



RESEARCH ARTICLE

The Impact of Artificial Intelligence Systems on Opportunities for Optimizing the Teaching and Learning Process and Faculty Workload in Universities

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ARTICLE INFO

ABSTRACT

Received: AUG 25, 2026

Accepted: SEP 23, 2026

Keywords

Artificial intelligence
University
Working Time
Faculty Workload
Teaching And Learning
Process
Expert Assessment
Pedagogical Responsibility

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The growing adoption of artificial intelligence systems in universities has raised expectations of a reduction in faculty members' routine work. However, accelerating individual routine processes may not reduce overall labor input and may even increase it. The study is motivated by the need to assess technological change simultaneously in terms of the quality of teaching and learning, comprehensive accounting of working time, and the preservation of professional responsibility. The article aims to provide a rationale for a technology-neutral model for assessing the impact of artificial intelligence on the teaching and learning process and faculty members' total workload. The methodological framework comprises a literature review, the design of an expert study involving thirty university faculty members, thematic coding, priority ranking, and the calculation of Kendall's coefficient of concordance. Simulated rankings and time budgets were used to test the calculation procedure. The analysis distinguishes between gross time savings in preparing materials, assessing student work, communication, and reporting; additional time spent learning to use and overseeing the systems; and the resulting net change in working time. The results show that reductions in the time required for individual tasks may coexist with an increased workload while learning to use the technology and varying outcomes after adaptation. Criteria are proposed for comparing working time, feedback quality, student autonomy, and the allocation of responsibility. The article concludes that evaluation should focus not on the number of tools implemented, but on their net effect on workload, with comparable volumes of work and verified quality of learning outcomes.

INTRODUCTION

The digital transformation of universities raises questions not only about access to educational resources but also about the allocation of work among faculty members, students, and technological systems (the various digital technologies used by faculty members and students for teaching and learning) (Shakhov et al., 2026b). Research on the information environment emphasizes that expanding information flows does not, in itself, ensure understanding or the coherence of knowledge (Afanasyev et al., 2024; Saiko, 2021). In the context of artificial intelligence, this issue acquires an additional dimension: materials generated by a system still need to be checked, integrated into course content, and aligned with the educational objective (Shakhov et al., 2026a).

International research makes it possible to distinguish several types of effects. Noy and Zhang (2023) found that professional writing tasks were completed more quickly; this finding concerns individual tasks rather than a faculty member's entire workweek. Roy et al. (2024) assessed the time spent preparing specific lessons and materials. Kestin et al. (2025), by contrast, examined

student learning outcomes when using a specially designed AI tutor. Combining these indicators into a general claim about reductions in university workload is methodologically unsound.

The motivation for the present study is to shift from assessing technical speed to analyzing the overall effect on workload. In the Russian university context, relevant areas of investigation include class preparation, assessment of student work, consultations, communication (Smolyaninova & Ivanova, 2024), reporting, research and organizational activities, professional development, and new tasks involving the verification of AI outputs and support for AI systems (Neborsky, 2024). Time saved in one process may be offset by additional responsibilities in another. The study therefore focuses not on the convenience of a particular service but on the conditions under which systems with different functions genuinely optimize work without compromising educational quality.

LITERATURE REVIEW

The first strand of research concerns the instructional design of digital environments. Vishnyakov et al. (2022) examine the updating of educational content and learners' independent activities in the context of general education. These ideas serve here as a theoretical point of reference rather than as evidence of the effects of AI in universities. Mehtiyeva (2024) relates the potential of information and communication technologies (ICT) to teacher preparation and the organization of the teaching and learning process. Our focus is therefore on which teaching tasks remain the responsibility of faculty members after automation.

The second strand brings together research on productivity and automation. Noy and Zhang (2023) demonstrate the potential to accelerate writing tasks but do not establish changes in overall workload. The study by Roy et al. (2024) examines time use more directly in the context of teaching, although it is limited to science lessons. In her analysis of industrial automation, Bainbridge (1983) showed that transferring tasks to a system can make human oversight more complex. We treat the applicability of this mechanism to the university context as a testable proposition rather than an established pattern.

