Data-driven Decision Making in Higher Education Institutions: State-of-play

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Abstract*—The paper highlights the importance of using data-driven decision-making tools in Higher Education Institutions (HEIs) to improve academic performance and support sustainable development. HEIs must utilize data analytics tools, including educational data mining, learning analytics, and business intelligence, to extract insights and knowledge from educational data. These tools can help HEIs' leadership monitor and improve student enrolment campaigns, track student performance, evaluate academic staff, and make data-driven decisions. Although decision support systems have many advantages, they are still underutilized in HEIs, leaving field for further research and implementation. To address this, the authors summarize the benefits of applying data-driven decision approaches in HEIs and review various frameworks and methodologies, such as a course recommendation system and an academic prediction model, to aid educational decision-making. These tools articulate pedagogical theories, frameworks, and educational phenomena to establish mainstay significant components of learning to enable the scheming of superior learning systems. The tools can be utilized by the placement agencies or companies to find out their probable trainees/ recruitees. They can help students in course selection, and educational management in being more efficient and effective.

***Keywords*—Business intelligence; data analytics tools; decision-making framework; decision-making support systems**

I. Introduction

Assuring the high quality of the offered educational services is among the main goals of all higher education institutions (HEIs). Nowadays, many HEIs receive funding according to the number of students and the research activity. This necessitates continuous monitoring of the activities and management decisions that guarantee quality education of the educational services provided in HEIs [1-2]. HEIs' management bodies must make daily decisions to follow the institutions' strategies and achieve the set goals. This management context in higher education requires adequate and reliable support for making management decisions [1]. Higher education management is progressively realizing the priority of accurate and available information that endorses both basic operations and long-term strategic planning [3]. For this reason, many modern universities are searching for ways to improve their traditional management processes and solve the challenges linked to them.

Recently, HEIs have become increasingly dependent on data collection, storage, and processing [4]. Contemporary HEIs use software systems to automate their activities, e.g. student information systems, learning management systems, human resource systems, scientific activity reporting systems, and have rich data sets from external systems (registers, databases with scientific information, etc.) that can support management decisions to improve ongoing processes. The collected data has no real value if HEIs' leadership does not realize the strategic significance of the data and does not extract information from the data to make data-driven decisions.

It is very difficult for HEIs' leaderships to find the accordant information required for the decision-making when there is a plethora of systems [3]. Data collection and analysis require human resources involvement and manual perusing of ceaseless data streams. In addition, the presented data does not provide information about the HEI's current state of play and should be analysed again any time when HEI's manager needs up-to-date data. This leads to the increasing interest of HEIs' leadership in using collected and analyzed data to support decision-making [5-6]. They are trying to apply new strategies and solutions for extracting data from software systems and turning it into knowledge that supports ongoing processes' optimization, management and improvement in all major areas [2, 7-9] and can be used to inform strategic decisions at all organizational levels.

The last requires investments in appropriate technologies which support all management processes [10], e.g. incl. semantic and linked-data technologies, Educational data mining, Learning analytics and Academic analytics, Business intelligence [11]. Data analysis tools allow automatic data extraction, analysis and classification from different systems [12]. They allow HEIs' leadership to track and analyse trends and KPI performance through intuitive dashboards [13-14] presenting summarized information in graphical form (charts, tables and measurement graphs [15]) and find hidden patterns in the data, trends or anomalies [16]. The resulting information helps HEIs' leadership manage the institution more effectively, measure the impact of their initiatives, make strategic decisions for improving the ongoing processes [17-18], and collect evidence for informed decision-making. By leveraging such tools, HEIs stakeholders can gain insight and monitor progress over time on almost all aspects of HEIs activities, such as student performance, enrollment trends, academic productivity, career development, cost management, regulatory compliance, research activity, collect data on ongoing educational and research processes and take measures for improvement. By using software solutions to support the decision-making process HEIs managers can offer alternative solutions [19], minimize the risk and negative impact of errors [2, 4, 20-21], increase the validity of the management decisions taken [22] and contribute to achieving sustainable development of HEIs, save time in discovering relevant information for decision-making and funds to pay experts to extract relevant information and give better insight and control over operations. Implementing and using decision-making systems in higher education reduce the cost and time needed to outline problems, complications or obstacles in higher education systems and make the best decisions [23-25]. Implementing and using decision-making systems in higher education reduce the cost and time required to outline problems and find the most appropriate solutions to distinguish complications or impediments of higher educational systems.

