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Data Analytics in Higher Education: An Integrated View

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ABSTRACT

Data analytics in higher education provides unique opportunities to examine, understand, and model pedagogical processes. Consequently, the methodologies and processes underpinning data analytics in higher education have led to distinguishing, highly correlative terms such as Learning Analytics (LA), Academic Analytics (AA), and Educational Data Mining (EDM), where the outcome of one may become the input of another. The purpose of this paper is to offer IS educators and researchers an overview of the current status of the research and theoretical perspectives on educational data analytics. The paper proposes a set of unified definitions and an integrated framework for data analytics in higher education. By considering the framework, researchers may discover new contexts as well as areas of inquiry. As a Gestalt-like exercise, the framework (whole) and the articulation of data analytics (parts) may be useful for educational stakeholders in decision-making at the level of individual students, classes of students, the curriculum, schools, and educational systems.

Keywords: Data analytics, Computer-assisted education, Learner-centered education, Data mining, General education, Domain knowledge

1. INTRODUCTION

Information Systems (IS) education is under increasing pressure to address the growing social demands and global changes. For instance, IS education must be adapted to embrace workplace attributes such as IT-related skills and innovation abilities. Students' concerns about job availability impact their intentions to choose Information Systems as a major (Zhang, 2007). It is challenging for IS educators and researchers to respond effectively and in time to the social demands and global changes (Lasi et al., 2014; Daniel, 2015). Fortunately, the advancement of data analytics has brought unique opportunities for dealing with these rapid changes (Daniel, 2015; Nguyen, Gardner, & Sheridan, 2017). For instance, data analytics addresses the challenges associated with finding helpful information at the right time to support institutional decision-making (Nistor and Hernández-Garcíac, 2018). Furthermore, data analytics has offered valuable insights into what is happening in a specific course and how to address performance issues (Daniel, 2015; Nistor and Hernández-Garcíac, 2018).

In this Information Age, the relentless progress of information and communication processes has become the driving force of social evolution, including educational transformation. Educational systems, including learning management systems and course authoring systems, generate enormous datasets during daily operation. Massive data generated by educational systems are becoming available for collecting and mining. This immense amount of data has heightened the need for well-established data management and analytics in the learning and teaching environment (Siemens and Long, 2011; Greller and Drachsler, 2012; Nguyen, Gardner, and Sheridan, 2017). The educational datasets, in particular, contribute to the evolution of learning theories, learning support, learning design, learner feedback, and the development of future learning support systems.

Over the past decade, rapid developments in the field of big data and analytics have led to an increased interest in educational data analytics (Baker and Inventado, 2014; Nguyen, Gardner, and Sheridan, 2018b). Several researchers have reviewed and analyzed the features and applicability of big data and analytics in education (Arnold and Pistilli, 2012; Dahlstrom, Brooks, and Bichsel, 2014; Chaurasia et al., 2018). For example, Pistilli, Arnold, and Bethune (2012) show the use of data analytics for improving student success by producing real-time feedback to students. From the attempts to apply data analytics in education, new disciplines have emerged called learning analytics, academic analytics, and educational data mining. While all of these concepts are related to the use of data analytics in education, they are completely overlapping. Learning analytics focuses on the application of data analytic techniques and tools for purposes of understanding and enhancing learning and teaching, whereas academic learning aims for the purposes of supporting institutional operations and decision making. Besides, educational data mining focuses on the development and evaluation of data analytics methods for exploring educational data. As a newly emerged area of research and practice, a variety of terms have been raised and adopted to describe similar concepts and processes (Nguyen, Gardner, and Sheridan, 2018b). However, the clarification and consensus of these terms are not yet understood fully (Barneveld, Arnold, and Campbell, 2012; Nguyen, Gardner, and Sheridan, 2017, 2018b).

In an effort to continue discussions to establish a common view of analytics in higher education, this paper proposes a comprehensive framework for data analytics in higher education that includes units of knowledge for learning analytics, academic analytics, and educational data mining. Although prior studies have attempted to establish an initial linkage between learning analytics and academic analytics (Barneveld, Arnold, and Campbell, 2012; Cooper, 2012) and learning analytics and educational data mining (Zouaq, Joksimovic, and Gasevic, 2013; Baker and Inventado, 2014; Sin and Muthu, 2015), a search of the literature failed to reveal any study that provided an integrated view of all these subfields collectively. As a result, our proposed framework is intended to integrate existing research areas on data analytics in higher education and to provide educators and practitioners an overview of objects and their relationship in an analytics-based educational context.

The next section will discuss the three main research streams of data analytics in higher education, namely Learning Analytics (LA), Academic Analytics (AA), and Educational Data Mining (EDM), and then provide an account of these research streams before offering an integrated view of them. We propose a set of unified definitions for data analytics in higher education and describe an integrated framework that may help stakeholders to better understand this type of educational technologies. We conclude by discussing future research directions and the implications of our work.

