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# TOWARD AI-ENABLED INSTITUTIONAL REPORTING: A CONCEPTUAL PROPOSAL WITH A CROATIAN HEI CASE STUDY

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***Abstract:*** *: The aim of this paper is to assess the possibilities and limitations of applying AI—huge language models (LLMs) and retrieval-augmented generation (RAG)—to support the preparation of institutional quality and performance reports. The study explores the key challenges of current reporting practices and assesses the potential of AI to enhance the quality, efficiency, and usefulness of reporting in higher education.*
*The methodology is based on a scoping literature review covering quality assurance in higher education, stakeholder information needs, institutional quality and performance reporting, and the use of LLMs and related AI technologies in reporting processes. A case study of a Croatian higher education institution was used to analyse stakeholder information requirements, types of existing reports, data sources and databases, reporting frequency, and the main limitations of current reporting practices. The findings show that stakeholders' needs differ significantly, requiring a range of report formats (e.g., KPIs, plans, self-assessment reports, survey results). Additionally, data sources are fragmented and dispersed across multiple systems, making data collection and analysis difficult and increasing the subjectivity of result interpretation.*
*Based on these findings, the paper proposes a conceptual model that links specific business and reporting challenges with potential AI-based solutions. The results suggest that AI can streamline and accelerate report preparation, while tailoring outputs to diverse stakeholder groups. However, due to institutional diversity, a universal "one-size-fits-all" solution is unlikely. Instead, institutions should conduct pilot projects using real documentation enriched with metadata and AI models adapted to the Croatian language and institutional context.*
*Following implementation, it will be necessary to critically evaluate the accuracy of AI-generated outputs, assess the ability to link conclusions with supporting evidence, and identify any unintended consequences.*

***Keywords:*** *Higher education, Quality assurance, Institutional reporting, Large Language Models, RAG*

***JEL classification:*** *I21, I23, C83, C88, O33*

## INTRODUCTION

Business organisations today face an increasing need for data analytics, business reporting, and evidence-based decision-making. In some cases, data analysis for reporting purposes must be carried out in real time, which presents a significant organisational and human resources challenge. Higher education institutions (HEIs) require efficient management and transparency, which is further emphasised by international and national standards and regulatory requirements. Stakeholder information needs differ considerably, and with limited staff resources, data analysis and report preparation represent a challenge. Additional issues arise from the fragmentation and incomplete datasets, the use of multiple databases, the large amount of manual processing, and the subjectivity in information interpretation. Given that increasingly available artificial intelligence (AI) tools can automate specific processes and contribute to faster, simpler, and more efficient reporting, the motivation for this study emerged. AI applications are gradually entering a developmental phase mature enough to allow for experimentation with their implementation in HEI reporting. Therefore, this research aims to evaluate the opportunities and limitations of its use for institutional quality and performance reporting. Based on the identified issues and research aim, the following research questions were formulated:

RQ1: What challenges are faced by individuals responsible for quality and performance reporting in HEIs, and what are the shortcomings of existing reports?

RQ2: What are the potential applications of AI in improving institutional reporting on quality and performance in higher education?

To address the research questions, the study employed the scoping literature review method to explore the main theoretical and practical approaches and to establish a foundation for developing a conceptual model of an AI-supported reporting system. Furthermore, institutional documents and reports from one HEI in the Republic of Croatia were analysed as a case study to identify challenges, practices, and potential opportunities for applying AI in quality and performance reporting.

The paper is structured into five chapters. The introductory section outlines the study's problems, motivation, and objectives, as well as the research questions related to quality reporting and AI applications. The second chapter provides an extensive review of relevant literature concerning quality assurance (QA) in higher education, stakeholders and their information needs, digital transformation and communication with stakeholders, as well as generative AI, RAG, and the evolution of reporting systems. The third chapter presents the applied methodology, which includes a literature review and a case study. The fourth chapter discusses the results of the institutional report analysis, together with a proposed conceptual model for intelligent reporting. The conclusion highlights contributions, limitations, and directions for future research.