The integrated software system that will support academic decision-makers to make timely and right solutions is a significant step in implementing new educational policies. Implementing analytical tools to support management decision-making is a long process that often does not run smoothly. In implementing such tools, HEIs face several technological challenges and challenges related to privacy and ethical and responsible use of data [26]. Furthermore, large datasets do not necessarily guarantee better decisions [26]. The implementation process usually goes through six steps (justification, planning, business analysis, design, construction, and deployment [27]). During this process, a thorough study of the ongoing processes has to be done [11, 28], incl. the selection of appropriate data for processing, selection of solutions for data extraction and visualization, implementation of data warehouses, integration of relevant data sources, etc. In addition, HEIs leaders should consider how they can use data analytics most effectively, address privacy and security issues, how data strategies can aid informed decision-making. At the end of this process, they have to integrate analytic tools as part of the HEI decision-making structure, which demands institutional strategic planning and resource allocation to reflect its rising relevance in supporting the institution's mission. The successful admission of a data-based decision-making culture in HEI requires trained staff, technologies for data integration, data management systems, and tools for reporting, analysis, and data visualization [26].

The paper highlights the importance of using data-driven decision-making tools in HEIs to improve academic performance and support sustainable development. It also focuses on how these educational data mining tools play a major role in the holistic improvement of learners and thus aids a paradigm shift from traditional to data-driven decision making by the HEIs. Section II summarizes the benefits of applying data-driven decision approaches in HEIs. Section III reviews developed tools that support HEIs leadership in decision-making. The Section IV summarizes the approaches used. Section V outlines the limitations of the paper and opportunities for future research in the field.

II. Application Areas and Benefits

Many studies have been conducted globally on the benefits of applying data analysis and management decision-making tools to improve processes for organizing and conducting student candidate campaigns, student training, academic staff development, effective resource allocation, etc.

HEIs' leadership can apply data analytics tools to optimize the student enrollment process. Data analytics tools allow them to monitor and evaluate current campaign performance versus previous periods, detect enrollment trends [29], identify actions related to student attraction and recruitment [30] and allocate resources for marketing campaigns. Modern analytical tools help the HEIs' managers to monitor the current candidate enrolment campaign and make informed decisions to optimize and improve the process of recruiting students, conduct a targeted marketing campaign based on data on the interest of prospective students in previous years and improving strategies for attracting suitable students and managing the enrollment process for future campaigns. Detailed analysis shows how well the institution is performing, and HEIs' leadership can use the results to identify key trends that could affect the overall success of HEIs' admissions.

Data analytic tools deepen the awareness of HEIs' managers of students' success rates and allow them to track trends over time [31]. The governing bodies have access to aggregate data for students' achievements, which allows them to monitor students' progress [24], identify at-risk students [24, 32] and predict graduation rate [33-34]. They can use this summarized information to identify the reasons for low graduation rates, develop intervention plans [32, 35-37], and improve students' completion rate [38-40]. Tools allow managers to identify the most effective and desired programs [33], to take measures to increase the quality of learning resources and training [41-43].

Data analytic tools can support HEIs' leadership in monitoring research activity and making informed decisions to stimulate it based on the summarized data from university systems, online libraries and databases. HEIs' leadership and people who are responsible for monitoring research activity can make comparisons between the achievements of teachers (e.g. published books and articles, citations, research grants and awards) at different levels (university, faculty, department) over different periods and based on the results to give recommendations to scientists to improve their research activities.

