

ISSN 2518-1726 (Online),

ISSN 1991-346X (Print)

**ACADEMIC SCIENTIFIC
JOURNAL OF COMPUTER SCIENCE**

**№2
2026**

ISSN 2518-1726 (Online),
ISSN 1991-346X (Print)



ACADEMIC SCIENTIFIC JOURNAL OF COMPUTER SCIENCE

3 (359)

JULY – SEPTEMBER 2026

**PUBLISHED SINCE JANUARY 1963
PUBLISHED 4 TIMES A YEAR**

ALMATY, NAS RK

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Academic Scientific Journal of Computer Science

ISSN 2518-1726 (Online),

ISSN 1991-346X (Print)

Owner: «Central Asian Academic Research Center» LLP (Almaty).

Certificate № KZ77VPY00121154 on the re-registration of the periodical printed and online publication of the information agency, issued on 05.06.2025 by the Republican State Institution «Information Committee» of the Ministry of Culture and Information of the Republic of Kazakhstan

Subject area: *information and communication technologies*.

Currently: *included in the list of journals recommended by the CCSES MSHE RK in the direction of «Information and communication technologies»*.

Periodicity: 4 times a year.

<http://www.physico-mathematical.kz/index.php/en/>

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Academic Scientific Journal of Computer Science

ISSN 2518-1726 (Online),

ISSN 1991-346X (Print)

Меншіктеуші: «Орталық Азия академиялық ғылыми орталығы» ЖШС (Алматы).

Ақпарат агенттігінің мерзімді баспасөз басылымын, ақпарат агенттігін және желілік басылымды қайта есепке қою туралы ҚР Мәдениет және Ақпарат министрлігі «Ақпарат комитеті» Республикалық мемлекеттік мекемесі **05.06.2025 ж.** берген **№ KZ77VPY00121154** Куәлік.

Тақырыптық бағыты: *ақпараттық-коммуникациялық технологиялар*

Қазіргі уақытта: *«ақпараттық-коммуникациялық технологиялар» бағыты бойынша ҚР БҒМ БҒСБК ұсынған журналдар тізіміне енді.*

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<http://www.physico-mathematical.kz/index.php/en/>

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Academic Scientific Journal of Computer Science

ISSN 2518-1726 (Online),

ISSN 1991-346X (Print)

Собственник: *ТОО «Центрально-азиатский академический научный центр» (г. Алматы).*

Свидетельство о постановке на переучет периодического печатного издания, информационного агентства и сетевого издания № **KZ77VPY00121154**. Дата выдачи **05.06.2025**

Тематическая направленность: *информационно-коммуникационные технологии.*

В настоящее время: *вошел в список журналов, рекомендованных КОКШВО МНВО РК по направлению «информационно-коммуникационные технологии».*

Периодичность: *4 раза в год.*

<http://www.physico-mathematical.kz/index.php/en/>

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ACADEMIC SCIENTIFIC JOURNAL OF COMPUTER SCIENCE
ISSN 1991-346X
Volume 3.
Number 359 (2026). 401–417

<https://doi.org/10.32014/2026.2518-1726.470>

IRSTI 28.25.23
UDC 004.8:378.147

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MACHINE LEARNING-BASED DETECTION OF AI-GENERATED CONTENT IN STUDENTS' WRITTEN WORKS

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Abstract. The rapid spread of generative artificial intelligence has complicated the interpretation of authorship in educational writing and increased the need for transparent methods that distinguish machine-generated from human-written text without treating automated detection as conclusive evidence of misconduct. This study compares lexical and content-independent stylometric approaches to detecting AI-generated educational essays. The experiments used 44,868 English-language texts from the DAIGT V2 multi-source corpus, including 27,371 human-written and 17,497 AI-generated essays. The lexical representation used TF-IDF unigrams and bigrams with a Linear Support Vector Machine, while the content-independent representation consisted of fourteen structural and stylometric features classified with Logistic Regression. Human and AI texts were additionally compared using the Mann–Whitney U test and effect-size estimates. The TF-IDF model achieved 99.69% accuracy, 99.60% F1-score and 99.98% ROC-AUC on a stratified held-out test set. The stylometry-only model achieved $87.90 \pm 0.40\%$ accuracy, $84.34 \pm 0.48\%$ F1-score and $95.08 \pm 0.17\%$ ROC-AUC under five-fold stratified cross-validation. Average word length showed the strongest selected stylometric separation, while differences were also observed in text length, lexical diversity and punctuation use. The findings show that lexical information provides highly discriminative signals in the analyzed corpus, but substantial predictive information remains even when direct vocabulary is removed. The

results support the use of stylometric indicators as an interpretable supplementary signal for educational text analysis, while also emphasizing that detector outputs should not be treated as definitive proof of AI use in individual student work. Robustness checks showed 99.75% accuracy after near-duplicate filtering, 96.46% accuracy for unseen prompts, and 95.39% accuracy when Llama-70B was held out, indicating measurable distribution sensitivity. The contribution is therefore a robustness-oriented comparison of established lexical and interpretable stylometric representations rather than a new classifier.

