Journal of Integrated Information Management electronic journal

An Academic E-government Platform for Managing Educational and Research Activities

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Article Info

Article history:

Received November 22 2022

Received in revised form December 12 2022

Accepted December 16 2022

http://dx.doi.org/jiim.v7i2.4513

Abstract:

Purpose - In this article, we propose the architecture of an E-government platform for Educational and Research Management (e-EDURES) in Higher Education Institutions. An integrated strategic planning and decision support system (DSS) is included at the center of the architecture for facilitating the decisions and the design of future actions, enabled by data mining and visual analytics techniques.

Design/methodology/approach - The platform study focuses on the development of services related to i) the management of educational data generated by blended learning, along with ii) the utilization of data related to R&D activities in higher education Institutions. The proposed approach studies the system architecture at four levels: data collection, data preparation, data mining, and knowledge discovery.

Findings - The e-EDURES platform should be based on data mining techniques to predict the potential learning progress of each student, whereas focusing on research, Social Network Analysis, and coauthorship networks modeling using graph metrics and Data Environment Analysis have been used as a measure of the effectiveness of the research activities.

Originality/value - The platform incorporates interactive visual interfaces to support Knowledge Discovery from Data Visualization, providing the user with enhanced assistance throughout the decision-making process.

Index Terms — E-government Platform, Digital Archives, Research Indicators, Visualization, Visual Analytics, Co-authoring, Knowledge Discovery, Graph Metrics, Data Mining.

I. Introduction

Assessment and overview of performance in academia are crucial for enhancing educational and research activity and contribute to the definition of the level of the offered services. Technology can enhance the work of policymakers (PM) by enabling them to get informed about the progress in academic activities (including both research and educational activities), with ultimately leads to the improvement of the academic processes and their outputs, to make recommendations based on the current status and estimate the effect of these recommendations to the future, according to current and past performance. In this paper, we study and propose the architecture of an e-Governance Platform for Educational and Research Management (e-EDURES) which supports centralized administration **[1]** using Interactive Data Visualization Interfaces for Knowledge Discovery (KDD-V). The main research issue we address is creating a user-friendly e-Government platform that will leverage a data-driven approach, allowing PM to use the extracted knowledge to make strategic decisions at an institutional or individual level. A set of primary Digital Government architecture characteristics are based on the fundamental principles described in the work of Baheer et al. **[2]**.

To be more precise, the operational/functional aspects considered are directly related to the research management requirements listed below:

- Archiving of Research Activities (including publications, funded projects, and patents).
- Archiving of Educational Data (i.e., visiting the course's page, accessing and downloading the educational material, grades, etc.).
- Identifying significant researchers and research areas at the institutional level.
- Support PM to get an accurate view of the performance of the academics, set priorities for their research activities, and form the institutional research policy.
- Monitoring and predicting the performance of the students.

- Ameliorating teaching through course analytics.

The main contribution of this study is a system that no-expert data analysts can use to analyze the effectiveness of collaborative structures within academic institutions. In addition, we offer a variety of social network analysis (SNA) and data mining methods to measure the performance of research activities at individual or institutional levels, as well as the evaluation of the learning process outcomes. The results of those methods are presented using visual analytics tools, namely graphs, parallel coordinators and regression lines.

The remaining paper is organized as follows: Section 2 offers a concise overview of current Research Information Systems (RIS), emphasising their functional role in supporting the management of research activity and literature review of the fundamentals of Decision Support Systems (DSS). In addition, the application of educational data mining methods is presented. Section 3 discusses data analytics methods of e-EDURES, and the proposed systems' architecture is presented in Section 4. The implications of the proposed methodology and the conclusions of our work are discussed in Section 7.

II. Literature Review

In developing an E-government platform for Educational and Research Management, we have implemented a decision support system, following the basic digital archiving methods to manipulate the data retrieval process. Decision Support Systems are computer-aided tools that involve assessing the available data and presenting the alternative results from multiple viewpoints to decide which one fits better to the specific problem. Based on the fundamental components of the systems which support decision-making **[3],** our system comprises the following:

- Data management is a cohesive method of aggregating data from one or more sources using a shared data structure.
- Model management focuses on developing analytical models to generate information from the primary data.
- Knowledge management related to the generation of knowledge from the data using machine learning and artificial intelligence techniques
- Data Archiving, keeping the data no longer relevant for the analysis, available for future reference.
- The user interface concerns the interaction among the user and all the different stages of the DSS process.