Data analysis and decision support tools make it easier for universities to deal with one of the most frequent obstacles continuously faced in the decision-making process – the selection of human resources. This process is significant for any HEI and determines its future stability and development. HEIs' managers can apply the tools to identify and differentiate candidates' personal and professional qualities [10] and to predict their advancement and performance determined for different occupations and hierarchy levels [10]. Based on generated reports on the structure of the academic staff and the free hours in separate units, the governing bodies can make informed decisions about announcing competitions for the development of the academic staff. Such tools help managers to improve the selection process [40, 45] and evaluate teachers' work, to select the most appropriate teacher for a new course based on course content and academic staff qualifications [10]. In addition, HEIs' leadership can make decisions to stimulate teachers to update curricula, learning resource and change teaching methods [46-48] and thus, to provide students with a better learning environment and enhance the quality of training [34].

Data analytics tools enable HEIs' managers to create and distribute various reports, incl. HEIs' annual performance reports with meaningful summarized historical data. Such annual reports assist managers to answer tactical questions for making data-driven decisions across all departments and divisions [31, 49-50] and determine whether measures are effective and sustainable.

HEIs' leadership can analyze and manage big data to provide transparency in management, predict future outcomes and identify potential problems [31]. In addition, HEIs' leadership can use data analytics tools to make the data-driven decision for cost reduction [40] and allocate resources more efficiently [43, 46-47, 50], meet the desire for accountability for internal and external stakeholders [51] and policymaking [52].

Data analytics tools allow stakeholders to conduct extensive education analysis and share findings across HEIs. From this point of view, HEIs' managers can use data analysis tools to monitor and improve the performance indicators and create a competitive strategy to increase the HEI rank among competing institutions [53].

HEIs' leaders understand that implementation of data-driven decision support tools can significantly transform how they work, enabling new ways to increase student enrolment, improve the quality of educational services, and increase the productivity of teachers and researchers. The proof of this is the large number of successful examples of implementing data-based decision-making solutions in various aspects of HEIs' activities. HEIs' leadership is applying data analytics tools to identify at-risk students and reduce drop-out rate [3, 54-59], provide better feedback [60], identify effective teaching strategies [32], track student engagement and predict student success [32, 56, 61-63], improve student success and graduation rate [61, 64-68], improve HEI evaluation results [61], outline realistic targets to strategically tackle inefficiencies and solve declining student enrolment problems [56]. There are also examples of successful experiments for using data analysis tools to help HEIs' leadership make data-driven decisions on quality assurance, improving institutional processes and student achievement, and reducing drop-outs [69-72].

III. Approaches and Tools

Today, HEIs use decision-making support systems to deal with various challenges, but their use is still partially implemented. According to Mora [1] there is still potential to utilize them at HEIs and corresponding knowledge gaps need to be studied further. The results of a study conducted [84] show that HEIs in developed countries are ready to deal with globalization and take steps towards implementing digital solutions to improve university processes.

Mansmann and Scholl [73] have presented a methodological approach that enables the assessment of educational capacity and the planning of its distribution and usage. They have also developed a decision support system that allows simulation and evaluation of different proposals and scenarios based on this approach. The system is designed to integrate input data from various sources into an autonomous data warehouse, extract meaningful details and dependencies from the data, and present them to decision-makers in an appropriate format. By utilizing this system, policymakers can expedite planning procedures, gain deeper insights into the data and the methodology, and ultimately improve academic administration efficiency.

Bresfelean and Ghisoiu [7] propose a system supporting decision-making about teaching, research, curricula, examination materials and procedures. The system has three main modules – Students, Teaching and Research. The modules extract and process data from university systems and databases, including a research activity management system, a library system, administrative systems (financial, accounting, etc.), management of school records application, web-based grade book, fee management application, distance education portal, e-mail, research management application, periodic academic quality assessments, research and teaching staff evaluations, surveys of PhD students and graduates, etc. The results from the data processing can be used for quality assessment, analysing the organization's practices, and making decisions on management issues.

