96.3%) formed the dataset for analysis. Table 3 presents the demographic and professional profile of these participants, and the Findings section describes it in detail.

The questionnaire was developed in line with the research objectives, the conceptual framework, and earlier empirical studies on AI adoption, technology acceptance, workload, productivity, and job satisfaction in higher education. It had four parts. The first part collected demographic information. The second part addressed the use and acceptance of AI, including the frequency of use, the types of tools used, and the purposes of use, and it also asked about satisfaction with AI assistance, perceived benefits of AI integration, readiness to continue using AI resources, and views on institutional support for AI. The third part addressed the perceived effects of AI on workload, which covered teaching, assessment, administrative, and research workload, and on productivity, which covered task efficiency, teaching preparation, assessment efficiency, and research productivity. The fourth part addressed job satisfaction, which covered work satisfaction, professional development, and motivation. In addition to the demographic questions, the questionnaire contained 46 Likert-scale items grouped according to the dimensions in Figure 1.

All items used a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree), a format that is widely used in educational and social science research to capture attitudes, perceptions, and experiences (Creswell & Creswell, 2023). Workload was therefore measured as perceived workload, meaning the extent to which lecturers agreed with statements about the effort required by teaching, assessment, administrative, and research tasks. The scores do not represent recorded working hours, task counts, or other objective indicators of workload, and the results should be read as the perceptions of lecturers. The internal consistency of each dimension was examined with Cronbach's alpha, and the results are reported in the Findings section.

The data were analyzed with the Statistical Package for the Social Sciences (SPSS) version 27. Descriptive statistics, namely frequencies, percentages, means, and standard deviations, summarized the demographic attributes of the participants and the levels of each dimension. Pearson correlation coefficients were calculated to examine the associations among AI use, workload, productivity, and job satisfaction. Simple linear regression was then used to examine the effect of AI use on workload, on productivity, and on job satisfaction.

RESULT AND DISCUSSION

Participant Profile and Levels of the Study Variables

Of the 400 questionnaires returned, 385 were complete and were retained for analysis, with 77 lecturers from each of the five universities. Table 1 presents the profile of these participants. The sample was predominantly male, and most participants were aged 40 to 49 years, held a master's degree, held the academic rank of lecturer, and had more than 15 years of teaching experience. The profile suggests that the respondents were experienced academic staff who may have been well placed to judge how digital tools and AI have changed their own work.

Table 1 Profile of the Participants (N=385)

Characteristic	Category	Percentage
Sex	Male	61.5
	Female	38.5
Age	30–39 years	38.5
	40–49 years	61.5
Academic qualification	Master's degree	57.8
	Doctoral degree	42.8
Academic rank	Lecturer	61.5
	Assistant professor	38.5
Teaching experience	11–15 years	38.5
	More than 15 years	61.5
University	Each of five universities	20.0

Source: Analyzed by the researchers (2026)

Table 2 presents the mean and standard deviation of each dimension on the 5-point scale. All dimensions had mean scores of 4.00 or higher, which indicates general agreement with the statements about AI use, workload, productivity, and job satisfaction. Among the AI use dimensions, the types of tools used had the highest mean (M = 4.30, SD = 1.40), followed by the frequency of use (M = 4.15, SD = 1.26) and the purposes of use (M = 4.10, SD = 1.36). Among the workload dimensions, teaching workload had the highest mean (M = 4.35, SD = 1.30), followed by administrative workload (M = 4.33, SD = 1.18), research workload (M = 4.27, SD = 1.31), and assessment workload (M = 4.07, SD = 1.42). Teaching preparation had the highest mean among the productivity dimensions (M = 4.40, SD = 1.20), followed by assessment efficiency (M = 4.27, SD = 1.16), task efficiency (M = 4.20, SD = 1.17), and research productivity (M = 4.07, SD = 1.56). Work satisfaction was the highest of the job satisfaction dimensions (M = 4.40, SD = 1.20), followed by motivation (M = 4.33, SD = 1.18) and professional development (M = 4.00, SD = 1.55).

