Combining BI and Analytics in Higher Ed

Krishna C Gonugunta[1], Meng Chen[2], Yong She[2]
[1]Sr. Database Admin/SCS Operational Manager, Nevada System of Higher Education (NSHE), 2601 Enterprise Rd, Reno NV 89512
[2]Centre for Innovative and Lifelong Learning, ICDT

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ABSTRACT

Data analytics in higher education offers distinct potential to analyze, comprehend, and model educational processes. As a result, the approaches and procedures supporting data analytics in higher education have resulted in distinct, highly correlated terminologies such as Learning Analytics (LA), Academic Analytics (AA), and Educational Data Mining (EDM), where the results of one may serve as the input for another. This study aims to provide IS educators and researchers with an overview of the present state of research and theoretical perspectives on educational data analytics. The document presents a comprehensive set of concepts and a cohesive framework for data analytics within higher education. By examining the framework, scholars may uncover novel settings and domains of investigation. The Gestalt-like process of integrating the framework (total) with the articulation of data analytics (parts) may prove beneficial for educational stakeholders in making decisions about individual students, student groups, curricula, schools, and educational systems.

Introduction

Education in Information Systems (IS) under mounting pressure to respond to escalating societal demands and worldwide transformations. For example, Information Systems education must be modified to incorporate workplace competencies, including IT-related skills and innovative capabilities. Students' apprehensions over employment availability influence their decision to select Information Systems as a major. IS educators and researchers find it difficult to adapt promptly and effectively to societal needs and worldwide transformations. The progress of data analytics has created distinct options to address these swift changes. Data analytics mitigates the difficulties of locating pertinent information promptly to facilitate institutional decision-making. Moreover, data analytics has provided significant insights into the dynamics of a particular course and strategies for mitigating performance concerns [1-3].

In the Information Age, the unceasing advancement of information and communication systems has emerged as the catalyst for societal evolution, encompassing educational revolution. Educational systems, encompassing learning management systems and course authoring systems, produce vast datasets during routine operations. Extensive data produced by educational systems is becoming accessible for collection and analysis. This substantial quantity of data has intensified the necessity for robust data management and analytics within the educational context. The educational datasets significantly advance learning theories, support mechanisms, design methodologies, learner feedback, and the creation of future learning support systems [4-16].

In the last ten years, swift advancements in big data and analytics have heightened interest in educational data analytics. A number of scholars have examined and evaluated the characteristics and relevance of big data and analytics in the field of education. The application of data analytics to enhance student achievement through the provision of real-time feedback to learners. Efforts to implement data analytics in education have led to the emergence of new fields: learning analytics, academic analytics, and educational data mining. Although all these concepts pertain to the application of data analytics in education, they are entirely distinct. Learning analytics emphasizes the utilization of data analytic methodologies and instruments to comprehend and improve learning and instruction, whereas academic learning seeks to facilitate institutional operations and decision-making. Moreover, educational data mining emphasizes the creation and assessment of data analytics techniques for the exploration of educational data. As a nascent field of inquiry and application, several words have been introduced and embraced to Elucidate analogous concepts and processes. Nonetheless, the elucidation and agreement on these terminologies remain incomplete [17-27].

This study presents a complete framework for data analytics in higher education, encompassing knowledge units for learning analytics, academic analytics, and educational data mining, to facilitate ongoing debates aimed at establishing a unified perspective on analytics in this sector. Despite previous research attempting to create a preliminary connection between learning analytics and academic analytics as well as between learning analytics and educational data mining, a review of the literature did not uncover any study offering a comprehensive perspective on these subfields collectively. Consequently, our suggested framework aims to amalgamate current study domains in data analytics within higher education and to provide educators and practitioners with a comprehensive overview of entities and their interrelations in an analytics-driven educational setting.

The subsequent section will examine the three primary study domains of data analytics in higher education: Learning Analytics (LA), Academic Analytics (AA), and Educational Data Mining (EDM). It will then present an overview of these domains before providing a cohesive synthesis of them. We offer a comprehensive set of definitions for data analytics in higher education and provide an integrated framework to enhance stakeholders' understanding of this category of educational technology. We end by examining prospective research avenues and the ramifications of our findings [28-38].

