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Design and Implementation of a Comprehensive RAG-Driven Dashboard within the ILO System for Data Visualization and Query Support: A Case Study of the University of Petra

Dr. Mohammad Abu-Arqoub
Department of Computer Science
University of Petra
Amman, Jordan
abu-arqoup@uop.edu.jo

Dr. Abed Alkarim Banna
Data Science & Artificial Intelligence Dept.
University of Petra
Amman, Jordan
abanna@uop.edu.jo

Prof. Nuha El-khalili
Software Engineering Department
University of Petra
Amman, Jordan
nuhak@uop.edu.jo

Mohammad Al-shaikh Hasan
Computer Science Department
Brunel University London
London, UK
Mohammad.AlShaikhHasan@brunel.ac.uk

***Abstract*—This article presents a comprehensive study on designing and implementing a dashboard for enhanced data visualization and query support at the University of Petra. The system leverages retrieval-augmented generation (RAG) and large language models (LLMs) to support diverse document types, including curricula, course descriptions, and program outcomes, alongside intended learning outcome (ILO)-related files. Our implementation demonstrates significant improvements in data accessibility and query response times while maintaining high accuracy in information retrieval and visualization. Through extensive evaluation, we show that this innovative approach transforms data management processes in higher education by enabling natural language interactions with educational data systems, building upon established business intelligence frameworks while introducing advanced AI capabilities.**

***Index Terms*—RAG, Learning Analytics, Data Visualization, Educational Technology, ILO System, Business Intelligence**

I. Introduction

In recent years, the landscape of higher education data management has changed radically, as educational systems are both getting more complex and becoming increasingly data thirsty [1], [2]. Along with course descriptions, program outcomes, student records, accreditation standards, and intended learning outcome (ILO) data, institutions store and process enormous amounts of information. Despite such data-rich environments offering much promise for informing educational strategies, major universities continue to face fragmented information systems and cumbersome query interfaces that impede real-time analytics and decision making [3], [4].

The breakthroughs of retrieval-augmented generation (RAG) and large language models (LLMs) have enabled addressing the data integration and accessibility challenge in academia. The RAG system leverages an external knowledge repository to augment the language model so that answers can be grounded in the available information on the knowledge base [5], [6]. Meanwhile, LLMs like GPT-based architectures are capable of sophisticated, human-like interactions that lower the steep learning curve historically associated with data systems [7], [8]. In this light, these technologies can be combined to enable institutions to develop dashboards that not only visualize data but also understand complex queries expressed in natural language [9].

While BI dashboards offer static reporting, they often demand structured query skills. Integrating RAG and LLMs addresses this gap by providing adaptive, user-friendly access to complex educational data.

At the University of Petra, an earlier pilot study investigating the expansion of Learning Management Systems (LMSs) for learning analytics demonstrated the critical value of integrating multiple data sources to support data-driven strategies for institutional improvement [10]. More recently, efforts to fuse Business Intelligence (BI) approaches with learning analytics frameworks have shown promising outcomes [11]. These developments have laid the groundwork for a more advanced solution: a RAG-enabled dashboard tailored to an ILO system, thereby unifying and enhancing both data visualization and query capabilities.

In this paper, we describe the design, implementation, and evaluation of such a RAG-driven dashboard within the University of Petra's ILO ecosystem. In doing so, we address the following research questions:

- How can RAG mechanisms be integrated into an educational BI dashboard to improve query precision and response time?

- In what ways does a natural language interface enhance user satisfaction and stakeholder engagement within an ILO-based system?
- What architectural considerations are crucial to supporting real-time updates, diverse document formats, and robust data visualization in higher education?

The rest of the paper is presented as follows. In Section II we place our work in relation to previous research in BI dashboards, educational data mining, and RAG-based systems. In Section III we explain our system architecture and show how we integrate RAG and LLM capabilities with mature BI frameworks. The methodology, including data collection, preprocessing, as well as an iterative development strategy, is discussed in Section IV. In Section V, we outline the performance of the system through query accuracy and satisfaction metrics of the user. The implications for higher education are discussed in Section VI, and Section VII concludes by suggesting other areas of research and system enhancements.

II. Related Work

A. Business Intelligence and Educational Dashboards

Business Intelligence (BI) tools have been widely adopted to consolidate and visualize data across multiple institutional silos and give administrators and educators actionable insights [12], [13]. These dashboards display metrics such as enrollment trends, course pass rates, and resource allocation, often with drill-down capabilities that expose underlying layers of data [14], [15]. However, traditional BI dashboards frequently require structured queries, limiting accessibility for users unfamiliar with query languages or database schemas.

