MASARYK UNIVERSITY

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Information Technologies for Countering Academic Fraud

Habilitation thesis

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Abstract

This habilitation thesis investigates the role of information technologies in addressing academic fraud and safeguarding academic integrity across educational and research contexts. Positioned at the intersection of computer science and educational science, the work evaluates how technological tools influence misconduct dynamics, institutional trust, and policy development. The findings show that integrity-supporting technologies do not need to be perfect to be effective. Their presence alone acts as a deterrent, reducing opportunities for misconduct and reinforcing expectations of accountability. However, technological outputs are inherently probabilistic and require human oversight, contextual interpretation, and procedural safeguards. Ethical challenges, therefore, cannot be solved through purely technological means.

Particular attention is given to plagiarism detection, contract cheating, authorship verification, and the disruptive impact of generative artificial intelligence. The thesis questions the reliability of AI-generated text detectors and argues against a technological arms race, advocating instead for pedagogical interventions and assessment redesign. Extending beyond education, the work highlights parallels with research misconduct, including paper mills and AI-assisted fabrication, emphasising their severe consequences for scientific trust. The thesis concludes that information technologies are essential but limited instruments for mitigating ethical risks in academia. Sustainable academic integrity depends on the integration of technology, human judgment, and institutional practice.

Description of how AI was used

During the elaboration of this thesis, I have used ChatGPT 5.2, Google Gemini and Grammarly, to the extent defined by AIAS as *Level 3 – AI collaboration* (Perkins et al., 2025), i.e. I have used AI to complete the task, including idea generation, drafting, feedback and refinement. I critically evaluated and modified all generated content.

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1 Introduction

According to the European Network for Academic Integrity (ENAI), the term academic integrity refers to *"compliance with ethical and professional principles, standards, practices and consistent system of values, that serves as guidance for making decisions and taking actions in education, research and scholarship"* (Tauginiene et al., 2023). The International Centre for Academic Integrity defines academic integrity as a commitment to six core values: **honesty, trust, fairness, respect, responsibility, and courage**, guiding all members of an academic community (students, faculty, staff) to uphold high standards of intellectual honesty in all their activities, even when it's difficult (ICAI, 2021). Overall, it is about fostering a culture where people act ethically, give credit to sources, and take ownership of their learning. On the contrary, academic integrity violations are considered academic misconduct or even academic fraud. ENAI defines academic misconduct as *"any action or attempted action that undermines academic integrity and may result in an unfair academic advantage or disadvantage for any member of the academic community or wider society"* (Tauginiene et al., 2023). Similarly, the Council of Europe defines education fraud as *"behaviour or action occurring in the field of education intended to deceive and obtain an unfair advantage"* (Tauginienė & Foltýnek, 2024).

Before I started writing this thesis, I was hesitating between two titles: *Information technologies for academic integrity*, or *Information technologies for countering academic fraud*. Although I personally prefer the first one, I ultimately chose the second because it better reflects the reality of this thesis. Nevertheless, before diving deeper into rather negative concepts like misconduct, fraud, plagiarism, contract cheating, fabrication, and falsification, let's focus on the positive side. Academic communities contribute to human society mostly in two areas: education and science. Thus, the term academic integrity encompasses both educational integrity and scientific integrity.

The purpose of education is to create or strengthen individual knowledge, skills and attitudes, i.e., to develop learners intellectually, socially, and ethically, so they can meaningfully participate in human society. Education equips people with critical thinking abilities, creativity, and curiosity, which are important for lifelong learning. Beyond preparing individuals for careers, education helps shape values, encourages informed citizenship, and empowers people to understand the world, communicate effectively, and contribute to the well-being and progress of their communities.

The purpose of science is to understand the natural world through observation, experimentation, and reasoning. It seeks to explain how and why things happen, to discover patterns and laws that govern the universe, and to generate reliable knowledge that can be tested and refined over time. Science also serves a practical purpose by enabling technological innovation. It helps human societies improve their health, conserve the environment, solve problems, and make informed decisions about issues that arise across all activities.

Both education and science critically depend on a key value: **trust** (Cologna et al., 2025). Without trust in education, university diplomas would never be accepted as certificates of one's knowledge, skills, and competences. Without trust in science, society never accepts scientific findings and never allows decision-makers and policymakers to follow them. Trust can be broadly defined as the belief that another entity will do what is expected. In the case of education, people generally expect that higher education institutions create an environment in which students can gain desired learning outcomes and then assess them fairly and reliably. The purpose of assessment is to certify genuine learning outcomes, and award degrees only to those who have demonstrably acquired the required knowledge, skills and competences (Newton & Jones, 2025). In the case of science, we expect that researchers follow established norms of methodological rigour and publish findings that can be confidently used as a sound basis for further research, professional practice, and evidence-based policymaking. When academic misconduct scandals arise, it is the key value of trust that is often broken.

1.1 Causes of Academic Fraud and the Role of IT

The motivation for unethical behaviour is often depicted by the **fraud triangle**—a foundational framework in fraud risk management and auditing that explains why individuals commit fraud: It suggests that fraud is most likely to occur when three conditions exist simultaneously—**pressure, opportunity, and rationalisation**. The underlying ideas were developed in the 1950s by American criminologist Donald R. Cressey through his research (Cressey, 1953), and were later popularised in fraud and audit literature; although Cressey himself never used the exact term “fraud triangle.

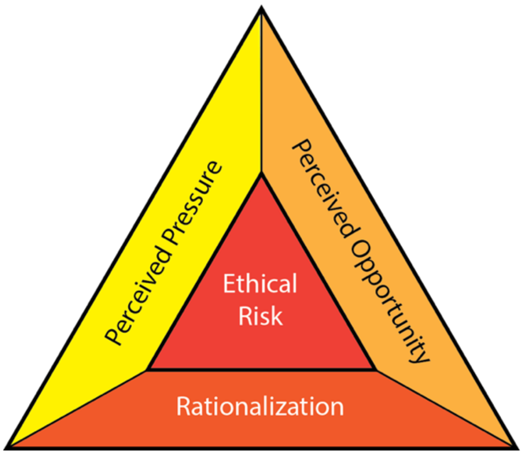

Figure 1.1: Fraud triangle[1]

Pressure, sometimes called motivation or incentive, is the internal or external force that drives an individual to consider fraud as a solution to a problem or need. In Cressey’s original work, this pressure was often a non-shareable financial problem—such as debt, medical bills, gambling obligations, or other personal financial stressors—that the individual felt unable to disclose or resolve through legitimate means (Cressey, 1953). Without such pressure, there is typically no personal incentive to risk engaging in fraudulent behaviour. In academia, pressure can have many forms, ranging from a necessity to finish a project, pressure to get a research grant, or the overall culture of “publish or perish”, creating pressure on academics to publish as many (high-quality) papers as possible (Goodstein, 2010). In an educational context, students may feel pressure to pass the exam, finish the course, finish their studies and get a degree, or pressure to get good marks. When people feel that these requirements are beyond their abilities, the risk of unethical behaviour increases (Foltýnek & Glendinning, 2015).

Opportunity refers to the circumstances that make fraud possible—typically weaknesses or gaps in controls, oversight, or monitoring within an organisation. If systems and processes are inadequately designed or poorly enforced, an individual with access to financial assets or

[1] Image source: David Bailey, 2015. https://commons.wikimedia.org/wiki/File:Fraud_Triangle.png

sensitive functions may perceive a chance to commit fraud with a low probability of detection. This element is often considered the component that organisations have the most ability to influence by strengthening internal controls, segregation of duties, and audit mechanisms (Cressey, 1953). A typical example in an educational setting is the lack of plagiarism detection (no text-matching software in use), which increases the likelihood that students submit someone else's work. Another example is improper exam vigilance, which again increases the likelihood that students will copy from each other or use unallowed aids (Pabian, 2015). This risk is especially pronounced in take-home online exams, where students are expected to complete their tasks without invigilation or oversight (Newton & Draper, 2025). In the scientific context, the opportunity to commit misconduct arises from a weak review process, which is unlikely to detect unethical practices such as plagiarism, data fabrication, or falsification.

Rationalisation is the cognitive process through which a potential fraudster justifies the act to themselves (Cressey, 1953). Even if a person feels pressure and sees an opportunity, they typically must reconcile the fraud with their own moral standards in a way that makes the wrongdoing seem acceptable. Common rationalisations include beliefs such as "I'm just borrowing the money and will pay it back," "I deserve this because I'm underpaid," or "everyone does it anyway." Without this internal justification, many individuals would likely resist acting on fraudulent impulses.

The three components of the fraud triangle have been proven effective for describing and understanding academic misconduct. For example, Stiles and Gair (2010) found that student misconduct is strongly influenced by how students perceive peer behaviour, interpret the seriousness of cheating, experience pressure to succeed, and observe faculty consistency in enforcing rules. Their study shows that misperceptions of norms (an impression that "everyone cheats"), weak enforcement signals, performance pressure, and scepticism toward honour codes together create an environment that normalises dishonest behaviour and allows students to justify it internally (Stiles & Gair, 2010). Their study is not an exception; these three categories of drivers of unethical behaviour are widely accepted in academic integrity literature (Bretag, 2019; Gallant, 2009).