Liu, Shaofeng, et al. **[4]** have demonstrated that the decision support process is a difficult task with limitations as the user faces problems in selecting the optimal answer among available alternatives or, in cases, several process steps must be changed. To address this issue, an interactive DSS **[5][6],** which enables user and process integration, must be developed. Furthermore, Fisher **[7]** suggests the most important element in the success of DSSs is the human-computer interface rather than the functionalities offered to solve a problem. In our approach, we have created a framework for Institutional Educational and Research Management consisting of various layers by building upon the KDD model **[5]**, which includes:

- Data collection,
- Data preparation,
- Data analysis and
- Knowledge discovery from data visualizations.

The evaluation process of the research activities involves accumulating a variety of qualitative or/and quantitative metrics among faculty members. According to the literature, there are various models which use different types of metrics based on the scope of the assessment. For example, Jong et al. **[8]** suggested an analytic network process for R&D project evaluation and ranking to identify the projects that should continue receiving funding. Carlos et al. **[9]** presented a multi-criteria-based decision-making model called Research Lab Evaluation (RELEV) to evaluate the research output of individuals or research institutes. Moreover, Cocci et al. **[10]** used different qualitative and quantitative indicators to measure faculty members' performance.

Social network analysis is employed to predict the evolution of prestigious members of a research community **[11]** or to examine the collaboration relationships of the researchers **[12]**, whereas VIVO **[13],** which stores the research activities of faculty members of an institution, allows recording, editing, searching, browsing, and visualizing scholarly activity.

Numerous systems and tools utilize machine-learning techniques to analyze research data and evaluate research outcomes. For instance, the National Institute of Health (NIH) has developed the Research Portfolio Online Reporting Tool (RePORT) **[14]** for the retrieval of research articles from PubMed **[15]**. It generates reports based on the analysis of research activities. Another approach, STAR Metrics **[16]**, measured various indicators, such as the publications, the citations, the environmental impact factors, the student mobility and employment, to estimate the impact of investment on scientific knowledge. Online Analytical Processing (OLAP) has been effectively used for educational purposes **[17]**.

Data-mining techniques are utilised to reveal insights and hidden patterns based on student behaviours concerning the analysis of the academic data produced during educational activities **[18]**. By applying Educational Data Mining **[19]** to data retrieved from learning management systems (LMS), meaningful results can be extracted, and potential problems during the educational activities can be identified. Datasets generated through educational activities have been used for early detection of failure of students **[20][21][22],** for prediction of students' performance **[23]**, for altering the learning material to be more personalized **[24]** and for the discovery of faculty behaviour on the usage of LMS **[25]**.

The main drawback of all these systems and techniques is that they focus on specific topics of research or educational activities, and they do not provide a holistic view of all the related aspects.

III. E-EDURES DATA ANALYTICS METHODS

The architecture we study and propose incorporates a decision support tool for educational and R&D activities. In this section, we examine the methods employed to evaluate R&D and the techniques used to assess learning activities.

A. Analysis of Co-authoring Networks

In our approach, to evaluate an academic institute's research outputs, we analyze and explore the scientific collaborations among the faculty members and determine their performance based on the R&D activities. As Chien Hsiang Liao, et al. **[26]** suggested, the ability of an institute to share the research results and acquired knowledge among faculty depends on academic collaboration. Due to the importance of analyzing research collaborations among faculty members, different methods have been involved: bibliographic metrics **[27]**, social network analysis **[28][12]**, qualitative methods **[29][30]** and surveys **[31]**. Using the Social Network Analysis method, we can identify the underlying structures and processes leading to specific apparent structures **[32]**. Using graph metrics **[33]** based on the graph network can also provide valuable results. For example, in **[12],** the construction of co-authoring networks was analyzed to identify the most "important" author.

In the proposed architecture, we have employed social network analysis on the coauthorship network of the faculty members, focusing on scientific publications as the parameter for the construction of the network. The analysis of the coauthorship through SNA enables the analysis and evaluate the importance of an author or author groups by employing graph metrics to quantify their collaboration. In addition, several useful measures pinpoint the significance of a specific node to the network topology **[34]**. We can explore the existing collaboration patterns using these measures on the co-authoring networks.

