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Artificial Intelligence Use in Professional Bachelor Thesis Writing: A Survey-Based Analytical Framework

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Abstract—This paper examines students' use of artificial intelligence (AI) in professional bachelor thesis writing and asks how those patterns can be described in a form useful for future support and governance in higher education. The study compared the 2024 and 2025 graduating classes at the same Lithuanian institution. The target population comprised 399 students, and the final sample included 258 respondents, with 129 from each graduating class. The questionnaire covered thesis-related tasks, named tools, perceived benefits and risks, attitudinal statements, and open-ended comments. Quantitative data were analysed in SPSS using frequencies, percentages, reliability analysis, Shapiro-Wilk tests, non-parametric comparisons, and Spearman correlations. Open-ended comments were grouped thematically. The results show a stable pattern: students used AI most often for paraphrasing and summarising, translation, grammar and style revision, and literature search. ChatGPT and Google Scholar clearly dominated the tool profile. Students valued AI mainly because it saved time and made writing easier to manage, but they also pointed to errors, weaker originality, and the need to verify AI-generated content. Lecturer guidance was the strongest attitudinal result, suggesting a practical need rather than a general wish for more regulation. The paper translates the survey evidence into a layered framework that separates student context, thesis tasks, named tools, perceived risks, and guidance expectations. This framework may inform later supervision dashboards, disclosure forms, or rule-based support systems for thesis administration. The study also identifies a limit in the available evidence: when reliable Lithuanian-language AI-detection data are not collected, self-reports and AI-use declarations should be treated as supervision and verification indicators, not as proof of misconduct.

Keywords—artificial intelligence, thesis writing, higher education, academic integrity, decision support, educational analytics

I. INTRODUCTION

Artificial intelligence entered thesis writing faster than universities managed to agree on clear rules for its use. In a professional bachelor thesis, this matters. A final thesis is tied to authorship, source use, method, and the public defence of one's own work. Students may use AI at different points in that process, but not all of those points carry the same academic weight. If institutions want workable guidance, they first need a clearer picture of where students actually use AI and what kind of help they expect from it.

Artificial intelligence entered thesis writing before universities had settled how to govern it. In the context of a professional bachelor thesis, this is not a technical add-on. The thesis is the document through which a student demonstrates the ability to select sources, make methodological choices, develop an argument, and defend the result. AI may support wording, searching, translation, and other limited steps, but those steps do not carry the same academic weight. This study therefore asks a deliberately concrete question: where, in theses that had already been defended, did students say AI had entered, and where did they still need guidance?

Recent research in higher education presents a mixed picture. On the one hand, students and teachers report practical benefits: AI can support wording, translation, summarising, feedback, and literature search [2]-[5]. On the other hand, the same literature identifies risks associated with integrity, disclosure, accuracy, and overreliance [6]-[11]. The discussion is therefore no longer simply about whether AI is present in academic work. The more difficult question is how it enters that work and where its boundaries should be drawn.

A less settled issue is the everyday pattern of AI use once a thesis has been written and defended. Much of the

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discussion remains general or policy-oriented, with less attention to the specific tasks for which students use AI, the tools they choose, and the points at which they still feel uncertain. Post-defence data are useful in this respect because they capture students' retrospective view of the whole writing process rather than one isolated moment within it.

The systems-design relevance of this paper is therefore practical. If a university later seeks to develop a rule-based guidance tool, a monitoring dashboard, or an AI-aware supervision system, it first needs clear input variables. Those variables do not begin with software; they begin with evidence about tasks, tools, risk signals, and guidance needs [14]-[16]. This study works at that requirements level.

II. Theoretical Background

A. *AI as Support in Academic Writing*

Students rarely use AI for a single purpose. The same tool may help with rewording, translation, summarising, literature search, or a first idea for structuring text [2]-[5]. Academic writing, however, is not a single task. It combines language work, search, planning, method, and argument. For that reason, AI use has to be read in relation to the task itself, not only in relation to the tool.

A thesis makes this especially visible. Some tasks are close to technical support, such as improving wording or finding a better translation. Other tasks move much closer to academic ownership, such as shaping the topic, choosing a method, or interpreting data. Recent work in higher education increasingly stresses that AI may assist writing, but it cannot replace responsibility for the final academic text [3], [4], [6].