## LITERATURE OVERVIEW

### Context and definitions of quality assurance

Globalisation, technological changes, and the growing demand for accountability and transparency in delivering quality education influence the continuous development of higher education institutions (HEIs) (Pramono & Widiyanto, 2024). QA plays a key role in this process. QA in higher education is a complex process aimed at ensuring that HEIs meet educational standards while continuously improving and acting responsibly in line with the expectations of students, staff, and society.

The concept of QA encompasses all internal and external activities aimed at maintaining and enhancing educational standards within an institution (Jafarov, 2024). To ensure quality management and confirm institutional legitimacy, HEIs develop an Internal Quality Assurance System (IQAS). IQAS can be described as the way HEIs organise their operations based on processes, planning, documentation, and resources used to achieve their mission and goals, while fostering the continuous improvement of the services they provide (Senal et al., 2008). Responsibility for the development of IQAS lies with the institutions themselves, namely, their management. External QA monitors the compliance of educational practices and programs with established standards (Westerheijden et al., 2007). It is carried out through accreditation, a formal process in which an external body evaluates the extent to which an institution or a specific program meets established standards. Institutions that systematically develop and document their IQAS can demonstrate compliance with standards more effectively. Therefore, a well-structured IQAS plays a crucial role in monitoring institutional processes and preparing for accreditation procedures (Budimir, 2020).

### European and National Framework for Quality Assurance in Higher Education

The orientation toward quality standards and accountability in European higher education has deep historical roots (Charles, 2007). However, the development of policies related to QA and their systematic implementation in the European Higher Education Area (EHEA) began at the end of the 20th century. National governments perceived QAS as a tool for increasing management efficiency, establishing trust between authorities and HEIs, and strengthening the connection between higher education and the labour market (Westerheijden et al., 2007). The recognition of higher education as a driver of economic growth and national progress led to the establishment of accreditation bodies, quality assurance agencies, and evaluation systems designed to monitor and enhance the effectiveness of HEIs (Kayyali, 2024)

Cooperation among European countries in the field of QA began with the European Association of Universities' initiative to introduce the Institutional Evaluation Program in 1993. The European Council of Ministers endorsed it, and a pilot project for quality evaluation in higher education was implemented in 17 countries between 1994 and 1995 (Yeremenko, 2018). The cooperation continued, and based on the Bologna Declaration, the European Council set the objective in 2002 of achieving recognition of the quality of education systems by 2010, as well as measuring progress toward the goals in relation to the "Reference Levels of European Average Performance" or "European Benchmarks" (Reinalda, 2008).

To ensure a unified framework and standards for QA activities within the EHEA, the Standards and Guidelines for Quality Assurance in the European Higher Education Area (ESG) (European Association for Quality Assurance in Higher Education (ENQA), 2005) were established, soon becoming the cornerstone for promoting quality in the EHEA (Zhang et al., 2019). The introduction of ESG 2005 marked the first formal definition of common internal and external QA standards in the EHEA. ESG fostered the development of IQAS and introduced requirements for systematic reporting, the use of indicators, and stakeholder involvement, thus laying the foundation for today's institutional quality reporting. The 2015 revision of the ESG emphasised transparency and accountability to stakeholders (European Association for Quality Assurance in Higher Education (ENQA), 2015). Reporting systems must be consistent and evidence-based, with reports made accessible to different stakeholders. Particular importance is therefore given to stakeholder feedback, information from student surveys, and key performance indicators (KPIs).

Among the main objectives of QAS is the provision of relevant and reliable information on the functioning of higher education, recorded outcomes, and potential for improvement (Gh Rosca et al., 2008).KPIs are recognised as essential instruments for monitoring institutional goal achievement, benchmarking with other institutions, and making evidence-based decisions. They enable the quantification of the effects of educational and managerial processes through specific metrics that can be monitored over time and assessed in relation to strategic goals (Javed & Alenezi, 2023). Udam & Heidmets (2013) propose a classification of KPIs into three main categories: inputs (resources) such as staff–student ratio, funding (per student), facilities (per student); process (interaction) such as study load, student support, student feedback on course delivery, alumni feedback; and outputs (results) such as time to degree and employment rates. These indicators play an important role in strategic planning and reporting in accordance with ESG requirements, as well as in self-evaluation, external quality assurance, and accreditation processes. However, many authors emphasise that qualitative interpretations should complement quantitative indicators to avoid misleading or overly simplified conclusions (Hou et al., 2024; Mourad, 2013).