Keywords: AI-generated text, educational writing, machine learning, stylometry, TF-IDF, text classification

For citations: Sultanali A.E., Kazbekova G.N. Machine learning-based detection of AI-generated content in students' written works. Academic Scientific Journal of Computer Science, 2026. — No.3. — P. 401–417. DOI: <https://doi.org/10.32014/2026.2518-1726.470>

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БІЛІМ АЛУШЫЛАРДЫҢ ЖАЗБАША ЖҰМЫСТАРЫНДАҒЫ AI- КОНТЕНТТІ МАШИНАЛЫҚ ОҚЫТУ АРҚЫЛЫ АНЫҚТАУ

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Аңдатпа. Генеративті жасанды интеллект құралдарының кең таралуы білім беру саласындағы жазбаша жұмыстардың авторлығын бағалауды күрделендіріп, машиналық жолмен жасалған мәтінді адам жазған мәтіннен ажыратуға мүмкіндік беретін ашық және тексерілетін әдістерге деген қажеттілікті арттырды. Сонымен қатар автоматтандырылған анықтау нәтижелерін академиялық бұзушылықтың түпкілікті дәлелі ретінде қарастыруға болмайды. Зерттеудің мақсаты — білім беру мәтіндеріндегі AI арқылы жасалған контентті анықтауда лексикалық және мазмұнға тәуелсіз стилометриялық тәсілдердің мүмкіндіктерін салыстыру. Экспериментке DAIGT V2 көпдереккөзді корпусынан 44 868 ағылшын тіліндегі мәтін енгізілді, оның 27 371-і адам жазған, ал 17 497-сі генеративті модельдер арқылы жасалған. Лексикалық ұсыну TF-IDF униграммалары мен биграммаларына негізделіп, Linear SVM классификаторы қолданылды.

Мазмұнға тәуелсіз стилометриялық ұсыну мәтіннің сөздік мазмұнын тікелей пайдаланбайтын 14 құрылымдық және стилометриялық белгіден құрылып, Logistic Regression әдісімен жіктелді. Адам жазған және AI арқылы жасалған мәтіндер Mann–Whitney U критерийі және әсер көлемі көрсеткіштері арқылы қосымша салыстырылды. TF-IDF моделі стратификацияланған тестілік жиынтықта 99,69% Accuracy, 99,60% F1-score және 99,98% ROC-AUC көрсетті. Тек стилометриялық белгілерге негізделген модель бес қатпарлы стратификацияланған кросс-валидация кезінде $87,90 \pm 0,40\%$ Accuracy, $84,34 \pm 0,48\%$ F1-score және $95,08 \pm 0,17\%$ ROC-AUC нәтижесіне жетті. Таңдалған стилометриялық белгілер ішінде орташа сөз ұзындығы ең айқын айырмашылықты көрсетті. Сонымен қатар мәтін ұзындығы, лексикалық әртүрлілік және тыныс белгілерін қолдануда жүйелі айырмашылықтар анықталды. Нәтижелер лексикалық ақпараттың зерттелген корпуста жоғары ажыратушылық қабілетке ие екенін, алайда тікелей сөздік ақпарат алынып тасталған жағдайда да стилометриялық құрылымда елеулі болжамдық сигнал сақталатынын көрсетті. Сондықтан стилометриялық көрсеткіштер білім алушылардың жазбаша жұмыстарын талдауда интерпретацияланатын қосымша құрал ретінде қолданылуы мүмкін. Дегенмен автоматты детектордың нәтижесі нақты білім алушының AI қолданғанының түпкілікті дәлелі ретінде қарастырылмауы тиіс. Тұрақтылықты тексеру барысында жақын қайталанатын мәтіндер алынып тасталғаннан кейін Accuracy 99,75%, бұрын көрілмеген тақырыптарда 96,46%, ал Llama-70B генераторы оқыту жиынынан толық шығарылған жағдайда 95,39% болды. Бұл нәтижелер модель сапасының деректер үлестіріміне белгілі бір дәрежеде тәуелді екенін көрсетеді. Сондықтан жұмыстың негізгі үлесі жаңа классификатор ұсынуда емес, қалыптасқан лексикалық және интерпретацияланатын стилометриялық тәсілдерді тұрақтылық тұрғысынан салыстыруда жатыр.

Түйін сөздер: жасанды интеллект арқылы жасалған мәтін; білім беру мәтіні; машиналық оқыту; стилометрия; TF-IDF; мәтінді жіктеу

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ОБНАРУЖЕНИЕ AI-КОНТЕНТА В ПИСЬМЕННЫХ РАБОТАХ ОБУЧАЮЩИХСЯ МЕТОДАМИ МАШИННОГО ОБУЧЕНИЯ

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Аннотация. Распространение генеративного искусственного интеллекта усложнило оценку авторства письменных работ в образовании и повысило потребность в прозрачных и проверяемых методах различения машинно-сгенерированного и написанного человеком текста. При этом результаты автоматизированного обнаружения не должны рассматриваться как окончательное доказательство академического нарушения. Цель исследования заключается в сравнении лексического и независимого от содержания стилометрического подходов к выявлению AI-контента в образовательных эссе. Эксперимент выполнен на 44 868 англоязычных текстах из многокомпонентного корпуса DAIGT V2, включая 27 371 текст, написанный человеком, и 17 497 текстов, созданных генеративными моделями. Для лексического представления использовались униграммы и биграммы TF-IDF с классификатором Linear SVM. Независимое от содержания стилометрическое представление включало 14 структурных и стилометрических признаков, не использующих непосредственно словарное содержание текста, и классифицировалось методом Logistic Regression. Дополнительно различия между текстами, написанными человеком и созданными ИИ, оценивались с помощью критерия Манна–Уитни и величины эффекта. Модель TF-IDF достигла Accuracy 99,69%, F1-score 99,60% и ROC-AUC 99,98% на стратифицированной отложенной тестовой выборке. Модель, основанная только на стилометрических признаках, при пятикратной стратифицированной кросс-валидации показала Accuracy $87,90 \pm 0,40\%$, F1-score $84,34 \pm 0,48\%$ и ROC-AUC $95,08 \pm 0,17\%$. Наиболее выраженное различие среди выбранных стилометрических признаков наблюдалось для средней длины слова; систематические различия также были выявлены в длине текста, лексическом разнообразии и использовании пунктуации. Полученные результаты показывают, что лексическая информация обладает высокой дискриминирующей способностью в исследованном корпусе, однако существенный прогнозный сигнал сохраняется и после исключения прямого словарного содержания. Стилометрические признаки могут использоваться как интерпретируемый дополнительный инструмент анализа образовательных текстов. Вместе с тем результат автоматического детектора не должен рассматриваться как окончательное доказательство использования AI конкретным обучающимся. Проверки устойчивости показали Accuracy 99,75% после удаления близких дубликатов, 96,46% на ранее не встречавшихся темах и 95,39% при полном исключении Llama-70B из обучающей выборки. Это указывает на измеримую чувствительность модели к распределению данных. Таким образом, основной вклад работы состоит не в разработке нового классификатора, а в сравнении существующих лексических и интерпретируемых стилометрических представлений с учетом их устойчивости.