In this study, thesis writing is treated as a layered process. One layer concerns the task itself. Another concerns the tool used for that task. A third concerns how students judge benefits, risks, and acceptable use. This simple division makes the pattern easier to describe and later easier to translate into a usable support model.

B. *Integrity, Disclosure, and Institutional Guidance*

Current discussions about AI and academic integrity are no longer well captured by a simple allowed-or-forbidden distinction. Greater attention is now given to transparency, disclosure, and proportionate use [7], [10]-[11]. In practice, students need to understand not only whether AI is permitted, but also when its use becomes problematic for authorship, source work, or method.

Institutional guidance matters for the same reason. Clearer rules help students make better decisions, and they also make later governance tools more transparent. A technical system is easier to trust when the logic behind its categories reflects academic norms and when users can see why some practices are low risk while others require closer review [15], [16].

For that reason, this article considers use, evaluation, and guidance together. These are connected rather than separate issues. A student may use AI often while still mistrusting its output; another may use it cautiously but still want clearer rules on originality or disclosure. The combination of task, tool, and attitude data is therefore especially important.

III. Methodology

A. *Design*

The study followed a comparative post-defence survey design. The same questionnaire was administered after the thesis defence period in two consecutive years, 2024 and 2025, in the same Lithuanian higher education institution. Students were asked how they had used AI during thesis preparation and how they evaluated that use after the process was finished. This made it possible to compare the 2024 graduating class with the 2025 graduating class while keeping the questions close to real thesis work.

B. *Participants and Instrument*

The target population comprised all students who defended a professional bachelor thesis in the two years under review: 198 in 2024 and 201 in 2025. A finite-population sample-size benchmark at 95% confidence and a 5% margin of error suggested a minimum of 196 responses. The study obtained 258 valid responses, 129 from the 2024 graduating class and 129 from the 2025 graduating class. The questionnaire followed the logic of thesis preparation. It began with background questions on study mode, funding, and study programme (A1–A3). It then moved to the task-related AI-use block (A4), which asked how often AI was used in eleven thesis-writing tasks, and the tool-use block (A5), which listed named systems and platforms. Two open-response blocks invited students to describe actual practice (A6) and expected guidance (A10). Between them, the benefits block (A7), the drawbacks block (A8), and the attitudinal block (A9) captured how students judged usefulness, risk, and institutional support.

TABLE I. SAMPLE ADEQUACY BENCHMARK AND ACHIEVED SAMPLE

Graduating class	**Population**	**Achieved n**
2024	198	129
2025	201	129
Total	399	258

Benchmark n was estimated using the finite-population sample-size formula at 95% confidence and a 5% margin of error.

As shown in Table I, the achieved sample was sufficient in aggregate and balanced across the two graduating classes. This gives the comparison a stable descriptive basis. At the same time, the study remains a single-institution survey based on voluntary participation, so the results should be read as informative rather than directly generalisable.

The questionnaire structure also supports content validity. It moved from background characteristics to task-level AI use, then to tools, evaluation, and guidance. Students were therefore not asked about AI in the abstract, but in a sequence that reflects how thesis work is usually experienced.

C. Data Analysis

Quantitative data were analysed in SPSS. Frequencies and percentages were calculated for background variables, the task-related AI-use block (A4), the tool-use block (A5), and selected indicators from the benefits and drawbacks blocks (A7 and A8). For the task-related AI-use block (A4) and the attitudinal block (A9), internal consistency was checked with Cronbach's alpha [13]. Shapiro-Wilk tests were used to assess distributional shape. Because the index distributions departed from normality, non-parametric procedures were preferred, and associations were examined using Spearman's rho.

Open-ended responses were grouped thematically through repeated reading, coding, and theme refinement in line with Braun and Clarke's approach [12]. This made it possible to retain the practical detail of student comments while still presenting the material in an organised way.

The task-related AI-use block (A4) and the tool-use block (A5) used the same five-point frequency scale from 1 (never) to 5 (always). The benefits block (A7) and the drawbacks block (A8) were coded as binary multiple-response indicators because respondents could select more than one option. The attitudinal block (A9) used a five-point agreement scale, and the open-response blocks (A6 and A10) were retained for thematic analysis. This coding strategy made it possible to move from broad patterns to more focused analytical links between tasks, tools, and governance signals.

