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PAPER

Big Data Analytics in Higher Education: A New Adaptive Learning Analytics Model Integrating Traditional Approaches

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ABSTRACT

Despite the explosion of interest in adaptive learning and learning analytics (LA) for higher education (HE), there has been relatively little research integrating educational approaches' indicators to build an adaptive learning analytics model. Adaptive learning analytics (ALA) models have grown in favor of HE due to their claims of enhancing student learning outcomes, providing personalized learning paths, and allowing students to interact with course material at their own pace. With focus on using data to personalize the learning experience and the environment in which the experience of learning occurs, LA centers on enhancing education through meticulous data analysis, while big data (BD) in education addresses the overarching challenges and opportunities arising from extensive and varied datasets. These concepts are interconnected, where LA and ALA specifically apply BD principles within the educational context. In this paper, we explain some BD concepts used in HE, define the essential perceptions related to LA, and analyze educational approaches to define the fundamental implications. Besides, we try to connect some LA model with educational approaches based on the big educational data collected in order to establish an efficient educational model. We include all steps cited before we try to build an ALA model in HE that resolves the limitations of the oldest models, thus improving the learner's learning process by adding and treating additional indicators.

KEYWORDS

higher education, learning analytics model, approaches, big data

1 INTRODUCTION

The fundamental goal of HE institutions revolves around creating an optimal learning environment for students. Traditionally, learning has taken place within a setting marked by consistent information, structure, and interface delivery. However, educational experts emphasize that tailoring instructional materials to individual needs

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significantly improves learning outcomes. This is especially crucial for individuals who have undertaken significant professional and familial responsibilities before embarking on academic pursuits, often facing time constraints for their educational endeavors.

Moreover, the presence of students with varying abilities and skills can present challenges for educators aiming to seamlessly integrate essential concepts into the curriculum. It is important to acknowledge that some students require more time than others to achieve mastery during the learning process. In this context, an ALA model offers a solution by enabling students to progress through their learning paths at their own pace while still completing course requirements within specified deadlines [1].

The ALA model offers students a flexible framework with contextual materials, fostering empowerment and choice in learning. Instructors benefit by continually enhancing teaching methods using analytics for insights into students' capabilities. This model often involves a blended and online learning environment, including Flipped Classroom and Digital Assignments, for a personalized learning experience. Monitoring learner progress, it dynamically adjusts content based on individual needs. To enhance learning achievements, researchers have devised diverse methodologies and tools. Adaptiveness, as suggested by [4], includes progressive learning, continuous assessment, and diverse pathways toward shared objectives.

Our research distinguishes itself by focusing on integrating educational methodologies' indicators into the ALA model during data analysis, emphasizing implications and prerequisites. This facilitates seamless connections between our model and theoretical frameworks, aiding effective communication during decision-making.

The rise in Massive Open Online Courses (MOOCs) and the demand for personalized education prompts institutions to explore adaptable technologies. To expand educational opportunities, institutions often turn to technology, such as flipped classroom models.

Our theoretical framework combines decision modeling and BD analytics, integrating approaches' indicators for analyzing diverse datasets. This process extracts valuable insights, enhancing decision quality within institutional contexts. In recent times, LA research has advanced rapidly, integrating methods such as text analysis, process mining, and social network analysis. This expansion aims to identify diverse outcomes and dispositions, including 21st-century skills, self-regulated learning, and learning strategies. The current trend focuses on delivering personalized feedback at scale, merging the capabilities of analytics with pedagogical knowledge and theoretical indicators to empower teachers. The ultimate goal of any designed intervention is to enhance student outcomes and satisfaction.

The structure of this paper is outlined as follows: Section 2 furnishes a concise overview of the backdrop concerning BD and LA within the domain of HE researches, including relevant works related to our study. In Section 3, we engage with analytical concepts that pertain to the confluence of BD and education. Section 4 provides an elucidation of the methodology employed and presents the resulting findings. Section 5 encapsulates the paper by presenting a proposed ALA model tailored for higher education. Lastly, in Section 6, we present the concluding remarks on our subject matter and outline potential directions for future research.