Ключевые слова: AI-сгенерированный текст; образовательное письмо; машинное обучение; стилометрия; TF-IDF; классификация текста

Introduction. Generative artificial intelligence has rapidly changed the conditions under which written assignments are produced and assessed. Large language models can generate coherent essays, explanations and argumentative responses within seconds, and their outputs may be difficult to distinguish from student writing by visual inspection alone. In controlled experiments, teachers were unable to reliably identify ChatGPT-generated essays among student-written texts and tended to be overconfident in their judgments (Fleckenstein et al., 2024). In higher education, this creates a practical problem for assessment: instructors need to evaluate the quality of submitted work while also recognizing that the apparent linguistic fluency of a text no longer provides reliable information about how it was produced.

Automated AI-generated text detection has therefore become an active research area. Existing approaches include statistical measures, supervised classifiers, neural detectors, watermarking, probability-based zero-shot methods and combinations of human and automated judgment (Crothers et al., 2023; Mitchell et al., 2023; Wu et al., 2025). At the same time, evidence from educational settings shows that detector outputs must be interpreted cautiously. Evaluations of commercial and open tools have reported substantial error rates, sensitivity to paraphrasing and obfuscation, and fairness concerns for non-native English writers (Weber-Wulff et al., 2023; Liang et al., 2023; Perkins et al., 2024b). Thus, the central research problem is not merely whether machine-generated text can be classified accurately on a fixed benchmark, but which textual signals support classification and how interpretable those signals are. A further methodological issue is that very high benchmark accuracy may reflect dataset-specific lexical patterns rather than general properties of machine-generated writing. Recent multi-generator benchmarks demonstrate that detectors often perform worse when the generator or domain at test time differs from the training distribution (Wang et al., 2024a; Li et al., 2024; Dugan et al., 2024). This limitation is especially important in education, where students may use rapidly changing generative systems, revise generated text manually, or combine human and machine writing. A detector that depends strongly on generator-specific vocabulary may therefore appear highly accurate under a random train-test split while remaining less informative in real educational practice. Stylometry offers a complementary perspective. Rather than relying directly on the words used in a document, stylometric analysis represents writing through measurable structural characteristics such as sentence length, word length, lexical diversity, punctuation and character patterns. Such features have a long history in authorship and style analysis and can provide interpretable evidence about differences between text populations (Potthast et al., 2018). In the context of LLM-generated writing, a stylometric model can help determine whether a detectable signal remains after direct lexical content is removed.

The aim of this study is therefore to compare lexical and content-independent stylometric representations for detecting AI-generated educational writing. Two research questions are addressed: (RQ1) How accurately can a classical TF-IDF-

based machine-learning model distinguish human-written from AI-generated educational essays within a multi-source corpus? (RQ2) To what extent can the same distinction be made using only interpretable stylometric characteristics without direct lexical representation? The contribution of the study lies in evaluating these two complementary representations on a large educational-writing corpus and in interpreting high detection performance in light of current concerns regarding robustness, fairness and responsible use in assessment.

The methodological contribution is deliberately positioned as a robustness-oriented comparison rather than as a proposal of a new classifier. TF-IDF with Linear SVM and compact stylometry are established techniques; their role here is to provide two transparent reference representations whose behaviour can be audited. The revised analysis therefore focuses on whether the near-perfect random-split score survives controls for topic, generator source and near-duplicate contamination, and on how much discriminative information remains in a compact interpretable representation. This framing shifts the contribution from algorithmic novelty to an empirical assessment of dataset sensitivity and responsible interpretation in educational use.

Literary review. Research on machine-generated text detection has expanded from early statistical and neural classification approaches to large multi-generator benchmarks and zero-shot methods. Crothers et al. (2023) organized the field around threat models and detection strategies, emphasizing that reliability, robustness and accountability are essential properties of practical detectors. DetectGPT introduced a different paradigm by using the curvature of a language model's probability function rather than training a separate binary classifier; the method demonstrated that model-internal statistical properties can provide useful evidence of machine generation (Mitchell et al., 2023). More recent surveys classify current approaches into statistical, neural, watermarking and human-assisted families and identify out-of-distribution evaluation, adversarial manipulation and real-world data as unresolved challenges (Wu et al., 2025).

The educational context makes these challenges particularly consequential. Weber-Wulff et al. (2023) evaluated a broad set of publicly available and commercial detectors and concluded that the tested tools were not sufficiently reliable for high-stakes academic decisions. Perkins et al. (2024a) investigated GPT-4-generated assessment texts in higher education and showed the value, but also the limitations, of combining academic judgment with software-based indicators. Fleckenstein et al. (2024) demonstrated that both novice and experienced teachers had difficulty identifying AI-generated student essays, confirming that unaided human judgment cannot be assumed to solve the problem. At the same time, Liang et al. (2023) showed that several GPT detectors disproportionately misclassified writing by non-native English authors, highlighting the fairness risks of using automated detection as evidence of misconduct.