According to Olsson [74], business intelligence tools are of great use for managing a HEI. The GLIS tool informs top-level governing bodies about the annual planning and reporting process. It also can be used by governing bodies at different levels for handling the admissions process, planning student intake, subsequent analysis of educational programs and bibliometric analysis of publications data.

Şuşnea [4] develops an intelligent support system for decision-making which increases the efficiency of academic processes. The system includes three integrated sub-systems: a sub-system for data management necessary for training the models (data on graduates, students, academic and non-academic staff, faculties, financial resources, educational resources, and e-learning), a sub-system for generating and managing models based on data from the data management sub-system and data extraction through data mining techniques and analytical tools, and user interface. The system provides users with access to data from many sources and the ability to choose a data aggregation level. In addition, it assists the decision-makers in monitoring, modelling and predicting the quality of higher education and contributes to knowledge transfers and collaboration between institutions interested in quality assurance.

Denley [75-77] created a system which suggests what sequence of courses a student should take to enhance his/her success. The Degree Compass system is based on an algorithm which instead of taking the student's choices and preferences, relies on grade and enrollment data. After retrieving all records of student attributes, enrollment choices and grades received, the system ranks the courses based on the chance of successful completion. Furthermore, the algorithm uses the same approach to design a pattern (i.e. the sequence of courses) and predict student's assessment in each course. A straightforward web-based interface, that gives students access to the ranking results, indicates the intensity of recommendation for different course combinations by designating stars (1 to 5). The algorithm that evaluates the courses also reflects on the decisions that students have already made, particularly about their major and prior exams. By analyzing huge datasets to produce predictions about the courses that are most likely to promote student success, the MyFuture add-on module offers details on degree paths and the transition between the HEI and the workforce.

Sarker [78] explored the applicability of the Linked Data technique to promote student retention, progress, and graduation. Two experiments were conducted with the developed academic prediction model – to predict the probability of students being at risk of dropping out and to predict students' academic performance/grades by using readily available data from internal institutional sources/data repositories and external open data sources.

In their work, Fulantelli [79] introduces a framework for mobile learning that facilitates educational decision-making by considering the connections between different types of interactions that occur during mobile learning activities and the relevant pedagogical tasks for each activity. To demonstrate how the framework may be used in mobile learning contexts, they produced a case study.

Lei et al. [80] propose a decision-making framework for educational institutions that aims to improve educational decisions and quality through following student development. The framework contains a student development system, educational data mining, and a decision process. Based on extracted data on student development, the framework supports decision-making to promote it.

Karlstad University invests in business intelligence solutions to help governing bodies find concerning financial, human resource and educational matters. The KULI tool [81] has sections for presenting pre-made and customized information presentations. The pre-made presentation allows monitoring of the budget based on historical economic data, planning of the recruitment process based on the age distribution among the staff data, and supporting the capacity planning process (number of classrooms, number of teachers) based on the data for study programmes and courses. The Custom Information Presentation module allows users to process and adapt data to extract the personalized information they seek.

Cadme and Piedra [82] use a Linked Data technique to explore scientific activity and help universities incorporate scattered teacher-researcher production into the network, form scientific networks, discover potential priority areas where legislators can help formulate science and technology policies.

Indrayani and Pardiyono [83] developed a system that helps future students to choose a HEI based on criteria from a service quality model. The system generates an ultimate decision according to a number of criteria (reliability, responsiveness, assurance, empathy, and tangibles) by using an analytical hierarchy process. Such a process has been used in developing other decision-support systems for educational environments [84].

Komleva et al. [85] developed a decision support system that automates the data collection process from conducted surveys. The system architecture allows working with different fine-grained data sets, which is a prerequisite for the constant development of the system.