D. Institutional Verification Context and Data Triangulation

To place the survey data in relation to institutional procedure, the final-thesis submission route was reviewed together with the questionnaire results. In the analysed institution, final theses were submitted through the Moodle virtual learning environment, and Turnitin was integrated into that workflow. The system therefore provided a formal route for similarity and originality checking during thesis submission.

Turnitin did not, however, provide a reliable basis for detecting AI-generated Lithuanian-language text in final theses during the period under review. For that reason, the institution did not produce a comparable register showing how many students were not admitted to defence, how many theses were rejected, or how many sanctions were imposed specifically because of unauthorised AI use. The paper therefore avoids reporting figures that the institutional evidence could not support.

The available institutional reference point was therefore procedural rather than numerical. Under the institution's guidelines for AI use in written assignments, and in line with broader ethical guidance on AI in study processes [11], students include an AI-use declaration in the final thesis. The survey findings are consequently interpreted as anonymous post-defence self-reports, read alongside a disclosure requirement, rather than as a disciplinary audit.

E. Engineering Relevance of the Analytical Model

The study does not present a deployed software tool. Its engineering contribution is preliminary: it organises the survey data into variables that a later tool could use in practice. The analytical model links four layers: student context (A1-A3), task-related use (A4), named tools (A5), and governance evidence drawn from benefits, risks, attitudes, and open comments (A7-A10). This ordering follows the thesis process itself, from student context to the tasks performed, the tools named, and the points at which clearer safeguards were expected.

For systems design, this boundary is useful rather than problematic. A dashboard, disclosure checklist, or rule-based guidance tool would gain little from a single overall attitude score. It would require separable signals: routine language support, limited use in topic and data work, reliance on a few familiar platforms, and explicit requests for rule clarification. The article stops before implementation, but identifies the type of evidence that implementation would require [14]-[16].

F. Validity, Reliability, Ethics, and AI-Use Disclosure

The questionnaire was researcher-developed, so its main strength lies in its close fit with the study aim and with the real sequence of thesis preparation. Content validity was supported by the instrument's progression from background variables to tasks, tools, benefits, risks, attitudes, and open comments. Internal consistency was checked for the task-use block (A4) and the attitudinal block (A9). The pooled alpha was .892 for A4 and .869 for A9, while year-specific alphas were also strong. This supports the use of composite indicators for careful interpretation.

The tool-use block (A5) produced an alpha of .797 in the pooled dataset, but this was not treated as evidence of a single latent scale. The block lists different kinds of tools, from chat-based systems to search tools and citation software. For that reason, A5 was interpreted mainly as a tool-use profile rather than as a single construct.

The survey was anonymous and voluntary, and the findings are reported only in aggregated form. Open-ended answers were used as contextual evidence and were not treated as material that could identify individual respondents. Participation implied consent to the use of responses for research and educational improvement purposes.

Because the paper itself deals with acceptable AI use in academic work, AI-use disclosure was treated as part of the methodology. OpenAI ChatGPT was used only for language editing and wording revision during manuscript preparation. It was not used to generate the survey data, run SPSS procedures, or produce the empirical results. The author reviewed all interpretations and retains full responsibility for the final text.

IV. Results

A. Respondent Profile

To describe the two graduating classes and the study contexts represented in the dataset, the background variables were examined (see Table II).

TABLE II. RESPONDENT PROFILE

Characteristic	2024	2025
Part-time	41	15
Full-time	38	54
Full-time sessional	50	60
State-funded	88	84
Self-funded	41	45
Primary Education	29	33
Childhood Pedagogy	63	63
Social Work	37	33

Values are frequencies.

Table II shows that the two graduating classes were equal in size but not identical in composition. The 2024 graduating class included more part-time students (31.8%) than the 2025 graduating class (11.6%), whereas the 2025 graduating class had more full-time students. Programme composition was more stable: Childhood Pedagogy was the largest group in both years, while Primary Education and Social Work were represented in smaller but still comparable numbers. Funding structure was also similar across the two year groups.

This matters for the year comparison. The two graduating classes were not identical populations. The main structural shift concerned study mode. Later differences in AI use should therefore be read as differences between year groups within a broadly similar study environment, not as evidence of two wholly different student populations.