2. DATA ANALYTICS IN HIGHER EDUCATION

2.1 Learning Analytics (LA)

As an emerging research discipline, Learning Analytics (LA) has been referred to with various terms and definitions in both general use and research. In a broad sense, LA can be interpreted as applications of data analytics in learning and teaching. In contrast to academic analytics and educational data mining, LA focuses on the learners and their learning processes. Learning analytics collects, integrates, and analyzes static and dynamic data about the learner profiles, learning materials, and learning context. Then it can offer descriptive modeling and prediction of learning elements in a scheduled or real-time basis. At the 1st International Conference on Learning Analytics in 2011, The Society for Learning Analytics Research (SoLAR) defined LA as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs." Recently, this definition has been widely adopted in the research community (Siemens, 2013; Nguyen, Gardner, and Sheridan, 2018a). However, we argue that this definition does not inclusively reflect all the applications of LA such as adaptive learning systems. Rather than reporting of data to inform actionable insights, adaptive learning systems perform actions to adjust the learning environment and materials to enhance learning (Kerr, 2016). Our proposed definition of LA is "the application of data analytic techniques and tools for the purposes of understanding and enhancing learning and teaching."

2.1.1 Types of learning analytics. *Content Analysis* is a subset of learning analytics used for contextualized interpretations of textual documents (Clow, 2013). *Content analysis* can be either manual or computer-assisted techniques that analyze texts to reveal underlying meanings. Although there are a variety of textual sources available in the educational context, the texts are categorized into five main groups, namely written text, oral text, iconic text, audio-visual text, and hypertext (Denzin and Lincoln, 2008). Recent developments in web analytics techniques, such as web crawling and machine learning algorithms, have led to a renewed interest in analyzing hypertext found on websites (Kitto et al., 2016; Nistor and Hernández-Garcíac, 2018).

Discourse Analytics tracks user interactions to explore meaningful information about the properties of the language used from the learning discourse. While *Content Analysis* is for revealing meaningful information from textual sources, *Discourse Analytics* focuses on examining the language used by learners. *Discourse analytics* listens to learners through channels where they are already interacting, such as online learning communities. Interactivity plays an essential role in the process of knowledge construction (Kent, Laslo, and Rafaeli, 2016; Howell, Roberts, and Mancini, 2018). Learning can be viewed as the socio-constructivist process involved with the network of interactions among the learners and content items (Hickey, 1997). The advance of text mining and log tracking has enabled the analytics of discourse data and metadata. By the same token, *social learning analytics* has emerged and gained interest within the field of learning and teaching. Whereas *discourse analytics* pays attention to the content and language used in learning discourse, *social learning analytics* tends to be concerned more with the collaboration among learners.

Social Learning Analytics is a distinctive subset of learning analytics that focuses on interaction and collaboration among students in learning (Hernández-García et al., 2015; Jan and Vlachopoulos, 2018). While *Discourse Analytics* investigates the language used by learners, *Social Learning Analytics* examines the learning process from the social perspective and suggests that gaining new knowledge and skills is not solely an individual's achievements in education. This can be illustrated briefly by previous studies on how social networks impact learning performance (Veletsianos, Collier, and Schneider, 2015; Vrieling, Beemt, and Laat, 2018). For instance, Hernández-García et al. (2015) conducted *social network analysis* (SNA) to study the relations between social network interactions and academic performance. The findings of this research indicate a need for further study on whether there are circumstances under which social network parameters are reliable predictors of student performance. However, the study advises against relying solely on social network factors for prediction. Furthermore, this study suggests that data visualization is a useful tool for social learning analytics.

Disposition Analytics explores educational data on students' background and learning engagement to discover students' dispositions and their underlying relationships to the learning process (Peña-Ayala, 2014; Bharara, Sabitha, and Bansal, 2018). In other words, this learning analytics method examines the factors that the students brought to the learning context to identify their learning styles and predict the preferred learning behaviors to improve learning and teaching. This can be seen in Bharara, Sabitha, and Bansal (2018) who use disposition analytics to analyze the effects of different factors on student performance. By interpreting this information, the instructor can make better decisions when selective alternative and optimal teaching tactics and strategies.

2.1.2 Learning analytics applications. Prior studies have identified several applications of learning analytics to support learning and teaching in higher education (Nguyen, Gardner, and Sheridan., 2017; Zhang et al., 2018). For instance, learning analytics applications provide up-to-date data about the learning activities, student engagement, student profile, and relevant historical data from previous semesters to model the learning process. Furthermore, by using learning analytics, educators and researchers have been able to forecast the student's future performance (Dietz-Uhler and Hurn, 2013; Gašević et al., 2016; Asif et al. 2017). Based on the predicted information, the instructor can make necessary interventions and focus more attention on at-risk students. For instance, Siemens and Long (2011) suggested that a model of successful student behaviors can support the faculty to encourage students to be more involved in regulating their learning behaviors for greater academic success. In particular, the model includes the frequency of accessing and using learning applications such as LMS tools and discussion boards as potential success factors. The model of successful student behaviors highlights learning activities that directly influence final grades. Thus, instructors may be confident of learning the goals while revising learning activities.