2 RELATED WORKS AND BACKGROUND

2.1 Related works

As far back as 2006, initial concepts regarding LA were introduced [5], with a focus on utilizing interaction analysis as a potential avenue for gaining deeper insights into learner behaviors. Subsequently, additional endeavors, notably led by Long and Siemens [6,7] emphasized the pivotal role of BD and analytics in shaping the trajectory of HE.

Subsequent research contributions have iterated the initial definition, broadening the scope to include a wider array of students' activities [8], and introducing descriptive models and frameworks. As time has progressed, numerous frameworks, models, and methodologies have surfaced, with the objective of facilitating the seamless incorporation and utilization of LA in educational institutions and among educators. The pivotal element of ALA model is the LA engine, which gathers and analyzes data in real-time based on various and significant indicators [9].

In their study, Grubisic [10] identified a cumulative count of 5924 papers associated with diverse topics, encompassing adaptive e-learning systems, intelligent tutoring systems, courseware generation, courseware sequencing, automatic courseware, dynamic courseware, adaptive courseware, and automatic generation of courseware. Noteworthy is the fact that 21% of these papers were specifically focused on adaptive e-learning systems that improve the learners' outcomes.

In their research, Hernandez and Conde [11] outline three fundamental layers of LA: the identification of relevant indicators, the identification, understanding, and interpretation of learning behaviors, and the development of adaptive learning mechanisms. A recent study [12] further delved into integrating theories and models from the domain of learning sciences into the design of learning dashboards targeted at learners.

In the study conducted by Peña [13], an exhaustive examination of LA was conducted with the purpose of illuminating the extensive endeavors within the LA domain, its research directions, and emerging trends. The results of this study underscore a dearth of research initiatives concentrated on delineating the evolutionary path of the field, offering holistic frameworks and elucidating the contributions made by the diverse stakeholders.

Based on data gathered from 32 Australian HE institutions, Colvin [14] introduces a dynamic framework that emphasizes strategic capabilities (including leadership, strategy, and institutional readiness) and operational capacities (encompassing resources and infrastructure) as pivotal factors influencing the incorporation of LA within the HE institutions (HEIs). Simultaneously, [15,16] employ the same dataset to examine the role of leadership in LA adoption utilizing the complexity leadership theory.

Challenges encountered by HE institutions in ALA model implementation encompass technological concerns and utilization [17], pedagogical and program delivery intricacies [18], difficulties with data analysis and management, as well as the incorporation of adaptive learning solutions into online platforms such as Blackboard [19]. Additionally, recent studies recognize that adaptive learning, despite its technological basis, is closely intertwined with educational practices. Similar to technological advancements such as Massive Open Online Courses (MOOCs) and mobile learning, adaptive learning is inherently grounded in technology and includes other relevant elements like instructional design, which profoundly influence the teaching and learning landscape [20,21].

2.2 Background

Big educational data analytics. BD analytics is characterized as the process of gathering, aggregating, and scrutinizing massive datasets (referred to as 'Big Data') with the intent of extracting meaningful insights and identifying discernible patterns. For researchers involved in BD, the extraction of valuable information from these datasets holds paramount importance. In the context of comprehending and enhancing learning, as well as the environments in which it transpires, the formal concept of LA pertains to the evaluation, compilation, analysis, and presentation of data concerning learners and their contextual circumstances.

For a variety of educational and administrative applications in higher education, BD concepts and analytics may be useful: tracking and monitoring learner performance, enhancing teacher ability, processing fees, market planning, and seeking donors [22].

The significance of classifying data types during acquisition or recording cannot be overstated. This section starts by elucidating the nature of learner-related data, drawing insights from the Knewton study [23]. Educational data falls into five primary categories derived from both learning management and tutoring systems.

Personality data: Encompassing essential learner identification and descriptive particulars like names, surnames, demographic data, application approvals, and administrative privileges.

System-wide data: Covering schedules, evaluations, administrative chronicles, and attendance data. While per-learner insights may have limited utility at a small scale, their significance escalates on a larger magnitude, facilitating more effective system-wide recommendations.

Conditional content data: Illustrating the potential for collaborative learning among segments of the learner community and aiding in gauging measurable shifts in learner comprehension due to specific learner types engaging with particular content segments.

User interaction data: Encompassing statistics like page visits, click rates, bounce rates, and more. These metrics play a pivotal role in enhancing user experience and engagement, serving as the bedrock for optimizing consumer-oriented websites. Accumulating this information is notably swift.