B. Thesis-Related Tasks in Which AI Was Used Most Often

To see in which parts of thesis writing AI was used most often, the task-related AI use block (A4) was examined (see Table III).

TABLE III. TASK-LAYER INDICATORS OF AI USE IN THESIS WRITING

Task	2024	2025	All
Topic selection	1.40	1.47	1.44
Literature search	1.96	2.00	1.98
Structure/content	1.71	1.81	1.76
Text generation	1.58	1.72	1.65
Grammar/style	1.87	2.33	2.10
Research gaps/errors	1.74	1.56	1.65
Text analysis	1.64	1.72	1.68
Paraphrase/summarise	2.27	2.35	2.31
Data collection/analysis	1.71	1.44	1.58
Translation	2.12	2.56	2.34
Plagiarism check	1.84	1.30	1.57

Mean values are based on the five-point frequency scale from 1 = never to 5 = always.

Table III shows a clear and stable pattern. In both year groups, AI use was strongest in language-related and search-related tasks rather than in the more conceptually sensitive parts of thesis writing. The highest means were found for paraphrasing and summarising (2.27 in 2024 and 2.35 in 2025), translation (2.12 and 2.56), grammar and style revision (1.87 and 2.33), and literature search (1.96 and 2.00). These results suggest that students mainly used AI to improve wording, polish text, and support source work.

The lower end of Table III is as informative as the top. Topic selection stayed low in both cohorts, and data collection or analysis also remained near the lower end of the scale. Plagiarism-related use was moderate in 2024 and lower in 2025. These are not merely low scores; they mark the parts of thesis preparation in which authorship, evidence, and formal accountability are most directly implicated.

The year-to-year difference is therefore better described as a shift in emphasis. In 2025, language correction and translation gained weight; in 2024, data-related help and plagiarism checking appeared somewhat more often. The overall shape of use, however, remained stable.

C. Students' Own Descriptions of AI Use

Students' open-ended responses to the question “Please describe in more detail how you typically used AI software during the process of writing your professional bachelor's thesis” help explain how the quantitative results were reflected in everyday thesis-writing practices. Students described AI as a tool for rephrasing sentences, shortening or clarifying passages, translating text, checking language, sketching a structure, and locating sources. Several comments suggested a narrower use still: the idea already belonged to the student, but AI helped find the first formulation.

The comments do not support a picture of simple copying from a chatbot into the thesis. Respondents referred instead to checking, rewriting, selecting, and treating generated wording as draft material. This detail matters because it places AI in an editorial support role while leaving responsibility for the final wording with the student.

D. Most Frequently Used Tools

To identify which tools shaped students' AI use most clearly, the tool-use block (A5) was examined (see Table IV).

TABLE IV. TOOL-LAYER PROFILE OF AI USE

Tool	2024	2025	All
ChatGPT	2.75	2.91	2.83
Google Scholar	2.36	2.67	2.52
Gemini	1.49	1.16	1.33
Grammarly	1.33	1.21	1.27
Turnitin	1.35	1.19	1.27
SPSS	1.33	1.00	1.17
Mendeley	1.19	1.00	1.10
Zotero	1.09	1.05	1.07

Mean values are based on the five-point frequency scale from 1 = never to 5 = always.

Table IV shows a highly concentrated tool profile. In both year groups, ChatGPT and Google Scholar stood clearly above the rest. ChatGPT had the highest mean in both years (2.75 in 2024 and 2.91 in 2025), while Google Scholar followed (2.36 and 2.67). The remaining tools stayed much closer to the lower end of the scale.

This suggests that students did not build a broad or diversified tool environment around thesis writing. Instead, reported activity clustered around a small number of familiar tools. The 2025 profile appears, if anything, even more concentrated than the 2024 profile.

The distribution adds an important detail. In 2024, some respondents had never used ChatGPT, although a group of regular users was already visible. In 2025, non-use became less common and repeated use became more routine. Google Scholar moved in the same direction, but more gradually. SPSS, Mendeley, Zotero, Grammarly, and Turnitin remained marginal in students' accounts of AI-assisted writing. Turnitin requires careful interpretation here: it belonged to the Moodle-based institutional checking route, but students did not describe it as a tool they used to compose or revise their theses.