Robustness studies further challenge the interpretation of near-perfect in-distribution scores. The M4 benchmark was designed specifically as a multi-

generator, multi-domain and multilingual testbed and showed that detectors tend to misclassify machine-generated text as human when confronted with unseen domains or LLMs (Wang et al., 2024a). MAGE similarly evaluated machine-generated text detection 'in the wild' and reported substantial difficulty in out-of-distribution scenarios, even though useful detection remained possible (Li et al., 2024). RAID expanded this line of research by testing detectors across multiple generators, domains, decoding strategies and adversarial attacks; its results showed that detector performance can deteriorate under unseen generators and relatively simple transformations (Dugan et al., 2024). The SemEval-2024 Task 8 benchmark also formalized binary, multi-source and mixed-authorship detection tasks, reflecting the increasing need for evaluation beyond a single generator and a single domain (Wang et al., 2024b).

Adversarial and post-editing effects are especially relevant to academic writing. Perkins et al. (2024b) demonstrated that relatively simple modifications can reduce the effectiveness of widely used GenAI detectors. Sadasivan et al. (2025) likewise showed that paraphrasing can substantially weaken multiple detection schemes, including neural, zero-shot and watermark-based approaches. These findings indicate that detector accuracy obtained from unedited benchmark texts should not be interpreted as a universal probability that any future student submission can be correctly attributed.

Dataset design is therefore central to the validity of detection research. The human-written component used in the present study is largely connected to the PERSUADE family of educational writing resources. PERSUADE 2.0 contains more than 25,000 argumentative essays written by students in grades 6–12 across 15 prompts and provides a large-scale basis for computational analysis of writing (Crossley et al., 2024). This provenance is important because it anchors the human class in authentic educational writing rather than generic web text. The AI class in DAIGT V2, by contrast, aggregates outputs from several generative systems, providing greater heterogeneity than a single-ChatGPT dataset.

From a feature perspective, lexical and stylometric representations answer different questions. TF-IDF is highly effective for sparse text classification because it captures words and short phrases that differ between classes. However, its strength can also become a limitation when lexical regularities are generator-, prompt- or dataset-specific. Stylometric analysis instead focuses on measurable writing behaviour. Earlier work in computational stylometry demonstrated that structural and functional characteristics can discriminate between text categories even when topic is not the intended target (Potthast et al., 2018). For AI-generated text, this motivates a direct comparison: if a stylometry-only model remains predictive after vocabulary is removed, then the corpus contains structural signals in addition to lexical ones.

The reviewed literature therefore reveals a clear methodological need. High-performing lexical detection is useful as a benchmark, but educational applications also require interpretable evidence about the characteristics on which

classification depends. Moreover, detector outputs must be situated within known limitations involving distribution shift, adversarial editing and demographic bias. The present study addresses this need by comparing a high-dimensional lexical representation with a compact, interpretable stylometric representation on the same large educational-writing corpus. The objective is not to claim definitive authorship attribution, but to quantify how much discriminative information is available from each representation and to identify structural differences that may support transparent analysis.

Materials and methods. Dataset and preprocessing. The experimental study used the DAIGT V2 multi-source corpus for AI-generated text detection. The analysed file contained 44,868 English-language educational essays and five variables: text, binary label, prompt name, source, and an auxiliary dataset indicator. The target label distinguished human-written texts (0) from AI-generated texts (1). The final corpus included 27,371 human-written texts (61.0%) and 17,497 AI-generated texts (39.0%). No missing values were detected in the analysed variables, and exact duplicate texts were checked before modelling. The human component was primarily associated with the PERSUADE educational essay corpus, while the AI component contained outputs from multiple generative systems, including ChatGPT, Llama-family models, Mistral, PaLM, Falcon, Claude, GPT-4 and Cohere sources. The original binary labels were retained as ground truth. The dataset was used for research analysis only; no personal identifiers were required for the experiments.

Duplicate and source-sensitivity audit. In addition to exact-string duplicate checking, the revised analysis normalized case, whitespace and punctuation and screened for near-duplicate essays using five-word shingles. Candidate pairs were identified with locality-sensitive hashing and verified with Jaccard similarity; a threshold of 0.90 was used for the sensitivity analysis. To test whether the 99.69% random-split result was driven by prompt or generator-specific source signals, three additional evaluations were performed. First, a prompt-group holdout split placed three complete prompts in the test set so that their topics were absent from training. Second, leave-one-generator-out tests removed all outputs of a selected LLM from training and evaluated them against human controls matched by prompt. Third, the lexical baseline was rerun after removing one member of every detected near-duplicate pair at Jaccard similarity ≥ 0.90 . These analyses were treated as robustness checks rather than as estimates of universal detector accuracy.

Experimental design and lexical representation. Two complementary feature representations were evaluated. The first experiment used lexical information. Essay texts were transformed with term frequency-inverse document frequency (TF-IDF), including unigrams and bigrams and limiting the sparse feature space to 60,000 dimensions. The dataset was divided into training and test subsets using a stratified 80:20 split with `random_state = 42`, preserving the Human/AI class ratio. A Linear Support Vector Machine was selected for the principal lexical classifier because linear margin-based methods are effective and computationally efficient

for high-dimensional sparse text representations. Performance on the held-out test set was evaluated with accuracy, precision, recall, F1-score, ROC-AUC and a confusion matrix. The positive class for precision, recall and F1 calculations was AI-generated text.

Stylometric representation and statistical analysis. The second experiment intentionally removed direct lexical representation and described each essay through fourteen automatically calculated stylometric characteristics. These included word count, sentence count, average sentence length, average word length, lexical diversity, frequencies of commas, semicolons, colons, question marks and exclamation marks, digit ratio, uppercase-character ratio, paragraph-related structure and overall punctuation-related characteristics. The features were standardized because they were measured on different numerical scales, and Logistic Regression was used as an interpretable classifier. Robustness of the stylometry-only model was assessed with five-fold stratified cross-validation. Mean and standard deviation were calculated for accuracy, precision, recall, F1-score and ROC-AUC. In addition, selected stylometric variables were compared between human and AI groups using the Mann-Whitney U test. Because the large sample size can make very small differences statistically significant, rank-biserial effect sizes were considered together with p-values. All numerical results reported in the article were derived programmatically from the experimental dataset. Generative AI was used only as an auxiliary tool for language support, literature organization and manuscript preparation; numerical experimental results were computed from the source data and remained subject to author verification.