Likewise, Arnold and Pistilli (2012) proposed an early intervention solution for academic faculty called "Course Signals." Their system uses educational data to predict student performance and reports the outcomes to the students via a personalized email. The collected data include not only grades but also past academic history, students' demographics, and learning engagement measures. The reported information contains a stoplight or traffic signal which is used to show how each student is performing. The students' emails make them aware of their current learning performance and, in the case of at-risk students, would detail needed changes to improve their probability of success. Thus, the utilization of the Course Signals system is also an example of using learning analytics at the student level.

Greller and Drachsler (2012) proposed a solution whereby learning analytics can inform teachers about the gaps in knowledge exhibited by the students. Their goal is to provide academic stakeholders, including students and teachers, with information to better understand learning needs and performance. In this instance, given the 'gap' analysis, they can provide students with additional resources to broaden and remediate their understanding of the essential learning content.

Learning analytics reports can be practically supported by visualizations to deliver more meaningful information to the users (Duval, 2011; Leony et al., 2012; Nguyen, Gardner, and Sheridan, 2017). The advantage of visualizations is to graphically communicate clearly and effectively large amounts of complex data to identifying trends, patterns, correlations, and urgent issues. Visualizations can be applied in education to display analyzed data captured from both students and teachers. However, in using learning analytics visualization tools, one needs to consider: data security, multi-user support, and accessibility. Several researchers have attempted to design visualization tools for learning analytics. For instance, Leony et al. (2012) proposed a web-based visualization platform GLASS (Gradient's Learning Analytics System). The visualization procedures, within GLASS, were developed based on a bottom-up methodology with a needs-must focus on the end-user. The tool was designed specifically to simplify the implementation of new visualizations – to display information related to students, instructors, and the learning process. Hence, GLASS can offer the creation of visualizations regarding learners' events and activities in a given context.

Finally, learning analytics has enabled learning personalization and adaptive learning systems in higher education (Greller and Drachsler, 2012; Kerr, 2016). *Adaptive learning systems*, also known as personalized or individualized learning applications, refer to those functions that can adapt to student interactions with the system based on a relatively insignificant amount of data generated by the student (Kerr, 2016). The learning analytics engine is the central component of an adaptive learning system as it collects and analyzes data on a real-time basis. For example, Hsieh et al. (2012) proposed a fuzzy logic-based, personalized learning system for enhancing adaptive English language learning. The system can recommend articles that are appropriate for a learner's level of English ability and their needs to review their vocabulary. The research results have confirmed that the proposed personalized learning system improves learning as well as sustaining the students' learning interest (Hsieh et al., 2012). Learning personalization and adaptive learning systems also allow for creating an inclusive learning environment (Clow, 2013; Nguyen, Gardner, and Sheridan, 2018a).

The current research briefly reviewed in this paper has identified important applications for learning analytics in the context of learning and teaching. An important policy priority should, therefore, be to work to formalize the potential of learning analytics research in the field of higher education (Nguyen, Gardner, and Sheridan, 2018b).

2.2 Academic Analytics (AA)

The term Academic Analytics (AA) was coined by Goldstein and Katz (2005) to describe the intersection of technology, information, organizational culture, and the application of data analytics to manage an institution. The term Academic Analytics, in brief, refers to business intelligence in education and, more specifically, as the process to discover insightful patterns in educational data to indicate academic issues, such as dropout rate, and to support strategic decision-making (Pistilli, Arnold, and Bethune, 2012; Chaurasia et al., 2018). The process mainly focuses on supporting institutional administrators and educational policymakers. Whereas students expect the use of data analytics to predict and support their learning performance, institutional administrators consider applying academic analytics to monitor and improve educational Key Performance Indicators (KPIs), such as student retention. Barneveld, Arnold, and Campbell (2012) defined academic analytics as "A process for providing higher education institutions with the data necessary to support operational and financial decision making." In contrast with learning analytics, we adapt this description and define academic analytics in a broader sense as "the application of data analytic techniques and tools for purposes of supporting institutional operations and decision making."

There is a wide range of educational stakeholders considered as beneficiaries of the applications of academic analytics. In particular, potential groups and individuals who benefit from academic analytics include the faculty, students, and executive officers. At each level, the applications of academic analytics offer valuable benefits yet raise potential concerns (Campbell and Oblinger, 2007).

Academic analytics can support faculty by revealing key factors for student success, providing insights into effective practices, and improving the scholarship of teaching and learning. Student success has been one of the central key performance indicators (KPIs) in higher education, thus most faculty are interested in monitoring and predicting student success. Furthermore, AA can extract meaningful knowledge from educational data to determine the most effective techniques and enable the faculty's pedagogical adjustments to satisfy the students' needs.

The executive officers may get useful information from academic analytics to support their decision-making. Academic analytics offers unique sets of KPIs that are not available in traditional educational systems. For example, the vice-chancellor may be informed of the percentage of at-risk students and thus request a review of the institution's learning and teaching strategy. The executive officers may also use academic analytics to optimize the use of resources. It is believed that academic analytics can improve the institution's accountability and enhance its reputation (Campbell and Oblinger, 2007; Wong, 2016). Despite the above benefits, the executive officers often question the costs associated with an academic analytics project (Daniel, 2015; Chaurasia et al., 2018). In addition, they will likely be concerned about the privacy and security issues when the system is up and running (Slade and Prinsloo, 2013; Pardo and Siemens, 2014).