E. Perceived benefits, risks, and evaluative attitudes

To understand how students weighed benefits against risks and what kind of guidance they expected, selected indicators from the benefits block (A7), the drawbacks block (A8), and the attitudinal block (A9) were reviewed together (see Table V).

TABLE V. BENEFIT, RISK, AND ATTITUDE INDICATORS RELEVANT TO AI GOVERNANCE

Indicator	2024	2025	All
Time saving	0.70	0.51	0.61
Productivity	0.39	0.33	0.36
Quality gain	0.33	0.42	0.38
Possible errors	0.76	0.70	0.73
Reduced originality	0.50	0.42	0.46
Needs extra knowledge	0.46	0.40	0.43
Recommend AI	3.33	3.42	3.38
Use in theses	3.31	3.35	3.33
Lecturer guidance	3.88	4.19	4.03

Benefit and risk indicators are proportions; attitudinal indicators are mean scores on a five-point agreement scale.

Table V presents a balanced picture. Among the benefits, time saving was the strongest response in both year groups, especially in 2024. Productivity and perceived quality gains were also visible, although less prominent. Among the risks, possible errors were the dominant concern in both years, followed by reduced originality and the need for additional knowledge when working with AI.

The attitudinal items point in the same direction. Students were neither clearly resistant to AI nor uncritically enthusiastic. Agreement was moderate for recommending AI and for its use in thesis writing, but it was strongest for lecturer guidance. This item reached 3.88 in 2024 and 4.19 in 2025, making it the clearest single signal in the attitudinal block.

Taken together, the results indicate careful use rather than enthusiasm for AI as such. Students valued speed and help with drafting, but their responses repeatedly returned to errors, originality, and verification. Their request for guidance therefore reads as a request for usable boundaries: how to work with familiar tools without weakening authorship or academic accountability.

F. Reliability, Distribution, and the Link Between Use and Attitude

To check whether the composite indicators derived from the task-use block (A4) and the attitudinal block (A9) were stable enough for interpretation and to see whether use and attitude moved together, reliability, distribution, and association results were reviewed (see Table VI).

TABLE VI. RELIABILITY, NORMALITY, AND ANALYTICAL ASSOCIATIONS

Indicator	2024	2025	All
Task-use block (A4) alpha	.917	.858	.892
Attitudinal block (A9) alpha	.880	.854	.869
AI use mean	1.80	1.84	1.82
Attitude mean	3.51	3.65	3.58
SW p: AI use	< .001	< .001	-
SW p: attitude	< .001	< .001	-
Spearman rho	.536***	.447***	-

*** $p < .001$. Shapiro-Wilk results are reported separately for each graduating class.

Table VI shows that both composite indicators were sufficiently stable for cautious interpretation. The task-use block (A4) reached alpha values of .917 in 2024, .858 in 2025, and .892 in the pooled sample. The attitudinal block (A9) also showed good internal consistency (.880, .854, and .869 respectively). The mean AI-use index remained low to moderate in both year groups (1.80 and 1.84), while the attitude index was higher and more stable (3.51 and 3.65).

The distribution tests are also relevant. Shapiro-Wilk results were significant for both indices in both year groups, indicating a departure from normality. This supports the choice of non-parametric procedures. In practice, the year comparison was therefore read cautiously. The descriptive tables showed some shifts in emphasis, but not a break in the overall logic of AI use.

The association results were more informative. In 2024, the link between the AI-use index and the attitude index reached rho = .536; in 2025, it reached rho = .447. The broader correlation matrices pointed in the same direction: tool use tended to align with the tasks for which those tools are best suited. Analytically, this matters because it shows that the model is not only descriptive. The variables also move together in a way that could support later rule-based or AI-assisted supervision logic [14]-[16].

G. What Guidance Did Students Expect from Thesis Organisation?

To understand what students expected from supervisors and thesis organisers, the open comments on guidance from the final open-response block (A10) were grouped into themes (see Table VII).

TABLE VII. OPEN-COMMENT THEMES RELEVANT TO GUIDANCE DESIGN

No.	Theme
1	Clear rules and boundaries
2	Practical training and examples
3	Verification of AI-generated material
4	AI as support, not substitution
5	Disclosure and originality

Themes were derived from open-ended responses and summarised in English by the author.

Table VII shows that students wanted practical clarity rather than abstract policy. The most common requests concerned clearer rules and boundaries, examples of acceptable use, stronger emphasis on checking AI-generated material, and a clear message that AI should support rather than replace student work.