Probably the most well-known researcher of lying and cheating is Dan Ariely. In his book *"The (honest) truth about dishonesty: how do we* *lie to everyone – especially ourselves"* he describes three rough categories of people: consistently honest people, moderate cheaters and extremely dishonest people (Ariely, 2013):

- **Consistently honest people:** Individuals who resist cheating opportunities even when there's little risk, and they could benefit. These people maintain ethical behaviour across situations because they feel a strong internal cost when they violate their own moral standards.
- **Moderate cheaters:** The largest group in Ariely's research include people who cheat a bit—often only as far as they can justify it to themselves psychologically—but avoid extremes that would make them see themselves as dishonest people.
- **Extremely dishonest people:** A smallest subset of people who show little internal constraint on lying or cheating and are relatively insensitive to moral reminders or situational cues working as a deterrent of cheating for other groups.

Even though Ariely is known for his popularisation efforts, his methodology had serious flaws (Heyman et al., 2020). Nevertheless, numerous other studies examining the prevalence of and propensity to cheating confirm the existence of the above-mentioned broad categories of people, as well as the claim that **most people tend to cheat just a little:** enough to benefit, but not so much that it threatens their self-image as a "good person." The research consistently shows that dishonesty is shaped heavily by context and moral reminders (Fischbacher & Föllmi-Heusi, 2013; Gerlach et al., 2019).

How to use these findings to address the three components of the Fraud triangle? Presuming that pressure in the academic environment is predominantly given by external and systemic factors (Pabian, 2015), the space for institutions and individuals narrows down to rationalisation and opportunity. Addressing rationalisation of dishonest behaviour encompasses a longitudinal multifaceted approach known as building a **culture of academic integrity** (Bretag, 2019) – an environment where it is normal (and expected) to act with integrity, where the educators' focus is not on how to prevent cheating, but how to support learning (Bertram Gallant, 2017). Simple measures like signing an honesty pledge, recalling moral rules, or reminding students of ethical standards can dramatically reduce cheating, often more than increasing punishments or surveillance. The importance of the institutional context was proved by

McCabe, Treviño, and Butterfield, who showed that at US schools without honour codes, about 71% of students admitted serious cheating, compared to 44–54% at honour-code institutions (McCabe et al., 2001).

Nonetheless, the mere establishment of a culture of academic integrity and the implementation of "soft" measures targeting students' internal honesty would not be enough. Such measures would be teethless without enforcement. And this is where IT comes into play. There are not many technological possibilities to reduce pressure or rationalisation, but there is certainly high potential to reduce opportunities for unethical behaviour, typically by supporting the detection of misconduct. Accurate detection tools, when used properly, not only uncover unethical behaviour but also serve as a deterrent – a piece in the mosaic that can significantly shift perceptions of whether a certain form of misconduct can pay off. (Curtis & Vardanega, 2016)

A traditional form of misconduct that is not only addressable by IT but also widely researched is **plagiarism**. Long-term evidence from large student cohorts demonstrates that plagiarism detection systems, when deployed in isolation, function primarily as a weak deterrent, but their impact increases dramatically when integrated into learning management systems and paired with technology-supported formative interventions (Owens & White, 2013). These tools reduce opportunities for misconduct not merely by increasing the risk of detection, but by making improper practices visible early in the writing process. The findings suggest that an early exposure to IT-supported enforcement and feedback can recalibrate students' cost–benefit calculations and internalise expectations of accountability. In the early 2000s, many researchers were concerned about students' use of technology, which greatly expanded their opportunities for misconduct (e.g., easy access to online sources) (Szabo & Underwood, 2004). Later research showed that technologies simultaneously enable scalable enforcement and education mechanisms that reduce those same opportunities. The long-term experience from universities that deployed detection technologies for plagiarism, accompanied by appropriate pedagogical interventions, showed a significant decrease in student plagiarism (Curtis & Vardanega, 2016), indicating that well-implemented detection technologies do not merely deter misconduct but can also contribute to an overall decrease in unethical practices. In this sense, IT-based detection tools play a crucial role in enforcement not only by detection and punishment, but mostly by stabilising expectations of detectability, thereby reinforcing institutional norms and increasing the credibility of the institutional assessment system.

1.2 Extent and Consequences of Misconduct

Surveys of students consistently show that academic cheating—including plagiarism, exam dishonesty, and assignment outsourcing—is widespread. McCabe, Treviño, and Butterfield (2001) synthesised multi-institution research on student academic dishonesty and found that about 75–82% of college students admit to at least one serious act of academic dishonesty over their college careers, depending on cohort and survey year. A meta-study by Newton found that the percentage of students admitting to commercial contract cheating ranges from 3 to 7% (Newton, 2018). These numbers confirm that students are not different from the general population. A small percentage of them try to complete their studies by any means, whereas most are "small cheaters" whose behaviour is largely influenced by contextual factors and rationalisation.

The extent of scientific misconduct is difficult to measure exactly. The obtained percentages depend strongly on the scope and framing of the research questions. Serious misconduct, typically denoted as **FFP** (fabrication/falsification/plagiarism), occurs quite rarely (Bouter et al., 2016). A meta-analysis of surveys found that about 2% of scientists admitted to having fabricated, falsified, or modified data or results at least once (Fanelli, 2009). A large, modern national survey of 6813 scientists in the Netherlands used the randomised response method designed to reduce social-desirability underreporting, and found that 4.3% of scientists admitted fabrication and 4.2% admitted falsification over the prior 3 years (Gopalakrishna et al., 2022). A meta-analysis covering work through 2020 estimated the pooled prevalence of "research misconduct" (FFP) at 2.9% (Xie et al., 2021). Much larger percentages are consistently reported when examining so-called *"questionable research practices"* (QRPs), which constitute cutting corners rather than outright fraud. QRPs include practices such as selectively reporting results, inadequate documentation, and dropping "inconvenient" data without disclosure. In the Netherlands study, 51.3% respondents reported engaging frequently in at least one of 11 QRPs in past three years. Similarly, a US survey published in Nature reported 33% admitting to at least one of a set of "top" questionable behaviours within the past three years (Martinson et al., 2005).

Academic misconduct has serious consequences for both students and higher education institutions, most notably by eroding **trust** in university diplomas and credentials. When plagiarism, contract cheating, and other forms of misconduct become widespread, diplomas no longer reliably signal graduates' knowledge and skills. This undermines the core social function of higher education as a certifying authority and weakens trust among employers, professional bodies, and the public. Students who graduate honestly may find their qualifications devalued due to suspicion generated by others' misconduct, while institutions risk reputational damage and declining credibility. Over time, this dynamic can lead to credential inflation, increased reliance on external testing, and greater scepticism toward academic assessment as a whole. In this sense, academic misconduct not only disadvantages individual students but systemically weakens the legitimacy of higher education as a merit-based institution.

The consequences for science and society are even more far-reaching. Research misconduct undermines the reliability of scientific knowledge, distorts meta-analyses, and wastes public resources by building further research on compromised results. More fundamentally, as argued by Tudoroiu (2017), high-profile cases of academic misconduct among political and societal elites contribute to a broader loss of trust in expertise, institutions, and democratic governance. When academic titles and research credentials are shown to be fraudulent, citizens may question not only individual scholars but the integrity of science-based policymaking itself. Tudoroiu links plagiarism scandals involving political leaders to declining confidence in democratic institutions, suggesting that academic misconduct can indirectly threaten democracy by eroding its fundamental pillars, such as trust, informed public debate, and legitimate authority (Tudoroiu, 2017). In this perspective, safeguarding academic integrity is not merely an educational or scientific concern, but a matter of public trust and democratic resilience.

1.3 The Goal of the Thesis

The findings reviewed above show that academic misconduct is neither rare nor limited to individual moral failure. It emerges from a combination of pressure, opportunity, and rationalisation (Cressey, 1953), and affects all members of academic communities, as well as society as a whole. While student misconduct receives most attention, unethical behaviour by academics, teachers, and researchers is at least as damaging. When those responsible for assessment, supervision, and knowledge production violate academic integrity, the consequences extend far beyond individual cases and directly undermine trust in education and science as social institutions (Sijtsma, 2023).

The severity of the consequences creates an urgent need to address not only academic misconduct as such, but primarily its underlying causes. In this context, information technologies play an important, though inherently limited, role. Digital tools have undeniably expanded opportunities for misconduct, but they have also enabled new forms of detection, verification, and procedural consistency (Curtis & Vardanega, 2016; Owens & White, 2013). When used appropriately and embedded within pedagogical and institutional frameworks, IT-based tools can significantly reduce opportunities for unethical behaviour and strengthen the enforcement of rules and norms. Their primary contribution lies not in punishment, but in stabilising expectations of detectability and fairness, thereby influencing behaviour long before formal sanctions are considered.

This thesis is positioned at the **intersection of computer science and educational science**, drawing from the academic integrity research and showing how IT can address related challenges. It does not claim that technology can replace ethical education, human judgment, or responsible governance. Neither does it claim that IT is capable of solving the ethical issues in academia. Instead, it examines *how* information technologies can support these elements by providing scalable, evidence-based mechanisms to reinforce institutional norms. By addressing misconduct among students as well as academics and researchers, the thesis argues that academic fraud can be meaningfully countered and that information technologies, when used with care and restraint, are a crucial part of this effort.

In the following chapters, we will dive into the specific academic integrity issues: plagiarism, assignment outsourcing (contract cheating), unauthorised content generation (primarily using AI), and scientific paper mills. After examining the inherent limitations of pure detection, the final chapter goes beyond detection and presents the opportunities of IT in safeguarding academic integrity in the post-plagiarism era.

The overarching goal of my research is to inform academic communities and the general public about both opportunities and limitations of information technologies in countering academic fraud. Only when the expectations of users and policymakers align with the software tools' actual capabilities can these tools reliably serve their purpose.