After the establishment of a common European framework for QA through the ESG, the EHEA member states committed to implementing it within their national systems. The Republic of Croatia introduced the Act on Quality Assurance in Science and Higher Education (Government of the Republic of Croatia, 2009) and its revised version from 2022 (Government of the Republic of Croatia, 2022). Under this Act, HEIs are required to establish, develop, and regularly evaluate their IQAS. Institutional reporting plays a key role in this process, encompassing the regular preparation of reports on quality and performance, as well as the implementation of strategic and other planning documents. The purpose of such reports is multifaceted. In addition to enabling management to make evidence-based decisions and effectively govern the operations of HEIs, their role is also to provide transparent information to internal and external stakeholders. The importance of these reports is particularly evident in external quality evaluation processes, especially accreditation.

As previously noted, the roots of QA lie in the establishment of accreditation bodies and the evaluation of quality. A culture of evaluation through internal and external quality reviews (audit, accreditation, assessment, external examination) (Hou et al., 2024) is now well established worldwide. Accreditation represents a mechanism of external QA in which an authorised body evaluates the extent to which an institution or a specific program meets established educational standards (Jafarov, 2024). In organising their operations, HEIs today pay close attention to meeting national standards (Zadayeva et al., 2024) while in pursuit of stronger international positioning, some HEIs also undergo accreditation processes conducted by international accreditation agencies and ranking providers (Mourad, 2013).In the contemporary academic environment, accreditation represents a crucial process through which HEIs maintain their reputation and ensure the provision of quality education for students.

To strengthen trust in the higher education system and ensure independent quality evaluation, accreditation agencies are most often established at the national level. Their tasks include developing standards and evaluation methodologies, organising and implementing evaluation procedures, and ensuring transparency and credibility. An example of such an agency is the Croatian Agency for Science and Higher Education (ASHE). Based on ESG standards and in consultation with relevant stakeholders, ASHE developed the Quality Standards in Higher Education and Scientific Activity, as well as other documents used in external quality evaluation procedures (Agency for Science and Higher Education, 2023; Government of the Republic of Croatia, 2022). In external QA procedures, particularly accreditation, HEIs are required to prepare and submit a comprehensive self-evaluation Westerheijden et al., 2007). A self-evaluation report typically involves an institution's evaluation against the standards and indicators defined by quality assurance agencies. It is based on both quantitative and qualitative indicators and must be evidence-based, with institutional reports playing a key role. Beyond serving as the foundation for critical evaluation by external reviewers, the self-evaluation also provides institutions with internal reflection on their own processes, outcomes, and strategies, offering opportunities for organisational learning and development (Hou et al., 2024; Westerheijden et al., 2007)

## Stakeholder Information Needs

Effective reporting on quality and performance is shaped mainly by the requirements of stakeholders, the users of reports (Armijos et al., 2024; Bach et al., 2014; Beerkens & Udam, 2017; Lyytinen et al., 2017; Saurbier, 2021; Westerheijden et al., 2013). Stakeholders in the higher education system are typically divided into internal and external groups, and their interests influence the content, format, and purpose of institutional reports (Elken & Stensaker, 2018; Hou et al., 2024).

Internal stakeholders include the institution's management structures (e.g., deans, vice-deans, department heads), academic staff, administrative staff, and students. Their information needs are oriented toward strategic decision-making, operational management of teaching, monitoring learning outcomes, as well as participation in self-evaluation and quality enhancement processes (Westerheijden et al., 2013). Students are becoming increasingly important users of quality-related information, which they use to evaluate the value of study programs, employability, available support, and opportunities for personal and professional development (Saurbier, 2021). Their perception of quality also includes informal aspects, such as the study experience and sense of belonging to the community (Pramono & Widiyanto, 2024)