Inferred learner data: Indicating the level of comprehension of concepts and the percentile proficiency among learners. It also helps identify reasons behind incorrect answers, offering insights into the likelihood of a learner taking a quiz next week and suggesting methods for enhancing their performance.

Integrating all five data sets can be challenging for many educational institutions. However, a comprehensive approach involves addressing each data category adequately when implementing a unified platform.

Learning analytics. LA involves "measuring, gathering, analyzing, and reporting learner data and their contexts to understand and enhance learning and the conditions in which it occurs" [24]. Another definition characterizes it as "the use of intelligent data, learner-generated data, and analytical models to uncover insights, social connections, and predict and provide guidance for learning." The educational community presents diverse perspectives; some researchers view LA as an alternative approach for collecting student-generated data to facilitate personalized learning experiences [25,26], while others emphasize identifying trends from students' learning activities for future instructional design decisions [27,28]. Long and Siemens [29] propose a comprehensive standpoint, asserting that LA serves as both a tool for gathering statistical educational data and a mechanism for leveraging this data to enhance learning and the surrounding educational community.

Research from this perspective has generated crucial insights, establishing frameworks for analytics and underscoring the significance of LA within higher education [30]. LA employs mathematical analysis to classify students based on present performance, discern patterns among at-risk and engaged students, predict future outcomes, and anticipate possible hurdles in advance [31]. Additionally, it has proven to serve as a motivating factor for instructors, tutors, and institutions to actively engage in the learning process, leading to the refinement of instructional practices through customized teaching methods and achieving positive results [32].

Fig. 1. Learning analytics process

Consequently, this allows an organization to attract pupils, increase total business through reducing pupil retention, concentrate on at-risk learners, maximize learning results, and provide teachers with major, optimized guidance to improve teaching criteria [33].

Learning analytics process. LA can be perceived as the application of analytics to educational outcomes. As outlined by Campbell and Oblinger [34], an institution of HE can find value in five distinct steps of the LA process, as depicted in Figure 1.

Capturing: Real-time data is generated and collected from various sources, including virtual learning environments (VLE), learning management systems (LMS), personal learning environments (PLE), web portals, forums, chat rooms, and student information systems [35].

Reporting: The collected information is employed to formulate comprehensive frameworks for defining and evaluating student achievement. Frequently, visualization is integrated into LA dashboards to enhance data comprehension [36].

Predicting: The information is utilized to evaluate predictors of student performance, discern outcomes, and identify students who may be at risk. Additionally, it guides course adjustments and the allocation of resources, informing administrative decision-makers [37].

Acting: The insights gleaned from the data collection process are employed to ascertain effective strategies, including educating or providing assistance to students who are at risk of failing or leaving their studies [38].

Refining: The acquired data is iteratively employed to consistently enhance the teaching and learning paradigm [39,40].

3 THE ACHIEVED OUTCOMES

3.1 Methodology

Researchers undertook a literature review to address the research query, adhering to Cooper's method [41] for literature synthesis. This approach facilitated problem formulation, data collection, assessment of data relevance, analysis and interpretation of pertinent data, and the structuring and presentation of results. Subsequently, the findings were juxtaposed with current issues within a higher education institutional context concerning big data.

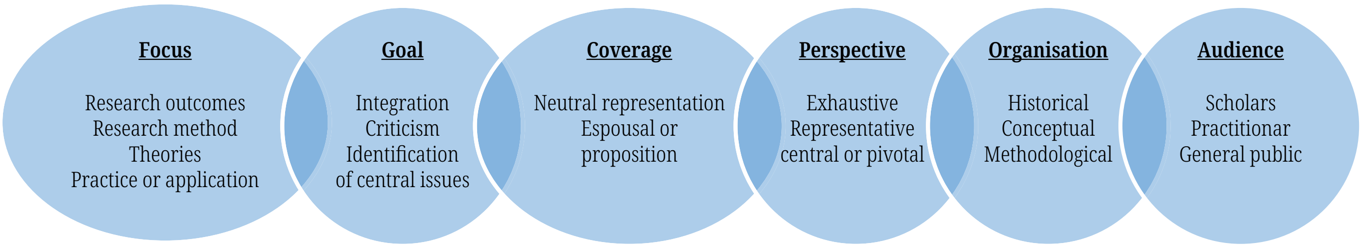

Fig. 2. Cooper's method adapted from [41]

3.2 Formulating the problem

In order to adeptly utilize LA for stakeholders within HE, it is imperative to offer a more comprehensive understanding of these three pivotal elements. Educators are faced with the task of navigating a substantial volume of information to acquaint themselves with LA approaches, methodologies, and models.