2 Plagiarism

2.1 A Systematic Literature Review

My first significant contribution to this area was the paper ***"Academic Plagiarism Detection: A Systematic Literature Review",*** which I co-authored with Norman Meuschke and Bela Gipp (2019) and was published in the prestigious D1 journal *ACM Computing Surveys*. It offers a comprehensive synthesis of computational methods for detecting academic plagiarism to date. Based on a thorough review of 239 studies published between 2013 and 2018, the paper makes several contributions.

A key technical contribution is its detailed taxonomy of plagiarism-detection approaches. Apart from the traditional distinction between *extrinsic* (comparing documents against external sources) and *intrinsic* (detecting anomalies within a single document) plagiarism detection methods, the paper introduces an orthogonal classification based on the levels of linguistic representation. The paper classifies plagiarism forms and detection techniques across lexical, syntactic, semantic, and idea-based levels. We also highlight the evolution of the field from basic text-matching to citation-, image-, and math-based detection systems, and to more sophisticated semantic and machine-learning-based methods capable of identifying obfuscated plagiarism.

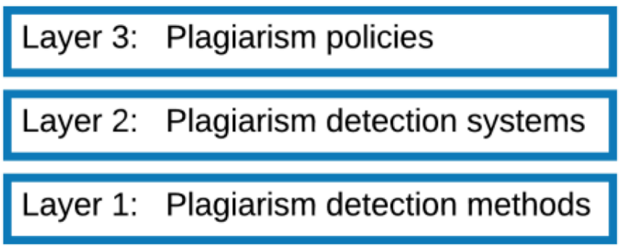

Figure 2.1. Three layers of addressing plagiarism (Foltýnek et al., 2019)

The second contribution goes beyond the technical perspective and introduces a three-layered model for addressing plagiarism, comprising **methods**, **systems**, and **policies.** This distinction allows for a clear structuring of the analysis of academic plagiarism as a technological and institutional problem. The survey also emphasises that none of the layers can solve the problem alone, and that they cannot work separately. The methods must be implemented by the systems, where scalability is often an issue. And, the use of the systems has to be mandated by institutional policies.

The third contribution of the paper lies on the policy level and, over time, proved to have the most significant practical impact. Based on a thorough review, we proposed a **definition of academic plagiarism** as follows. In accordance with Teddi Fishman (2009), we define academic plagiarism as *"the use of ideas, content, or structures without appropriately acknowledging the source to benefit in a setting where originality is expected"* (Fishman, 2009; Foltýnek et al., 2019). Over the years, this definition has proved to capture crucial aspects of academic plagiarism and has been adopted by several impactful initiatives:

In 2020, nine Czech and Moravian universities joined forces in a project aimed at initiating an intensive debate and practical cooperation in the field of academic integrity and the prevention of fraudulent practices in academic writing. In 2021, the number of participating universities increased to 20, and the follow-up project focused on the risks and opportunities of remote teaching and assessment methods. By 2022, 26 universities were involved in the project, directing their attention to social safety at Czech universities in the context of academic integrity as a guarantee of a safe, fair, and ethical academic environment. Within the first project, a pair of handbooks about plagiarism was published:

- How to Avoid Plagiarism: Student Handbook (Foltýnek et al., 2021a)
- How to Prevent Plagiarism in Student Work: A Handbook for Academic Staff (Foltýnek et al., 2021b)

Both handbooks are available in Czech and English. The Czech version is also available as audio. Moreover, the student handbook is also available in sign language. By adopting the above-mentioned definition, the handbooks, together with other project results, shaped the discussion about plagiarism in the Czech academic environment.

The above-mentioned definition was also taken to the glossaries, which are considered authoritative in the European academic environment: The Glossary for Academic Integrity published by the European Network for Academic Integrity (Tauginiene et al., 2023), and the Council of Europe's Glossary of terms related to ethics and integrity in education (Tauginiené & Foltýnek, 2024). Probably the most impactful context in which this definition appears is the Council of Europe's Recommendation CM/Rec(2022)18 on countering education fraud (Council of Europe, 2022). The Recommendation defines plagiarism as *"using work, ideas, content, structures or images without giving appropriate credit or acknowledgement to the original source(s), especially where originality is expected."* This recommendation constitutes a ground for numerous national and supra-national initiatives in the field of educational integrity across Europe and beyond.

Key elements of the definition that proved to be particularly useful are:

- The definition does not limit plagiarism to text only, but mentions content, ideas or structures reflecting a wide *variety of forms* of content that are being plagiarised.
- The definition does not bind the original content to a particular *person*, but rather talks about a *source*, which includes self-plagiarism.
- An explicit mention of the *expectation of originality* excludes copying for educational purposes or legal documents.

The success of the definition and its wide impact were made possible only because of our thorough consideration of various options drawn from the studies under the survey.

Finally, the paper underscores persisting research gaps and future directions. Despite technological progress, most of the methods presented in scientific literature lack sufficient scalability. In the literature review, we advocate for integrating heterogeneous analysis methods—combining textual, semantic, and structural indicators through machine learning—to address complex, obfuscated, and cross-modal plagiarism. The survey also identified a lack of rigorous evaluations for real-world plagiarism detection systems and the continued dominance of text-based approaches. It also emphasises that effective detection must be complemented by institutional policies and educational strategies to sustain academic integrity. It calls for a more holistic, interdisciplinary approach to combating plagiarism in academia.

2.2 Plagiarism detection methods

My research focused on improving plagiarism detection by moving beyond simple text matching toward semantic and structure-aware methods that remain effective under obfuscation. I worked on scalable source retrieval and heuristic techniques to improve the efficiency of large-scale online plagiarism detection. Then, I explored source code plagiarism detection, developing token-based and Greedy String Tiling approaches that capture structural similarity rather than relying on fragile text comparisons. Later, I concentrated on semantic analysis and machine-generated obfuscation. My colleagues and I showed that combining Explicit Semantic Analysis with scored matching techniques enables robust cross-language source code plagiarism detection. More recently, I investigated AI-driven paraphrasing tools, demonstrating that, at the time, word embeddings and transformer-based models could reliably distinguish human-written from machine-paraphrased text.

My first contribution at the level of plagiarism detection methods was a source-retrieval system developed for the PAN competition at CLEF 2013 (Veselý et al., 2013). Our approach combines an optimised "naïve approach" to dynamic query-sizing with passage-selection heuristics based on a pre-suspiciousness index. The naïve method incrementally increased the query length to find the last non-empty result set. Then, we weighted the retrieved URLs using the search engine's weight values and downloaded the top candidates. To avoid exhaustively querying entire documents, the system probed the text in two phases: An initial probe phase sampling every 100 words to estimate suspicious regions via optimal query length, and a heuristic progress phase that prioritised gaps by their index until 20% of words were queried. Our approach scored slightly above the average competition performance (Potthast et al., 2013), and showed potential for future improvements and cross-engine comparisons.

Next, I focused on source-code plagiarism detection for the PHP language (Všianský et al., 2017). We developed a system for detecting plagiarism in PHP source code by combining PHP-native tokenisation with the Greedy String Tiling (GST) algorithm. Instead of unreliable text-based comparisons, our approach converted PHP programs into token sequences, then identified maximal token-substring matches above a defined threshold (7 tokens) to reveal structural similarities resilient to common obfuscation tactics such as renaming identifiers, modifying comments, and swapping code blocks. The system recorded match positions and similarity ratios in a database and provided a graphical interface highlighting overlapping code segments and string-level similarities. Evaluation on both artificial test cases and 66 real student assignments showed that our system successfully detected all tested plagiarism patterns and, compared with tools like jPlag, achieved higher practical accuracy for PHP, though false positives emerged due to PHP's limited token vocabulary.

The next step was the development of a programming-language-independent method for cross-language source code plagiarism detection that combined Explicit Semantic Analysis (ESA) with a modified GST algorithm (Foltýnek, Všianský, et al., 2020). We represented programs as ESA concept vectors derived from ~30,000 English Wikipedia articles related to programming and mathematics. This approach allowed us to preserve semantic information across identifiers and tokens; similarity was then computed using Scored GST, which matched token vectors that exceeded a certain cosine similarity threshold. Our evaluation on a synthetic dataset of calculator implementations in C++, Java, JavaScript, PHP, and Python with multiple obfuscation strategies (identifier renaming, style changes, restructuring, partial reuse) showed very high similarity scores for monolingual (≈99%) and high scores for cross-language cases (≈89%), while correctly separating unrelated code.

In 2017 and 2018, some studies alerted the academic integrity community of students using online paraphrasing tools to evade text-matching plagiarism detection systems (Prentice & Kinden, 2018; Rogerson & McCarthy, 2017). To address this concerning trend, I changed my focus to detecting machine-obfuscated plagiarism. Our first study in this area (Foltýnek, Ruas, et al., 2020) framed the detection of machine-obfuscated plagiarism as a binary classification problem. We used large-scale datasets built from high-quality English Wikipedia articles and their paraphrases generated by the system SpinBot. We evaluated multiple word embedding models (including GloVe, word2vec, fastText, USE, and PV-DBOW) and combined them with several classifiers (kNN, Random Forest, Logistic Regression, SVM, Naïve Bayes). Our results showed extremely high effectiveness at the document level (up to 99.0% accuracy) and strong performance at the paragraph level (up to 83.4%), with word2vec + SVM offering the best trade-off between accuracy and efficiency. The study further demonstrated that our approach outperformed human experts and exposed weaknesses in traditional plagiarism detection systems, which often fail when only small passages are machine-paraphrased. It is worth noting that the detection success of our method was largely caused by atypical word choices introduced by paraphrasing tools.