External stakeholders encompass a diverse range of actors, including public authorities and regulatory agencies, funding bodies for higher education, employers, the business sector, alumni communities, media, local and regional governments, and the general public (Elken & Stensaker, 2018; Zhang et al., 2019). This group expects reliable, comparable, and timely information that supports evidence-based policy-making, informs the allocation of financial resources, facilitates the assessment of how well educational provision aligns with labour market needs, and ensures the quality of both qualifications and institutions (Jafarov, 2024; Mourad, 2013). Regulatory agencies, for instance, expect structured reporting in accordance with predefined quality standards, evidence-based and supported by measurable indicators, including a comprehensive self-evaluation as a key element of evaluation (European Association for Quality Assurance in Higher Education (ENQA), 2015). The emphasis is placed on process transparency, stakeholder involvement, and public accessibility of reports. The general public, on the other hand, expects clear, concise, and understandable information that provides insight into the institution's work, its mission, social responsibility, and educational outcomes. Employers expect the QAS to guarantee graduates' competencies and the relevance of curricula to labour market needs, as well as data that allow inter-institutional comparison (benchmarking), thereby fostering competitiveness and institutional accountability (Kayyali, 2024). Ensuring the transparency, credibility, and accessibility of reports thus becomes an essential requirement for building stakeholder trust and ensuring the functionality of the entire quality assurance system (Hou et al., 2024).

### Data Sources, Challenges, and the Need for Integration

QA processes, as well as the need for strategic management and transparency toward stakeholders, rely on a complex set of information concerning students, resources, teaching processes, research activities, industry cooperation, the achievement of strategic goals, and compliance with quality standards. This information is collected through various methods (e.g., surveys, internal reports), provided by different actors (e.g., students, staff, alumni, employers, scientific and professional organisations, local communities), stored in diverse formats (e.g., Excel, Word, PDF), and maintained within different information systems. All collected information is processed and used to prepare quality and performance reports.

Given the evident heterogeneity of stakeholders in the higher education system, quality and performance reporting must address the highly diverse information needs of these stakeholders. Regulatory bodies require structured, detailed, and comparable reports that include standards, key indicators, and supporting evidence; institutional management expects quantitative indicators, charts, and trend interpretations for strategic decision-making; students seek concise and accessible information about study quality, teaching, and employability; while the general public and external stakeholders prefer narrative, straightforward, and easily understandable presentations that confirm the institution's legitimacy and social responsibility.

To meet the diverse information needs of stakeholders, it is necessary to collect and process data from various sources, including student and teacher surveys, databases, strategic and financial documents, reports from internal and external evaluations, and stakeholder feedback. The lack of uniform formats, multiple data owners, reliance on manual data entry, and the absence of automated tools further complicate the consolidation of this information into comprehensive and analytically meaningful reports. So-called “data silos” represent a problem in all business organisations. Patel (2019) provides a valuable overview of the challenges associated with structured and unstructured data, as well as the financial consequences of insufficiently integrated systems. Javed & Alenezi (2023) also emphasise that QAS must be integrated at the level of the entire institution (rather than “data silos”) and that processes must be interconnected, with standardisation and automation established before the implementation of analytics.

Pramono & Widiyanto (2024) analysed 2,578 articles published in the Scopus database between 2013 and 2023 on QA in higher education. They identified four developmental areas (clusters) of quality in higher education: (1) institutional and policy frameworks, (2) student perceptions, satisfaction, and service quality, (3) accreditation processes, and (4) leadership engagement. Although each of these clusters encompasses specific aspects of QAS, they share a reliance on diverse data sources and the need for integrated analysis within institutional reports.

In light of these challenges, there is a growing demand for the application of new technologies in reporting. As a logical step, the use of AI and digital tools is emerging, facilitating data processing, pattern recognition, and the creation of structured, evidence-based reports.

### Digital Transformation and Communication with Stakeholders

From the above, it is clear that HEIs collect and generate large amounts of information, which they then store, analyse, systematise, and use for reporting or publishing through various media such as websites, social networks, or newspaper articles. When preparing and publishing such information, it is essential to consider the target audience, as texts and materials are tailored differently when intended for accreditation bodies and the relevant ministry compared to when they are aimed at students or industry professionals. Similarly, materials are prepared differently depending on the format—whether intended for print or for online and social media publication.

According to Tiron-Tudor et al. (2022) the reporting of public HEIs is shaped by various factors such as regulatory requirements, stakeholder profiles, and institutional objectives. These factors determine how information is collected, structured, and presented, which aligns with the need to adapt content to different audiences and formats.