Piri et al. [86] use visual information to support the decision-making process. They form the KPIs through structured interviews with 30 people in management positions in the HEI. After analyzing the results, they organized 85 KPIs in the digital dashboard. The developed system has a three-layer architecture – user interface, business layer and database layer. The dashboard utilizes a combined dataset from the learning management, e-learning, accounting and research information systems. The dashboard allows executives to apply filters to view different results and charts. Visualized information helps academic managers identify trends, strengths and weaknesses and make decisions as quickly as possible. In this way, they can improve the quality of all university services, track the university's performance in national and international rankings and conduct advertising campaigns to attract students and PhD students.

Chitpin [87] proposes an Objective Knowledge Growth Framework (OKGF) that helps managers make more effective decisions in solving practice problems. The OKGF framework can improve institutional performance and increase student achievement.

Alisan and Serin [88] propose a decision support system that maintains the quality and positioning of departments and courses offered. This system works in three steps – collecting Internet data by using web scraping methods, converting it into meaningful and processable information using natural language processing methods, and ranking the alternatives using multi-criteria decision-making methods. The suggested system provides useful information to various stakeholders – universities, teachers and students. The qualities of the proposed decision support system in terms of application and reliability are demonstrated by conducting information extraction experiments on computer engineering job postings and university course content in Turkey.

Ashour [44] offers an educational ontology that governing bodies can follow when selecting the most appropriate and qualified teacher for a new course. The ontology summarizes the long steps of mapping course content and faculty member profiles. In a subsequent study, Ashour [10] proposed a solution to support the selection process through the Linked data. They apply the technique to generate a link between university semantic data and research data from online libraries. The Linked Data generation methodology has three steps – initialization (selection of local data source and university ontology, selection of external data source, specification of the linked data set), innovation (identification of restrictions and writing of linkage rules), validation (publication and evaluation). The proposed solution is tested at King Abdulaziz University.

Tadić, Marasović, and Jerković [87] have created a fuzzy multi-criteria decision support model for appointing research and teaching staff in HEIs, which is based on the technique for order preference by similarity to ideal solution (TOPSIS). The model uses both quantitative and qualitative selection criteria, as well as the competencies of experts, in a hierarchically structured manner. The authors have successfully applied this model to the selection of teaching and research staff in higher education institutions in Croatia.

Prasetyo [2] designed a decision support system for determining the HEI's resource need. The system comprises three sub-systems for managing model, data and user interface. The system manages the model base that stores the mathematical model (sessions, estimates of the number of new students, financial income, financial expenses, educational and student operational costs) and result values. By altering the data for the number of lecturers, classrooms, students and guest lecturers, the simulation's outcome value may be determined. Simulation models help management identify problems and use the results to support decision-making.

Makki et al. [90] proposed an admission/decision support system for capacity planning based on a framework for student enrollment and HEI admission.

Du [91] used a decision support system to improve the curriculum. The system uses mobile learning technologies to analyze students' feedback at the end of training. The resulting dataset is used as input to the fuzzy logic system for analysis. The experimental results indicate that the mobile learning technology combined with the fuzzy logic system offers a more effective approach for decision-making analysis related to curriculum optimization for both students and teachers.

To address the challenges of European mobility programs that seek to involve students with multidisciplinary competencies, Teixeira, Alves, Mariz & Almeida [92] have developed a decision support system for selecting students for short-term Erasmus+ mobility. The researchers utilized an analytic hierarchy process based on a four-layer model that collects information about the specifics of each project and student profile and promotes greater inclusion and homogenization of project teams. They tested the proposed system with 6 test scenarios, and the results demonstrate that the proposed model can be applied with various selection criteria among students and consider their hard and soft skills. The system can support decision-making to build project teams where students' knowledge is aligned with the technical skills required to complete the projects.