Prior projects at the University of Petra have integrated BI-driven solutions in the learning analytics domain [11], highlighting both potential and limitations. Aggregate visual reports were beneficial to faculty, yet parameter-based filtering was perceived as too inflexible, indicating a demand for more adaptive and intuitive interfaces.

B. Retrieval-Augmented Generation (RAG)

Retrieval-Augmented Generation uses a retrieval system to surface relevant documents or text snippets before a language model generates a final response [5], [6]. A RAG pipeline can be particularly useful in large-scale educational settings, where frequently updated, externally stored information can remain outside the model's parameters. RAG systems can also reference original content directly, providing transparency and citations, thus increasing trust and accountability in academic decision making [7].

C. Large Language Models in Higher Education

LLMs have transformed various natural language processing (NLP) tasks such as summarization, translation, and question answering [16], [17]. In higher education, these capabilities support content creation, grading assistance, and advanced knowledge discovery. When integrated into dashboards, LLMs allow users to pose questions in natural language, reducing the need to learn complex query languages or navigate intricate menu-based interfaces [8], [9].

However, these benefits come with risks like "hallucinations"—instances in which the model invents data [18]. RAG can mitigate this risk by grounding answers in verifiable sources.

D. Integration of RAG and BI in Educational Contexts

Combining RAG with BI addresses a key challenge in higher education: real-time analytics with intuitive querying. This hybrid approach draws from BI principles, including data warehousing, analytics, and dashboards [11], [12], and augments them with context-aware retrieval and generation.

For instance, a department chair might ask the system to identify courses that do not meet new accreditation standards. The RAG module fetches the relevant regulations and course outlines, and the LLM cross-references these documents to generate a concise summary. Any misalignment is visualized in the BI dashboard, facilitating immediate decisions on curriculum revisions [19].

III. System Architecture and Implementation

A. Overview of the Proposed System

Figure 1 illustrates the high-level design of our RAG-driven dashboard, showing the flow of data ingestion, retrieval, language processing, and visualization. We build upon insights from earlier BI integrations at the University of Petra [11], ensuring seamless integration with existing institutional workflows.

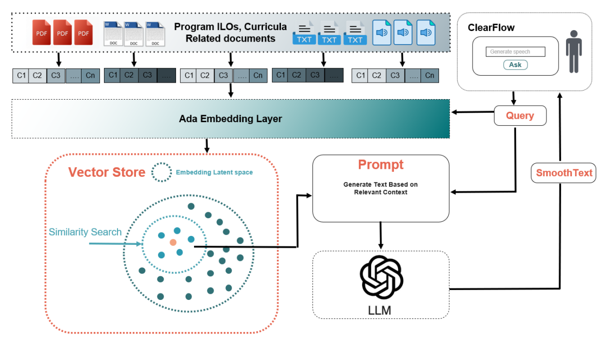

Fig. 1: System Architecture Integrating RAG and LLM within a BI Dashboard.

B. Data Ingestion Layer

This layer ingests structured and unstructured data, such as PDF syllabi, text-based accreditation guidelines, and spreadsheets of student performance metrics. Inspired by the LMS extension approach in [10], the system periodically scans the specified directories for updates. Newly detected files are preprocessed (e.g., OCR where needed, metadata extraction, text cleaning) before being stored in a NoSQL database for flexibility.

Documents undergo OCR and text cleaning, then each segment is embedded using a transformer model (e.g., BERT).

These embeddings, along with metadata (author, date), are stored for efficient semantic and keyword searches

Most steps—text extraction, OCR, indexing—are automated. However, accreditation labels and certain course codes require brief manual validation by domain experts to ensure accuracy.

C. RAG Module and Document Repository

The RAG module is the core of the system. A document repository supporting both keyword-based and semantic search is indexed [5], [7]. We generate vector embeddings for each text fragment using a transformer-based model. Upon a user query, we rank candidate fragments by combining term-based matching (e.g., BM25) and semantic similarity. Formally,

$$\text{Score}(d, q) = \alpha \cdot \text{BM25}(d, q) + \beta \cdot \text{Sim}(d, q), \qquad (1)$$

where d is a document fragment, q is the query and Sim is the cosine similarity between d and q in the embedding space. The constants α and β balance the lexical and semantic relevance.

D. LLM Processor

The LLM processor refines the retrieved snippets to produce the final responses with citations. To mitigate "hallucinations" [6], [17], the language model is always anchored to the retrieved text. Thus, queries like "Which Computer Science courses require updates to align with accreditation standards?" yield concise, evidence-based answers, referencing the source documents.