In a follow-up study (Wahle et al., 2022), we compared traditional word-embedding-based classifiers with modern transformer language models across diverse academic text sources. Using a SpinBot-paraphrased Wikipedia training set and three evaluation corpora (arXiv papers, student theses by English language learners, and Wikipedia articles), we tested multiple embeddings (GloVe, word2vec, fastText, doc2vec) with LR/SVM/NB classifiers and eight transformer models (including BERT, RoBERTa, ELECTRA, XLNet, and Longformer). Our results showed that while GloVe/word2vec baselines performed reasonably well on the SpinBot data, transformer models dramatically outperformed them, with several achieving F1 scores above 99% on the SpinBot data. Human evaluators performed notably worse, and text-matching systems such as Turnitin and PlagScan frequently failed when paraphrasing intensity increased. The study concluded that attention-based transformer models, especially Longformer, effectively captured artefacts of automated paraphrasing and could complement plagiarism detection systems.

2.3 Plagiarism detection tools

In the study *"Testing of Support Tools for Plagiarism Detection"* (Foltýnek, Dlabolová, et al., 2020), my colleagues and I directly addressed the main research gap identified in the 2019 literature review: the lack of systematic, comparative testing of plagiarism detection systems. To conduct this research, I collaborated with researchers from seven countries, all members of the European Network for Academic Integrity. The study evaluated 15 web-based text-matching systems across eight languages (Czech, English, German, Italian, Latvian, Slovak, Spanish, and Turkish). The research systematically assessed two key aspects: *coverage* (the extent to which known plagiarism was detected) and *usability* (how effectively the tools supported educators). We emphasise that such systems cannot detect plagiarism per se, only textual similarity, and that human interpretation remains essential.

The main methodological contribution lies in the rigorous, multilingual, and empirically grounded testing framework. We constructed an extensive corpus of test documents featuring various plagiarism strategies—copy-and-paste, synonym substitution, paraphrasing, and translation—along with multi-source and original texts to evaluate false positives. We scored each system's performance across languages, source types, and disguising methods. The testing revealed that systems performed relatively well on verbatim copying but failed on paraphrased and translated texts, especially in less-resourced languages. Coverage was strongest for Germanic, and Romanic languages, while Slavonic languages posed greater challenges. Urkund, Turnitin, PlagScan, and StrikePlagiarism ranked highest in overall detection accuracy.

In terms of practical impact, the paper made crucial contributions to evidence-based policy and procurement in the field of academic integrity management. The usability analysis—covering workflow, report clarity, data handling, and support—identified Urkund, Turnitin, Unicheck, and PlagScan as leading in user experience. However, the study concluded that current systems are only partially useful for academic institutions: they support the identification of suspicious similarities but do not reliably detect all types of plagiarism. We issued recommendations for both vendors and educators, advocating for the incorporation of semantic analysis, transparent reporting, and greater awareness that *textual overlap* is not equal to *plagiarism*.

Since the time of the study, there has been significant progress in the market of support tools for plagiarism detection. In June 2020, Turnitin acquired Unicheck (Turnitin, 2020). Then, the main European market players—Urkund and PlagScan—responded to Turnitin's growing monopoly by merging into one company, Ouriginal (Duque, 2020). One year later, in November 2021, Turnitin acquired Ouriginal (Turnitin, 2021), virtually killing any competition in the field of text-matching software tools.

2.4 Plagiarism and Academic Integrity Policies

Plagiarism (or plagiarism detection) policies form a third layer of the efforts to address plagiarism (Foltýnek et al., 2019). Although this topic lies on the borderline of informatics, or maybe even beyond it, my research in this area revealed important insights into how information technologies designed to counter academic fraud are used in real-world scenarios. We should note that academic integrity literature focused mostly on plagiarism till around 2015. Then, the emphasis started moving to other issues too, mainly to contract cheating. I conducted research in this area mostly between 2010 and 2019 within three European projects: IPPHEAE, SEEPPAI, and PAICKT.

The IPPHEAE (Impact of Policies for Plagiarism in Higher Education Across Europe) project was an EU-funded initiative (2010–2013) that systematically examined how higher education institutions across all 27 EU member states address plagiarism and academic integrity. Using large-scale surveys of students, teachers, senior managers, and national bodies—supplemented by interviews and focus groups—the project mapped policies, practices, preventative strategies, sanctions, and the use of detection tools, and identified substantial inconsistencies and gaps across Europe. A key outcome was the Academic Integrity Maturity Model (AIMM), which enabled structured comparison of national and institutional approaches and highlighted wide variation in the maturity, transparency, and effectiveness of academic integrity systems. Overall, the project found that many institutions relied on ad-hoc or opaque practices, while examples of good practice existed but were unevenly distributed. This led to clear recommendations for more coherent policies, stronger prevention and education, and greater consistency to support quality and comparability in European higher education (Foltýnek & Glendinning, 2015).

The SEEPPAI (South-East European Project on Policies for Academic Integrity) project was commissioned by the Council of Europe as a follow-up to IPPHEAE. The project was conducted in 2016–2017 to examine academic integrity policies and practices in higher education across six South-Eastern European countries (Albania, Bosnia and Herzegovina, Croatia, Montenegro, Serbia, and North Macedonia). Building on the IPPHEAE methodology, SEEPPAI combined surveys, interviews, focus groups, institutional visits, and document analysis to assess how universities address plagiarism, exam cheating, contract cheating, ghost-writing, and related forms of academic misconduct. The project found widespread policy fragmentation, weak oversight, inconsistent enforcement, and strong cultural and systemic challenges. The forms of widespread misconduct included exam cheating, contract cheating, and, in some cases, bribery, alongside limited staff development. At the same time, SEEPPAI identified notable examples of good practice and strong demand for education-based prevention. The project also applied the Academic Integrity Maturity Model (AIMM) to benchmark the region against EU countries. The project produced concrete recommendations for governments, quality agencies, institutions, and individuals, emphasising coordinated policy frameworks, stronger quality assurance, education-focused prevention, and regional peer learning to support long-term improvement in academic integrity (Glendinning et al., 2018). The SEEPPAI project results were important input to Montenegro's Law on Academic Integrity (Boskovic, 2023).

The PAICKT (Project on Academic Integrity in Armenia, Azerbaijan, Georgia, Kazakhstan and Turkey) was also commissioned by the Council of Europe as a follow-up to IPPHEAE and SEEPPAI. It was conducted in 2018–2019 under the newly established *Pan-European Platform for Ethics, Integrity and Transparency in Education* (ETINED)[2]. The project goal was to map academic integrity policies, perceptions, and practices in five countries not previously covered. Using a mixed-methods approach—including national policy reviews, large-scale surveys of students, teachers, and senior managers, interviews, focus groups, and institutional visits—the project examined plagiarism, exam cheating, contract cheating, and corruption-related risks in higher education. PAICKT applied the Academic Integrity Maturity Model (AIMM) to benchmark national systems against 33 previously surveyed European countries, revealing uneven policy development, inconsistent enforcement, limited training, and ongoing challenges related to assessment security and corruption, alongside growing awareness and recent reform efforts. The project identified examples of good practice and produced evidence-based recommendations for governments, quality agencies, and institutions, emphasising transparency, consistent sanctions, staff and student education, effective use of tools, and coordinated national strategies to strengthen academic integrity and educational quality (Glendinning et al., 2021).

The three projects mentioned above covered all European countries except for Russia, Ukraine and Belarus. Their results form a cumulative evidence base that is highly relevant, particularly for the design, evaluation, and responsible deployment of plagiarism detection and authorship-verification technologies. Across all three projects, large-scale, multi-country empirical data consistently show that plagiarism detection systems operate within complex socio-technical environments: they are embedded in institutional policies, disciplinary procedures, language contexts, and human decision-making, including interpretation biases such as widespread myth of plagiarism threshold – a "magic" numeric value defining borderline between acceptable and unacceptable

[2] https://www.coe.int/en/web/ethics-transparency-integrity-in-education

percentage of text match (at the time of writing this thesis still used, e.g., by the journal Studies in Language Education[3] or Yildiz Technical University in Turkey[4]). These conditions, which are typically abstracted away in algorithmic research, directly affect system validity and impact in educational settings.

From the IT perspective, the project results demonstrate that algorithmic performance alone (e.g., similarity detection accuracy) is insufficient to characterise tool effectiveness. Technical metrics should be situated within institutional workflows and decision processes. Findings from IPPHEAE, SEEPPAI and PAICKT further expose failure modes relevant to computer science research, such as false confidence induced by similarity percentages, lack of robustness across non-English languages, and the inability of text-matching approaches to identify ghost-written texts. The results suggest usability of complementary approaches such as stylometry, authorship verification, and assessment design-aware systems (see following chapters).