Table 2 Descriptive Statistics of the Study Dimensions (N = 385)

Variable	Dimension	M	SD
AI use	Frequency of use	4.15	1.26
	Types of tools used	4.30	1.40
	Purposes of use	4.10	1.36
Workload	Teaching workload	4.35	1.30
	Assessment workload	4.07	1.42
	Administrative workload	4.33	1.18
	Research workload	4.27	1.31
Productivity	Task efficiency	4.20	1.17
	Teaching preparation	4.40	1.20
	Assessment efficiency	4.27	1.16
	Research productivity	4.07	1.56
Job satisfaction	Work satisfaction	4.40	1.20
	Professional development	4.00	1.55
	Motivation	4.33	1.18

Source: Analyzed by the researchers (2026)

Two features of this pattern need to be considered. The means occupy a narrow band between 4.00 and 4.40, and several dimensions share identical means, which limits how far the dimensions can be separated from one another. The standard deviations, which range from 1.16 to 1.56, show at the same time that individual responses varied considerably around these high means. The results therefore indicate that the lecturers agreed broadly with the statements in the questionnaire, and they should be read as perceptions and not as measures of actual use, effort, or output.

Reliability of the Measurement and Data Quality

Internal consistency was examined with Cronbach's alpha for each dimension, and the coefficients are presented in Table 3. The values ranged from .984 to 1.000 across the nine dimensions for which results were available. The frequency of AI use, the types of tools, the purposes of use, and the four workload dimensions had coefficients between .984 and .994, and task efficiency and teaching preparation reached 1.000.

Table 3 Reliability of the Dimensions

Dimension	Number of items	Cronbach's alpha
Frequency of AI use	4	.994
Types of tools used	4	.993
Purposes of use	4	.993
Teaching workload	4	.994
Assessment workload	3	.991
Administrative workload	3	.987
Research workload	3	.984
Task efficiency	3	1.000
Teaching preparation	3	1.000

Source: Analyzed by the researchers (2026)

Coefficients at this level do not indicate that the instrument measured the constructs with exceptional precision. Alpha values above approximately .95 usually signal that items are close to duplicates and add little distinct information, and an alpha of 1.000 means that respondents gave identical answers to every item of a scale. Such patterns can arise when respondents select the same option throughout a scale or when items are phrased too similarly. The reliability results are therefore interpreted as evidence of redundancy among items and not as evidence of strong measurement quality.

The consequences of this redundancy extend to the analyses that follow, because composite scores built from near-identical items vary together and can inflate the associations among them. Reliability coefficients for assessment efficiency, research productivity, work satisfaction, professional development, and motivation were not available for this report. The associations reported in the next section should be read with these limitations in mind.

Associations Among AI Use, Workload, Productivity, and Job Satisfaction

Pearson correlation analysis showed positive and statistically significant associations ($p < .001$) between AI use and workload, between AI use and productivity, between AI use and job satisfaction, between workload and job satisfaction, and between productivity and job satisfaction. Every coefficient was reported as 1.000. A correlation of exactly 1.000 between conceptually distinct constructs means that the composite scores are statistically indistinguishable, which

is not plausible for attitudinal measures. The correlations are therefore interpreted only for their direction, which was positive in every case, and not for their strength.

Table 4 Pearson Correlations among the Variables

Relationship	r	p
AI use and workload	1.000	< .001
AI use and productivity	1.000	< .001
AI use and job satisfaction	1.000	< .001
Workload and job satisfaction	1.000	< .001
Productivity and job satisfaction	1.000	< .001

Note. *Only the direction of the relationsgips is interpreted.*
Source: Analyzed by the researchers (2026)

Simple linear regression, presented in Table 5, showed that AI use positively predicted workload (B = .973, β = .997, R^2 = .994, p < .001), productivity (B = .952, β = 1.000, R^2 = 1.000, p < .001), and job satisfaction (B = .979, β = .998, R^2 = .996, p < .001). Explained variance close to 100% from a single predictor is not credible for perceptual outcomes, and it follows from the near-perfect correlations described above. The coefficients are reported for completeness, and only the positive direction of the relationships is interpreted.

Table 5 Simple Linear Regression of the Outcomes on AI Use

Outcome	B	SE	β	t	R^2	F(1, 383)	p
Workload	.973	.004	.997	242.219	.994	58,670.196	< .001
Productivity	.952	.001	1.000	1,216.977	1.000	1,481,033.056	< .001
Job satisfaction	.979	.003	.998	308.768	.996	95,337.718	< .001

Note. *Only the direction of the relationsgips is interpreted.*
Source: Analyzed by the researchers (2026)

Table 6 summarizes the decisions for the seven hypotheses. H1, which proposed a significant effect of AI use on workload without a direction, was supported, and the effect was positive, so higher AI use was associated with higher perceived workload. H2 was supported, since higher AI use was associated with higher productivity. H3 was not supported because workload was positively and not negatively associated with job satisfaction. H4 was provisionally supported by the positive correlation between productivity and job satisfaction, although no regression with both workload and productivity as predictors was estimated. H5, H6, and H7 could not be evaluated because no mediation analysis was performed, and correlations cannot establish indirect effects.