A co-authoring network comprises nodes (individual researchers or research groups) connected to one another through edges, representing their coauthorship and collaboration activities. The network topology is determined by the edges between the authors who have co-authored at least one publication. To better understand the significance of each node, various metrics have been developed based on the network's structure. The definitions of both nodes and edges can vary based on the research questions being explored. The methods used to measure the importance of a node by examining the whole network and its participants are described below:

- Degree Centrality measures the number of links a node (author) has.
- Closeness Centrality **[35]** indicates the number of short paths a node (author) has to the others.
- Betweenness Centrality **[36]** captures the significance of each node (author). We calculate the short paths that pass through nodes using the betweenness centrality.
- Clustering Co-efficient **[37]** indicates the one hoop connections between the neighbours of a node to all the possible connections between its neighbours.
- The Eigenvector Centrality **[38]** of a node (author) is the sum of its connections to other nodes, weighted by their centrality.

B. The efficiency of academic units using Data Envelopment Analysis

Another intriguing issue is the design of the appropriate methodology for the efficiency measure of the R&D activities among the faculty members, as the inputs and outputs are often of broad scope and intangible **[39]**. Data Envelopment Analysis (DEA) is one of the most commonly used methods **[40][31]** for efficiency measure, as it takes into account a dataset containing information on research inputs and outputs and measures the research efficiency among academic units.

Previous research on university efficiency has primarily explored the relationship between efficiency and productivity within the departments of the same institution or across different universities. In the work of Lee et al. **[41]**, they have applied an efficiency measure technique to economic departments in Australian universities. They separate the data into input, corresponding to teaching and research personnel, and output variables, including the graduates and the publications. Then they analyzed how government policy can influence productivity. Another study conducted in USA [40] examined the efficiency among 42 academic units. They have used the staff, financial resources and infrastructures as inputs, whereas the number of students, the full-time equivalent (FTE) enrolments and grant awards are assumed as outputs. Tommaso Agasisti et al. **[42]** use as starting points the laboratories and the high-qualified human resources, while the yearly number of publications, the citations per article, the h-index, the research funded through regional or national grants, the research funded through international grants, and the applied research through externally funded orders are considered as outputs.

Our research relies on the criteria outlined by the European Association for Quality Assurance in Higher Education (ENQA) to assess research and development at higher education institutions (HEIs). ENQA developed the European Standards and Guidelines report to standardize quality assurance across Europe's higher education setting **[43]**. The main reasons for selecting these criteria were to ensure the alignment with commonly adopted standards across European institutions and use it as a case study at a Greek institution. Table 1 displays the specific criteria (indicators) utilized in our study.

Table 1. *Data Description for criteria of our study*

Index	Description
1	International Journal Articles (JAI)
2	National Journal Articles (JAN)
3	International Conference Papers (CPI)
4	National Conference Papers (CPN)
5	Citation indexes (CIT)
6	Book Chapters (BC)
7	Research Project that one of the faculty members has the role of Coordinator (RPC)
8	Research Project that one of the faculty members participates as partner -member of the research group- (RPP)
9	Research Project and partnership with external institutes (RPE)
10	Research Areas of Research Activities (RA)

In our system, we separate the indicators as:

- Inputs: human resources.
- Outputs (table 1) are grouped into publications, projects and financial support (e.g., grants) related.

DEA is a multi-factor productivity analysis model for computing the relative efficiencies of a homogenous set of decision-making units (DMUs). The efficiency score **[44]** in the presence of multiple input and output factors is defined as follows:

$$\text{Efficiency} = \frac{\text{weighted sum of inputs}}{\text{weighted sum of outputs}}$$

$$\max \quad \frac{\sum_{k=1}^{s} v_k y_{kp}}{\sum_{j=1}^{m} u_j x_{jp}}$$

$$\text{s.t.} \quad \frac{\sum_{k=1}^{s} v_k y_{kp}}{\sum_{j=1}^{m} u_j x_{jp}} \leq 1 \qquad \forall i$$

$$v_k, u_j \geq 0 \qquad \forall k, j \ \forall i$$

Where

- x_{ji} = amount of input j utilized by DMU i,
- v_k = weight given to output k,
- u_j = weight given to input j.
- k = 1 to s, j = 1 to m, i = 1 to n,
- y_{ki} = amount of output k produced by DMU i,
- s=the number of outputs, m= the number of inputs and i= the number of DMU's.