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The comments from the two year groups were similar in tone, but the later group expressed the need for procedural clarity more strongly. Students wanted lecturers to explain what could be done, what had to be reported, and how much rewriting or checking was expected when AI had been used.

Read together with Table V, these comments explain why lecturer guidance became the strongest attitudinal item in the whole study. Students were not only using AI; they were also asking institutions to state more clearly how that use should be handled in everyday thesis work.

V. Discussion

The findings show that AI had already become part of thesis-writing practice, although in a limited and recognisable way. Students used it most often for paraphrasing, translation, grammar and style revision, and literature search. Much less use was reported in tasks closer to topic ownership, data work, or formal control. This suggests a fairly clear boundary in students' own practice between support functions and academically sensitive functions.

The tool profile reinforces that interpretation. ChatGPT and Google Scholar clearly dominated, while specialised tools remained secondary. This is consistent with studies showing that actual student use often concentrates around a small number of accessible platforms rather than around a large and evenly used ecosystem [3]-[5]. From a practical viewpoint, students seem to prefer tools that fit easily into writing and searching routines they already know.

The evaluative results also fit recent integrity and policy discussions. Students valued AI because it saved time and made writing easier to manage, but they also identified errors, weaker originality, and the need for verification [6]-[11]. This is not blind enthusiasm. It is closer to cautious adoption: students are willing to use AI, but they do not fully trust it and still expect institutions to define clearer boundaries.

From a systems perspective, the study does not argue for automated judgement about student writing. Its contribution is more modest and, in this context, more realistic. The results identify a usable set of variables for future support tools: task-sensitive indicators, tool profiles, and governance cues drawn from perceived risks and guidance needs. A future system built on this logic would not replace supervisors. Its role would be to support them with clearer signals and more consistent guidance.

Several limitations should be kept in mind. The study was conducted in one institution and relied on voluntary self-report after thesis defence. It therefore reflects students' remembered practice rather than direct observation of writing behaviour. The paper also does not test a deployed AI system, so its engineering contribution remains at the analytical and requirements level. This limitation is important rather than incidental: weak variables lead to weak tools.

The main triangulation limit is institutional, not merely methodological. In the period analysed, final theses passed through Moodle and a Turnitin-supported checking workflow. That workflow did not yield reliable Lithuanian-language AI-detection data for final theses. As a result, no comparable institutional register existed for AI-related thesis rejections, non-admissions to defence, or sanctions in the two cohorts. The study therefore cannot test self-reports against such records. It can show, however, why AI-use declarations, supervisor reading, and task-sensitive verification become important when automated evidence is unavailable.

At the institutional level, a policy statement is only a starting point. Thesis supervision also needs working rules: which uses of AI are acceptable, when they must be declared, and which parts of the thesis require closer human review because students' ownership of argument, sources, or data may be affected.

A first support tool could be simple. It could ask students to indicate whether AI was used for translation, language editing, source searching, or idea development; link each answer to a short guidance note; and show supervisors where closer review is advisable. The present data suggest that such prompts should focus on language polishing, translation, literature search, and uncertain cases in which students do not know whether rewriting, checking, or acknowledgement is required.

VI. Conclusion

This study showed that AI was already part of professional bachelor thesis writing at the surveyed Lithuanian institution, but mainly as a support tool for wording, translation, grammar and style revision, and literature search. Students did not report equally strong use across all thesis tasks, which suggests that they still distinguished between low-risk support and tasks that remained more clearly their own responsibility.

The comparison between cohorts should therefore be read cautiously. The 2025 cohort gave slightly more weight to translation and language correction, but the same task structure remained visible in both years. Tool use also remained narrow: ChatGPT and Google Scholar stood apart from the rest.

The practical conclusion is pedagogical as much as technical. Students expected lecturers to explain which AI uses are acceptable in thesis preparation, how such use should be disclosed, and which uses still require verification. For the conference audience, the paper offers not a finished technical artefact but a compact analytical framework for later AI-aware supervision or decision-support systems. Its main caution is also clear: when reliable language-specific AI-detection statistics are unavailable, governance should combine declared use, supervisor review, and task-sensitive verification rather than rely on automated detection alone.