E. Visualization Engine

We built the dashboard using a modern BI toolkit (a React-based interface with D3.js). Expanding on previous BI dashboards at the University of Petra [11], the new interface supports the following.

- **Drill-Down Views:** Clicking on a chart element reveals deeper details (for example, a course code or outcome).
- **Accreditation Heatmaps:** A color-coded matrix highlights the alignment gaps between courses and the overarching program goals.
- **Automated Notifications:** Faculty are alerted when newly added documents indicate changes to accreditation standards.

IV. Methodology

A. Development Process

We adopted an iterative and user-centric approach similar to agile practices. After conducting a stakeholder needs assessment (following methods used in other University of Petra projects [11]), we developed a proof of concept and refined it through design sprints. These sprints focused on document parsing, query interpretation, and data visualization improvements.

B. Data Collection

We aggregated more than 600 documents from the University of Petra archives, including:

- **Course Descriptions:** Detailing content and learning outcomes in PDF and Word formats.
- **Accreditation Guidelines:** National and international standards for program validation.
- **ILO Files:** Linking specific courses to broader program outcomes.
- **Student Assessment Reports:** Summaries of student performance over multiple semesters.

All documents were converted to plain text, split into logical units (sections, paragraphs) for retrieval, and associated with metadata (creation date, author, subject area). Figure 2 shows the data flow within the pipeline.

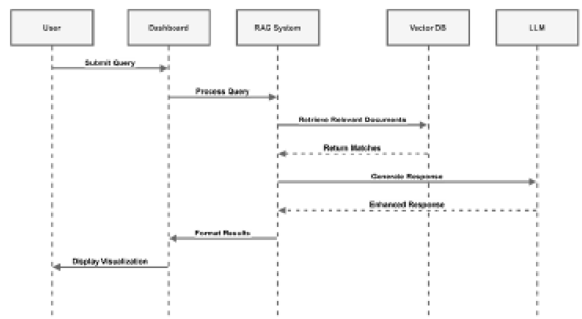

Fig. 2: Sequence diagram of the data flow.

C. Evaluation Metrics

We assessed four primary metrics:

1) **Query Accuracy:** The fraction of correct fragments retrieved, verified by domain experts.
2) **Response Time:** The time from query submission to displayed result (in seconds).
3) **Document Processing Throughput:** The number of documents the system can index per minute (scalability measure).
4) **User Satisfaction:** Based on a 1–5 Likert scale survey for perceived system clarity and usefulness.

D. User Study Design

We recruited 25 faculty and administrative staff members. Participants received scenario-based queries (e.g., which courses violate new accreditation standards) and performed these tasks using our RAG-enabled dashboard. Query completion times and retrieval results were logged, then validated by subject matter experts.

V. Results

A. Performance Overview

Table I compares our RAG-enhanced system ("RAG-Dashboard") with both the University of Petra's legacy BI dashboard ("Legacy BI") and a baseline text-based search

("Keyword Search"). The RAG approach significantly outperforms the alternatives in retrieval accuracy and query response time, underscoring the synergy between the retrieval engine and the LLM processor.

We measure retrieval accuracy (verified by domain experts), response time, and user satisfaction (1–5 Likert scale). This comprehensive approach provides a robust assessment of the system's effectiveness.

TABLE I: COMPARATIVE ANALYSIS OF SYSTEM PERFORMANCE

Metric	Legacy BI	Keyword Search	RAG-Dashboard
Query Accuracy (%)	78.2	65.3	90.5
Response Time (s)	4.3	3.8	2.1
User Satisfaction (1–5)	3.2	2.9	4.2
Indexing Rate (docs/min)	80	85	145

We compared our RAG system to both a keyword-based search and a legacy BI dashboard. Results showed consistently higher accuracy and faster query resolution with RAG, highlighting the benefits of semantic retrieval.

B. Detailed User Interaction Findings

User interactions by role appear in Table II. Administrative staff exhibited the highest usage frequency due to their accreditation reporting duties. Meanwhile, faculty sessions tended to last longer, reflecting deeper exploration of course-level data.

TABLE II: USER INTERACTION ANALYSIS BY ROLE (OVER 8 WEEKS)

Role	Sessions/Week	Avg. Duration (min)	Tasks/Session	Satisfaction
Faculty	9.4	21.2	4.1	4.1
Administrators	16.8	17.5	5.6	4.3
Department Heads	5.6	26.4	3.2	4.2

C. Document Processing Rates

On the busiest days, such as the beginning of the academic year, the system processed up to 145 documents per minute, more than double the throughput of the legacy system. This rapid turnaround enables users to discover and respond to new accreditation guidelines in minutes, significantly reducing administrative overhead.