2.3 Educational Data Mining (EDM)

The International Educational Data Mining Society (IEDMS – http://educationaldatamining.org/about/) defined the term Educational Data Mining (EDM) as "an emerging discipline, concerned with developing methods for exploring the unique and increasingly large-scale data that come from educational settings and using those methods to better understand students and the settings which they learn in." Data mining, also called Knowledge Discovery in Databases (KDD), refers to a subfield of computer science related to extracting useful information and knowledge from the raw data sources (Chakrabarti et al., 2006). Correspondingly, previous research defined educational data mining as a practice of developing data mining methods for studying complex educational datasets and using those methods to get insights of students and educational systems (Siemens and Baker, 2012). The EDM process applies computational approaches to convert raw data from educational systems into useful information which can address educational questions.

2.3.1 Types of educational data mining. There are several types of educational data mining. Baker (2010) suggested that all educational data mining methods could be categorized into five general groups, namely *prediction, clustering, relationship mining, discovery with models,* and *distillation of data for human judgment.* The EDM research community has commonly recognized the first three categories, whereas the last two have only reached specific prominence within the field of educational data mining (Peña-Ayala, 2014).

In educational data mining, *prediction*, as the term implies, aims to model an educational outcome derived from other data factors. The forecast factor is called a predicted variable, while input factors are labeled as the predictor variables. An example of *prediction* EDM could be the participation-based prediction model using interpretable Genetic Programming by Xing et al. (2015). The model predicts students' final performance by using six constructed variables for students' online participation in the CSCL (Computer-supported Collaborative Learning), namely Subjects, Rules, Tools, Division of Labour, Community, and Object. Another example is Xing et al.'s (2015) prediction model that uses interaction data as predictor variables. The accuracy of this model was validated by generalizing with additional students in a range of different contexts.

The second type of educational data mining is *clustering* which focuses on grouping raw data into a set of clusters and finding the borderlines between these groups. *Clustering* can be based on several possible grain-sizes, such as clustering students to categorize students into groups and clustering student activities to produce patterns of behavior (Asif et al., 2017). This group of educational data mining methods can involve predefined hypotheses or no preceding hypotheses (Baker, 2010).

The third type of educational data mining is *relationship mining* which seeks to determine possible relationships among a dataset with several variables. While *clustering* is the task of grouping a set of objects, *relationship mining* aims to discover interesting relationships between variables in the data. *Relationship mining* is classified into four sub-categories, namely *association rule mining*, *causal data mining, correlation mining,* and *sequential pattern mining* (Baker, 2010; Peña-Ayala, 2014). *Association rule mining* aims to discover if-then rules between the variables. In particular, these data mining methods find those relationships that if any set of variables are defined, another variable is likely to have a specific value. For example, Garcia et al. (2011) used their proposed collaborative *association rule mining* to discover the following rules: If the number of messages read in the forum is high, then the score of the assignment tends to be high. *Causal data mining* methods are used to find "casual relationships" that involve an event being the cause of another. The causal relationship can be both unidirectional or bidirectional. Moving to the last two groups of *relationship mining, correlation mining* aims to determine any positive or negative linear correlations between variables whereas *sequential pattern mining* focuses on temporal associations. For example, Mudrick, Azevedo, and Taub (2018) used *sequential pattern mining* to understand processes underlying multimedia learning by integrating metacognitive judgments and eye movements.

The fourth type of educational data mining is *discovery with models* in which a model of a phenomenon is constructed through other EDM methods or knowledge engineering and then used as an element for another investigation. Baker (2010) suggested that *discovery with models* often implements the verified generalization of a prediction model across different contexts. The central application of this EDM type is discovering relationships between student behaviors and contextual factors in the learning environment (Baker and Inventado, 2014).

The last research area within educational data mining is *distillation of data for human judgment*. Human activities can influence the datasets, and the process can surpass the scope of automated data mining approaches. As a result, this area of interest focuses on using visualizations to distill data for human judgment (Baker, 2010). Unlike typical information visualization systems, data visualizations for education mining are usually constructed around a particular structure of educational data and used to deliver meaning around that structure (Leony et al., 2012). Furthermore, a *distillation of data for human judgment* can be applied to support the development of a prediction model by labeling the data sets.

2.3.2 Educational data mining applications. There have been a wide variety of educational data mining applications that are categorized into four general groups. Those are related to improving student models, discovering or improving models of the knowledge management, examining the learning application's pedagogical support, and scientific discovery about learners and the learning process.

In improving student models, EDM applications collect the raw data about each learner and model them to provide meaningful information about that leaner's characteristics, learning status, and the differences among the learners. The generated information includes, but is not limited to, student behavior, performance, learning motivation, and attitudes. For example, Tair and El-Halees (2012) implemented EDM to improve graduate students' performance by extracting useful knowledge from educational data. Several EDM methods are used in this case, and these include clustering, association rules mining, classification, and outlier detection.