References

[1] UNESCO, Guidance for Generative AI in Education and Research. Paris, France: UNESCO, 2023.

[2] H. Crompton and D. Burke, "Artificial intelligence in higher education: The state of the field," International Journal of Educational Technology in Higher Education, vol. 20, art. no. 22, 2023, https://doi.org/10.1186/s41239-023-00392-8

[3] M. I. Baig and E. Yadegaridehkordi, "ChatGPT in higher education: A systematic literature review and research challenges," International Journal of Educational Research, vol. 127, art. no. 102411, 2024, https://doi.org/10.1016/j.ijer.2024.102411

[4] A. Barrett and A. Pack, "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, vol. 20, art. no. 59, 2023, https://doi.org/10.1186/s41239-023-00427-0

[5] C. K. Y. Chan and W. Hu, "Students' voices on generative AI: Perceptions, benefits, and challenges in higher education," International Journal of Educational Technology in Higher Education, vol. 20, art. no. 43, 2023, https://doi.org/10.1186/s41239-023-00411-8

[6] D. R. E. Cotton, P. A. Cotton, and J. R. Shipway, "Chatting and cheating: Ensuring academic integrity in the era of ChatGPT," Innovations in Education and Teaching International, vol. 61, no. 2, pp. 228-239, 2024, DOI: 10.1080/14703297.2023.2190148.

[7] C. K. Y. Chan, "A comprehensive AI policy education framework for university teaching and learning," International Journal of Educational Technology in Higher Education, vol. 20, art. no. 38, 2023, https://doi.org/10.1186/s41239-023-00408-3

[8] J. Delcker, J. Heil, D. Ifenthaler, S. Seufert, and L. Spirgi, "First-year students' AI competence as a predictor for intended and de facto use of AI tools for supporting learning processes in higher education," International Journal of Educational Technology in Higher Education, vol. 21, art. no. 18, 2024, https://doi.org/10.1186/s41239-024-00452-7

[9] D.-K. Mah and N. Gross, "Artificial intelligence in higher education: Exploring faculty use, self-efficacy, distinct profiles, and professional development needs," International Journal of Educational Technology in Higher Education, vol. 21, art. no. 58, 2024, https://doi.org/10.1186/s41239-024-00490-1

[10] H. Wang, A. Dang, Z. Wu, and S. Mac, "Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines," Computers and Education: Artificial Intelligence, vol. 7, art. no. 100326, 2024, https://doi.org/10.1016/j.caeai.2024.100326

[11] Office of the Ombudsperson for Academic Ethics and Procedures of the Republic of Lithuania, "On approving guidelines for the ethical use of artificial intelligence in research and study processes (Order No. V-14)," Apr. 29, 2024. [Online]. Available: https://e-tar.lt/portal/lt/legalAct/56254af0061111efbcbfb318996800a8

[12] V. Braun and V. Clarke, "Using thematic analysis in psychology," Qualitative Research in Psychology, vol. 3, no. 2, pp. 77-101, 2006, https://doi.org/10.1191/1478088706qp063oa

[13] L. J. Cronbach, "Coefficient alpha and the internal structure of tests," Psychometrika, vol. 16, no. 3, pp. 297-334, 1951, https://doi.org/10.1007/BF02310555

[14] G. Siemens and R. S. J. d. Baker, "Learning analytics and educational data mining: Towards communication and collaboration," in Proc. 2nd Int. Conf. Learning Analytics and Knowledge (LAK '12), Vancouver, BC, Canada, 2012, pp. 252-254, https://doi.org/10.1145/2330601.2330661

[15] H. Khosravi, S. Buckingham Shum, G. Chen, C. Conati, Y.-S. Tsai, J. Kay, S. Knight, R. Martinez-Maldonado, S. Sadiq, and D. Gasevic, "Explainable artificial intelligence in education," Computers and Education: Artificial Intelligence, vol. 3, Art. no. 100074, 2022, https://doi.org/10.1016/j.caeai.2022.100074

[16] M. Bond, H. Khosravi, M. de Laat, N. Bergdahl, V. Negrea, E. Oxley, P. Pham, S. W. Chong, and G. Siemens, "A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour," International Journal of Educational Technology in Higher Education, vol. 21, Art. no. 4, 2024, https://doi.org/10.1186/s41239-023-00436-z