Data Analytics in Higher Education

Learning Analytics (LA)

Learning Analytics (LA), as an emerging study topic, has been described using numerous words and meanings in both common usage and academic literature. LA may be broadly defined as the application of data analytics in education and instruction. Unlike academic analytics and educational data mining, learning analytics emphasizes learners and their learning processes. Learning analytics gathers, combines, and examines both static and dynamic data concerning learner profiles, educational content, and the learning environment.

It can provide descriptive modeling and prediction of learning aspects on a planned or real-time basis. During the inaugural International Conference on Learning Analytics in 2011, the Society for Learning Analytics Research (SoLAR) articulated learning analytics (LA) as “the measurement, collection, analysis, and reporting of data concerning learners and their contexts, aimed at comprehending and enhancing learning and the environments in which it transpires.” This definition has since gained considerable acceptance within the research community. We contend that this definition fails to comprehensively encompass all applications of Learning Analytics, including adaptive learning systems. Instead of only providing data to provide actionable insights, adaptive learning systems actively modify the learning environment and resources to improve educational outcomes. We define learning analytics (LA) as "the utilization of data analytic methodologies and instruments to comprehend and improve learning and teaching" [39-49]

Categories of Learning Analytics

Content Analysis is a branch of learning analytics employed for contextual interpretations of textual sources. Content analysis encompasses both human and computer-assisted methodologies that examine texts to uncover latent meanings. In the educational setting, textual sources are classified into five primary categories: written text, oral text, iconic text, audio-visual text, and hypertext. Recent advancements in online analytics methodologies, including web crawling and machine learning algorithms, have sparked a resurgence of interest in the analysis of hypertext present on websites.

Discourse Analytics monitors user interactions to investigate significant insights on the characteristics of the language employed in the learning discourse. Content Analysis aims to extract significant information from textual sources, whereas Discourse Analytics concentrates on analyzing the language employed by learners. Discourse analytics engages with learners via platforms where they are already participating, such as online learning forums. Interactivity is fundamental to the process of knowledge production. Learning is perceived as a socio-constructivist process characterized by the interactions between learners and content. The progression of text mining and log tracking has facilitated the analysis of discourse data and metadata. Similarly, social learning analytics has evolved and garnered interest in the domain of education. While discourse analytics focuses on the substance and language utilized in learning discourse, social learning analytics is primarily concerned with learner cooperation.

Social Learning Analytics is a specific subset of learning analytics that emphasizes student involvement and participation in the learning process. Discourse Analytics analyzes the language employed by learners, whereas Social Learning Analytics evaluates the learning process from a social standpoint, positing that the acquisition of new information and skills is not only an individual accomplishment in education. This may be succinctly demonstrated by prior research on the influence of social networks on learning outcomes performed social network analysis (SNA) to examine the relationship between social network interactions and academic achievement. The research findings suggest the necessity for more investigation into the conditions under which social network factors reliably predict student achievement. The study cautions against only depending on social network elements for prediction. This study indicates that data visualization serves as an effective instrument for social learning analytics.

Disposition Analytics examines educational data on students' backgrounds and learning engagement to identify their dispositions and the intrinsic linkages to the learning process (Peña-Ayala, 2014; Bharara, Sabitha, and Bansal, 2018). This learning analytics technique analyzes the aspects students contribute to the learning environment to determine their learning styles and forecast preferred learning behaviors, so enhancing both learning and teaching. Bharara, Sabitha, and Bansal (2018) employ disposition analytics to examine the impact of several variables on student performance. Through the analysis of this information, the teacher may enhance decision-making.

Discriminative Alternatives and Effective Pedagogical Approaches and Procedures

Applications of Learning Analytics.