Gaftandzhieva, Doneva and Bliznakov [93] propose software tool for monitoring the career designed for different stakeholder groups (faculty staff, members of quality committees, head of departments, top and middle management) having a role in stimulating career paths in academy. The AcadStaffAnalyst tool allows them to monitor the career development of the faculty staff based on the 68 quantitative indicators divided into 7 groups (Acquisition of scientific degrees, Occupying scientific positions, Occupying management positions, Publishing activity, Projects activity, Activity in scientific events, Gender gap) and make data-informed decisions to stimulate career paths, ensure equal access to options for career growth, set priorities and adjust them when the situation allows it. The tool can generate self-assessment reports with data for the faculty staff for the need of accreditation procedures. Indicator values are obtained by extracting and processing data from human resource systems, academic staff development systems, and research reporting system.

To help university decision-makers make decisions to increase retention rate and improve student success rate Gaftandzhieva, Doneva and Bliznakov [94] offer a tool for monitoring student success from. The StudAnalyst tool allows programme managers, deans and rector to monitor 42 quantitative indicators divided into 3 groups (Student success during the training, Student success in graduation, Gender gap) and generate reports for each indicator with retrieved values when s/he wants to see the current situation in the faculty/university depending on its user role. The tool can also generate such reports automatically following the predetermined schedule and store them in its repository. Reports contain summarized data visualized in tables and diagrams and help users to perform various analyses and make data-informed decisions.

IV. Discussion

Studies cited in this paper show that data-driven decision-making tools can improve decision-making in HEIs. HEIs are complex organizations with multiple stakeholders, making decision-making a challenging task. By using data-driven decision-making tools, HEIs can make more informed decisions leading to better performance, higher student achievement, and increased competitiveness of departments and courses offered.

One of the approaches proposed to support decision-making is using decision-support systems. Such systems can collect data from various sources, analyse the data, and present the results in a meaningful format to different stakeholders. The studies by Alisan and Serin [88] and Prasetyo [2] proposed decision support systems for capacity planning and determining the need for higher education resources, respectively. These systems can help management identify problems in operating systems and use the results to support decision-making.

Another approach proposed is the use of fuzzy multi-criteria decision support models. The study by Tadić et al. [89] developed a fuzzy multi-criteria decision support model for research and faculty staff in HEIs' appointments based on the technique for order preference by similarity to the ideal solution (TOPSIS). The model uses hierarchically structured quantitative and qualitative selection criteria and the competencies of the experts. The proposed model, which refers to a specific set of rules and procedures, has been implemented for the purpose of choosing faculty members who will be involved in both teaching and research activities in Croatia. This process likely involved analysing various factors such as educational qualifications, research experience, and other relevant criteria in order to make informed decisions about the candidates most suitable for the job.

The studies by Ashour et al. [10, 44] proposed educational ontology and linked data techniques to support the process for selecting the most appropriate and qualified teacher for a new course. The ontology summarizes the long steps of mapping course content and faculty member profiles, while the linked data technique generates a link between university semantic data and research data from online libraries.

Finally, the study by Du [91] used a data-driven decision support system to improve the course curriculum. The system uses mobile learning technologies to analyze students' feedback at the end of training. The dataset of student responses is set as input to the fuzzy logic system to perform the analysis. The results of experiments showed that mobile learning technology with the fuzzy logic system offers improved decision-making analysis for curriculum optimization for the student and teachers.

In conclusion, the studies reviewed in this article demonstrate the potential of data-driven tools to support decision-making in HEIs. By using these tools, HEIs can make more informed decisions leading to better performance, higher student achievement, and increased competitiveness of departments and courses offered. Further research is needed to determine the most effective tools and approaches for supporting decision-making in HEIs.

Table I presents a summary of the reviewed tools. The “Data Sources" column contains a brief description of the source types, as mentioned in the references. The "Users" column refers to the intended audience for each tool. The "Purpose" column provides a concise statement of what problem the tool is designed to solve.