During these projects, I discovered a huge gap between the research findings, policies, technology and everyday real-world practice. To bridge this gap, I was the founder and main driving force of the European Network for Academic Integrity (ENAI), which functioned as the primary translation mechanism between large-scale empirical research and operational practice. ENAI established respected professional spaces where these issues could be addressed collaboratively (Eaton, 2021). Annual ENAI conferences institutionalised cross-disciplinary dialogue between computer scientists, educational researchers, policymakers, quality agencies, and software providers, enabling direct discussion of real-world failure modes of detection systems, as well as sharing of good practice. ENAI's summer schools, training programmes, and working groups further operationalised these insights by embedding them into capacity-building activities targeted at both technical and non-technical audiences. Summer schools translated project findings into hands-on training on how plagiarism detection systems should be evaluated, configured, and interpreted, explicitly addressing the socio-technical risks highlighted in SEEPPAI and PAICKT, such as over-reliance on software tools. The core of ENAI activities lies in its working groups—particularly those focused on technology, academic integrity policies, or contract

[3] https://www.journalsle.com/index.php/sle/similarity_and_plagiarism

[4] https://fbe.yildiz.edu.tr/page/GRADUATION/PLAGIARISM-CHECK/429

cheating (Foltýnek & Glendinning, 2024). These working groups not only disseminated research outputs; they converted them into an iterative feedback loop where empirical evidence shapes professional practice and practitioner experience. ENAI also informs new research agendas, including my later work on authorship verification and AI-generated text detection.

3 Assignment Outsourcing (Contract Cheating)

In this chapter, we will deal with one specific form of plagiarism, which is characterised by the production of an original work, likely undetectable by extrinsic plagiarism detection methods. Both the terminology and delimitation of the phenomenon vary significantly across academic literature.

To my knowledge, the first authors who researched this phenomenon were Thomas Lancaster and Robert Clarke, who coined the term "contract cheating" as *"the process of offering the process of completing an assignment for a student out to tender"* (Clarke & Lancaster, 2006). During this time, the definition underwent some changes. The current version can be obtained from Thomas Lancaster's website[5]:

> *Contract cheating describes the process through which students can have original work produced for them, which they can then submit as if this were their own work. Often this involves the payment of a fee and this can be facilitated using online auction sites.*

In 2020, Rebecca Awdry, in a paper reporting about the largest global survey on contract cheating, introduced the term *"assignment outsourcing"*, which encompasses not only commercial services provided by specialised companies but also unauthorised help from students' peers or relatives. According to Awdry, "*assignment outsourcing can be defined as the act of a student obtaining their assignment (by request), whether or not for academic gain, from another party. This is applicable irrespective of the method, mode or purpose of the outsourcing and is relevant for assignments in any format"* (Awdry, 2020). Awdry did her best to develop a general definition encompassing a broad range of fraudulent behaviour. Nonetheless, this definition also includes obtaining another student's assignment solely for learning purposes. As long as such material is neither provided elsewhere nor submitted as a student's own work, it can hardly constitute academic miscoduct.

[5] https://thomaslancaster.co.uk/contract-cheating/

Apart from preventative measures and detection strategies that universities adopted to combat contract cheating, there have been several regulatory and legislative measures taken across the world. In 2022, the UK amended the Skills and Post-16 Education Act to criminalise commercial contract cheating services. According to this legislation, it is now illegal in England (and mirrored elsewhere in the UK) to provide, arrange, or advertise services that complete all or part of a student's assignment with the intent that the work will be submitted for academic credit as the student's own (Skills and Post-16 Education Act, 2022). Similar legislation has also been adopted in Ireland, Australia and New Zealand, i.e., in countries where written assignments elaborated as student homework are an important component of student assessment. In continental Europe, including countries that have adopted specific legislation on academic integrity, such services are generally legal, and the sole perpetrators of misconduct are students submitting work written by someone else.

The release of ChatGPT in November 2022 and subsequent wide public availability of the LLM-based tools capable of producing human-like textual output raised some doubts about whether the definitions of contract cheating and assignment outsourcing also include the unallowed use of generative AI. To address this uncertainty, a new term was introduced in the ENAI Recommendation for Ethical Use of Artificial Intelligence in Education (Foltýnek et al., 2023):

> *Unauthorised content generation (UCG) is the production of academic work, in whole or part, for academic credit, progression or award, whether or not a payment or other favour is involved, using unapproved or undeclared human or technological assistance.*

In general, the LLM-based services widely available for contract cheating providers, as well as for students themselves, created an urgent need to redesign assessment strategies previously heavily relying on student-written assessments (Roe & Perkins, 2024; Weber-Wulff et al., 2023). We will get back to this topic in the following chapter.

3.1 My Research on Contract Cheating

My research on contract cheating started in 2016. By that time, nobody had explored this phenomenon in Czechia. The studies I supervised or co-authored provide the first systematic insight into how and why students in Czechia engage with essay mills and ghost-writing services. The paper *"Analysis of the Contract Cheating Market in Czechia"* (Foltýnek & Králíková, 2018), offered baseline quantitative data: 8% of Czech university students admitted having submitted work written by someone else, most often by a friend or classmate rather than a commercial provider. About a third of surveyed students knew someone who had engaged in such behaviour, and nearly 90% were aware of companies offering ghost-writing. The main motivations were lack of time, misunderstanding of the topic, and convenience, while more than half of non-cheating students stated they would "never" outsource work. The study also mapped gender and disciplinary differences, finding that men and engineering students cheated more often. The study argued that universities should focus on intrinsic motivation, personalised assessment, and open dialogue rather than purely on detection tools.

The follow-up study, *"Global Essay Mills Survey in Czechia: Insights into the Cheater's Mind"* (Králíková et al., 2018), expanded this research with a larger, internationally coordinated dataset and a more detailed behavioural analysis. Among 574 Czech respondents, 19.7% were identified as cheaters—more than double the previous estimate, mainly because the criteria were broader and included also unauthorised help of friends or relatives. Again, most respondents (14%) obtained ghostwritten work from friends or family, with only around 5% paying for professional services. Cheaters were significantly more likely to know others who cheated, to excuse the practice under pressure or poor support, and to propose lenient consequences such as resubmission without any other penalty.

Overall, we found that the extent of admitted contract cheating in Czechia corresponds to the findings from other countries (Newton, 2018), and so do the main reasons why students resort to cheating (Foltýnek & Králíková, 2018). Despite some cultural differences between Eastern European and Western cultural contexts (Mahmud et al., 2018), our results indicate that measures that Western universities adopt to address contract cheating could be transferred to the Czech context.

3.2 Limitations of Contract Cheating Research

Even though research in this area is attractive, the methods are limited to questionnaires for self-reported data or to focus groups for more in-depth qualitative insights. We have elaborated on the limitations of these methods in a book chapter titled *"Limitations of contract cheating research"* (Krásničan et al., 2022), which critically examines methodological weaknesses in contemporary research on contract cheating, with a particular focus on studies that estimate prevalence through self-reported student questionnaires. While such studies are widely cited and influential in public and policy discourse, we argue that they suffer from systematic limitations that undermine the validity, comparability, and interpretability of their findings. Drawing on (1) expert brainstorming within the European Network for Academic Integrity Survey Working Group and (2) a structured review of 18 peer-reviewed studies published between 2017 and 2021, we have identified recurrent problems across the research lifecycle. These include unclear or culturally ambiguous terminology, use of morally charged language that amplifies social desirability bias, reliance on closed multiple-choice items, high survey dropout rates, and systematic sampling biases—most notably gender imbalance, small or unrepresentative samples, and over-reliance on single-institution data. These issues lead to interpretation problems and misleading generalisations, especially when results are amplified by the media.

We have also shown that many studies either insufficiently acknowledge these limitations or omit them entirely, despite their clear impact on reported prevalence rates. To address this, we proposed a detailed methodological checklist intended to guide future survey-based research on contract cheating. The checklist covers survey design, language use, sampling strategies, treatment of demographic data, mitigation of social desirability bias, statistical validation, and transparent reporting of limitations. Therefore, our study makes a significant meta-methodological contribution by shifting attention from headline prevalence figures to the epistemic quality of the research that produces them. We argue that improving methodological rigour is essential not only for academic credibility, but also for responsible policy-making and public communication about contract cheating.

Having these limitations in mind, we attempted to obtain more reliable data via observing student behaviours in a real-life setting. The proposed research project included establishing a fake contract cheating service to be advertised via social media. Despite our efforts to minimise the harm to research participants (no collection of personal data and immediate appearance of a debriefing site after placing an order), our project was not approved by Masaryk University's Research Ethics Committee. Therefore, the real prevalence of contract cheating remains hidden behind the above-mentioned methodological imperfections.

The most tangible and practically applicable output drawing from our research findings is a handbook for teachers, *"How to prevent contract cheating"* (Mach et al., 2022). The handbook is written in Czech and targets Czech higher education teachers and policymakers. It builds on our previously mentioned research and on previous studies exploring academic integrity issues in Czechia (Pabian, 2015), taking into account the cultural specifics of our region (Mahmud et al., 2018).

4 Generative AI & Unauthorised Content Generation

Generative AI for text has its roots in the mid-20th century, when Claude Shannon used Markov chains to develop a statistical model that counted the frequencies of n-grams. The first chatbot—ELIZA—was a rule-based system developed at MIT in 1966. Rule-based systems and statistical language models coexisted until the early 21st century, when machine learning approaches accelerated the progress (Ghaseminejad Raeini, 2025). At that time, systems could predict words from large corpora, but their outputs remained rigid and error-prone. Several turning points came in the 2010s: Vector space models (Mikolov et al., 2013), and, especially, the introduction of the attention mechanism and transformer architecture (Vaswani et al., 2017) enabled models to capture meaning across long-range context. Large language models based on the transformer architecture and trained on massive datasets began producing fluent, coherent, and contextually appropriate writing. Despite the impressive fluency of models such as GPT-2 and GPT-3, their impact was often framed as incremental or experimental, confined to specialist domains rather than everyday student practice. As a result, academic integrity frameworks, assessment design, and institutional policies continued to rely on notions of authorship, originality, and detectability that assumed a clear boundary between human and machine-produced text.