Previous research has recognized several uses of learning analytics to enhance learning and instruction in higher education. Learning analytics tools furnish current data regarding learning activities, student involvement, student profiles, and pertinent historical data from prior semesters to model the learning process. Moreover, with the application of learning analytics, educators and researchers have successfully predicted students' future performance. Utilizing the projected data, the instructor may implement requisite interventions and concentrate additional efforts on at-risk individuals. A model of effective student behaviors can assist faculty in promoting student engagement in self-regulating their learning behaviors to achieve enhanced academic performance. The approach specifically incorporates the frequency of accessing and utilizing learning applications, such as LMS tools and discussion boards, as possible determinants of success. The paradigm of effective student behaviors emphasizes learning activities that directly impact final grades. Consequently, educators may be certain of understanding the objectives while refining instructional activities [50-55].

Similarly, Arnold and Pistilli (2012) introduced an early intervention strategy for academic staff named “Course Signals.” This system utilizes educational data to forecast student performance and communicates the results to students through a tailored email. The gathered data include grades, historical academic performance, student demographics, and metrics of learning engagement. The given information includes a traffic signal that indicates each student's performance level. The students' emails inform them of their present academic performance and, for at-risk pupils, outline necessary modifications to enhance their likelihood of success. Consequently, the implementation of the Course Signals system exemplifies the application of learning analytics at the individual student level.

Greller and Drachsler (2012) offered a strategy in which learning analytics can elucidate the knowledge deficiencies displayed by students to educators. Their objective is to furnish academic stakeholders, such as students and educators, with information to enhance comprehension of learning requirements and performance. In this case, based on the 'gap' analysis, they might furnish pupils with supplementary resources to enhance and rectify their comprehension of the fundamental learning material.

Visualizations may effectively enhance learning analytics reports by providing users with more significant information. The benefit of visualizations is to graphically convey substantial volumes of intricate data, facilitating the identification of trends, patterns, connections, and pressing concerns. Visualizations may be utilized in education to present analyzed data obtained from both students and educators. When utilizing learning analytics visualization tools, it is essential to consider data security, multi-user support, and accessibility. Numerous academics have endeavored to develop visualization tools for learning analytics. A web-based visualization tool called GLASS (Gradient's Learning Analytics System). The visualization techniques in GLASS were created using a bottom-up approach, emphasizing the requirements of the end-user. The instrument was engineered explicitly to facilitate the integration of novel visuals for presenting data pertinent to students, educators, and the educational process. Consequently, GLASS can provide the development of visualizations pertaining to learners' events and actions inside a certain setting.

Ultimately, learning analytics has facilitated personalized learning and adaptive learning systems in higher education. Adaptive learning systems, sometimes referred to as customized or individualized learning applications, denote functionalities that adjust to student interactions with the system based on a minimal quantity of data produced by the learner. The learning analytics engine serves as the fundamental element of an adaptive learning system by gathering and analyzing data in real time. Suggested a fuzzy logic-based customized learning system to enhance adaptable English language acquisition. The algorithm may suggest articles suitable for a learner's English proficiency and their vocabulary refresher requirements. The research findings have validated that the suggested customized learning system enhances educational outcomes and maintains students' engagement in learning. Personalized learning and adaptive learning systems facilitate the establishment of an inclusive educational environment. This study succinctly reviews current research that has revealed significant uses of learning analytics in the realm of education. A key policy objective should be to codify the promise of learning analytics research in higher education.

Academic Analytics (AA)

The phrase Academic Analytics (AA) was introduced by Goldstein and Katz to denote the convergence of technology, information, organizational culture, and the utilization of data analytics for institutional management. Academic Analytics denotes the application of business intelligence within the educational sector, specifically involving the identification of significant patterns in educational data to highlight academic challenges, such as dropout rates, and to facilitate strategic decision-making. The method primarily emphasizes assisting institutional managers and educational policymakers. Students anticipate the utilization of data analytics to forecast and enhance their academic achievement, while institutional administrators contemplate the implementation of academic analytics to oversee and augment educational Key achievement Indicators (KPIs), including student retention. Barneveld, Arnold, and Campbell characterized academic analytics as “a process for supplying higher education institutions with the data essential for operational and financial decision-making.” In distinction from learning analytics, we refine this definition to encompass a broader interpretation: “the utilization of data analytic methodologies and instruments to facilitate institutional operations and decision-making.”