Table 6 Summary of Hypothesis Testing

Hypothesis	Path	Statistics	Decision
H1	AI use to workload	B = .973, β = .997, R^2 = .994, p < .001	Supported (positive direction)

Hypothesis	Path	Statistics	Decision
H2	AI use to productivity	B = .952, β = 1.000, R^2 = 1.000, p < .001	Supported
H3	Workload to job satisfaction	r = 1.000, p < .001	Not supported (positive, not negative)
H4	Productivity to job satisfaction	r = 1.000, p < .001	Provisionally supported
H5	AI use to job satisfaction through workload	Not tested	No decision
H6	AI use to job satisfaction through productivity	Not tested	No decision
H7	AI use to job satisfaction through workload and productivity	Not tested	No decision

Source: Analyzed by the researchers (2026)

Workload, Productivity, and Satisfaction in Light of Existing Evidence

The most notable finding is that lecturers who used AI more reported higher and not lower workload across teaching, assessment, administrative, and research tasks (H1). The expectation that AI relieves lecturers of routine work comes from reviews of early studies, which listed the reduction of staff workload among the benefits of AI in higher education (Liang et al., 2025). The present result suggests that such relief is only one part of the picture. Another systematic review described generative AI as a technology that transforms academic workload, because routine and procedural tasks become more efficient while new responsibilities such as quality review of AI outputs, ethical judgment, and the monitoring of academic integrity appear (Su et al., 2026). A lecturer who uses AI to draft materials and feedback still has to check, correct, and take responsibility for the output, and this additional effort may explain why heavier AI use went together with heavier perceived workload. The cross-sectional design cannot establish this mechanism, because lecturers with heavier workloads may also turn to AI more often to cope with their duties.

Higher AI use was also associated with higher productivity (H2) and with higher job satisfaction. These associations fit evidence that adopting AI tools can accompany better experiences at work, since a study of university faculty linked ChatGPT adoption to greater happiness and energy and to lower stress (Cambra-Fierro et al., 2025). The productivity result is similar in direction to findings from public sector organizations, where digital transformation predicted service delivery efficiency, although that study also found significant contributions from organizational culture and leadership and concluded that technology depends on a supportive workplace (Sain et al., 2025). The present study did not measure these organizational conditions, so it cannot say whether the favorable pattern among lecturers depends on institutional support. Two further studies cannot be compared

directly with the present results. Performance expectancy was unrelated to satisfaction with generative AI tools among academic staff , but that study measured satisfaction with the tools and the present study measured satisfaction with the job (Baig & Yadegaridehkordi, 2025). Job satisfaction had no direct effect on performance among company employees, but that study examined the reverse direction from the path tested here, which runs from productivity to satisfaction (Budiyanto, 2025).

The positive association between workload and job satisfaction (H3) was unexpected. In JD-R theory, job demands erode well-being unless resources buffer their effect, so a heavier workload should have accompanied lower satisfaction (Bakker & Demerouti, 2017). One explanation is that lecturers experienced the workload linked to AI as a challenging but manageable demand that came with resources such as faster preparation and feedback, a possibility consistent with the later development of the theory (Bakker et al., 2023). A more cautious explanation is that the result reflects the measurement problems described in the Results, namely uniform agreement across items and composite scores that move together, in which case the data give no basis for questioning the theory. The mediating roles of workload and productivity (H5 to H7) were not tested, so the central mechanism of the conceptual framework remains open.

Practical Implications, Limitations, and Future Research Agenda

If the associations reported here are confirmed with verified data, they suggest that universities should plan AI integration with attention to the work that AI creates as well as the work it saves. Institutions need clear protocols for the appropriate use of AI in teaching, research, assessment, and administration. Training should go beyond operating the tools and include evaluating AI-generated content, preserving academic integrity, and protecting data, which follows from the added responsibilities identified in the literature, such as quality review and ethical judgment (Su et al., 2026).

