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The Construction and Validation of a Business Intelligence Model to Enhance Learning Analytics in Higher Education Institutes

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Abstract: *As any estimation or quality assurance process in HEIs, seeking progress indicators, require advancing on preparation to demonstrate on students' learning, and there is a growing need in universities for an evidenced-based Learning Analytics (LA) model to employ big data for the benefit of their students, researcher build this novel but practical, step by step framework. The objective of this article is to fill the void in literature by develop and validate a framework that integrates BI software solutions, LA and students' performance, for analyzing useful knowledge from the student learning experience by predictive analytics, to improve learning outcomes for the students and the society. In this article, researcher review literature in design and modeling LA frameworks and its correlation with other related fields. The novel practical Business Intelligence Enhance Learning Analytic Framework (BIELA), that represent meaningful guidance on effectiveness use of LA in HEIs, keeping up with the revolution of ICT and the dynamic "big data" growing exponentially, toward growth in HEIs, the extraordinary turbulent environment*

Keywords: *Learning Analytics; Design and modeling perspectives, higher education institutes; Enhance learning*

1. Introduction

Analytics is the smart use of historical datasets combined with current one and trends to predict actionable insights and addressing complex issues using technologies from computer science, mathematics and statistic, [1]; [2].

Learning Analytics in higher education is a promising approach, emergent concept of rapid growth latest datamining technique for understanding and modeling the learning process [3], [4], evolving many disciplines, like DM, AI, Information retrieval, statistics, action analysis and visualization [5], to discourse, capacity, gathering, investigation, understand, analyze, visualize, assess, advice, predict and report learners' needs, their context, performance and the learning environment in a verification based decision making, which would ultimately empower teachers and education institutes to tailor educational prospects to individual student's need, as a vital area of technology enhance learning (TEL), and provide effective involvements and smart learning infrastructure [6];[3];[7]; [8]; [5]; [9]; [10].

2. Design and Development LA Models

As learning analytics is a new field, and latest datamining technique [3], [9], most of the researches are concentrating on developing reference model for defining the concept, enhance user acceptance, raising responsiveness, understanding the power and capabilities of learning analytics and it's critical dimensions, (see fig (1&2), [8]; [5]; [11].

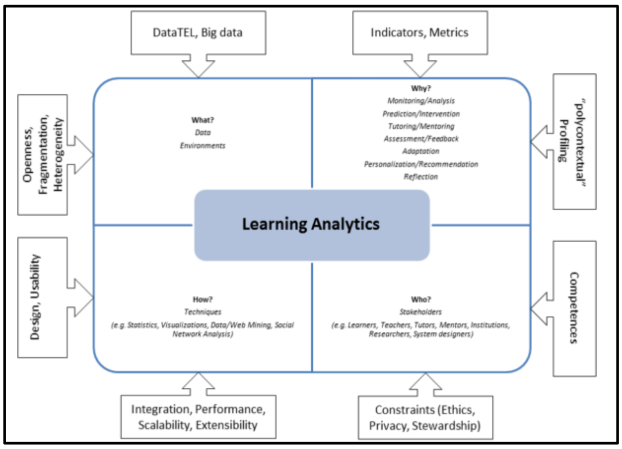

Fig1. *LA reference model, Source: [5]*

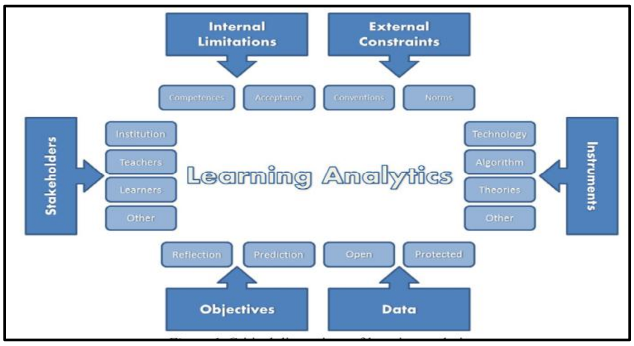

Fig2. *Critical dimensions of LA, Source: [11]*

In the literature, there is focusing on analytics of virtual learning environments (VLEs) e.g. Blackboard and Moodle, like the case study in [12], that use the log file delivered by LMS, fewer of them validate their app in real cases, due to ethical barriers, which should be considered prior the implementation [4]. Most of LA applications are deployed in an online/blended environment rather than traditional classes[12];[9]; [13], generating VLE usage data, such as the number of clicks, number of words in blogs, content usage, the number of blogs, .. etc. [8]. Most findings in literature, are correlated between students' usage of learning resources and academic performance [4].