In discovering or improving models of the knowledge structure of the domain, the studies seek to establish methods that can be used for rapidly identifying appropriate domain models directly from data. These applications often integrate psychometric models with advanced space-searching algorithms and prediction problems in the process of discovering new models (Barahate, 2012).

In examining the learning tool's pedagogical support, each form of educational help for a student is mapped to the academic success with particular weights. State-of-the-art learning systems have offered a variety of learning support to the students thus quantifying the available support has become an essential task in education (Peña-Ayala, 2014; Sin and Muthu, 2015). EDM has been applied to evaluate the pedagogical support of a specific learning tool and recommend potential improvements.

The last group of EDM applications focuses on scientific discovery about learners and the learning process. The implementation of educational data mining methods in addressing problems in the other EDM applications discussed above can enhance the scientific significance (Baker, 2010). The central type of educational data mining in the applications for scientific discovery is a *discovery with models*.

2.4 Research Ontology for Educational Data Analytics

Previous research has attempted to illustrate the communities and draw a distinction between LA, AA, and EDM (Siemens and Long, 2011; Siemens, 2012, 2013; Chatti et al., 2014; Dahlstrom, Brooks, and Bichsel, 2014). Referring to the level or object of analytics and the beneficial stakeholders, Siemens and Long (2011) present the differences between LA and AA (Table 1).

LA targets the micro (Learner) and macro (Faculty) levels of educational stakeholders, whereas AA benefits the stakeholders placed higher in the hierarchy – macro (Institution) and mega (Governance) levels (Siemens and Long, 2011; Ifenthaler, 2015). As the data analytics need to serve different purposes regarding the level or object of analysis, LA and AA gather distinctive datasets and apply diverse analysis methods to deliver appropriate outcomes.

Zouaq, Joksimovic, and Gasevic (2013) conducted an ontological analysis to examine research trends in Learning Analytics (LA) and Educational Data Mining (EDM). The study investigated research publications of two well-known communities of educational data analytics, namely Learning Analytics & Knowledge (LAK) and Educational Data Mining (EDM). The top-ranked concepts demonstrate the similarities and distinctions between LA and EDM. In particular, these two branches share mutual interests in a number of concepts, such as *students*, *data*, and *model*.

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, funders, marketing
	Regional (state/provincial): comparisons between systems	Funders, administrators
	National and international	National governments, education authorities

Table 1. Learning and Academic Analytics (Siemens and Long, 2011)

However, there are some significant differences between the research streams. The distinct concepts for LA are aligned with *teachers, knowledge, social_factor, social_learn, effective_learn, learn*, and *informal_learn.* On the other hand, top-ranked concepts for EDM focus on skill, method, tool, system, feature, item, and parameter. This illustrates that LA focuses more attention on the learning process and interactions within the learning environment, whereas EDM focuses on methods and approaches for the data pipeline (Siemens, 2013; Zouaq, Joksimovic, and Gasevic, 2013; Dahlstrom, Brooks, and Bichsel, 2014).

It can be said that Learning Analytics (LA), Academic Analytics (AA), and Educational Data Mining (EDM) focus on different parts of the whole picture of educational data analytics, yet they are intimately related. The progress of any research stream would result in dynamic impacts on the other streams. For instance, from the evolution in EDM, robust analytic methods and tools are likely to emerge that would change the landscape of LA and AA research. In particular, the emergent methods and tools can be implemented to provide new understanding of the learning and teaching process and the surrounding environment. Thus, it is necessary to have an integrated view of educational data analytics for better decision-making as well as the implementation of these technologies.

2.5 Educational Data Analytics Frameworks

The growth of educational data analytics has encouraged the emergence of research that focuses on providing frameworks and guidelines to assist as guidance for research and application. This has been seen in the case of the Learning Analytics Reference Model designed by Chatti et al. (2014). The model demonstrates the connections between learning analytics and related fields in Technology Enhanced Learning (TEL), such as recommender systems and personalized adaptive learning. The reference model is based on four central dimensions which are data and environments (what?), stakeholders (who?), objectives (why?), and methods (how?). The model establishes fundamental concepts on learning analytics and further identifies potential research directions in the emergent field of learning analytics. In particular, researchers could investigate the educational data or learning context and aim specifically at the topics of context modeling and learning analytics in various educational environments.

Human factors need to be considered in correspondence to the LA process and LA stakeholders (Nguyen, Sheridan, and Gardner, 2016). The Learning Analytics Reference Model demonstrates the crucial components of educational data analytics (Chatti et al., 2012), yet the model does not address the relation between educational data analytics and different stakeholder levels of the educational ecosystem.

Greller and Drachsler (2012) propose a hierarchical model to describe educational information between the key stakeholders in the educational system. The primary level represents students, the central focus of higher education. Most educational data for analytics are obtained from the students' interactions and characteristics. The intermediate layer is the teachers who play a focal role between the institution and the students. The teachers can receive benefits from the students' data analysis as they can apply performance and engagement information to adjust their pedagogical strategies. In the next layer, the institution can use both students' and teachers' information to plan and create institutional policies. The top of the pyramid is the governance layer in which educational policies are established from the analysis of cross-institutional data.