The following questions were employed as a guiding framework for this review, aimed at addressing the identified issue:

What are the various methods employed for conducting LA within the educational context?

How can the research model be effectively integrated using educational approaches?

What constitutes the proposed ALA model utilized in the realm of LA in HE?

3.3 Data collection

The goal of the data collection was to uncover empirical research that covers a wide range of approaches, including quantitative, qualitative, mixed methods, and literature reviews, all published in peer-reviewed journals since 2001. The intention was to pinpoint the methodologies and models employed in the context of LA within higher education. Various search terms were employed, including combinations such as "learning analytics and methodologies", "learning analytics and theory" and "learning analytics and consequences". Additionally, keywords like "pedagogy and higher education", "learning analytics and higher education", "Big Data analytics", and "learning analytics models" were used. The research process encompassed sources like Google Scholar, the Educational Resources Information Center (ERIC), and other relevant databases.

3.4 Data evaluation and analytics

Following the described methodology, a total of 123 articles were uncovered. Among these, 16 delved into the synergy between BD and LA approaches, 8 concentrated on the integration of pedagogy, and 6 were centered around models. The remaining publications were excluded from this assessment as they did not directly contribute to addressing the study's core questions. Inclusion criteria were confined to papers directly linked to learning analytics and educational approaches, Big Data, pedagogy, and models.

The systematic literature review was guided effectively by Cooper's methodology [41]. Employing the previously outlined approach, alongside the specified keywords and databases, the researchers meticulously combed through the literature.

It's important to note that the literature search was limited to the chosen keywords and databases predetermined by the researchers. Consequently, this literature compilation might not encompass sources that weren't identified within the set search criteria and databases. The references cited in the findings section have been compiled in Table 1 for reference.

Table 1. Sources revealed that answered the research questions

Focus	Sources
Approaches Implications in Learning Analytics	Knight, Buckingham, and Littleton, K. (2013). Greene, Muis, and Pieschl, (2010) Hofer, (2004) Hofer, (2001) Hwang, Tsai, and Tseng, (2008) Janssen, and Bodemer, (2013) Jelfs, Buckingham and De L. (2011) Johnson, Reimann, Bull, and Fujita, (2011). Buckingham and Ferguson, (2012) Ferguson, Rebecca and Buckingham (2012). Shaffer, Hatfield, Navoa Svarovsky, Nash, Nulty, Elizabeth Bagley, Frank, Rupp, and Mislevy, (2009) Haythornthwaite, De Laat, (2010). Ali Darvishi, Hassan Khosravi, Shazia Sadiq, Dragan Gašević (2022) Asmalina Saleh, Tanner M. Phillips, Cindy E. Hmelo-Silver, Krista D. Glazewski, Bradford W. Mott, James C. Lester (2022) Christopher C. Y. Yang & Hiroaki Ogata (2022) Abhinava Barthakur, Srecko Joksimovic, Vitomir Kovanovic, Michael Richey, Abelardo Pardo (2022)
Connecting Learning analytics model with Educational Theories	Serrano-Laguna, Torrente, Moreno-Ger, (2014). G. E. Jeroen, Anouschka, Brekelmans, (2014). Tempelaar, Rienties, Giesbers, (2015). Bali, (2017). Xing Wanli, Rui, Petakovic, (2015). Gayane Sedrakyan a b, Jonna Malmberg c, Katrien Verbert a, Sanna Järvelä c, Paul A. Kirschner (2020) Xieling C, Haoran Xie, Di Zou, Gwo-Hwang (2020) Hui-Ching, K Hsu, Cong Chantal Levesque-Bris (2019)
Integrating Learning Approaches: Proposal Adaptive Learning Analytics Model in higher education	Yi Li, Xiaoning Zhai, (2018). Y. Li, P. Li, F. Zhu and R. Wang, (2019). Pratsri, Sajeewan, Nilsook, Prachyanun, (2020). Cartney, P. (2010) Rameshwar Dubey, Angappa Gunasekaran, Stephen J. Childe, Constantin B, Than os P (2019). Surajit Bag a, Lincoln C. Wood b c, Lei Xu d e, Pavitra Dhamija f, Yaşanur Kayikci (2020)

4 THE RESEARCH FINDINGS AND DISCUSSION

This section presents the outcomes derived from the literature review, addressing the three research questions posed earlier.