A diverse array of educational stakeholders is seen as benefactors of academic analytics software. Specifically, the stakeholders who gain from academic analytics encompass academics, students, and executive officers. At every level, the utilization of academic analytics provides significant advantages while also presenting possible issues.

Academic Analytics may Assist Academics by Uncovering Critical Insights

Determinants of student achievement, offering insights into efficacious approaches, and enhancing the scholarship of teaching and learning. Student success is a primary key performance indicator (KPI) in higher education, prompting most faculty to monitor and anticipate it. Moreover, AA may derive significant insights from educational data to identify the most successful methodologies and facilitate faculty pedagogical modifications to meet students' demands.

The executive officers may obtain valuable insights from academic analytics to enhance their decision-making. Academic analytics provides distinct key performance indicators that are absent in conventional educational systems. The vice-chancellor may be apprised of the proportion of at-risk pupils and thereafter solicit a review of the institution's pedagogical plan. The executive officers may utilize academic analytics to enhance resource optimization. Academic analytics is thought to boost institutional responsibility and bolster its reputation. Notwithstanding the aforementioned advantages, executive officers frequently scrutinize the expenses linked to an academic analytics initiative. Furthermore, people will probably be apprehensive regarding privacy and security concerns once the system is operational.

Educational Data Mining (EDM)

The International Educational Data Mining Society (IEDMS) characterizes Educational Data Mining (EDM) as “an emerging discipline focused on devising methods to investigate the distinctive and progressively extensive data originating from educational environments, utilizing these methods to enhance comprehension of students and their learning contexts.” Data mining, alternatively termed Knowledge Discovery in Databases (KDD), pertains to a subfield of computer science dedicated to the extraction of valuable information and insights from raw data sources. Previous research characterized educational data mining as the development of data mining techniques for analyzing intricate educational datasets and employing these techniques to derive insights about students and educational institutions. The EDM process employs computational methods to transform raw data from educational systems into valuable information that helps resolve educational inquiries.

Categories of Educational Data Mining

Various categories of educational data mining exist. Baker proposed that all educational data mining techniques may be classified into five overarching categories: prediction, clustering, relationship mining, model-based discovery, and data distillation for human interpretation. The EDM academic community has widely acknowledged the initial three categories, whereas the latter two have gained very limited recognition within the domain of educational data mining.

In educational data mining, prediction seeks to simulate an educational result based on several data elements. The forecast factor is referred to as the predicted variable, whilst input components are designated as predictor variables. An instance of prediction EDM is the participation-based prediction model employing interpretable Genetic Programming as proposed. The model forecasts students' ultimate performance utilizing six created factors related to their online engagement in Computer-supported Collaborative Learning (CSCL): Subjects, Rules, Tools, Division of Labour, Community, and Item. Prediction model serves as another example, utilizing interaction data as predictor variables. The model's accuracy was confirmed by generalizing with supplementary students across several scenarios.

The second category of educational data mining is clustering, which emphasizes the organization of raw data into distinct clusters and the identification of boundaries between these groupings. Clustering may utilize various grain sizes, including the categorization of students into groups and the analysis of student actions to identify behavioral trends. This category of educational data mining techniques may incorporate established assumptions or operate without any prior notions.

The third category of educational data mining is relationship mining, which aims to identify potential correlations within a dataset comprising many variables. Clustering involves the categorization of a collection of items, whereas relationship mining seeks to uncover significant associations across variables within the data. Relationship mining is categorized into four subcategories: association rule mining, causal data mining, correlation mining, and sequential pattern mining. Association rule mining seeks to identify if-then relationships among variables. Specifically, these data mining techniques identify connections wherein the specification of a set of variables predicts a particular value for another variable. association rule mining to identify the following rules: A high number of messages viewed in the forum correlates with a high assignment score. Causal data mining approaches are employed to identify "causal relationships" wherein one occurrence precipitates another. The causal link may be either unidirectional or bidirectional. The last two categories of connection mining are correlation mining, which seeks to identify positive or negative linear correlations between variables, and sequential pattern mining, which emphasizes temporal links. Sequential pattern mining to elucidate the processes governing multimedia learning by synthesizing metacognitive assessments and ocular movements.