Romero and Ventura (2013) illustrate the educational knowledge discovery and data mining process as shown in Figure 1. Raw data are collected from the educational environment according to hypothesis formation. The data are processed and fed into data mining instruments to produce models or patterns for interpretation and evaluation by the users. Finally, the results are used to refine the educational environment as well as hypothesis formation. To some extent, the processes of hypothesis formation, testing, and refinement can also be applied to learning analytics. Accordingly, learning analytics also begins with the collection of raw data then goes through the data processing and reporting process.

Ifenthaler (2015) proposes a general learning analytics framework that focuses on the learner and learning process. The integrated LA framework illustrates the workflow of learning analytics through the process of collecting data, analyzing data, and reporting information to users in an educational context. In addition, Ifenthaler (2015) describes another model of learning analytics associated with different stakeholder levels (Figure 2). The model illustrates the data flow between educational stakeholders and the position of LA in the learning context. The learning activities happen at the micro level in which learners interact with the learning environment. The curriculum and learning design are supported by analytics at the macro level. At this level, educational data analytics provides teachers and learning designers with insightful information about learning processes and outcomes to support design decision-making. The macro level allows for institution-wide analytics which offer a better understanding of learner cohorts, the effectiveness and efficiency of operational processes, and resource allocation. The highest level of the LA framework is referred to as mega-level which incorporates data from all lower levels. At the mega level, cross-institutional analytics

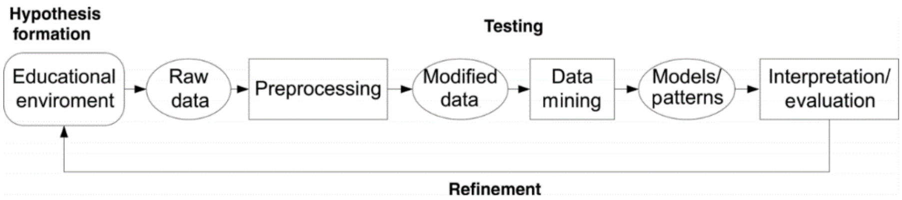

Figure 1. Educational Knowledge Discovery and Data Mining Process (Romero and Ventura, 2013)

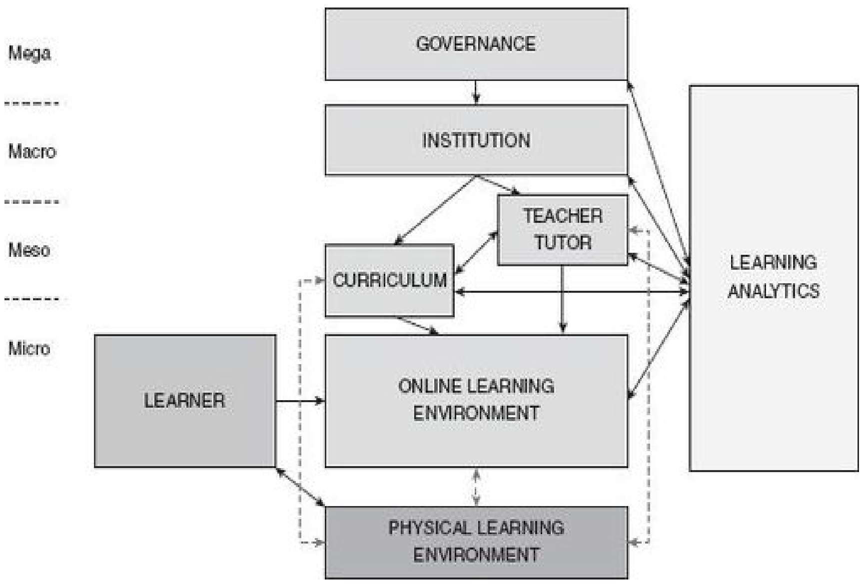

Figure 2. Learning Analytics Associated with Stakeholder Levels (Ifenthaler, 2015)

provide support for governance with valuable insights through the identification and validation of patterns within and across institutions. Furthermore, predictive analytics and simulation assist in educational policymaking.

Ifenthaler's (2015) frameworks were designed to illustrate learning analytics, yet they step beyond learning analytics and demonstrate elements of academic analytics. The macro and mega levels of the LA framework can also fit purposes other than optimizing learning and the learning environment, thus matching the definition of learning analytics. For instance, academics analytics would be applied in the institutional (macro) level to optimize resource allocation. As a result, this hierarchy of stakeholder levels can also be used for representing the position of educational data analytics in general (Barneveld, Arnold, and Campbell, 2012).