4.1 Learning analytics and approach implications

Exploring the interrelation between LA and pedagogy holds significance due to their intrinsic connection within epistemology. This section aims to explicitly establish the correlation between various well-established pedagogical approaches and LA. Rather than exhaustive assessments, these explorations offer concise insights into potential conceptualizations of the interplay between pedagogy and LA.

Transactional approach. LA grounded in transactional methods often prioritize straightforward metrics like test scores, potentially overlooking the need for a deeper exploration of intricate artifacts or the methodologies behind their generation.

Constructivist approach. LA aligned with a constructivist approach will emphasize progress, primarily by monitoring and assessing modifications implemented to a set of materials, resources, or tools designated and organized by the educator.

Subjectivist or affect-based approach. In alignment with other perspectives, LA rooted in the subjectivist paradigm is likely geared towards offering motivational assessments, elucidating the motivations behind an individual's engagement (or lack thereof) in particular activities. Such analytics could revolve around self-reported data gathered through survey tools or could employ affect-based semantic markup techniques, like blog tagging [42], in conjunction with automated approaches such as textual sentiment analysis.

Apprenticeship approach. LA rooted in apprenticeship methods are inclined to focus on classifying users as either professionals or novices, tracing their progression from initial stages to becoming experts. This analysis could involve identifying behavioral markers resembling those exhibited by "experts," albeit without necessarily delving into the underlying reasons or implications of such transitions. To provide an example, consider the situation of conducting epistemic network analysis on user data extracted from gaming environments. The primary aim here is to measure the degree to which learners display behaviors that are esteemed within a skilled community [43].

Connectivist approach. Predominantly, the connectivist perspective employs network exploration to assess the "connectedness" of a learner's knowledge and the overall web of connections. Analytics within this framework would specifically examine how the volume, quality, and evolution of these networks can serve as indicators for successful learning outcomes [44].

Pragmatic, Socio-cultural approach. Pragmatic approaches have typically placed less emphasis on assessing the outcomes of learning (unless they are applied for a specific purpose) and have focused more on the learning process itself. Analytics frameworks from a sociocultural standpoint encourage learners to center their attention on their specific activities, aiming to comprehend how they can enhance their skills in data processing within their unique contexts [45]. Analytics aligned with this approach might primarily address the quality of discourse for learning and foster a shared understanding of perspectives inherent in collaborative information-seeking tasks.

4.2 The simple learning analytics model

In summary (Figure 3), researchers are required to incorporate various strategies into their analytical investigations to improve modern educational models, ensuring their flexibility and effectiveness. This entails contextualization and continuous updates to stay in sync with current educational trends.