C. Evaluate Student Performance

To measure and evaluate the efficiency of learning activities, we have to examine the students' performance and progress, as well as the availability and use of learning materials. The scope of the analysis is to identify the factors that affect students' performance and the correlation among them. We can extract hidden predictive information from datasets by employing data mining techniques. Various data mining approaches have been employed to evaluate university educational activities **[45][46]**. For instance, Wu **[47]** utilized k-means cluster analysis to identify the grouping patterns among faculty members and attempted to classify them into similar groups by comparing multiple characteristics. In addition to clustering techniques, rule-based association mining has been utilized in several studies **[48]**.

According to the literature, classification techniques have been used to analyze student performance, such as decision trees **[49]**, artificial neural networks **[50]**, support vector machines[51], regression **[52]**, etc. For example, in a study **[49],** naïve Bayes and a decision tree classifier have been used to estimate a model to predict low academic performance. In the work of Alkhasawneh et al. **[50],** Neural Networks have been selected to assist in predicting students' retention behaviours in Science and Engineering Disciplines.

Our system (e-EDURES) offers diverse data mining methods for clustering and classification. More specifically, we support a variety of techniques for knowledge extraction, ranging from k-means clustering and apriori association rule mining for identifying current efficiency to Bayesian network analysis for predicting future performance.

Although using those algorithms, the user could get useful insights about the current performance of faculty members, some hidden information may remain undiscovered. Data visualization techniques can aid in uncovering hidden patterns within the data, ultimately enhancing the decision-making process **[53][54]**. For instance, Chen **[55]** utilized a combination of information visualizations and data mining activities to conduct a comprehensive analysis.

The proposed approach involves developing various visualization methods to offer alternative representations, allowing users to identify the underlying patterns that may not be evident using conventional visualization techniques. The user can repeat the process by selecting the appropriate one among different visualizations until a correct solution is reached to the problem at hand.

IV. E-GOVERNMENT PLATFORM FOR EDUCATIONAL AND RESEARCH MANAGEMENT

The proposed architecture is based on the interoperability of two different functional subsystems developed in the context of our previous research activities:

1) The Institutional Research Management Information System (IREMA) **[56]** examines the academic performance based on the conducted research, including the authorship of research publications and participation in research projects. Based on the quantity and the quality of the research of academics, their research work is evaluated, and the system presents those that outperformed, the research hubs that show better performance than others, and an overview of the research activities and collaborations of all the faculty.

2) The system proposed by Chytas et al. **[57]** retrieves educational, participation and socialization data. In this system, the evaluation is focused on the students and how they utilize the online educational services to succeed in a course and their actual performance on the specific course. The gathered information can inform the stakeholders about students at risk, and the retention rate of the courses. As a direct consequence, the implicated academics can take corrective actions.

In the context of e-government, we illustrate the proposed architecture described in Figure 1. This architecture facilitates the centralized administration of the two subsystems to provide PM useful information and support decision-making activities.

In Figure 1, the advanced users (power users) are responsible for: a) setting the main parameters (criteria) of the decision-making process, b) modifying the set of evaluation criteria (by adding or deleting criteria) and c) setting the criteria for weights or the type of the corresponding data mining process, as well as the associated parameters. On the other hand, the developers have full access to all the features of the multicriteria evaluation process. To elaborate, they can add data mining processes or develop custom functions based on the advanced users' needs. Apart from the advanced (power) users and developers, the DSS includes a user-friendly interface that facilitates the preparation of several reports in graphical and tabular format.

B. Application Layer

The advanced users who are responsible for the design of the data-mining process are connected to the system via the application layer. The initial phase is the data collection, which is held by each one of the subsystems separately. For the IREMA system **[56],** the collected data incorporates information from SCOPUS bibliographical database by using web Services; The aggregated data includes the authors, the publications, the research areas and the number of citations; then, a list with the faculty members sorted by the department is loaded, and the external collaborators are filtered out. Subsequently, the research areas for each one of the faculty members are automatically defined and assigned to them based on the data retrieved from Scopus. Finally, the data are enriched with the R&D activities of the faculty members from files which are uploaded coming from the University's R&D office/department.

Concerning the application system proposed by Chytas et al. **[57]**, the data are retrieved in real-time from the synchronous and asynchronous LMS platforms of the Institute. The faculty member's email is the common field of integrating the dataset for those two subsystems.

The advanced (power) users execute the DM process; observe the results, and they can change the process until the desired goal is reached. The data analysis is based on the design and implementation of decision-making workflows. Advanced users/experts design the workflows with different decision-making methods.