Results.

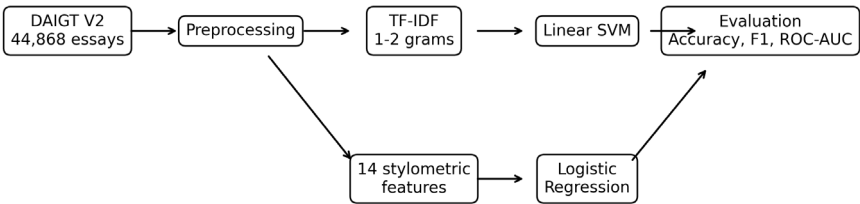


Figure 1 — Experimental workflow for AI-generated text detection

The final dataset contained 44,868 educational essays. Human-written texts accounted for 27,371 records (61.0%), while 17,497 texts (39.0%) were AI-generated. The AI class contained texts from several LLM sources rather than a single generator.

Table 1 — Composition of the experimental dataset

Authorship class	Number of texts	Proportion, %
Human-written	27,371	61.0
AI-generated	17,497	39.0
Total	44,868	100.0

Note: Compiled by the authors based on the experimental dataset.

Exploratory stylometric analysis showed systematic differences between the two authorship groups. Human-written essays were longer on average, whereas AI-generated texts had greater average word length, lexical diversity and comma frequency. Average word length produced the largest selected effect size (rank-biserial correlation approximately 0.630). Because of the large sample size, p-values were interpreted together with effect magnitude.

Table 2 — Selected stylometric characteristics of human-written and AI-generated texts

Characteristic	Human	AI-generated	p-value	Effect size
Word count	417.15	330.21	<0.001	-0.243
Sentence count	21.43	18.40	<0.001	-0.161
Average sentence length	21.33	18.78	<0.001	-0.110
Average word length	4.43	4.93	<0.001	0.630
Lexical diversity	0.440	0.474	<0.001	0.187
Comma frequency	14.36	19.91	<0.001	0.367
Semicolon frequency	0.217	0.033	<0.001	-0.103
Question-mark frequency	0.746	0.397	<0.001	-0.185
Digit ratio	0.0020	0.0008	<0.001	-0.236
Uppercase ratio	0.0211	0.0177	<0.001	-0.163

Note: Compiled by the authors based on the experimental dataset.

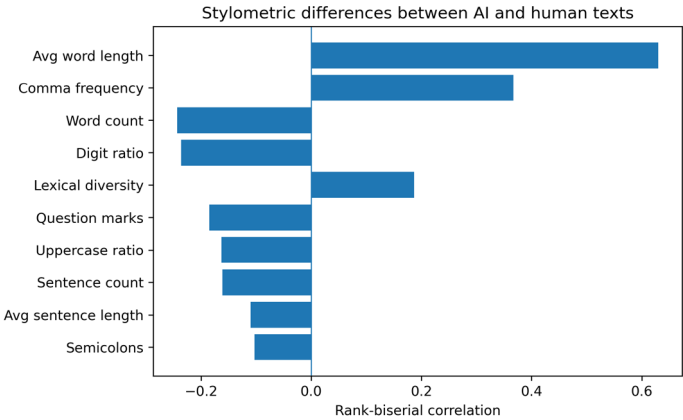


Figure 2 — Effect sizes of selected stylometric differences between human-written and AI-generated texts

The TF-IDF representation combined with Linear SVM achieved 99.69% accuracy on the held-out test subset. Precision for the AI-generated class was 99.97%, recall was 99.23%, F1-score was 99.60%, and ROC-AUC was 99.98%. Of 8,974 test texts, 28 were misclassified: 27 AI-generated texts were predicted as human-written and one human-written text was predicted as AI-generated.

Robustness checks reduced the likelihood that the near-perfect random-split result was explained only by trivial overlap. After normalization, 16 exact normalized duplicate rows were identified. The near-duplicate audit detected

393 pairs with five-word-shingle Jaccard similarity ≥ 0.90 ; none crossed the Human/AI label boundary. Removing 389 redundant rows and repeating the lexical experiment yielded 99.75% accuracy, 99.68% F1-score and 99.97% ROC-AUC. A stricter prompt-group holdout, in which three complete prompts were absent from training, reduced accuracy to 96.46% and F1-score to 92.87% (ROC-AUC 99.26%). Generator holdout produced heterogeneous results: when all ChatGPT-source texts were excluded from training, prompt-matched testing achieved 99.52% accuracy and 99.52% F1-score; when Llama-70B was held out, accuracy decreased to 95.39% and AI recall to 90.78% (F1-score 95.17%). Thus, the original 99.69% score is not attributable to exact/near duplicates alone, but the performance drop under unseen prompts and one unseen generator confirms that source and distribution effects contribute to the benchmark result.

Table 3 — Performance of the TF-IDF-based detector

Metric	Value, %
Accuracy	99.69
Precision	99.97
Recall	99.23
F1-score	99.60
ROC-AUC	99.98

Note: Compiled by the authors based on the experimental dataset.

Table 4 – Robustness checks for the TF-IDF + Linear SVM detector

Evaluation	Test condition	Accuracy, %	Precision, %	Recall, %	F1, %
Random split	Original 80:20 split	99.69	99.97	99.23	99.60
Near-duplicate filtered	389 redundant rows removed	99.75	99.91	99.46	99.68
Prompt holdout	3 unseen prompts	96.46	95.63	90.27	92.87
Generator holdout	ChatGPT unseen	99.52	99.88	99.17	99.52
Generator holdout	Llama-70B unseen	95.39	100.00	90.78	95.17

Note: Generator-holdout human controls were matched by prompt. The checks assess sensitivity to overlap, topic and generator distribution; they do not eliminate the broader provenance difference between the human and AI classes.