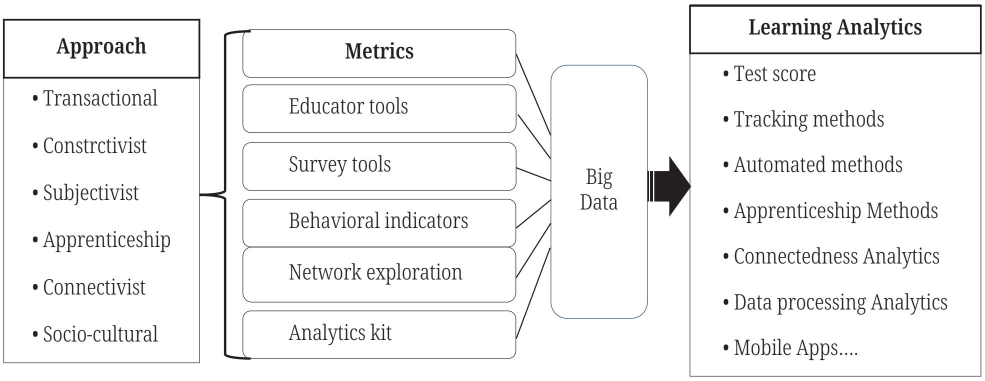

Fig. 3. Basic learning analytics model using approaches

4.3 Connecting learning analytics model with educational approaches

The central goal of LA researchers is to enhance the learning process by systematically examining data linked to learning and instruction. This analysis aims to furnish insightful feedback to stakeholders, ultimately facilitating tailored learning opportunities for learners, educators, and institutions. A pivotal dimension of LA research involves the prediction of students' learning performances. For instance, typical LA studies endeavor to recognize or anticipate learners who might encounter challenges in their learning path, at times in real-time scenarios [46]. The anticipation of dropout and retention rates holds notable significance for LA researchers. Notably, a substantial body of LA research focused on student retention has found that predictive models encompassing demographics, academic integration, social integration, and psycho-emotional/social factors effectively forecast students' academic achievements [47]. Moreover, the LA approach has been harnessed to track student interactions and individual assessments across the educational approaches indicators.

To thoroughly understand factors impacting learning and performance, researchers must incorporate instructional theories into their data analysis in LA [48]. Feature selection in LA becomes critical due to potential declines in statistical prediction accuracy with a multitude of variables. Unlike computational fields, educational research relies on the researcher's discernment, guided by educational theories, for feature selection. LA researchers must establish a link between study findings and educational theories, recognizing the true value of research in contributing to instructional and learning design knowledge [49]. However, selecting suitable educational theories for both feature selection and result interpretation is complex. Therefore, LA researchers should carefully evaluate pedagogical foundations before commencing research.

Preparing a modern generation for big data analytics in education integrating big data. All contributors involved (developers, instructional participants, educators, and trainers, among others) are expected to respond to these critical modern educational analytics challenges by improving or offering new approaches to HE that take into account the most recent educational and technological advances. To enable more widespread use of LA in HE, the government must highlight the need for institutional remedies in both pedagogical provision and institutional policy reform.

Preparing teachers. Teachers and educational leaders ought to be afforded appropriate autonomy to govern their classrooms and institutions, grounded in the notion that they harbor the most profound understanding of their learners' requirements. The role of automated analyses in bolstering this autonomy gains significance when teachers and educational leaders are empowered to mold the learning milieu within their spheres. In the absence of such empowerment, even cutting-edge tools yield limited influence. It's a misperception to propose that novel technologies can replace teachers; educators continue to be fundamental in the educational realm [50]. Furthermore, teachers are the ones who determine the timing and methods for effectively integrating advanced tools.

To cultivate a thriving learning environment, teachers should actively participate in continual dialogues with students regarding the enhancement of learning methodologies. Furthermore, teachers assume a pivotal role in imparting skills and competencies that are less susceptible to automation by machines.

Preparing students. In the realm of LA, it is frequently observed that students display a noticeable lack of interest or motivation within educational settings. This specific behavior poses challenges not only in terms of correction but also in its potential negative impact on classroom dynamics. It erodes the positive atmosphere that teachers strive to cultivate, aiming to establish rapport with students and foster a sense of community.

Hence, it is imperative for educators to establish robust relationships with their students, meeting them at their individual levels and making a genuine effort to comprehend their perspectives. To accomplish this, educational institutions must formulate a strategy that functions as an effective instructional management plan. Such a plan facilitates the cultivation of targeted thought patterns among teachers, students, and all stakeholders, contributing to the successful attainment of desired learning objectives.

Here are the strategies these can implemented to foster student engagement in the learning process:

- provided chances to determine their learning goals
- create an innovative opportunity to discover and learn independently
- empowered to cultivate the self-assurance to independently research and learn in the future
- equipped with the essential array of critical thinking, inductive reasoning, and analytical abilities to construct a conceptual grasp of big data and its applications
- assisted in formulating the subsequent phases of their learning journey
- given opportunities to assess one another's work.

Preparing researchers. Teachers must not only be prepared to comprehend and embrace emerging technological possibilities and the evolution of significant educational data, but the history of educational progress is also marked by untapped potential due to a lack of understanding of teacher practices and school culture. For new educational opportunities to flourish, contemporary innovators must engage in collaborative dialogues with educators, content developers, and multidisciplinary experts. Researchers should outline practical strategies, evaluate their viability, and ultimately establish their widespread relevance. The matter of feasibility assumes utmost significance in the context of school learning, as certain approaches may conflict with the prevailing school framework and even the teaching profession as a whole.