The public release of conversational system ChatGPT in November 2022 made the capabilities of LLMs widely accessible for the first time, transforming text generative AI from a niche research area into a mainstream tool and revealing its profound implications for communication, creativity, and education. Crucially, these models do not “copy” existing texts but probabilistically generate new pieces of text based on learned patterns, producing outputs that evade traditional plagiarism detection and often appear indistinguishable from competent student writing. This exposed a mismatch between long-standing academic assumptions and technological reality: the problem was no longer misuse of sources, but the collapse of reliable signals of authorship in text-based assessment. In this sense, ChatGPT formed a significant milestone towards the post-plagiarism era (Eaton, 2023), forcing academia to confront the limits of detection-based approaches and accelerating a shift toward process-oriented, dialogic, and programmatic forms of assessment that emphasise learning, judgment, and ethical responsibility over textual originality alone. Whereas contract cheating had often been overlooked or framed as a marginal problem, the existence of tools generating "original" human-like text forced universities to act.

At that time, academia urgently needed to draw a line between the ethical use of AI and academic misconduct. I significantly contributed to the policy debate by publishing the *"ENAI Recommendation on Ethical Use of AI in Education"* (Foltýnek et al., 2023), which proposes the definition of **Unauthorised content generation** as *"the production of academic work, in whole or part, for academic credit, progression or award, whether or not a payment or other favour is involved, using unapproved or undeclared human or technological assistance."* (Foltýnek et al., 2023). The Recommendation frames AI as a rapidly evolving set of tools that offer both opportunities and ethical risks for teaching, learning, and assessment. The recommendations stress transparency, appropriate acknowledgement of AI tools, human accountability for submitted work, and awareness of limitations such as bias or inaccuracy in AI outputs. They also underline the need for systematic education for both students and staff on ethical AI use, rather than relying solely on detection or prohibition approaches.

From a policy perspective, the document's importance lies in its balanced, pragmatic approach to AI in education. Rather than proposing strict bans or purely technical solutions, it calls for developing or revising national and institutional policies that clearly define acceptable and unacceptable uses of AI, with an emphasis on flexibility at the course level. This is particularly important because the ways of using AI that contribute to learning and are allowed in one course may hinder learning in other circumstances and therefore constitute cheating in another course. The recommendations caution policymakers against overreliance on AI-detection tools by highlighting the difficulty of reliably distinguishing AI-generated from human-produced content. Instead, they advocate for capacity building, clear communication of expectations, and alignment of assessment practices with learning outcomes.

Due to my involvement in the Masaryk University's working group on AI in education, the overall narrative of the ENAI Recommendation was reflected in the "Statement on the application of artificial intelligence in teaching at Masaryk University" (Masaryk University, 2023b) and in the subsequent "Recommendations on the use of artificial intelligence tools in fulfilling study requirements" (Masaryk University, 2023a). The Statement on the Application of AI establishes high-level principles for the use of AI across the university, emphasising human responsibility, transparency, and alignment with existing legal and ethical frameworks. It explicitly rejects a purely prohibitive stance and instead frames AI as a legitimate tool whose acceptability depends on purpose, context, and disclosure. This reflects the ENAI position that AI use is not inherently unethical, and that misconduct arises primarily from undeclared or unauthorised use rather than from the technology itself (Masaryk University, 2023b).

The more operational Recommendations on the Use of AI in fulfilling study requirements translate these principles into guidance for teaching, learning, and assessment. In line with ENAI, the document stresses the need for clear communication of expectations at the course level, explicit rules on when and how AI tools may be used, and systematic education of both students and teachers about ethical and responsible AI use. The recommendations encourage thoughtful assessment design, acknowledgement of AI assistance, and pedagogical reflection on learning outcomes (Masaryk University, 2023a). Both Masaryk University documents can be seen as concrete institutional implementations of ENAI's framework: they adopt its core concepts (such as transparency, accountability, and policy coherence) while embedding them within the university's quality assurance and governance structures.

4.1 Test of AI-generated Text Detectors

The paper *"Testing of Detection Tools for AI-Generated Text"* (Weber-Wulff et al., 2023) extends prior work on text-matching systems (Foltýnek, Dlabolová, et al., 2020) to the new challenge of identifying content produced by generative AI models such as ChatGPT. The study evaluates 14 detection tools (12 free web-based and 2 commercial ones) using a rigorous methodology and 54 controlled test cases. These cases included human-written texts, AI-generated texts, AI outputs edited by humans or paraphrasing tools, and human-written texts translated by a machine. The research aimed to answer whether current tools can distinguish between human and AI writing, and how translation and obfuscation affect detection. The authors conclude that none of the tested tools was both accurate and reliable enough, with most showing a strong bias toward classifying content as human-written.

Methodologically, the study's main contribution lies in the standardised evaluation framework. It introduces five-level classification scales for both human and AI-generated texts. Using several accuracy metrics (binary, semi-binary, and logarithmic), it examines both false-positive (false accusation) and false-negative (missed case) rates. Results show that overall accuracies seldom exceeded 80%—Turnitin performed best (≈ 79–81%), while most others, including free online detectors, performed inconsistently. Detection accuracy dropped sharply for machine-translated texts (~20%), manually edited AI texts (~50%), and especially for AI-paraphrased content (~75%), meaning such obfuscation easily fooled all systems.

The paper's broader contribution is mainly for academic integrity policy-makers in the era of AI writing. We emphasise that detection tools—like earlier plagiarism checkers—cannot determine authorship or intent, and their probabilistic outputs should never be used as sole evidence in misconduct cases. We call for transparent communication about tool limitations, better benchmark datasets for multilingual and obfuscated AI texts, and an institutional shift toward educational and policy responses rather than technological "arms races." In doing so, the study provides the first large-scale, systematic benchmark of AI-text detectors and sets methodological standards for evaluating emerging integrity-related technologies.

Our study directly inspired a follow-up study, *"Simple Techniques to Bypass GenAI Text Detectors: Implications for Inclusive Education"* (Perkins et al., 2024). Building on our findings that AI detectors are neither accurate nor reliable and can easily be deceived by translation or paraphrasing, Perkins et al. extended this work through systematic adversarial testing, showing that even minor edits or linguistic variations (e.g., introducing spelling errors, increasing burstiness of sentence length, paraphrasing) further undermine detector accuracy. Together, these studies helped to reframe the policy conversation—from reliance on flawed detection technologies toward a holistic integrity framework that integrates ethical AI literacy, inclusive assessment design, and cautious, transparent use of detection tools rather than punitive enforcement.

The study received significant attention from educators, researchers, and policymakers. It was the main subject of Turnitin Blog post (Rowell, 2023), and article in MIT Technology Review (Williams, 2023), and it was cited – among many others – from the Handbook on the ethics of artificial intelligence (Gunkel, 2024), University of Oxford's Centre for Teaching and Learning report (University of Oxford, 2023), or Nature Scientific Reports paper on Fabrication and errors in the bibliographic citations generated by ChatGPT (Walters & Wilder, 2023). It was also cited by Tomáš Mikolov's team in a paper explaining that reliable detection of AI-generated text is impossible (Májovský et al., 2024). The authors also note that *"solving a primarily ethical problem by technological means is, by nature, doomed to fail"*, which further underlines our call to pedagogical rather than technological solutions.

A comprehensive elaboration on the unsuitability of AI detectors in education can be found in the paper *"Heads we win, tails you lose: AI detectors in education"* (Bassett et al., 2026). The authors argue that generative AI detection tools are methodologically flawed, procedurally unfair, and conceptually incompatible with how writing is produced in the era of AI. The authors show that AI detectors rely on unverifiable probabilistic estimates and cannot be validated in real-world academic integrity cases, where the true origin of a text is unknown. Attempts to "confirm" detector results through linguistic markers, use of multiple detectors, comparisons with AI-generated exemplars, past student work, or confessions are shown to introduce confirmation bias rather than independent evidence. The authors also critique surveillance-based responses such as keystroke monitoring, hidden prompts, and revision-history analysis, arguing that these approaches undermine trust, distort student writing practices, and are increasingly easy for advanced AI systems to mimic. The paper also explains a major flaw that the AI detection systems are based on – a dichotomy between "human-written" and "AI-generated" text. In reality, contemporary academic writing is hybrid, iterative, and often produced *with* AI rather than *by* AI, making binary classification meaningless. The paper concludes that reliance on AI detectors does not safeguard academic integrity but undermines it (Bassett et al., 2026). In compliance with our study (Weber-Wulff et al., 2023), it calls for a shift toward assessment redesign, transparency about AI use, and pedagogical approaches that recognise AI as part of the learning environment rather than a problem to be policed.

4.2 Authorship Verification via Cloze Test

The problem of unauthorised content generation—whether by ghost-writers or generative AI—poses a serious challenge to current academic integrity practices. Traditional plagiarism detection technologies rely primarily on extrinsic comparison, identifying text overlaps between a suspicious document and a reference corpus. However, when the submitted text is entirely original (as in unauthorised content generation), there is no source to compare against. Intrinsic plagiarism detection and stylometric analysis can, in principle, identify authorship anomalies by analysing linguistic style. Yet these methods face two critical limitations: (1) they require an existing corpus of a person's authentic writing for comparison, which may not always be available; and (2) individual writing style evolves with time, genre, and context, making rigid modelling impractical. Furthermore, if a student consistently outsources work to the same person, stylometric methods will fail to reveal any inconsistency.