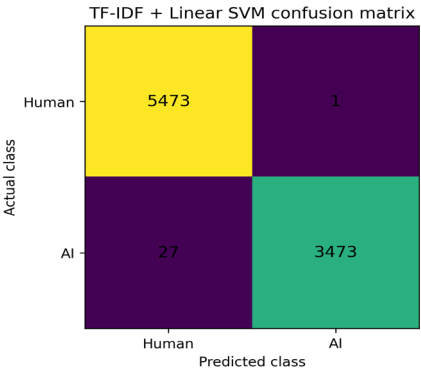


Figure 3 — Confusion matrix of the TF-IDF + Linear SVM model

The stylometry-only model retained substantial discriminative performance despite excluding direct lexical content. Across five stratified folds, mean accuracy was 87.90% with a standard deviation of 0.40 percentage points. Mean F1-score was 84.34%, and mean ROC-AUC was 95.08%. Fold accuracies were 88.67%, 87.86%, 87.70%, 87.56%, and 87.70%, indicating relatively stable performance across partitions.

Table 5 — Five-fold cross-validation using stylometric features

Metric	Mean, %	SD, %
Accuracy	87.90	0.40
Precision	85.15	0.68
Recall	83.55	0.40
F1-score	84.34	0.48
ROC-AUC	95.08	0.17

Note: Compiled by the authors based on the experimental dataset.

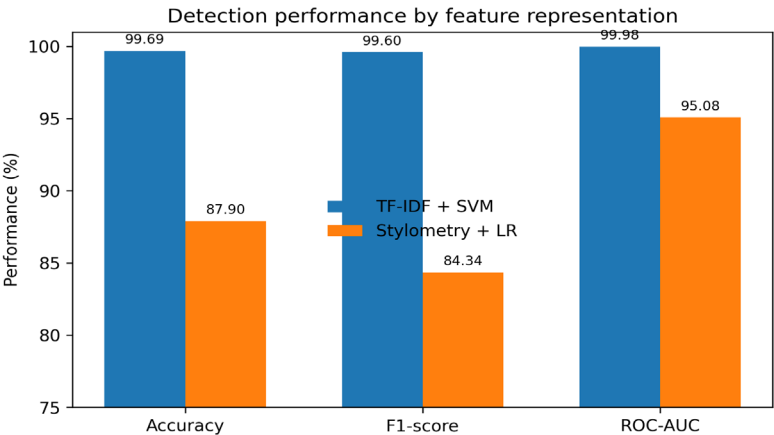


Figure 4 — Performance of lexical and stylometric detection approaches (evaluation protocols differ)

The two results should not be interpreted as a direct statistical ranking of the classifiers because different evaluation procedures were used. Rather, they demonstrate that lexical information provides extremely strong discrimination in this corpus, while substantial predictive information remains when direct lexical content is excluded.

Discussion. The experiments demonstrate a pronounced difference between lexical and content-independent representations of AI-generated educational writing. The TF-IDF and Linear SVM model achieved 99.69% accuracy and 99.98% ROC-AUC on the held-out test set, showing that the analysed corpus contains extremely strong lexical signals separating the two classes. By contrast, the model based on only fourteen stylometric characteristics achieved 87.90

$\pm 0.40\%$ mean accuracy and $95.08 \pm 0.17\%$ ROC-AUC under five-fold cross-validation. The reduction in accuracy is expected because direct word and phrase information was removed. Nevertheless, the stylometry result is substantively important: structural characteristics alone retained considerable discriminatory information.

The high TF-IDF performance should be interpreted as an in-corpus classification result rather than a universal detector accuracy. Multi-generator studies have repeatedly shown that performance obtained when training and test data share distributions can overestimate robustness to unseen generators and domains. M4 reported that detectors often classify machine-generated texts as human when confronted with unseen LLMs or domains (Wang et al., 2024a). MAGE reached a similar conclusion in a broad testbed and reported that even its strongest detector achieved substantially lower performance in out-of-domain settings than typical in-distribution results (Li et al., 2024). RAID further showed that changes in generation strategy, adversarial attacks and unseen generators can substantially reduce detector reliability (Dugan et al., 2024). Consequently, the near-perfect lexical result obtained here is evidence of separability within DAIGT V2, not evidence that arbitrary future LLM output can be identified with 99.69% accuracy.

The stylometric findings help explain why classification remains possible when direct lexical content is removed. Human-written essays in the corpus were longer on average, whereas AI-generated essays showed greater average word length and lexical diversity and used commas more frequently. Among the selected variables, average word length produced the largest effect size (rank-biserial correlation approximately 0.630), followed by comma frequency. These patterns indicate that the two text populations differ in measurable aspects of construction and surface style. Importantly, such group-level patterns should not be converted into deterministic rules for individual documents. A human writer may naturally produce long words, high lexical diversity or dense punctuation, and an AI-generated passage may be edited until these characteristics resemble human writing. Stylometric indicators are therefore probabilistic features rather than authorship proofs.

The difference between 99.69% lexical accuracy and 87.90% stylometric cross-validated accuracy also illustrates a trade-off between predictive power and interpretability. TF-IDF provides tens of thousands of lexical dimensions and can exploit highly specific words and bigrams. This is useful for classification but makes it difficult to determine whether performance arises from general machine-writing characteristics, prompt effects or source-specific expressions. The fourteen-feature stylometric model is weaker but substantially easier to interpret. Its ROC-AUC above 95% suggests that content-independent structure carries a strong signal in the analysed corpus. For educational analytics, such a model can therefore serve as a transparent supplementary layer alongside other evidence rather than as a replacement for pedagogical judgment.