The fourth category of educational data mining is model discovery, wherein a phenomenon's model is created using other EDM techniques or knowledge engineering and thereafter employed as a component for further analysis. Discovery through models frequently applies the validated generalization of a predictive model in many circumstances. The primary use of this sort of Educational Data Mining (EDM) is to uncover correlations between student actions and contextual elements inside the learning environment.

The final study domain in educational data mining is the distillation of data for human evaluation. Human actions can affect datasets, and this effect may exceed the capabilities of automated data mining techniques. This area of research is on employing visualizations to clarify data for human assessment. In contrast to conventional information visualization systems, data visualizations for educational mining are often designed around a specific framework of educational data and utilized to convey significance pertaining to that framework. Moreover, a synthesis of data for human evaluation may be utilized to enhance the creation of a predictive model through the annotation of data sets.

Applications of Educational Data Mining

A diverse array of educational data mining applications is classified into four primary categories. These are pertaining to the enhancement of student models, the identification or refinement of knowledge management models, the evaluation of pedagogical assistance within learning applications, and the scientific exploration of learners and the learning process.

EDM apps enhance student models by gathering raw data on each learner and analyzing it to yield significant insights into the learner's attributes, learning progress, and the variations across learners. The produced information include, but is not restricted to, student behavior, performance, learning motivation, and attitudes. Educational Data Mining (EDM) to enhance graduate students' performance by collecting valuable insights from educational data. This instance employs many EDM approaches, including clustering, association rule mining, classification, and outlier identification. The investigations aim to develop techniques for swiftly selecting suitable domain models directly from data while developing or enhancing models of the domain's knowledge structure. These applications frequently amalgamate psychometric models with sophisticated space-search algorithms and predictive challenges in the process of identifying novel models.

The pedagogical support of the learning tool is analyzed by correlating each type of educational assistance for a student with academic performance, assigning specific weights to each. Cutting-edge learning technologies have provided diverse help to students, making the quantification of accessible assistance a crucial endeavor in education. EDM has been utilized to assess the instructional efficacy of a certain learning instrument and suggest possible enhancements.

The last category of EDM applications concentrates on scientific exploration about learners and the learning process. The deployment of educational data mining techniques to resolve issues in the aforementioned EDM applications might augment scientific relevance (Baker, 2010). The primary kind of educational data mining utilized in scientific discovery applications is model-based discovery.

Research Ontology for Educational Data Analytics

Prior studies have endeavored to delineate the communities and differentiate between Learning Analytics (LA), Academic Analytics (AA), and Educational Data Mining (EDM) delineate the distinctions between LA and AA, referencing the degree or object of analytics and the advantageous stakeholders (Table 1).

LA focuses on the micro (Learner) and macro (Faculty) levels of educational stakeholders, while AA serves stakeholders at the macro (Institution) and mega (Governance) levels. Due to the varying objectives of data analytics, Learning Analytics (LA) and Academic Analytics (AA) collect unique datasets and employ various analytical techniques to produce suitable results.

An ontological analysis to investigate research trends in Learning Analytics (LA) and Educational Data Mining (EDM). The research examined articles from two prominent groups in educational data analytics: Learning Analytics & Knowledge (LAK) and Educational Data Mining (EDM). The highest-ranked themes illustrate the similarities and differences between LA and EDM. Specifically, these two fields possess shared interests in several topics, including students, data, and models.

Table 1. Learning and Academic Analytics

Type of Analytics	Level or Object of Analysis	Who Benefits
Learning analytics	Course-level: social networks, conceptual development, discourse analysis, intelligent curriculum	Learners, faculty
	Departmental: predictive modelling, patterns of success/failure	Learners, faculty
Academic analytics	Institutional: learner profiles, performances of academics, knowledge flow	Administrators, funder marketing
	Regional (state/provincial): comparisons between systems	Funders, administrators
	National and international	National governments, education authorities

Nonetheless, there exist notable distinctions among the study streams. The unique ideas for LA are associated with educators, knowledge, social factors, social learning, effective learning, learning, and informal learning. Conversely, leading notions for EDM emphasize talent, technique, tool, system, feature, item, and parameter. This demonstrates that Learning Analytics (LA) prioritizes the learning process and interactions within the educational environment, whereas Educational Data Mining (EDM) emphasizes methodologies and strategies for the data pipeline.