5 INTEGRATING EDUCATIONAL APPROACHES: PROPOSAL FOR ADAPTIVE LEARNING ANALYTICS MODEL IN HIGHER EDUCATION

LA can be succinctly defined as the comprehensive analysis of extensive data generated throughout the learning journey to assess the academic process, predict recommendations, and identify potential risks. This substantial educational data stems from both explicit student actions, such as assessments and assignments, and implicit behaviors, including online interactions (social networks, forums, mobile applications, etc.). The central aim of our theorical model is to equip educators and institutions with the ability to construct an educational framework that extract the relevant indicators included in the educational approaches, and harmonizes with the unique capabilities of individual students, all within a foundation of personalized methodologies and encompasses all the LA process from the evaluation process to the decisional and the feedback process.

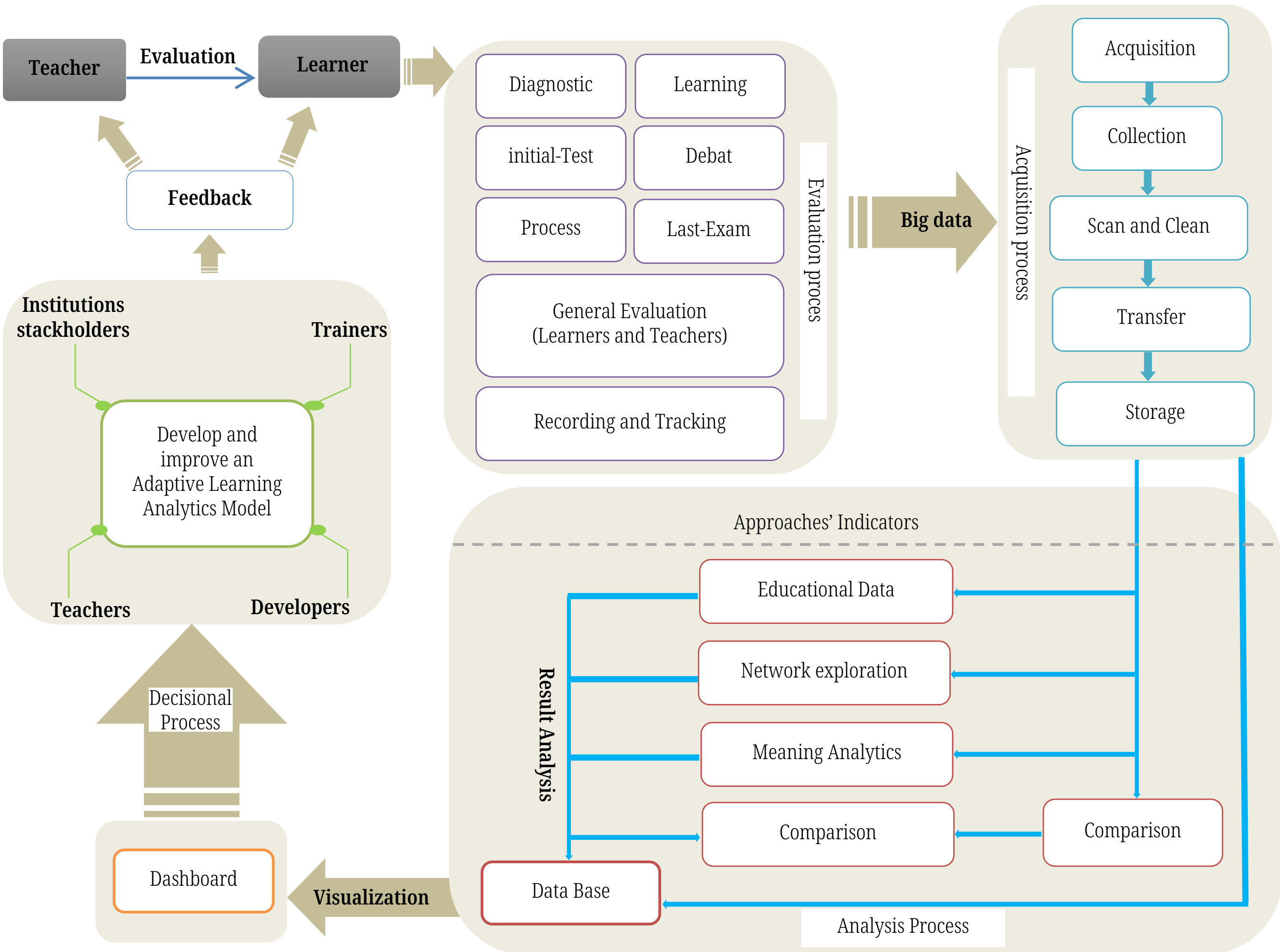

Fig. 4. ALA model includes approaches' indicators adapted from [51]

Related to Figure 4, the model encompasses the subsequent processes:

5.1 Evaluation process

Incorporating functional components like interactive discussion forums, pre-tests, quiz cards, teacher evaluations, peer assessments, and more, a learning contract primarily serves to outline learning objectives, progress, and assessment criteria. This serves a dual purpose: offering learners personalized options while also functioning as a contractual framework, outlining shared engaging content to motivate and guide learners.

5.2 Data acquisition and storage process

Comprising four crucial components—Data Acquisition, Data Cleaning, Data Conversion, and Data Hybrid Storage System—this framework's data analysis efficacy hinges on both quantity and quality of mined data. When collecting a substantial data volume via data acquisition, extraneous data such as advertisements may be generated; this is addressed through data cleaning. Streamlining data mining analysis involves employing conventional data conversion techniques, such as classification variable reorganization. To safeguard against data loss and enable seamless database integration, a hybrid storage system combining relational and NoSQL databases is employed for subsequent mining analysis [52].

5.3 Analysis process

Positioned at the core of the entire system, it primarily encompasses dual databases and three data processing technologies. The databases consist of a standards database housing evaluation criteria and indexes, and a result database with three sources: unprocessed data like duration and grades, technically processed data from mining and analysis, and results compared with the standards. The data processing technologies comprise education data mining, social network analysis, and semantic analysis. The first tailors knowledge recommendations based on learning patterns; the second assesses learners' interactions and enthusiasm in groups; and the third enhances system intelligence and mitigates weaknesses. Crucially, analysis steps align with indicators from diverse educational approaches for optimal results, thereby fostering strategies to formulate tailored intervention models for each educational system under study [53].