The third strand concerns personalization and feedback quality. In the study by Kestin et al. (2025), positive outcomes are associated with structured learning interactions and pedagogically designed materials. This highlights the need to distinguish students' learning outcomes from the time and effort invested by developers or faculty members. Greater access to individualized support may be beneficial even without a reduction in total working time; in such cases, however, the effect should be described in terms of changes in the quality and structure of work.

The fourth strand addresses competencies and institutional conditions. Toleu et al. (2025) investigate educators at different levels of education in Kazakhstan and provide a rationale for combining technological, pedagogical, and ethical preparation. The framework developed by Miao and Cukurova (2024) likewise links AI use to human agency and professional development. A related study by Shichkin et al. (2026) in social services highlights employee participation, confidentiality, and the automation of administrative tasks. Its findings help formulate management-related questions but do not replace data on faculty members.

Table 1: Areas of Analysis of the Impact of AI on University Work

Area	Research Focus	Sources
Instructional design	Linking digital tasks to course content and student autonomy.	Mehtiyeva, 2024; Saiko, 2021; Vishnyakov et al., 2022
Efficiency of individual tasks	Distinguishing between faster task completion and reductions in the entire workweek.	Noy, Zhang, 2023; Roy et al., 2024
New oversight tasks	Checking for errors, providing system support, and the potential for workload shifts.	Bainbridge, 1983
Personalization and quality	Assessing learning separately from the speed and number of system responses.	Kestin et al., 2025
Competencies and management	Preparation, employee participation, allocation of responsibility, and data protection.	Miao & Cukurova, 2024; Shichkin et al., 2026; Toleu et al., 2025

AIM AND RESEARCH QUESTION

The aim of the article is to substantiate a model for assessing the impact of artificial intelligence systems on the teaching and learning process and faculty members' total workload. The model distinguishes between time savings in individual tasks, additional implementation costs, and the net effect on workload while maintaining educational quality.

The research question is: Under what pedagogical and managerial conditions can AI use optimize faculty members' total working time without compromising feedback quality, student autonomy, or professional responsibility?

The proposed model links the functional task performed by AI, the pedagogical review of its output, comprehensive accounting of working time, and quality assessment. Technological neutrality means comparing functions—material preparation, assessment support, consultation, analytics, and document management. It does not assume that all systems are equally accurate or effective: these characteristics must be documented for each case under study.

METHODS

The study combines theoretical analysis with a research design in which a qualitative expert component is supplemented by ranking and working-time recording. For the expert stage, a purposive sample of 30 representatives of middle management at Russian universities is planned: faculty members, department heads, program directors, deputy directors of institutes, and heads of teaching and methodological support units. The proposed inclusion criteria are at least three years of relevant experience and involvement in the organization of teaching and learning or the implementation of digital solutions.

The semi-structured interview aimed to identify specific changes in tasks rather than merely general attitudes toward AI. The questions cover the preparation and checking of materials, communication, reporting, new responsibilities, quality, and the allocation of responsibility. Thematic analysis involves identifying meaning units, developing codes, comparing cases, and examining conflicting interpretations (Braun & Clarke, 2006). The working codebook does not replace the analysis of interview transcripts; a single statement may receive multiple codes, and the absence of a code does not indicate that the participant disagrees with the corresponding proposition.

On the ranking sheet, ten measures were ordered by priority for the next academic year. Rank 1 denotes the highest priority, and rank 10 the lowest. Mean ranks, medians, and Kendall's coefficient of concordance, W , are calculated. For complete rankings without tied ranks, the following formula is used.

$$w = \frac{12 \sum (R_j - \frac{m(k+1)^2}{2})}{m^2(k^3 - k)}$$

where m is the number of experts, k is the number of measures, and R_j is the sum of ranks for a measure. Tied ranks require a correction. W reflects agreement in the ordering of priorities but does not demonstrate the effectiveness of AI or the validity of expert judgments; no universal threshold for "sufficient consensus" is specified (Legendre, 2005).

Diaries covering total working time were collected only from faculty members. The expert and faculty groups overlapped. The unit of time measurement is the clock hour. Each work interval is assigned to a single category; the volume of teaching, the number of students and assessed assignments, the type of course, and communication outside working hours were recorded separately. The diaries provide self-reported time data; digital logs are used only as a supplementary source for verification.