Learning Analytics (LA), Academic Analytics (AA), and Educational Data Mining (EDM) concentrate on distinct aspects of educational data analytics, however they are closely interconnected. The advancement of any research domain will provide dynamic effects on other domains. For example, advancements in EDM are expected to yield sophisticated analytical methods and instruments that will transform the field of LA and AA study. The emerging methodologies and technologies may be utilized to enhance comprehension of the learning and teaching process and its context. Therefore, an integrated perspective on educational data analytics is essential for enhanced decision-making and the execution of these technologies.

Frameworks for Educational Data Analytics

The proliferation of educational data analytics has stimulated research aimed at developing frameworks and recommendations to facilitate research and implementation. This is seen in the Learning Analytics Reference Model. The model illustrates the relationships between learning analytics and associated domains within Technology Enhanced Learning (TEL), including recommender systems and customized adaptive learning. The reference model is founded on four principal dimensions: data and environments (what?), stakeholders (who?), objectives (why?), and

Methods (how?). The model delineates essential principles of learning analytics and subsequently offers prospective research avenues within the nascent domain of learning analytics. Researchers might explicitly examine educational data or learning contexts, focusing on context modeling and learning analytics across diverse educational environments.

Human elements must be taken into account regarding the LA process and its stakeholders. The Learning Analytics Reference Model illustrates the essential elements of educational data analytics, however it fails to consider the relationship between educational data analytics and various stakeholder tiers within the educational ecosystem.

A hierarchical approach to elucidate educational information among the principal stakeholders in the educational system. The main level signifies students, the focal point of higher education. The majority of educational data for analytics is derived from students' interactions and attributes. The intermediate layer consists of professors who serve a pivotal function between the institution and the pupils. Educators can get advantages from the study of student data, since they can utilize performance and engagement metrics to modify their instructional approaches. The institution can utilize information from both students and professors to formulate and develop institutional policies in the subsequent layer. The apex of the pyramid represents the governance layer where educational policies are formulated based on the study of cross-institutional data surroundings in accordance with hypothesis formulation. The data is analyzed and input into data mining tools to generate models or patterns for user interpretation and assessment. The results are ultimately employed to enhance the teaching environment and to formulate hypotheses. The steps of hypothesis development, testing, and refinement can be partially applied to learning analytics. Consequently, learning analytics starts with the acquisition of raw data, followed by data processing and reporting.

Ifenthaler (2015) presents a comprehensive learning analytics paradigm centered on the learner and the learning process. The integrated LA framework delineates the workflow of learning analytics by including data collection, data analysis, and information reporting to users within an educational setting. Furthermore, Ifenthaler (2015) delineates an alternative architecture of learning analytics linked to several stakeholder tiers. The model depicts the data flow among educational stakeholders and the role of Learning Analytics (LA) inside the learning environment. Learning activities occur at the micro level, where learners engage with the learning environment. The curriculum and instructional design are informed by macro-level analytics. At this level, educational data analytics furnishes educators and instructional designers with valuable insights into learning processes and results to facilitate informed design decisions. The macro level facilitates institution-wide analytics that enhance comprehension of learner cohorts, assess the efficacy and efficiency of operational operations, and optimize resource allocation. The apex of the LA structure is termed mega-level, which integrates data from all subordinate levels. At a macro level, cross-institutional analytics facilitate governance by offering useful insights through the detection and confirmation of patterns both inside and among institutions. Moreover, predictive analytics and simulation facilitate educational policymaking.

Ifenthaler's (2015) frameworks were created to elucidate learning analytics, but they extend beyond this domain to encompass aspects of academic analytics. The macro and mega levels of the LA architecture can serve goals beyond only maximizing learning and the learning environment, so aligning with the concept of learning analytics. For example, academic analytics might be utilized at the institutional (macro) level to enhance resource allocation. This hierarchy of stakeholder levels can also symbolize the position of educational data analytics.