TABLE I. SUMMARY OF THE RELEVANT TOOLS

Authors & References	Data Sources	Users	Purpose
Mora et al. (2017) [1]	Various data sources	Higher education institutions’ (HEIs) managers and decision-makers	Provide open opportunities to apply decision-making support systems in HEIs
Mansmann & Scholl (2007) [73]	Autonomous data warehouse, different sources	HEIs’ policymakers and decision-makers	Assess educational capacity and plan distribution and utilization
Bresfelean & Ghisoiu (2010) [7]	University systems and databases	HEIs’ management staff	Support decision-making about teaching, research, curricula, examination materials and procedures
Olsson et al. (2012) [74]	GLIS tool	Top-level governing bodies at HEIs	Inform about annual planning and reporting processes, handle admissions processes, plan student intake, balance student load, analyse educational programs, and bibliometric analysis of publication data
Şuşnea (2013) [4]	Alumni, students, academic and non-academic staff, faculties, financial and educational resources, e-learning	HEIs’ senior management, students, and teachers	Provide a scientific base for decision-making, increase the efficiency of academic processes, and improve the quality of higher education at national and international levels
Denley (2012-2014) [75-77]	Grade and enrollment data	Higher education students	Suggest the best patterns of courses to maximize student success, and predict grades obtained in each exam
Sarker (2014) [78]	Internal institutional and external open data sources	First-year university students and HEIs’s management staff	Promote student retention, progress, and graduation
Fulantelli et al. (2015) [79]	Mobile learning interaction types	Educational decision-makers and policymakers	Aid educational decision-making
Gaftandzhieva et al., 2023 [93]	Human resources systems, academic staff development systems, research reporting system	Stakeholder groups (faculty staff, members of quality committees, head of departments, deans and vice-deans, rector and vice-rector) having a role in stimulating career paths in academy	Make data-informed decisions to stimulate career paths, ensure equal access to options for career growth
Gaftandzhieva et al., 2023 [94]	Student Information system	Programme managers, deans and rector	Monitoring student success in a timely manner

V. CONCLUSIONS

HEIs are complex organizations that require effective decision-making to improve performance and increase competitiveness. This article reviewed several studies that proposed data-driven tools for supporting decision-making in HEIs. The studies proposed decision-support systems, fuzzy multi-criteria decision-support models, educational ontology, linked data techniques, and mobile learning technologies to analyse student feedback.

The studies showed that data-driven decision-making tools are able to support decision-making in HEIs. These tools can help management identify problems in operating systems and use the results to support decision-making. The studies also demonstrated that HEIs’ leaders could use different approaches to support decision-making, incl. decision support systems, fuzzy multi-criteria decision support models, educational ontology, linked data techniques, and mobile learning technologies.

Overall, the studies reviewed in this article highlight the importance of data-driven decision-making in HEIs. By using these tools, HEIs can make more informed decisions leading to better performance, higher student achievements, and increased competitiveness of departments and courses offered.

The cited works highlight that data-driven decision-making methods can support decision-making in HEIs. However, HEIs need to consider certain limitations when applying these methods. One limitation is the lack of quality data. Much data collected in HEIs can be inconsistent, incomplete, or unavailable. Therefore, it is significant to ensure HEIs collect relevant and reliable data. Another limitation is the difficulty in identifying the right questions to research. To successfully apply data-driven decision-making methods, it is significant to identify the right questions for research. This requires knowledge of the decision-making process and specific challenges that HEIs face.

Data-driven decision-making methods have many areas of application, including analysis of student feedback, monitoring of student success, identification of trends in course selection, and optimization of resource management. They also help the companies in the campus placement and help all the stakeholders of the education system at one go. Despite their wide application in various fields, these methods should be adapted to the specific HEI's needs.

Given the limitations and application areas, further research is needed to determine which tools and approaches are most effective in supporting decision-making in HEIs.

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