3. AN INTEGRATED VIEW OF DATA ANALYTICS IN HIGHER EDUCATION

The learning and teaching domain is complex, dynamic, and multifaceted (Ifenthaler and Widanapathirana, 2014). The components of the educational ecosystem are multidimensional and unstable. For example, each stakeholder may have a number of contemporary interests and proclivities. Moreover, instruments such as data mining and machine learning methods are changing over time. As a result, adjustments within the educational ecosystem must be considered regarding the impacts on each of its vital components and their interoperation. Researchers and practitioners must be cognizant of that intervention as one level of analytics in education may affect the other levels. For example, implementation of learning analytics for learner's self-reflection at the course-level would modify the characteristics and settings of those educational data mining projects at the institutional level that collect and process learning data. In this case, educational data mining at the higher level offers an evaluation of the LA implementation at scale. As a result, we proposed unified definitions (Table 2) and an integrated framework for data analytics in higher education (DAHE) (Figure 3) in an effort to provide an

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
			Departmental 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	Faculty Level Institutional 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	Regional National International

Table 2. Proposed Definitions for Data Analytics in Higher Education

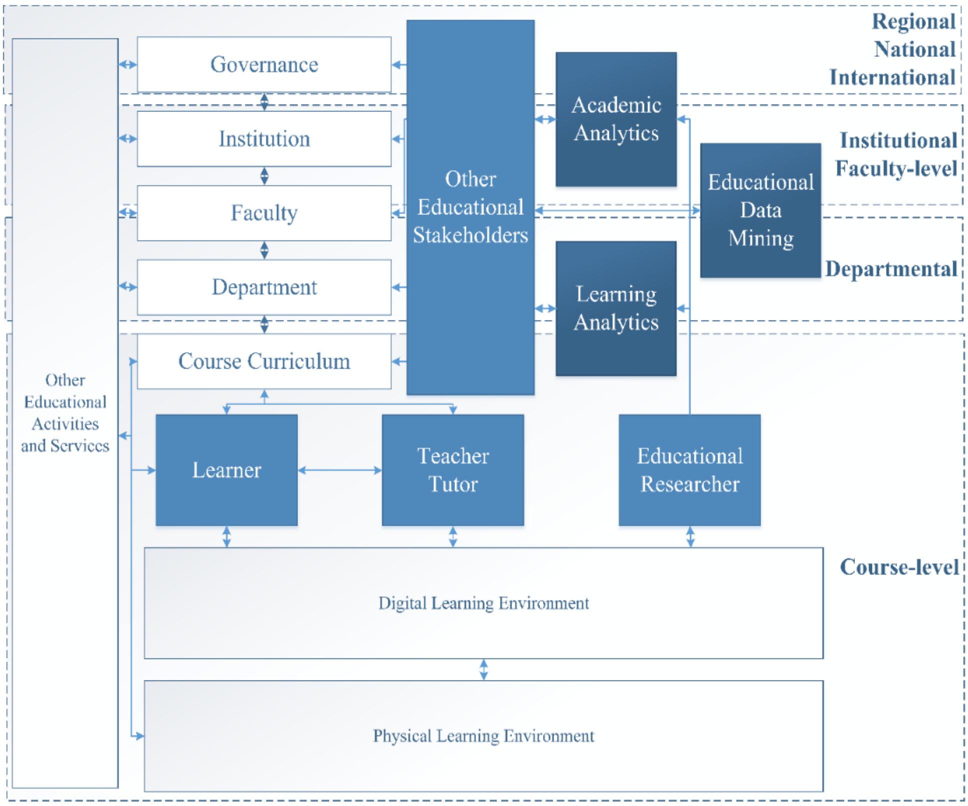

Figure 3. An Integrated Framework for Data Analytics in Higher Education (DAHE)

overview of the field of analytics in higher education. The framework was designed based on the review of research ontologies for educational data analytics and existing frameworks.

The DAHE framework outlines critical components of education data analytics and the relationships between them in each level of the education system (dotted-lines). The framework, which involved learning analytics, academic analytics, and educational data mining, demonstrates how each data analytics field interacts with educational elements and each other. It offers an overview of the emerged fields in the higher education environment.

As proposed by Barneveld, Arnold, and Campbell (2012), academic analytics focuses on the institutional and faculty-level management in which educational data is essential to support operational and financial decision making. Furthermore, Siemens and Long (2011) suggested that academic analytics can address comparisons between systems to benefit educational funders, administrators, authorities, and governments. In other words, academic analytics reflects the role of data analytics in institutional, regional, national, and international levels. It might also be observed that academic analytics is more aligned with traditional business intelligence in higher education. IS education researchers should investigate academic analytics for studies focusing on a broad educational context with multiple institutional or social factors.

Educational data mining focuses on the development and evaluation of techniques, tools, and methods designed for automatically extracting and analyzing meaning from large repositories of educational data (Siemens and Baker, 2012). The field seeks to develop and improve methods and techniques for exploring the large-scale data that come from educational settings (Tair and El-Halees, 2012). Educational data mining offers unique and essential values to educational management and decision-making. The field has strong origins in learner behavior modeling and predicting course outcomes (Siemens and Baker, 2012). Educational data mining benefits stakeholders at different levels of the education system but most likely from the institutional to the departmental level.