LA can make use of big learners' data for investigating and understanding their requirements; improve the learning process, satisfaction, retention, inform quality assurance([table 1], illustrate analytics capabilities for assessment one instance in QA processes), and stakeholders [fig 3]. Using LA, models produced, can predict future processes [14]; [15]; [16]; [17]; [18]; [7], [19].

Table1. *Analytics capabilities for assessment strategy evaluation [20]*

	→ Analytical Complexity →		
Analytics categories	**Descriptive Analytics**	**Predictive Analytics**	**Prescriptive Analytics**
Generic Analytical Capability	Measure/monitor performance	Project, Analyse relationships	Model decisions, Optimise
Instance: Assessment Strategy Review	Overview of assessment activity across entire programme	Examination of relationship between assessment events	Determine modules that have most and least effect on programme award
Analytics Tool (e.g.)	Programme schedule report	Correlation and regression analysis tools	Statistical modelling tools enabling user modification of parameters

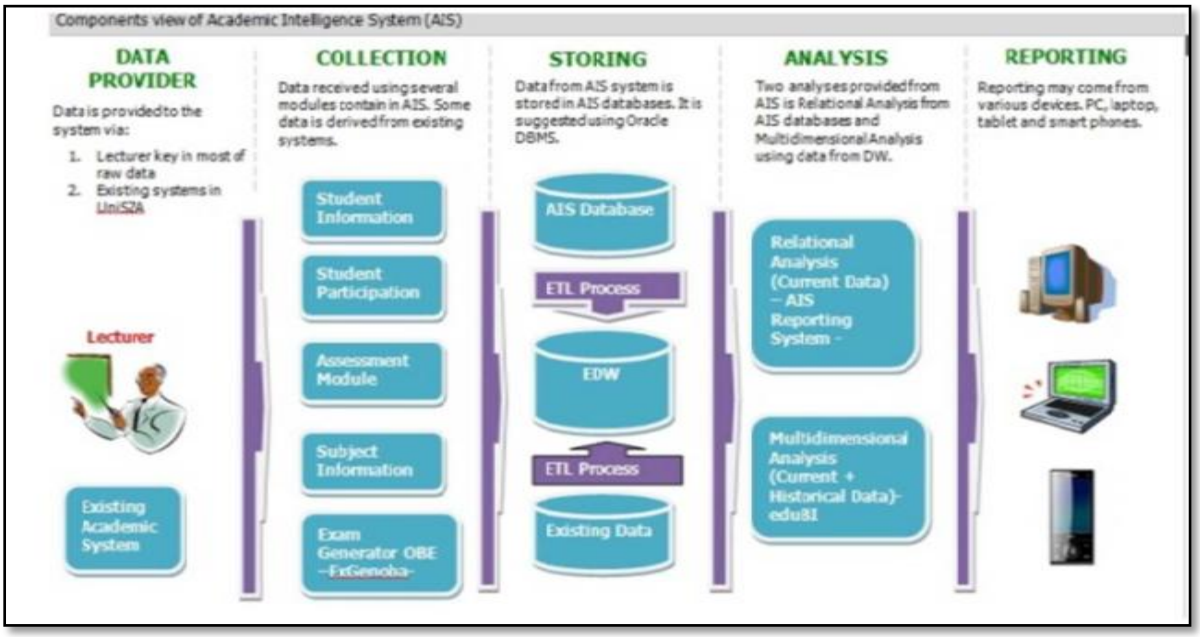

Fig3. *An educational intelligence framework, Source: [16]*

An international community and events such as SoLAR (the Society for Learning Analytics Research) has been developed [21], since the emergence of LA in North American, Europe and Australia, with smaller pockets of motion developing in other regions [21].

The effective LA challenge is how to use big datasets and analytics to care about students; refining learning outcomes [2], knowledge, inform decisions, satisfaction, enjoyment, confidence, meeting career needs and promptly rising as a significant area of TEL (Technology-Enhanced Learning) research [15].

The "big data" that daily increases due to growth in the use of online learning in VLE or LMS including Blackboard and Moodle is the main challenge in LA [20]; [22], and business engagement analytics to cutting value from such datasets [15]; [22].

Fig.5 shows the LA continuous improvement cycle through which a high-quality data is produced to improve learning processes and students' satisfaction.