Universities should also invest in reliable connectivity, digital platforms, and support services so that lecturers have equitable access to AI tools, and leaders should create oversight and evaluation frameworks that track whether AI deployment lightens or adds to academic work. The role of supportive leadership and workplace culture in technology-driven efficiency points to the same need (Sain et al., 2025). Lecturers, for their part, should treat AI as an auxiliary instrument that supports their expertise, verify the accuracy of AI output, protect sensitive information, and observe ethical principles in teaching and research.

Several limitations qualify these findings. The most important concerns data quality, since near-perfect correlations, regression coefficients, and reliability values indicate that the composite scores cannot be treated as distinct and independent measures. The sample was obtained by equal quota allocation across five universities in one city, so the results cannot be generalized statistically. All

variables were self-reported on agreement scales, and workload was measured as perceived workload and not as recorded hours or tasks. The cross-sectional design prevents causal conclusions, and no mediation analysis was performed, which leaves H5 to H7 untested.

Future studies should verify the dataset and rebuild the composite scores from items with adequate but not excessive reliability. They should test the mediation model with regression-based path analysis or structural equation modeling, measure workload through frequency, duration, or intensity indicators, and use probability sampling proportional to institutional size. Longitudinal or mixed-methods designs would show whether AI reduces, redistributes, or intensifies the work of lecturers over time, and measures of institutional support would show the conditions under which AI use accompanies higher satisfaction.

The results support earlier research in three respects. The combination of higher productivity and higher workload agrees with the view that generative AI transforms academic workload and does not simply reduce it, and the positive associations with job satisfaction and productivity agree in direction with evidence on favorable faculty experiences of AI and on efficiency gains from digital technology (Cambra-Fierro et al., 2025; Sain et al., 2025; Su et al., 2026). The study extends this research by placing AI use, workload, productivity, and job satisfaction in a single model, by showing that perceived workload and productivity rose together with AI use and therefore behave as separate pathways, and by adding lecturers at five universities in Phnom Penh to the settings covered by the studies discussed above.

The results contradict two expectations. They contradict the expectation that AI reduces the workload of lecturers, and they contradict the JD-R expectation that workload lowers job satisfaction, although the second contradiction is probably an artifact of the measurement problems discussed above (Bakker & Demerouti, 2017; Liang et al., 2025). These judgments are provisional. The contribution of the study depends on verification of the dataset, and until the composite scores are rebuilt and the mediation hypotheses are tested, the findings establish the direction of the associations and not their size or the mechanisms behind them.

CONCLUSION

This study set out to establish how AI use relates to the workload, productivity, and job satisfaction of lecturers at five universities in Phnom Penh, Cambodia. Among the 385 lecturers surveyed, AI use was positively associated with perceived workload and with perceived productivity, so both H1 and H2 were supported, and it was also positively associated with job satisfaction. The positive association between workload and job satisfaction ran against the expected direction, so H3 was not supported. The link between productivity and job satisfaction gave provisional support to H4, and the mediation hypotheses H5 to H7 could not be evaluated. Taken together, the findings point to a pattern in which AI

use accompanies gains in productivity and heavier perceived workload at the same time. They do not support the view that AI simply reduces the burden of academic work.

The practical message is that AI adoption in universities should be managed as a change in the content of academic work and not as a simple saving of effort. Institutions can respond by setting clear protocols for the use of AI in teaching, research, assessment, and administration, by training lecturers to evaluate AI-generated output, uphold academic integrity, and protect data, and by providing dependable digital infrastructure and support services. Monitoring how AI affects the workload of lecturers over time would allow leaders to see whether the technology lightens or adds to academic duties. Lecturers can contribute by using AI as an auxiliary tool that supports their own expertise and judgment.

These conclusions must be read with caution. Near-perfect correlation and reliability coefficients show that the composite scores cannot be treated as independent measures, so only the direction of the associations can be interpreted. The equal quota allocation, the self-reported agreement scales, the use of perceived workload, and the cross-sectional design further limit generalization and causal inference. Future research should verify the dataset, test the mediating roles of workload and productivity through path analysis or structural equation modeling, measure workload with frequency, duration, or intensity indicators, and apply probability sampling and longitudinal designs to clarify whether AI reduces, redistributes, or intensifies the work of lecturers.

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