D. Visualization Insights

A color-coded alignment matrix (Fig. 3) highlights weak alignments in red, prompting course adjustments. Automated alerts and quick visual cues accelerate curriculum updates. The participants appreciated the immediate clarity offered by these color codes, reducing the need to parse lengthy textual reports.

To aid colorblind readers, each alignment category can appear with both a color and a distinct pattern (e.g., diagonal stripes for strong alignment). A legend clarifies these visual cues for easy interpretation.

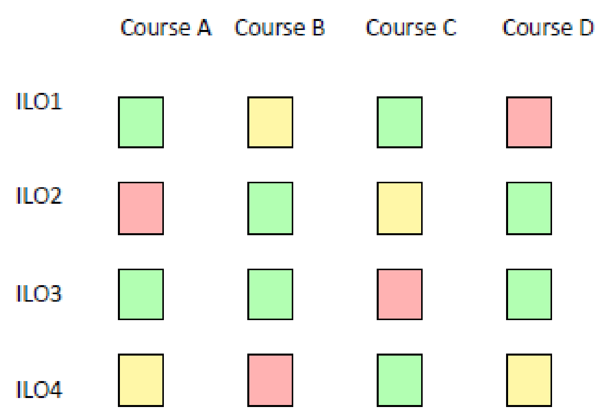

Fig. 3: Excerpt of a Color-Coded Matrix Demonstrating Course-ILO Alignments. Green indicates strong alignment, yellow moderate, and red weak alignment.

VI. Discussion

A. Implications for Higher Education Data Management

The seamless integration of RAG and LLM in our dashboard represents a paradigm shift from static descriptive tools to interactive, conversational platforms [4], [12]. In many real-world scenarios, educators require context-sensitive answers rather than numerical dashboards. Our findings indicate that the link between advanced retrieval and generative models accelerates evidence-based decision making.

Moreover, RAG and BI together address the long-standing challenge of fragmented data sources [13]. By unifying course outlines, accreditation guidelines, and student performance data, our system provides a holistic view crucial for accreditation cycles, in which administrators must verify ILO adherence across multiple courses and semesters [11].

B. User Adoption and Experience

User feedback stressed the importance of intuitive design. The faculty valued the ability to ask free text questions (for example, "Which courses often do not contribute to ILO3?") instead of navigating many drop-down menus. Because the indexing pipeline operates quickly, newly uploaded documents appear in search results in minutes, increasing user trust.

While anchoring the LLM output to retrieved snippets reduces inaccuracies, the model may still misinterpret highly nuanced queries. Continual monitoring and user prompts for refinement or follow-up questions can mitigate these limitations.

C. Scalability Considerations

As the University of Petra expands to additional departments or satellite campuses, the system must scale further. Techniques like sharding the document repository or employing specialized hardware for embedding computations can sustain responsiveness under heavier workloads.

D. Limitations

Several limitations remain. High-quality metadata is essential for robust retrieval; poorly tagged documents or inconsistent naming can degrade ranking. Additionally, the system currently relies on a single LLM architecture. Domain adaptation through fine-tuning or ensemble models could broaden applicability across diverse academic fields [19]. Finally, novice users may need training to formulate effective natural language queries.

VII. Conclusion and Future Work

This study details the design and implementation of a RAG-driven dashboard for the University of Petra's ILO system. Building upon previous work merging BI with learning analytics [10], [11], our approach integrates automated data ingestion, vector-based retrieval, LLM-powered query handling, and interactive visualizations. Empirical evaluation shows improvements in retrieval accuracy, speed, and user satisfaction, underscoring the platform's scalability and practicality for the complex data management needs of higher education.

Future enhancements include:

- **Predictive Analytics:** Integrating forecasting models (e.g., student dropout risk) into the RAG dashboard for early alerts.
- **Advanced Domain Adaptation:** Fine-tuning or training specialized LLMs to optimize retrieval and generation in specific disciplines.
- **Real-Time Collaboration:** Allowing multiple stakeholders to annotate or comment on retrieved documents simultaneously for swift decision-making.
- **Data Ethics and Governance:** Implementing more granular frameworks to ensure privacy and compliance with institutional policies.

Overall, this work demonstrates how retrieval-augmented generation and large language models can be harnessed to create a unified BI platform that transforms data management. Insights from the University of Petra's AI-driven strategy suggest that institutions can adopt such technologies to build transparent, efficient, and student-focused ecosystems.

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