5.4 Decisional process

Our study identified three feedback subsystems based on the decisianal process: diagnostic, procedural, and final feedback-diagnostic. Diagnostic feedback is administered prior to assessments, procedural feedback offers real-time warnings during learning, and terminated feedback is used for teacher evaluation and final tests. A specific community (teachers, institutions, etc.) analyzes this feedback to enhance future learning models. Teachers significantly intervene when needed, and feedback data is presented on a dashboard for teachers and learners, promoting intuitive understanding [54].

6 CONCLUSION

Demonstrating the correlation between educational BD and analytics and improved performance, the results are translated into a suggested model. This model encompasses definitions of BD and analytics, crucial processes, theory, and the advantages of their application in achieving higher levels of excellence in higher education establishments.

The initial segment establishes the theoretical foundation and relevant terminology, with a specific focus on the significance of substantial educational data for institutions, all within the context of proposing a new ALA model. Building upon these findings, we outline implications related to educational methodologies. Additionally, this opportunity provides stakeholders (including learners, instructors, and institutions) with the potential to facilitate personalized learning.

The subsequent section of this paper introduces the ALA model, emphasizing the integration of indicators from various approaches into the educational system, facilitated by BD analytics for enhanced performance excellence in higher education. Comprising five key processes, namely evaluation, acquisition, analysis, and evaluation, the ALA model provides a comprehensive approach for institutions aiming for excellence. Its systemic adoption requires recognition of the complexity of educational systems and consideration of internal and external factors. Learning Analytics (LA) should be approached within the broader context of interconnected organizational, social, and political structures in educational institutions. Effective LA adoption demands the formation of multidisciplinary teams representing all relevant stakeholder groups.

A limitation of this study is that the ALA Model remains theoretical and has not been tested in practical application to address a real decision challenge within a BD context. Nevertheless, this work underscores the significance of combining BD and decision modeling in organizational decision-making processes, a facet that will be explored and assessed in forthcoming endeavors.

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