An Integrated Perspective on Data Analytics in Higher Education

The area of learning and teaching is intricate and dynamic multifaceted. The elements of the educational ecology are complex and volatile. Each shareholder may own various modern interests and inclinations. Furthermore, tools like data mining and machine learning techniques are evolving with time. Consequently, modifications within the educational environment must be evaluated about the effects on each of its essential components and their interrelations. Researchers and practitioners must recognize that interventions at one level of educational analytics may influence other levels. The introduction of learning analytics for learner self-reflection at the course level would alter the attributes and configurations of educational data mining initiatives at the institutional level that gather and analyze learning data. In this instance, educational data mining at an advanced level provides an assessment of the large-scale adoption of learning analytics

Table 2. Proposed Definitions for Data Analytics in Higher Education

The DAHE architecture delineates essential elements of education data analytics and their interconnections at each tier of the education system (dotted lines). The framework, encompassing learning analytics, academic analytics, and educational data mining, illustrates the interplay among these data analytics domains and their relationship with educational components. It provides a summary of the newly developed domains within the higher education landscape.

Term	**Proposed Definition**	**Focal Objects of Interest**	**Level of Education System**
Learning Analytics	The application of data analytic techniques and tools for purposes of understanding and enhancing learning and teaching.	Learner Learning settings	Course level
Educational Data Mining	The development and evaluation of data analytics methods for exploring educational data and using those methods to better understand learners and the learning environment (adapted from IEDMS).	Methods and Techniques	Departmental level
Academic Analytics	The application of data analytic techniques and tools for purposes of supporting institutional operations and decision-making.	Institutional operation and decision-making	Faculty Level Institutional Level

Academic analytics emphasizes institutional and faculty-level administration, whereby educational data is crucial for facilitating operational and financial decision-making. Moreover, the academic analytics can facilitate comparisons among systems to assist educational financiers, administrators, authorities, and governmental bodies. In other terms, academic analytics denotes the significance of data analytics across institutional, regional, national, and international dimensions. Academic analytics appears to be more congruent with conventional business intelligence inside higher education. Information Systems education academics ought to examine academic analytics for studies that encompass a wide educational environment, incorporating various institutional or social aspects.

Educational data mining emphasizes the creation and assessment of strategies, tools, and methodologies aimed at the automatic extraction and analysis of insights from extensive collections of educational data. The discipline aims to enhance methodologies and approaches for analyzing extensive data derived from educational environments. Educational data mining provides distinct and vital contributions to educational administration and decision-making. The discipline is firmly rooted in modeling learner behavior and forecasting course results. Educational data mining advantages stakeholders throughout many tiers of the education system, predominantly from the institutional to the departmental level.

Learning analytics emphasizes learners, their behavioral patterns, and the educational context. Unlike academic analytics, learning analytics entails a more focused examination aimed at "understanding and optimizing learning and the environments in which it occurs". Learning analytics study examines the data generated by the interactions between learners and educators within the learning environment. The learning environment may consist of physical settings (e.g., a classroom) or digital platforms (e.g., a learning management system). Learning analytics primarily investigates educational data at the course and departmental levels. Learning analytics research examines social networks, intelligent curricula, and discourse analysis at the course level. At the departmental level, learning analytics aims to deliver predictive modeling and identify patterns of success or failure.

Unlike educational data mining, learning analytics prioritizes human judgment in the discovery process, with automated discovery serving as a means to achieve this. To tackle the intricacies of learning and teaching, learning analytics prioritizes a holistic comprehension of systems. IS instructors and researchers may utilize learning analytics to improve their instructing and facilitating student engagement in learning.