C. Data Mining Layer

This layer involves the library with the data mining algorithms available to be used from the advanced users. The data are to be transformed to be used by algorithms. Therefore, in this step, we construct the co-authoring networks, where nodes represent the authors and the edges of the collaboration (co-authoring activity) among them. After constructing the networks for all the faculty members, the graph metrics are calculated for each one based on the network topology.

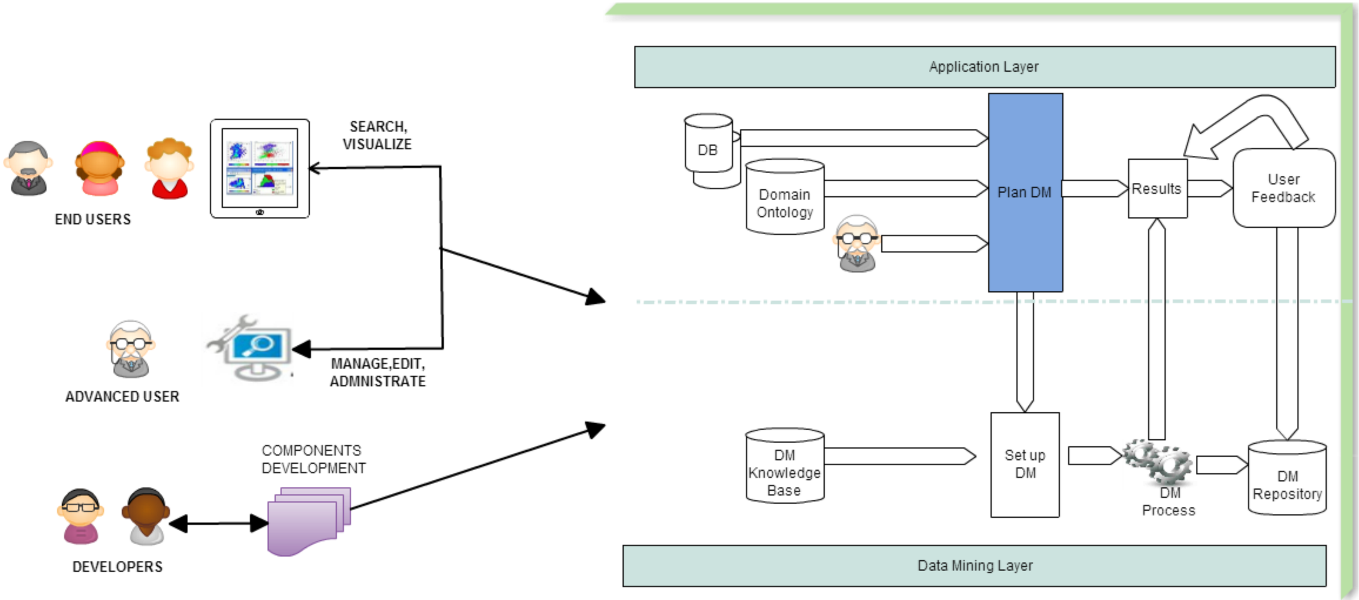

Fig. 1. *System Architecture*

D. Knowledge Discovery (SEARCH-VISUALIZE)

In this layer, the various interactive visual interfaces are integrated to support Knowledge Discovery (KD), which consists of the following:

- Co-authoring Graph, which is created on the basis of the collaboration among faculty members for the publication of a research paper.
- Parallel Coordinators, as an interactive representation, allow the user to apply a set of criteria (dynamic) depending on his objectives.
- Efficiency Line, which is used for the representation of the correlation among indicators.
- Map of Science, where each research area is represented through pie charts.

V. CONCLUSION

The assessment of the quality of services provided by higher educational institutes is related to the management of educational and R&D activities. Implementing a holistic, integrated decision support system is crucial for the involved stakeholders, as the knowledge extracted from the primary data (educational and R&D) can be apparent and used to inform strategic decision-making at institutional and individual levels. The e-EDURES allow the exploration of data and the discovery of valuable knowledge within the dataset and support the whole spectrum of academic activities. By presenting a selection of feasible alternatives, our system provides the most appropriate solution suited for policymakers' needs without requiring additional skills or knowledge. However, it gives more sophisticated options for expert users. e-EDURES is occupied with two of the most important dimensions of academia, education and research, providing the tools to present, assess and improve academic performance, and by extension, the offered services of a university.

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