The study by Fernández et al., (2023) examines the analytical methods used in higher education institutions and their digital transformation. The authors note that the introduction of new processes most often relies on advanced analytics (23%), cloud technologies (20%), and AI (16%), yet only 25% of institutions have adopted a digital strategy. Notably, more than half (56%) of the institutions studied had launched isolated projects that were not integrated into a unified plan, indicating that many HEIs manage information in a fragmented way and without clear direction. Therefore, a strategic, targeted, and format-adjusted approach to preparing and disseminating information is essential.

### Generative AI, RAG and the evolution of reporting systems

At the time of writing, generative AI tools for text creation have become widespread. ChatGPT, Grok, DeepSeek, Perplexity, and a range of similar tools are available free of charge (with certain limitations) to a broad base of potential users. Until recently, such systems did not exist, and the turning point was the concept of "foundation models," systematically described by Bommasani et al. (2022). These are large language models trained on extensive datasets and then fine-tuned for various tasks across different domains. This created, for the first time, opportunities to build systems capable of addressing problems across multiple domains while integrating previously disconnected systems. In short, the shift from "narrow" models—focused on specific tasks—to "general" models created the technological and organisational conditions for the widespread availability of today's generative tools. At the same time, this raised a series of questions concerning risks and safety, access to computational resources, and broader social impacts, which the authors clearly emphasise (Bommasani et al., 2022).

A hallmark of such "general" LLMs is their versatility and broad knowledge across domains, making them comparable to encyclopedias of global expertise. With the release of ChatGPT at the end of 2022, as one of the first user-friendly applications powered by LLMs, there was an "explosion" of capabilities that users worldwide quickly embraced. Although earlier versions of OpenAI's GPT were already available, they required Python programming, libraries such as Hugging Face Transformers, and substantial technical know-how. According to ChatGPT Usage Statistics: Numbers behind Its Worldwide Growth and Reach (2025), the service reached 1 million users within five days of its launch, surpassed 100 million users after two months, and is currently estimated to have around 800 million users. This represents one of the fastest-growing user bases among online services; for comparison, Facebook took more than seven years to reach 800 million users (ChatGPT Usage Statistics, 2025).

While highly effective for general research and text production, such general LLMs have limited applicability because they cannot deeply analyse an organisation's internal documents and specific data sources, which significantly constrains business use. This led to the development of Retrieval-Augmented Generation (RAG), which combines the generative capabilities of LLMs with access to external knowledge bases (Lewis et al., 2020). Instead of relying solely on training data, RAG enables the retrieval and use of information from an institution's own documents or databases. The technical backbone is vector databases, which enable semantic search over documents and their vector representations. Semantic search goes beyond literal keyword matching to "understand" the meaning of queries and documents, linking them by concepts and context. This reduces hallucinations, improves accuracy, and allows institutions—including HEIs—to use their own data effectively in combination with LLMs. Moving from concept to practice, Iusztin et al. (2024) propose an operational architecture (FTI) and implementation patterns (vector storage, retrievers, evaluation), making RAG repeatable and measurable in production (Iusztin et al., 2024; Lewis et al., 2020).

In just a few years—from 2021, when modern generative AI tools were practically non-existent, to today—technological progress has enabled numerous possibilities, including concepts such as GenAISys platforms. In his work, Tomczak (2024) introduces the term GenAISys to describe new and complex platforms. He argues that classical large models alone cannot solve today's business problems because they lack modularity, integration with other systems, and additional encoders and modules for data storage and retrieval. In the GenAISys model (Rothman, 2025; Tomczak, 2024) the LLM is only one component of a larger AI system. GenAISys platforms use natural language as the main interface, add modality-specific encoders for input/output processing, and extend capabilities with tools (e.g., calculators, route planners) and knowledge sources that communicate via RAG modules for retrieval and storage (Bourne & Es, 2024; Rothman, 2025; Tomczak, 2024).

This concept provides sufficient capabilities to build business reporting systems applicable across sectors, including HEIs (Bourne & Es, 2024; Rothman, 2025; Tomczak, 2024). It is also notable that a growing number of studies on the application of various forms of AI in the field of R&D are being conducted by domestic authors. Papers exploring the possibilities of automation based on technologies that were previously unavailable are becoming increasingly common, whether in the hospitality, telecommunications, or banking industries (Lovrinčević et al., 2025; Nikolić & Sredojević, 2025).