The educational implications require particular caution. Fleckenstein et al. (2024) found that teachers could not reliably distinguish ChatGPT-generated essays from student writing, while Perkins et al. (2024a) showed that AI-generated assessment texts can resemble authentic submissions closely enough to complicate academic judgment. Automated methods can assist in screening large volumes of work, but the consequences of false accusations are substantial. Weber-Wulff et al. (2023) concluded that tested AI detectors were not reliable enough to serve as sole evidence, and Liang et al. (2023) identified a strong bias against non-native English writers in several detectors. These findings are directly relevant to the present work because the analysed texts are English-language essays and the stylometric variables include characteristics that may also vary with language proficiency. A future educational implementation would therefore require validation on the actual student population, language context and assignment type before operational use.

Adversarial robustness is another limitation. Students or other users may revise AI-generated text, paraphrase passages, combine generated and human-written sections, or use humanization tools. Perkins et al. (2024b) showed that simple techniques can bypass several GenAI detectors, while Sadasivan et al. (2025) demonstrated that recursive paraphrasing can reduce the performance of multiple detection paradigms. The present experiments use corpus texts in their available form and do not simulate extensive post-editing. Accordingly, the reported results represent detection under the analysed benchmark conditions and should not be extrapolated to heavily edited or mixed-authorship submissions.

The study has several additional limitations. First, the human essays are educational texts written by school students rather than a representative sample of university coursework; therefore, the article uses the broader terms educational writing and student-written essays rather than claiming a university-only population. Second, the corpus is English-language, and both lexical and stylometric signals may differ in Kazakh, Russian or other languages. Third, the lexical and stylometric experiments use different evaluation designs: the TF-IDF model is reported on a fixed 80:20 held-out split, while stylometry is summarized with five-fold cross-validation. Their numerical values therefore illustrate the discriminative information available from each representation but should not be treated as a controlled head-to-head statistical test of classifier superiority. Fourth, the current analysis does not establish generalization to entirely new LLM families.

These limitations suggest several directions for further research. A particularly important extension is leave-one-generator-out evaluation in which all texts from one LLM are excluded from training and used only for testing. Prompt-controlled evaluation could further separate generator-specific style from topic effects. Another direction is multilingual validation using authentic student writing in Kazakh and Russian. Finally, AI-text indicators could be integrated into broader intelligent assessment systems as one contextual signal alongside rubric-based quality assessment, provenance information and teacher review. Such integration would better reflect the educational objective: supporting fair and evidence-based assessment rather than automatically assigning misconduct labels.

Overall, the results support a layered interpretation of AI-generated text detection. Lexical models can provide very high discrimination on a known corpus, while compact stylometric models reveal interpretable structural differences that persist without direct vocabulary. At the same time, current evidence from the wider literature makes clear that detector reliability depends on generator, domain, editing and writer characteristics. The practical value of the proposed approach therefore lies in analytical support and research on writing characteristics, not in automatic disciplinary decision-making.

The robustness checks sharpen this interpretation. The decrease from 99.69% under a random split to 96.46% under unseen prompts and 95.39% for the held-out Llama-70B source demonstrates measurable distribution sensitivity. At the same time, the DAIGT V2 design still does not permit complete separation of authorship from provenance: most human texts originate from PERSUADE, whereas AI texts were assembled from generated sources. Consequently, the revised manuscript does not claim that the classifier has learned a source-invariant property of machine writing. A definitive test would require paired human and AI texts collected under the same prompts, population, genre and acquisition pipeline.

Kazakhstan-specific language transfer deserves separate validation. During revision, a newly available Kazakh benchmark (KazAI-Detect) was identified; it contains balanced human and AI-generated Kazakh texts and an out-of-distribution test set, but its principal domains are consumer reviews, news and encyclopedic text rather than student essays (Anekesh & Ualiyeva, 2026). Because a small cross-domain pilot on that corpus would simultaneously change language, genre, human-text provenance and generator, its score would not isolate a language effect and could be misleading. We therefore do not merge such a pilot with the present educational-essay results. Instead, we now state this limitation explicitly and define matched Kazakh/Russian educational writing - with human and AI texts produced for the same prompts and assignments - as the required next validation step. This is preferable to translating the English corpus or generating an ad hoc local sample, both of which would introduce new provenance artefacts.

Conclusion. This study compared lexical and content-independent stylometric approaches for detecting AI-generated educational writing in a multi-source corpus of 44,868 essays. The TF-IDF representation combined with Linear SVM achieved 99.69% accuracy, 99.60% F1-score and 99.98% ROC-AUC on a stratified held-out test set. When direct lexical information was removed, a Logistic Regression model based on fourteen stylometric characteristics still achieved $87.90 \pm 0.40\%$ accuracy, $84.34 \pm 0.48\%$ F1-score and $95.08 \pm 0.17\%$ ROC-AUC under five-fold cross-validation. The statistical analysis also identified systematic group-level differences in text length, average word length, lexical diversity and punctuation patterns, with average word length showing the strongest selected effect.

The findings demonstrate that AI-generated and human-written educational essays in the analysed corpus differ at both lexical and structural levels. Lexical features provide the strongest discrimination, whereas stylometric features offer a

more compact and interpretable representation that remains informative without access to specific vocabulary. However, the reported performance is corpus-dependent and does not establish definitive authorship attribution for individual student submissions. Evidence from current detection research indicates that unseen generators, paraphrasing, domain shifts and writer characteristics can reduce reliability and create fairness risks. For this reason, automated AI-text detection should be used as a supplementary analytical signal rather than as standalone proof of academic misconduct. Future work should evaluate cross-generator generalization, multilingual educational writing and the integration of interpretable AI-content indicators with broader intelligent assessment models.

Additional robustness checks showed that near-duplicate removal did not explain the high lexical score, whereas unseen-prompt and unseen-generator evaluations reduced performance, confirming that the benchmark result is partly distribution-sensitive. The main contribution is therefore not a new detection algorithm but a controlled comparison of lexical and interpretable stylometric representations together with an explicit audit of overlap and source sensitivity.