In addition to prior frameworks, the model incorporates many activities and services, including participation in student groups, departmental events, and the job hub. Research indicates that these activities may affect student development and performance. The elements affecting a student's sense of belonging inside the school encompass both academic pursuits and extracurricular as well as non-academic activities. A substantial and positive correlation exists between students' reported sense of belonging within the institution and their learning engagement and performance. An additional instance is the application of educational data analytics for recommending employment options to students. This integrated framework provides educational technologists with a comprehensive perspective on data analytics in higher education, enabling them to explore advancements beyond the current state, including the utilization of artificial intelligence (AI) to deliver novel insights to all educational stakeholders.

Future Research Directions

The conceptual framework was created to illustrate the connection between analytics and stakeholders at various tiers within the higher education system. Information Systems instructors and researchers may utilize DAHE to identify their analytics area of interest, hence conserving time and effort in literature study. Ongoing research on data analytics in higher education will enhance comprehension of institutional data and the prerequisites for efficient data preparation for analytics, facilitating data-driven decision-making and practices. Improving communication across many facets of data analytics in higher education is a problem. Further investigation is required on the use of educational data analytics from many viewpoints. For example, stakeholders at various levels of the education system own divergent interests regarding data utilization, and their ethical concerns vary according to their perspectives.

This research seeks to enhance a standardized lexicon for educational data analytics. Our comprehensive definitions and cohesive architecture offer educators and researchers an overview of several fields of data analytics in higher education. Table 3 presents a collection of examples of analytics at each application level of DAHE.

The utilization of data analytics in higher education provides valuable insights that assist educational stakeholders in executing their responsibilities and making informed decisions. The creation of programs and technologies that utilize integrated data analytics to enhance learning and teaching is essential for boosting performance at both the course and institutional levels. Nonetheless, information systems instructors may contemplate future inquiries on felt belonging using data analytics. The automated updating of information pertaining to student activities may signify their institutional affiliation and social engagement. This information may enhance our understanding of the influence of social engagement on student development and success. By utilizing this information, institutional management might eradicate less productive activities while endorsing beneficial after-class events for pupils.

Table 3. Examples of Analytics at each Application Level of DAHE

Application Level	**Educational Stakeholder**	**Examples of Analytics**
Course-level	Learners, Lecturers, Tutors, Researchers	Patterns of learning behaviour Modeling self- regulation in learning. Intelligent curriculum
Departmental	Lecturers, Researchers, Administrators	Predictive modeling Identification of at-risk students' Performance or Achievements
Faculty-level	Administrators, marketing	Modeling knowledge flow Optimising Resources allocation
Institutional	Administrators, funders, marketing	Learner profiles Performance of academics. Job suggestion services
Regional	Funders, administrators	Cross-institutional analysis Institutional performance

National and International	National governments, education authorities	Decision support systems for educational policy making Demographic analysis of educational stakeholders

Moreover, the use of artificial intelligence (AI) may provide critical signs that stakeholders at a particular level have not previously contemplated. For example, the new AI applications may analyze the actions of both educational decision-makers and associated stakeholders. Consequently, the applications may propose novel elements or patterns pertinent to the area of interest.

Conclusion

The design and development of educational data analytics would advantage all educational stakeholders in several ways. Such technologies might facilitate self-regulated learning, enhance student success, optimize instructor effectiveness, and aid institutional decision-making. The utilization of data analytics in higher education would enable institutions and instructors to promptly address societal demands and worldwide transformations. Despite the growing complexity and competitiveness of higher education, stakeholders have made decisions without the insights derived from analyzing vast educational data sources. An study of data from diverse sources inside an institution would provide a more robust basis for educational decision-making. This article offers a comprehensive review of data analytics in higher education to better inform information systems educators, researchers, educational providers, institutional officials, and others educational stakeholders to enhance their implementation and promotion of educational data analytics. This analysis of data analytics in higher education underscores the ongoing significance of collaborative initiatives to enhance and actualize these technologies. Given that educational data analytics is now in a pre-paradigmatic phase, there is an urgent necessity to create a cohesive framework to systematize the field's information for academia, institutional decision-makers, developers, and other stakeholders. The literature reveals a scarcity of efforts toward a cohesive framework for aspects within the educational data analytics domain. Consequently, our proposed framework aims to create a basis for the advancement and execution of data analytics to enhance learning and teaching in higher education.

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