## METHODOLOGY

For the purposes of defining the theoretical framework of the research, a scoping review of relevant scientific literature was conducted on QA in higher education, the information needs of stakeholders, institutional reporting on quality and performance, and the application of large language models and AI-related technologies in reporting systems. According to Munn et al. (2018), a scoping literature review is used when the aim is to broadly map the field of literature, clarify concepts, and identify gaps in knowledge (research gaps). Since this study focuses on the application of large language models in QAS and institutional reporting—a field that has gained importance only recently due to the availability of AI technologies and related services—it is expected that the scientific literature still contains a limited number of works on this topic.

To cover the development of the system and the normative framework of reporting, papers, guidelines, and regulations published between 2005 (the establishment of ESG) and the present were included. To gain deeper insight into institutional practices, challenges, and limitations in quality and performance reporting, content analysis was applied through a case study. For this purpose, the institutional quality reporting system of one faculty in Croatia was analysed. The analysis included strategic documents, quality and performance reports, accreditation documentation, as well as internal databases and data sources used in the preparation of reports. This enabled the mapping of key reporting patterns of the HEI (Faculty).

In the first step, the categories of users, purposes of using reports, basic types of reports, types of information and data sources, frequency and method of report creation, content (i.e., the key information provided), as well as the challenges and shortcomings of each report were identified. Based on this mapping, the challenges and weaknesses of existing reports were summarised to identify priority areas suitable for applying AI technologies and large language models.

In the second step, the informational requirements and heterogeneity of existing databases/documents that need to be integrated for timely and reliable reporting were analysed. The scoping literature review also encompassed recent works on AI and advanced analytics in education and other sectors, exploring their potential applications in developing a more efficient and automated reporting system for quality and performance in higher education. Considering the identified requirements, the following

AI technologies were reviewed and conceptually considered: large language models (LLM), retrieval-augmented generation (RAG) with vector databases, and orchestration/agent workflow solutions (MCP). Their role was seen as a prerequisite for establishing an institutional AI server for business intelligence and reporting, as outlined in faculty documents.

Unlike previous studies, which address specific aspects of QAS or the application of AI technologies in other domains, this study connects the needs of different stakeholders with the possibilities of automating reporting using AI tools. Through the literature review, analysis of a real institutional environment (one HEI in the Republic of Croatia), and exploration of AI technologies (LLM, RAG, MCP), a framework was developed to identify areas where the reporting process can be improved. This creates opportunities for AI solutions tailored to the complex requirements and reporting practices in higher education.

## RESULTS AND DISCUSSION

### Challenges and Shortcomings of Quality and Performance Reporting

The analysis has shown that users' information needs vary significantly depending on their specific requirements. Internal decision-makers (management, heads of departments, teachers, quality committees, etc.) use reports for strategic and operational management, curriculum planning, and the improvement of teaching and student support. They require structured indicators, variance analyses, survey results, and trend data. External regulators (agencies, ministries) rely on reports for accreditation and supervision, where compliance with standards (through self-evaluation) and the precise documentation of indicators, quality reports, and improvement plans are essential. Students (both prospective and enrolled) need information that helps them make informed study choices, including employability, pass rates, teaching quality, and available support. External stakeholders (the public, media, alumni, employers, and the local and regional community) use reports to assess social responsibility, partnerships, employability, and the quality of education. For them, data on graduate profiles, industry connections, and community contributions are especially relevant. Although overlaps exist, they are not evenly distributed, which results in different reports being produced for different user groups.

The following reports on Faculty quality and performance were identified:

- Report on implemented improvement measures in accordance with the Quality Assurance Activity Plan
- Reports on the implementation of strategic action plans
- Report on key performance indicators
- Report on survey findings and performance outcomes
- Report on the implementation of stakeholder recommendations
- Dean's report on strategy implementation and operations
- Follow-up report on the implementation of the Quality Assurance Action Plan — internal audit
- Self-evaluation report
- Report on the implementation of the Quality Assurance Activity Plan in the follow-up phase – reaccreditation

In addition to these, quality and performance information is also prepared and submitted as needed, including reports on the implementation of the university strategy, program contract implementations, study program elaborations, and various web and social media publications.