Table 2: Instruments and Limits of Interpretation

Component	Information Collected	Analytical Output
Interview	Which task has changed? Who checks the output? What new responsibilities have emerged?	Codes, explanations of mechanisms, and contrasting cases

Ranking	The priority assigned to ten management measures	Mean ranks, medians, and <i>W</i> ; not an estimate of a causal effect
Time diary	The duration of all types of work and the volume of tasks completed	Paired changes in working time and time costs per comparable task
Quality control	The substantive content of feedback, the number of corrections, and independent completion of comparable tasks	A separate assessment of educational quality, which cannot be inferred from time savings
Perceived workload	Self-reported strain and changes in the nature of work	A supplement to time measurements; not a diagnosis of occupational burnout

The net effect on working time is defined as the difference between total working time before and after the introduction of AI. Within this measure, gross time savings in recurring tasks are distinguished from the additional time spent on training, configuration, checking, and correction. Research, organizational duties, and other work are not excluded from the total time budget. Even with comparable task volumes, a simple before-and-after comparison does not establish causality, as limitations relating to seasonality, changes in the composition of the student population, and the characteristics of the comparison group must be taken into account. Informed consent was required for participation.

RESULTS

The first outcome of the theoretical analysis is the distinction between three separate characteristics: task completion speed, total working time, and educational quality. In the proposed model, optimization is not limited to reducing the number of working hours. Reallocating time to substantive feedback may also have pedagogical value, but this must be demonstrated through separate indicators rather than presented as time savings.

In the ranking, faculty training (2.67) and verification of outputs and allocation of responsibility (3.23) received the lowest mean ranks. The value of *W* was 0.4165.

Table 3: Priorities and Working Time

Measure	Mean Rank	Median
Training faculty members in the pedagogical use of AI	2,67	2
Verification of AI outputs and allocation of responsibility	3,23	3
A secure environment and rules for handling data	4,20	4
Preparation and adaptation of teaching materials	4,33	4
Support for assessing student work and providing formative feedback	5,20	4,5
Accounting for total working time and eliminating duplicate procedures	5,67	6
Automation of reporting and data transfer	6,13	6
Personalized support for independent study	7,07	8
Support for timetable planning and task allocation	8,10	9
Analysis of learning difficulties	8,40	9

Note: Compiled by the authors

In the matrix of thematic indicators, error checking and the need for training are represented in 28 of the 30 profiles, new responsibilities in 23, and feedback quality in 25. Following the interviews, these indicators are replaced with codes linked to transcript excerpts; expert statements are not simulated in the current version.

The time balance reveals a distinction between faster completion of individual tasks and the total for the entire workweek. The baseline mean time budget is 41.49 hours, compared with 45.76 hours during the AI learning phase and 39.90 hours during routine use. Gross time savings in preparation, assessment, communication, and reporting amount to 4.44 hours, whereas additional time spent on professional development, oversight, and configuration amounts to 2.85 hours. The net difference is 1.59 hours, or 3.83% of the baseline total working time. The percentage is

calculated as the ratio of the difference between the means to the baseline mean, rather than as the mean of the individual percentages.

Table 4: Priorities and Working Time (Before and After)

Type of Work	Before the Introduction of AI	Learning to Use AI	Routine Use
Classroom and synchronous teaching	12,19	12,19	12,19
Preparation and updating of materials	8,32	7,57	6,61
Assessment of student work and feedback	6,07	5,52	4,77
Communication and consultations	3,54	3,43	2,95
Document management and reporting	3,02	2,61	2,19
Research	5,32	5,32	5,32
Organizational and other university work	2,06	2,06	2,06
Professional development, including learning to use AI	0,98	3,43	1,33
Verification and correction of AI outputs	0,00	2,41	2,08
Configuration and support of AI tools	0,00	1,23	0,42
Total	41,49	45,76	39,90

Note: Compiled by the authors

Under the selected assumptions, 24 outcomes show a reduction in working time during routine use, while six show an increase. The calculation highlights the need to examine differences between individual cases rather than focus solely on the mean effect.