The method proposed in the paper *"Authorship Verification Using Cloze Test with Large Language Models"* (Foltýnek et al., 2025) offers a promising alternative. Instead of comparing stylistic fingerprints, it tests whether the purported author can accurately fill in cloze test items—strategically blanked words from their own text—based on contextual understanding. The hypothesis is that genuine authors recall or intuitively reconstruct their phrasing more successfully than non-authors. We have developed a method using a multilingual transformer model (mT5) to select the most discriminative words, i.e., the words which genuine authors likely guess correctly, whereas non-authors don't. If the method is used to construct a ten-item cloze test, we are able to classify authorship with 98.8% accuracy and an F1 score of 0.937. Unlike stylometric verification, this method does not require previous samples of writing and remains robust even when style changes naturally over time.

Within the project "Web Application for Authorship Verification", supported by the Technology Agency of the Czech Republic (TQ01000110), we have developed an initial method that selects the most frequent nouns, such that the mT5 model fails to fill in correctly (Kancko, 2023). Subsequent experiments then proved that the mT5 model is suitable for this task, as its suggestions match non-authors' answers the best (Polák, 2025). We have also explored a wider range of selection methods and experimented with unigrams, bigrams, and trigrams. We have also considered various parts of speech, as well as probability and position given by the mT5 language model (Hitzinger, 2025).

The drawback of the proposed approach is the necessity for in-person interaction in a supervised environment. However, it empowers educators to confirm authorship through controlled testing, minimising false accusations and preserving the pedagogical value of written assignments. The cloze-test-based AVer system could be integrated with existing academic integrity tools to provide a second-stage verification step whenever doubts about authorship arise. At the time of writing this thesis, our method is implemented in the NorValid system (recently acquired by Studiosity and currently being integrated) and is being implemented in Masaryk University's Information System and in the Theses system, which serves as the Czech national text-matching system. Another significant drawback is that our method can't provide evidence of unauthorised content generation, but merely the probability of authorship based on known probabilities of authors' and non-authors' correct answers (Foltýnek et al., 2025), and prior probability of contract cheating (Newton, 2018). In the era of writing with AI, the percentages taken from (Newton, 2018) may no longer be relevant. Therefore, we see its potential as a component of a subsequent exam rather than a part of disciplinary procedure.

5 Scientific Paper Mills

Scientific paper mills are commercial entities that produce and sell fabricated or manipulated research manuscripts for submission to scholarly journals (Abalkina & Bishop, 2023). Unlike student-oriented essay mills, which target coursework and academic assignments, paper mills operate at the level of scientific publishing and typically offer complete manuscripts, fabricated datasets, manipulated images, authorship slots on pre-written papers, and sometimes even coordinated submission strategies designed to evade editorial scrutiny. The phenomenon represents a structural threat to research integrity because it combines elements of fabrication, falsification, and misrepresentation within an industrialised production model.

The broader conceptual roots of paper mills can be traced to contract cheating, defined by Thomas Lancaster and Robert Clarke (2006) as the outsourcing of academic work to a third party. While contract cheating was initially studied in the context of student misconduct, the underlying logic—delegation of authorship under conditions of performance pressure—has extended into research environments. The rapid growth of paper mills during the 2010s (Candal-Pedreira et al., 2022) coincided with intensified "publish or perish" cultures, metric-driven evaluation systems, and the globalisation of research assessment regimes. In some national contexts, financial rewards or career advancement are directly tied to publication counts or impact factors, creating strong incentives for researchers to secure publications in indexed journals. Such systemic pressures have been identified as key drivers of questionable research practices more generally (Fanelli, 2009). Paper mills exploit these pressures by offering apparently legitimate publication outputs without the time-consuming and uncertain process of genuine research.

Operationally, paper mills tend to rely on standardised templates, recycled structures, and data fabrication techniques that can be replicated across multiple manuscripts (Cardenuto et al., 2024). Particularly in biomedical fields, investigations have uncovered repeated reuse of manipulated Western blot images, duplicated microscopy panels, and statistically implausible datasets (Bik et al., 2016).

Detection efforts increasingly rely on forensic analysis rather than textual comparison. Image forensics, metadata tracking, stylometric irregularities, and cross-journal pattern recognition have become central tools. Investigations conducted mostly by independent researchers have revealed clusters of submissions with similar structures, nonexistent author affiliations, and coordinated peer-review suggestions. Some paper mills have been shown to manipulate editorial workflows by suggesting fabricated reviewer identities or exploiting weaknesses in journal management systems (Else & Van Noorden, 2021). These practices highlight the vulnerability of decentralised peer-review infrastructures when confronted with coordinated industrialised misconduct.

Paper mills have severe consequences for the scientific community: Their publications contaminate the scientific record with fabricated findings that may be incorporated into meta-analyses, clinical guidelines, or funding decisions. Unlike plagiarism, which primarily concerns misattribution, paper mills frequently involve data fabrication, thus directly undermining the reliability of empirical knowledge. The long-term damage extends beyond individual journals to systemic trust in science.

The phenomenon must also be understood in relation to evolving technological contexts. Large language models now enable the rapid generation of scientifically plausible text that cannot be reliably distinguished from human-written content (Weber-Wulff et al., 2023). Addressing the problem, therefore, requires a multidimensional approach: reforming research evaluation frameworks, reducing publication-based performance pressures, strengthening editorial governance, and fostering cultures of responsible research conduct. Absent such reforms, the industrialisation of fabricated scientific results may continue to expand in both scale and sophistication.

6 Post-Plagiarism Era

Post-plagiarism refers to an era in human society in which advanced technologies, including artificial intelligence and neurotechnology such as brain-computer interfaces, are a normal part of life, including how we teach, learn, and interact daily (Eaton, 2023). Although we are certainly not yet there, the wide accessibility of generative artificial intelligence and a variety of available tools are rapidly disrupting teaching and learning. This disruption shifts academic integrity debates from traditional topics such as plagiarism and contract cheating to more nuanced discussions of teaching and learning, of desired learning outcomes, and of assessment methods that align with fundamental academic integrity values. According to Eaton, in the post-plagiarism era, advanced technologies such as artificial intelligence and emerging neurotechnology are so deeply embedded in knowledge creation that traditional definitions of plagiarism – focused on copying and textual ownership – are no longer sufficient. Authorship increasingly becomes hybrid and collaborative between humans and machines, making it impossible to draw clear boundaries between original and AI-assisted work (Eaton, 2023). These changes bring new challenges both to the learning process and assessment.

Several frameworks have been proposed to help educators make transparent, pedagogically grounded decisions about whether and how students may use AI in assessments. One of them is the Artificial Intelligence Assessment Scale (AIAS), which aims to shift the conversation from *"Is AI allowed?"* to *"What kind of learning is this assessment designed to support?"* (Perkins et al., 2025). The AIAS defines six levels of permitted AI use in assessment:

- **Level 1 – No AI:** AI tools are not permitted at any stage of the task. Students must complete the work entirely without AI assistance, similar to traditional closed or invigilated assessments.
- **Level 2 – AI planning:** AI may be used for background support, including general preparation activities such as brainstorming topics, clarifying concepts, or exploring ideas, but not for producing any part of the submitted work.
- **Level 3 – AI collaboration:** Students may use AI to complete the task, including idea generation, drafting, feedback and

refinement. Students are expected to critically evaluate and modify all generated content.

- **Level 4 – Full AI:** Students may use AI extensively throughout their work to achieve assessment goals. The evaluation is centred on judgment, problem-solving, and effective deployment of AI, demonstrating critical thinking skills.
- **Level 5 – AI exploration:** This level is future-facing, encouraging educators and students to design novel tasks, artefacts, or systems that extend beyond existing disciplinary and technological norms, with learning demonstrated through innovation, evaluative judgement, and critical AI literacy.

The way AIAS is designed clearly shows that—except for the Level 1 (No AI) —the emphasis shifts away from detection and punishment toward ethical responsibility, transparency, and integrity in how tools are used. AI is an integral part of learners' toolkit, and therefore learning should be designed to enable ethical and transparent human-AI collaboration rather than attempting to prohibit it. Instead of asking whether work is plagiarised or created by AI, the post-plagiarism era centres on broader, transdisciplinary questions of ethics, accountability, and fairness in technologically mediated learning (Eaton, 2023).

6.1 Assessment Redesign

It is clear that some traditional assessment methods, such as written assignments or take-home exams, require thorough redesign. Some authors propose reimagining **oral examinations** as a powerful and underutilised assessment method for the AI era, because live, unscripted dialogue makes it far harder for students to rely on AI-generated content without genuine understanding. Oral exams enable educators to probe students' reasoning in real time, assess deeper conceptual understanding, and evaluate critical thinking and adaptability rather than surface-level recall (Eachempati et al., 2025). While acknowledging challenges such as subjectivity, student anxiety, and scalability in large cohorts, the authors argue these can be mitigated through clear rubrics, examiner training, supportive practices, and selective use of technology (including AI-assisted question generation and virtual oral exams).

Another opportunity to address the challenges of the post-plagiarism era is **programmatic assessment**, which reframes assessment as a longitudinal, evidence-based process instead of a single moment of judgment. It replaces reliance on high-stakes, one-off assessments – those most vulnerable to AI misuse – with the continuous collection of multiple low-stakes data points across a programme, combined with rich feedback, reflection, and mentoring. Because student learning is evidenced over time through diverse activities (e.g., drafts, presentations, observations, reflective writing, oral exams, peer feedback), no single artefact needs to "prove" authorship. Instead, integrity is established through coherence, progression, and consistency across evidence. Therefore, plagiarism or undisclosed AI use is both less attractive and less consequential (Carter et al., 2025).