Learning analytics focuses on the learners, their learning behavior, and the learning environment (Siemens, 2013). In contrast to academic analytics, learning analytics involves more specific analysis for the purposes of "understanding and optimizing learning and the environments in which it occurs" (Siemens, 2011). Learning analytics research investigates the data created by the interactions of learners and teachers with the learning environment. The learning environment can be either physical environments (i.e., a classroom) or digital environments (i.e., a learning management system). Learning analytics mostly explores educational data at the course-level and departmental level. For example, learning analytics studies investigate social networks, intelligent curriculum, and discourse analysis at the course-level (De Liddo et al., 2011; Ifenthaler and Widanapathirana, 2014). At the departmental level, learning analytics seeks to provide predictive modeling and patterns of success or failure (Dietz-Uhler and Hurn, 2013).

In contrast to educational data mining, learning analytics considers leveraging human judgment as the center of discovery, whereas automated discovery is a tool to accomplish it (Siemens and Baker, 2012). In order to address the complexity in learning and teaching, learning analytics emphasizes understanding systems as a whole. IS educators and researchers can apply learning analytics to enhance their teaching and engage student learning.

Complementing previous frameworks, the model also considers other activities and services, such as engagement with student associations, departmental events, and/or the career hub. The literature has shown that these activities could influence student growth and achievement (Gibson, Bejínez, and Hidalgo, 2004; Robles-Gómez, Ros, and Martínez-Gámez, 2017). For instance, the factors influencing a student's sense of belonging in the institution include not only learning activities but also extracurricular and non-academic activities. There is a significant and positive relationship between students' perceived sense of belonging in the institution and both their learning engagement and performance (Gibson, Bejínez, and Hidalgo, 2004). Another example is the use of educational data analytics for the recommendation of job opportunities to students (Robles-Gómez, Ros, and Martínez-Gámez, 2017). To summarize, this integrated framework offers educational technologists a holistic view of data analytics in higher education so that they can consider further development beyond the current state, such as the application of artificial intelligence (AI) for delivering novice insights to each educational stakeholder.

4. FUTURE RESEARCH DIRECTIONS

The conceptual framework was designed to demonstrate the relationship between analytics and stakeholders at different levels in the higher education system. IS educators and researchers can also use DAHE for determining the analytics field of interest, thus saving time and effort in reviewing the relevant literature. Continued research on data analytics in higher education would offer a better understanding of institutional data and the requirements for effective data preparation for analytics to allow data-driven decision-making and practice (Daniel, 2015). However, it is a challenge to improve communication between different aspects of data analytics in higher education (Macfadyen and Dawson, 2012). More research is also needed concerning the implementation of educational data analytics from various perspectives. For instance, the stakeholders at different levels of the education system would have distinguished interests in the use of data, and their ethical concerns would differ based on their viewpoint.

This study aims to contribute to a standard terminology of educational data analytics. Our set of unified definitions and integrated framework provide educators and researchers an overview of different domains of data analytics in higher education. For instance, Table 3 shows a set of examples of analytics at each application level of DAHE.

The application of data analytics in higher education offers useful insights that support educational stakeholders in performing their tasks and decision-making. As such, the development of initiatives and tools that enhance learning and teaching by integrated data analytics is crucial to improving the course-level and institutional success. Nevertheless, information systems educators may have future considerations of investigating perceived belonging by data analytics. The automatic update of information related to student activities could indicate their institutional belonging and social involvement. This information could extend our knowledge about the impact of social involvement on student growth and achievement. By applying this information, the institutional managers could eliminate less-effective activities while promoting useful after-class programs to the students.

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

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

Furthermore, the application of artificial intelligence (AI) may suggest essential indicators that stakeholders at a specific level have not considered previously. For instance, the new AI applications may digest the activities of not only educational decision-makers but also those of related stakeholders. As such, the applications may recommend new factors or patterns reflecting the subject of interest.

5. CONCLUDING REMARKS

The design and development of educational data analytics would benefit all educational stakeholders in several ways. For instance, such tools could support self-regulated learning, improve student success, leverage teachers' performance, and support institutional decision-making. As such, the application of data analytics in higher education would help institutions and educators to effectively respond to social demands and global changes in a timely manner. Although higher education is an increasingly complex and competitive environment, the stakeholders have made decisions without insights available from processing immense educational data sources. The analysis of data from various sources across an institution would offer a better foundation for educational decision-making.

This paper provides an overview of data analytics in higher education to better inform IS educators, researchers, education providers, institutional policymakers, and other educational stakeholders so that they can more effectively implement and promote educational data analytics. This review of data analytics in higher education reflects the continued importance of collaborative efforts to improve and realize these technologies.

As educational data analytics is in a pre-paradigmatic stage, there is a critical need to establish an integrated framework to organize the field knowledge for academia, institutional decision-makers, developers, and others. In reviewing the literature, there have not been many attempts on a unified structure for elements in the educational data analytics sector. Therefore, our suggested framework hopes to establish a foundation for further development and implementation of data analytics to support learning and teaching in higher education.

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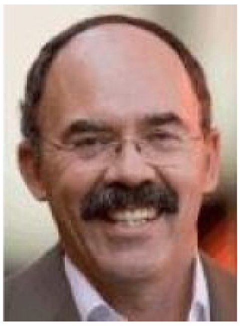

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