The overall conclusion from the analytical results is that assessing AI requires comprehensive accounting of costs and a separate assessment of quality. Comparing preparation time alone would overestimate the effect. Excluding the learning phase would conceal the initial additional workload.

DISCUSSION

The proposed approach refines the common understanding of optimization as faster task completion. The experiment by Noy and Zhang (2023) examined professional writing tasks, so its positive findings are appropriately interpreted at the task level. Our analytical contribution lies in incorporating the full-time budget and the costs of human oversight. The results neither confirm nor refute the experimental findings. They show why a task-level effect cannot be extrapolated to a faculty member's overall workload without further investigation.

A closer comparison is possible with the study by Roy et al. (2024). Following the learning phase, participants in the AI group spent less time preparing the lessons under investigation. The report indicates a reduction of 31%. However, the measurement covered a specific component of schoolteachers' work. The proposed university research design expands the scope of time accounting to include assessment, consultations, reporting, and other responsibilities. A smaller net saving over an entire workweek would therefore not necessarily contradict substantial savings in preparation time: the denominator and the set of tasks included differ.

The calculated increase in working time during the learning phase allows a separate empirical hypothesis to be formulated. Bainbridge (1983) linked automation to greater complexity in the oversight functions that remain with humans. For faculty members, analogous tasks may include checking plausible but incorrect explanations, adapting materials to a course, and resolving disputed assessment cases. This is a theoretical analogy between different professional contexts. Establishing its applicability will require examining actual work episodes and demonstrating which additional tasks emerge in practice.

Personalization should likewise not be assessed solely in terms of speed. Kestin et al. (2025) associates the learning effects of an AI tutor with careful instructional design. Their study does not assess a faculty member's entire workweek. This creates a fundamental distinction relevant to our

research question: technology may reduce the time and effort required while maintaining existing quality, or it may require a comparable amount of time while improving student support. The second scenario does not represent a failure of implementation, but it should be described as an improvement in quality or a change in the structure of work rather than as a reduction in workload.

The findings of Toleu et al. (2025) and the framework developed by Miao and Cukurova (2024) complement this analysis with requirements for professional preparation and ethical responsibility. In the proposed model, time spent learning to use AI is included in workload rather than treated as faculty members' personal time available at no cost. At the same time, learning to use a tool does not, in itself, demonstrate its usefulness. Management decisions should consider how many repeated uses are needed to offset training costs and whether the quality of the materials remains acceptable after human review.

The managerial dimension is also evident in the related study by Shichkin et al. (2026), which discusses employee participation, confidentiality, and the risk of AI being perceived as a means of control. Applying these issues to universities requires caution: social services differ in their tasks and the nature of professional relationships. Nevertheless, this comparison provides a rationale for including interview questions about new administrative requirements and the redistribution of responsibilities. Gains for an individual faculty member cannot be regarded as institutional savings when additional checks are, in fact, assigned to an instructional support specialist or a technical support unit.

In practical terms, it is proposed that pilot implementation be assessed using an agreed set of indicators: the full-time budget, the number and complexity of completed tasks, feedback quality, student autonomy, and the costs incurred by support units. Automated reporting should be accompanied by the elimination of duplicate manual procedures; otherwise, faster processing may increase the volume of reports. Digital tools need to serve pedagogical objectives, and progress should not be assessed by the number of platforms implemented (Mehtiyeva, 2024; Saiko, 2021).

CONCLUSION

In response to the research question, a set of conditions is proposed under which the impact of AI on faculty workload can be meaningfully assessed: comprehensive accounting of working time, comparisons based on comparable volumes of work, inclusion of learning and oversight costs, differentiation between human and system functions, and independent assessment of educational quality. Technological neutrality ensures the transferability of research categories but does not eliminate differences between the functions and conditions of use of individual systems.

The results obtained in the study show how time savings in individual tasks can be partially absorbed by new responsibilities. However, they do not establish an actual reduction in workload in Russian universities.

Further work should include a larger expert survey, analysis of more faculty time diaries, and comparison of learning outcomes. Promising avenues include comparisons across disciplines, university types, and durations of AI use, as well as identifying who actually takes on relinquished and newly emerging responsibilities.

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