Conflict of interest. *The authors declare no conflict of interest.*

References

- Crothers E.N., Japkowicz N., & Viktor H.L. (2023) Machine-generated text: A comprehensive survey of threat models and detection methods. *IEEE Access*, 11. — P. 70977–71002. <https://doi.org/10.1109/ACCESS.2023.3294090> (in Eng.)
- Crossley S.A., et al. (2024) A large-scale corpus for assessing written argumentation: PERSUADE 2.0. *Assessing Writing*, 61. — 100865 p. <https://doi.org/10.1016/j.asw.2024.100865> (in Eng.)
- Dugan L., Hwang A., Trhlik F., Zhu A., Ludan J.M., Xu H., Ippolito D., & Callison-Burch C. (2024) RAID: A shared benchmark for robust evaluation of machine-generated text detectors. *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics*. — P. 12463–12492. <https://doi.org/10.18653/v1/2024.acl-long.674> (in Eng.)
- Fleckenstein J., Meyer J., Jansen T., Keller S.D., Köller O., & Möller J. (2024) Do teachers spot AI? Evaluating the detectability of AI-generated texts among student essays. *Computers and Education: Artificial Intelligence*, 6. — 100209 p. <https://doi.org/10.1016/j.caeai.2024.100209> (in Eng.)
- Li Y., Li Q., Cui L., Bi W., Wang Z., Wang L., Yang L., Shi S., & Zhang Y. (2024) MAGE: Machine-generated text detection in the wild. *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics*. — P. 36–53. <https://doi.org/10.18653/v1/2024.acl-long.3> (in Eng.)
- Liang W., Yuksekgonul M., Mao Y., Wu E., & Zou J. (2023) GPT detectors are biased against non-native English writers. *Patterns*, 4(7). — 100779 p. <https://doi.org/10.1016/j.patter.2023.100779> (in Eng.)
- Mitchell E., Lee Y., Khazatsky A., Manning C.D., & Finn C. (2023) DetectGPT: Zero-shot machine-generated text detection using probability curvature. *Proceedings of the 40th International Conference on Machine Learning*, 202. — P. 24950–24962. <https://proceedings.mlr.press/v202/mitchell23a.html> (in Eng.)
- Perkins M., Roe J., Postma D., McGaughran J., & Hickerson D. (2024a) Detection of GPT-4 generated text in higher education: Combining academic judgement and software to identify generative AI tool misuse. *Journal of Academic Ethics*, 22. — P. 89–113. <https://doi.org/10.1007/s10805-023-09492-6> (in Eng.)
- Perkins M., Roe J., Vu B.H., Postma D., Hickerson D., McGaughran J., & Khuat H.Q. (2024b) Simple techniques to bypass GenAI text detectors: Implications for inclusive education. *International Journal of Educational Technology in Higher Education*, 21. — 53 p. <https://doi.org/10.1186/s41239-024-00487-w> (in Eng.)

Potthast M., Kiesel J., Reinartz K., Bevendorff J., & Stein B. (2018) A stylometric inquiry into hyperpartisan and fake news. *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics*, — P. 231–240. <https://doi.org/10.18653/v1/P18-1022> (in Eng.)

Sadasivan V.S., Kumar A., Balasubramanian S., Wang W., & Feizi S. (2025) Can AI-generated text be reliably detected? Stress testing AI text detectors under various attacks. *Transactions on Machine Learning Research*. <https://openreview.net/forum?id=ROFQeJ2bkh> (in Eng.)

Wang, Y., Mansurov, J., Ivanov, P., Su, J., Shelmanov, A., Tsvigun, A., Whitehouse, C., Afzal, O. M., Mahmoud, T., Sasaki, T., Arnold T., Aji A.F., Habash N., Gurevych I., & Nakov P. (2024a) M4: Multi-generator, multi-domain, and multi-lingual black-box machine-generated text detection. *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics*. — P. 1369–1407. <https://doi.org/10.18653/v1/2024.eacl-long.83> (in Eng.)

Wang Y., Mansurov J., Ivanov P., Su J., Shelmanov A., Tsvigun A., Afzal O.M., Mahmoud T., Puccetti G., & Arnold T. (2024b) SemEval-2024 Task 8: Multidomain, multimodel and multilingual machine-generated text detection. *Proceedings of the 18th International Workshop on Semantic Evaluation (SemEval-2024)*. — P. 2057–2079. <https://doi.org/10.18653/v1/2024.semeval-1.279> (in Eng.)

Weber-Wulff D., Anohina-Naumeca A., Bjelobaba S., Foltýnek T., Guerrero-Dib J., Popoola O., Šigut P., & Waddington L. (2023) Testing of detection tools for AI-generated text. *International Journal for Educational Integrity*, 19. — 26 p. <https://doi.org/10.1007/s40979-023-00146-z> (in Eng.)

Wu J., Yang S., Zhan R., Yuan Y., Chao L.S., & Wong D.F. (2025) A survey on LLM-generated text detection: Necessity, methods, and future directions. *Computational Linguistics*, 51(1). — P. 275–338. https://doi.org/10.1162/coli_a_00549 (in Eng.)

Anekesh D., & Ualiyeva I. (2026) Detecting AI-Generated User Reviews in Kazakh: A Study on BERT Model Performance and False Positive Reduction. *Proceedings of the Analysis of Images, Social Networks and Texts (AIST 2026)*, Springer LNCS, accepted paper. <https://aistconf.org/program/accepted/> (in Eng.)

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ISSN2518-1726 (Online),

ISSN 1991-346X (Print)

Managing Editor: *A.Shormakova*

Editors: *D.S. Alenov, T. Apendiev*

Computer layout: *G.D. Zhadyranova*

Signed for print: September 30, 2026

Format: 70×90 1/16. 26.5 printed sheets. Order No. 3.