The results of the analysis indicate that reports are produced in annual cycles (ranging from 1 to 5 years) and are manually created in Word and/or Excel format. Considering the different information needs of stakeholders and the dynamics of reporting, it is necessary to continuously collect data from various sources (Higher Education Information System – ISVU, Croatian Research Information System – CroRIS, internal information systems, internal reports, internal records, surveys, evaluations, databases, the Faculty's website, various plans and documentation of internal committees). Discrepancies between these documents, duplication of work, and the risk of human error are evident. This results in a significant amount of time needed for preparing and verifying information.

Content analysis reveals that most reports contain a mix of descriptive, quantitative, and qualitative information. The following challenges and shortcomings were identified:

- Fragmented and misaligned data sources (ISVU, CroRIS, internal systems, internal documentation, etc.), different storage formats (Word, Excel, PDF, web, e-mail)
- Manual integration, verification, and subjectivity in assessment (depending on the person producing the reports)
- Lack of standardised templates for narrative interpretation of KPIs and variances
- Limited linkage to evidence and sources
- Poor searchability and lack of thematic filtering (e.g., by ESG, program, year)
- Limited data visualisation, status flags, and trend analysis
- Limited possibility of comparison over time and across different reports
- Weak alignment of reported results with goals, plans, and standards
- Reports are often voluminous (sometimes exceeding 100 pages), which makes them difficult to review and understand, as well as inadequate for decision-making

It is concluded that reporting on quality and performance in higher education suffers from dispersed data sources, manual processing, lack of clarity, and the use of unconnected digital solutions (platforms). This naturally increases the workload of staff, slows down decision-making, and complicates communication with stakeholders.

### AI approaches, limitations, and implementation issues

As highlighted in the literature review, AI can support the automation of data processing, natural language analysis, and report generation, thereby accelerating processes, improving accuracy, and enabling the adaptation of reports to different users. Table 1 provides an overview of the main reporting challenges and potential AI solutions, linking the business perspective with technological capabilities to develop a more efficient reporting system.

**Table 1.** Business challenges and AI solutions in reporting on quality and performance

| Problem/challenge (business perspective) | AI technology/approach (possible solution) |
|---|---|
| Dispersed and misaligned data sources (Word, Excel, PDF, ISVU, CroRIS, e-mail) | Automation of data collection and cleaning using Robotic Process Automation (RPA) + AI integrations with ISVU/CroRIS (ETL processes, semantic data mapping) |
| Manual data entry and slow consolidation of information | Natural Language Processing (NLP, LLM) for automatic recognition, categorisation, and linking of information from different formats |
| Limited clarity of reports, lack of visualisations | AI tools for visualisation and interactive dashboards (e.g., integration with BI tools + generative AI for explaining trends) |
| Subjectivity in interpretation (especially student surveys, qualitative comments) | Sentiment analysis and thematic clustering via NLP; LLM for generating consistent summaries and recommendations |
| Insufficient linkage between reports and strategic goals | Generative LLMs (e.g., ChatGPT, Claude), or local instances that reliably support Croatian, for drafting data-driven reports |
| Insufficient linkage between reports and strategic goals | LLM + RAG systems for linking data to ESG standards and strategic documents |
| Limited ability to search and compare reports | LLM + RAG systems (vector databases and semantic search) that enable quick retrieval and comparison of information across years |
| Disconnected islands (silos) of automation. | GenAISys platforms – modular AI systems that connect LLM, RAG, databases, and specialised tools into a unified architecture. Application of MCP. |

Source: authors' elaboration based on the conducted case study analysis and literature review

Other authors report similar organisational challenges. Buaton et al. (2022) note that AI can significantly contribute to internal audits through a digitised framework (documentary and field audit, knowledge base, inference engine), thereby indirectly supporting the improvement of study programmes and graduate quality. Their study focuses on an AI-assisted internal system for QAS in higher education, with an emphasis on standards and accreditation criteria, representing an essential but narrower segment of the broader QAS.