The third option, which is often considered cheat-proof, is authentic assessment. **Authentic assessment** is commonly defined as an assessment that engages students in real-world, complex, and professionally meaningful tasks, often emphasising fidelity to workplace practice, higher-order thinking, and opportunities for reflection and feed-forward, and it is widely promoted as a promising alternative to traditional exams and essays (Gulikers et al., 2004). As Fawns et al. argue, this promise is attractive: authentic assessment appears better aligned with learning for uncertain futures and is often assumed to increase engagement while simultaneously "designing out" cheating (Fawns et al., 2025). However, these hopes are overstated and empirically unsupported. Drawing on large datasets of contract-cheating orders and detected breaches, Ellis et al. show that assessments with low, medium, and high levels of authenticity are all routinely outsourced, directly contradicting the claim that authenticity assures academic integrity (Ellis et al., 2019). Fawns et al. extend this critique, arguing that treating authenticity as a panacea risks complacency, masks trade-offs, and obscures other problems: authentic tasks can increase cognitive and logistical burden, reproduce inequitable professional norms, create new accessibility barriers, and even increase incentives to cheat when tasks are complex and high-stakes. Therefore, even though authentic assessment can be pedagogically valuable, it neither eliminates cheating nor avoids significant design challenges, and must therefore be approached critically.

6.2 Beyond Detection: IT for the Post-Plagiarism Era

The assessment redesign described earlier also requires new approaches and technological support tools to safeguard assessment security and academic integrity. The landscape of the software tools for academic integrity is currently very diverse and changing rapidly. The features these tools offer, as well as educators' and policymakers' expectations, are the focus of my current research. So far, it seems that we will be able to identify three broad categories of tools:

- **Process-based tools** tracking the writing process and collecting metadata on how the resulting text has been developed;
- Tools supporting **verification of learning outcomes** achievement, providing educators with support in consultations or oral exams based on submitted work;
- Tools calculating various **stylometric features**, which can provide some indication of authorship or the use of LLMs during the writing process.

The process-based approach has its roots in earlier attempts to detect plagiarism or contract cheating by looking beyond the text itself, treating student submissions as digital artefacts that contain rich forensic evidence in their underlying structure and metadata. Drawing on established forensic methods – such as metadata analysis (notably the XML structure of Word files) – it is possible to use features like revision histories, editing patterns, cropped images, hidden text, and anomalous creation timestamps to flag potential misconduct (Johnson et al., 2022). Trackers that monitor each keystroke, edits, pasting larger portions of the text, and other modifications, are already available (e.g., Turnitin Clarity[6] or Cadmus[7]). Nonetheless, we can already identify at least two significant drawbacks of this approach. The use of such tools raises serious concerns about students' privacy and well-being. Students' distress at being constantly watched may negatively affect their performance. Moreover, we can reasonably expect that if universities start relying on such tools on a large scale, students will soon begin using tools that emulate the human writing process, such as OpenAI's Operator[8].

[6] https://www.turnitin.com/products/feedback-studio/clarity

[7] https://cadmus.io/news/academic-integrity-with-cadmus/

[8] https://openai.com/index/introducing-operator/

An example of a software tool that combines verification of learning outcomes and stylometry is Auth+. This tool quizzes students on the content, style, and wording of their own assignments, serving as a scalable alternative to viva voce for addressing contract cheating. Quesnel and Stoesz (2025) conducted an empirical study to investigate whether quizzing students on their submitted work can both promote learning and serve as a valid indicator of authorship. Their results show that while students generally found Auth+ easy to use and believed it could deter cheating, they also reported increased anxiety and limited perceived learning benefit. Crucially, Auth+ scores were not correlated with other indicators of contract cheating or with grades, but were significantly related to working memory capacity, suggesting that quiz performance reflects cognitive factors unrelated to authorship. The findings raise concerns about the validity of quizzing-based authorship verification as a detection mechanism, particularly given that students who outsourced or AI-generated their work could still perform well on the quizzes (Quesnel & Stoesz, 2025). The takeaways from this study are twofold. First, the construction of quizzes designed to distinguish authors from non-authors should be evidence-based, and second, such tools should not be used as standalone detection tools but incorporated into multifaceted approaches that support ethical assessment design in the post-plagiarism era.

7 Conclusion and Future Work

This thesis, based on the research evidence, shows that technological tools are inherently imperfect. Similarity detection does not equal plagiarism detection; AI-generation scores do not constitute proof of authorship; automated classifications are probabilistic rather than evidential. For this reason, human-in-the-loop is not an optional, nice-to-have component but a structural necessity. Interpretation, contextual judgment, and procedural fairness cannot be delegated to software systems. Technologies do mitigate ethical risks, but they do not eradicate them. Ethical problems in academia, by their nature, resist purely technological solutions. Nevertheless, information technologies deployed in the context of academic integrity do not need to be perfect to be valuable. Their mere existence already produces measurable positive effects. Detection systems, verification tools, and integrity-supporting infrastructures alter behavioural incentives, reduce opportunities for misconduct, and act as deterrents for most students (Curtis & Vardanega, 2016; Owens & White, 2013). Equally important, they help preserve institutional trust, which remains the foundational condition for both education and science.

These insights become even more critical when moving from the educational domain to the research domain. The mechanisms of misconduct are strikingly similar: contract cheating mirrors paper mills; ghostwriting parallels fabricated authorship; AI-assisted assignment production resembles AI-fabricated research. Nevertheless, the consequences differ dramatically. While student misconduct primarily threatens assessment validity, research misconduct contaminates the scientific record, distorts knowledge accumulation, misleads policy, and erodes public trust in science (Else & Van Noorden, 2021). The technological aspects of detection and verification remain largely comparable across contexts, but the societal impact of research misconduct is substantially more severe.

The recent emergence of generative AI has fundamentally changed the landscape. There is no longer meaningful space for a technological arms race to outpace AI capabilities (Perkins et al., 2024; Weber-Wulff et al., 2023). AI systems are already capable of generating, transforming, and imitating nearly any form of output. Attempts to design tasks that AI cannot handle are therefore strategically misguided (Májovský et al., 2024). Similarly, reliance on detectors of AI-generated text is both methodologically fragile and conceptually unsound (Bassett et al., 2026). Detection technologies cannot reliably distinguish human from AI-assisted production, particularly in hybrid writing environments. The pursuit of purely technical countermeasures risks creating false confidence while missing underlying educational and ethical challenges.

Consequently, the path forward lies not in developing detection mechanisms but in pedagogical and institutional adaptation. Academic integrity must increasingly be safeguarded through assessment redesign, process-oriented evaluation, verification of learning outcomes, and cultivation of the academic environment. Technologies retain an important supportive role, but they cannot substitute for educational strategies.

Experience exchange and international cooperation emerge as crucial stabilising factors (Foltýnek & Glendinning, 2024). The research projects and network initiatives discussed in this thesis repeatedly show that institutions benefit most when practices, failures, and solutions are shared across disciplinary and national boundaries. Academic integrity challenges are global, technologically mediated, and rapidly evolving; isolated responses are insufficient. Protecting academic integrity is therefore not merely an extension of common academic activities but an essential condition for preserving the credibility of education and science.

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Collection of Articles

Article A: Foltýnek, T., & Králíková, V. (2018). Analysis of the contract cheating market in Czechia. *International Journal for Educational Integrity*, *14*(1), 4. https://doi.org/10.1007/s40979-018-0027-8

Article B: Mahmud, S., Bretag, T., & Foltýnek, T. (2018). Students' Perceptions of Plagiarism Policy in Higher Education: A Comparison of the United Kingdom, Czechia, Poland and Romania. *Journal of Academic Ethics*. https://doi.org/10.1007/s10805-018-9319-0

Article C: Foltýnek, T., Meuschke, N., & Gipp, B. (2019). Academic Plagiarism Detection: A Systematic Literature Review. *ACM Comput. Surv.*, *52*(6), 112:1--112:42. https://doi.org/10.1145/3345317

Article D: Foltýnek, T., Dlabolová, D., Anohina-Naumeca, A., Razı, S., Kravjar, J., Kamzola, L., Guerrero-Dib, J., Çelik, Ö., & Weber-Wulff, D. (2020). Testing of support tools for plagiarism detection. *International Journal of Educational Technology in Higher Education*, *17*(1), 46. https://doi.org/10.1186/s41239-020-00192-4

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Article G: Wahle, J. P., Ruas, T., Foltýnek, T., Meuschke, N., & Gipp, B. (2022, February). Identifying Machine-Paraphrased Plagiarism. *Proceedings of the iConference*. https://doi.org/10.1007/978-3-030-96957-8_34

Article H: Foltýnek, T., Bjelobaba, S., Glendinning, I., Khan, Z. R., Santos, R., Pavletić, P., & Kravjar, J. (2023). ENAI Recommendations on the ethical use of Artificial Intelligence in Education. *International Journal for Educational Integrity*, *19*(1), 12. https://doi.org/10.1007/s40979-023-00133-4

Article I: 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*(1), 26. https://doi.org/10.1007/s40979-023-00146-z

Article J: Foltýnek, T., Kancko, T., & Rychlý, P. (2025). Authorship Verification Using Cloze Test with Large Language Models. *Proceedings of the 15th International Conference on Recent Advances in Natural Language Processing - Natural Language Processing in the Generative AI Era*, 369–377. https://aclanthology.org/2025.ranlp-1.45