Although RAG in combination with LLMs greatly facilitates the search of internal documents through vectorisation and semantic comparison, it should not be assumed to be an out-of-the-box solution for the specific reporting needs identified in this paper. Wang et al. (2024) point out that current RAG technologies still have limitations in understanding conversational context, analysing structural information, and managing interactions across multiple documents. The linguistic dimension further amplifies these challenges, as most systems are trained and optimised for the English language; therefore, the choice of a model that reliably supports Croatian—as well as related components (e.g., embedding models and the vector database)—will likely have a significant impact on the extent of required testing and the pace of implementation.

This also raises methodological questions about evaluating the effectiveness of the final AI information system. Fleischer et al. (2024) emphasise that classical LLM metrics (e.g., BLEU, ROUGE) are insufficient for RAG and recommend a two-layer evaluation: (1) retrieval effectiveness and (2) generation quality, including accuracy, faithfulness, and usefulness relative to the retrieved context. Accordingly, future research will need to define and apply metrics that address both levels.

Aligned with this is the framework proposed by Es et al. (2024), which requires evaluation to explicitly cover: (a) faithfulness (whether the answer is grounded in the retrieved context), (b) answer relevance (whether the answer addresses the posed question), and (c) context relevance (whether the retrieved context is sufficiently focused). Such a three-layer approach to RAG evaluation increases the reliability of findings and reduces the risk of inconsistent model behaviour in real organisational tasks.

Finally, it is essential to highlight the problem of data security and the protection of confidential information stored in institutional RAG vector databases. When using public AI services (e.g., via UI or API), it is not always possible to know how the data will be handled or whether it will be used for further training of LLM models. Sending internal documents may be unacceptable if they contain confidential information, research data, or personal details. Therefore, before transmitting such data, it is necessary to apply minimisation, pseudonymisation, or anonymisation. One possible solution is to establish a dedicated AI server (on-premise) with a local vector database, or to implement a hybrid architecture that uses a local RAG on an internal server combined with a commercial LLM used as a frontend.

An on-premise solution raises questions about interoperability, Croatian language support, cost-effectiveness (including hardware, software, and electricity), and latency, but it ensures greater control over institutional data.

## CONCLUSION

QAS is a complex and highly regulated system, and ESG standards require the publication of comprehensive and transparent reports, as well as regular cycles of internal and external evaluation. Different user groups demand different formats and content—from concise summaries with recommendations for students and the public to comparable, evidence-based KPIs for management. Although ESG guidelines are standard for all higher education institutions in the EU, their implementation largely depends on the specific needs and characteristics of each institution.

Moreover, the quality of reporting depends on clearly defined procedures and consistent interpretation of the available information. An effective system, therefore, requires standardised templates, a clear hierarchy of evidence, and systematic linking of findings with the mission, vision, and strategic goals, together with the public availability of complete reports and tailored summaries for different target groups. Such an approach entails considerable human effort in locating, verifying, systematising, and preparing information and evidence—tasks that, in today's technological context, can be significantly facilitated by advanced methods and tools.

The analysis of relevant scientific and professional papers, along with recent solutions related to key technologies (primarily AI/LLM and RAG) and the necessary supporting infrastructure, confirmed the fragmentation of data into various "data silos" and heterogeneous databases. At the same time, it highlighted the potential of these technologies to automate existing processes.

This raises key questions concerning the choice of models and technologies, the level of Croatian language support, and the accuracy of information stored and retrieved through RAG. In addition, there is a need for systematic labelling of internal documents and the use of metadata, as well as for defining detailed procedures and guidelines according to which AI solutions will be implemented and subsequently evaluated with respect to accuracy, susceptibility to hallucinations, and execution speed.

It is reasonable to expect that there will be no universal one-size-fits-all solution, just as there is no single QA system that suits all HEIs. Nevertheless, the need to apply new tools is sufficiently strong that institutions should already be strategically planning and implementing AI-based reporting.

This study also has certain limitations. First and foremost, it is based on a scoping literature review and a case study of only one higher education institution, meaning that the results cannot be fully generalised. The analysed documents and reports reflect the particularities of the observed institution, which may limit their transferability to other institutions or national systems. Another significant limitation is the rapid development of technologies based on LLM and RAG architecture. Such dynamics create the possibility that many of the identified problems may, in the meantime, be mitigated or resolved through new software versions, without the need for more extensive interventions in system planning, testing, and implementation.

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