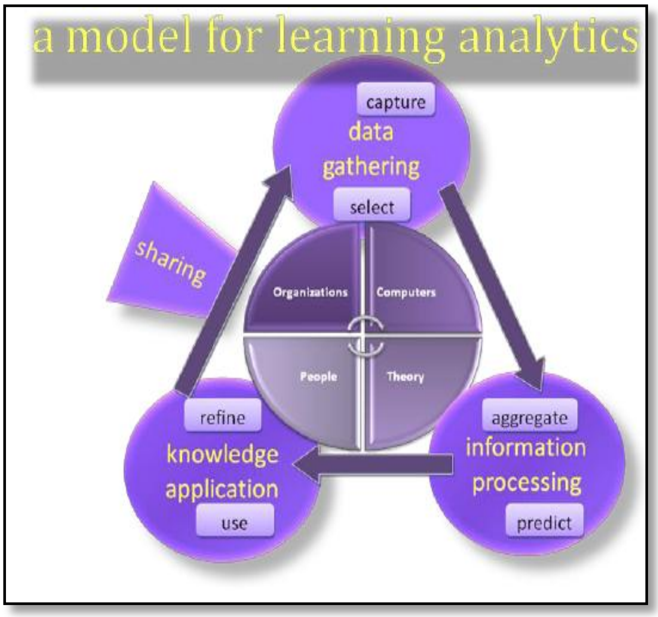

Fig4. *LA continuous improvement cycle, Source: [2]*

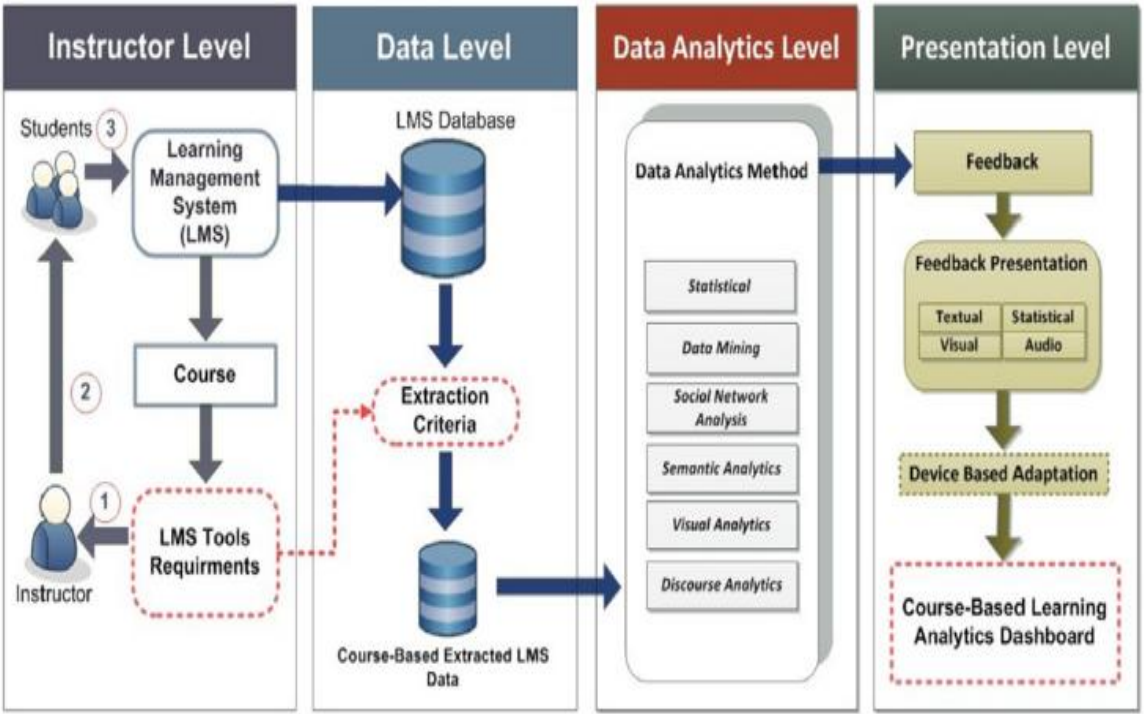

Fig5. *Course adapted student learning analytics framework*

Source: *[6]*

Fig. 6shows, one of the largest “course adapted student learning analytics “frameworks the framework has four different levels, Instructor, data, data analytics and presentation level. The framework is based and verified in a blended learning environment which is LMS, using dataset of 1200 students extracted from blackboard [6]. Eventually most types of data used in LA are automated online dialog and/or survey, or data extracted from school ecosystem [23].

3. Model Construction

Responding to the problem, that is lack of evidenced-based framework to enhance LA in HEIs, researcher tend to integrate BI technology, LA and students’ performance for analysis of university students’ data assets collected from heterogeneous resources, builds the foundation of a profound understanding of the students’ learning processes, it leads to a novel, but practical model that will fill the gap between the institution’s BI maturity level towards implementation of LA and the desired one.

This approach is based on, understanding the user ethical requirements for the predefined target groups (administrations, staff members, students, head departments and managers for academic and quality affairs) and the services that are dedicated to learners (main stakeholders that should be engaged in helping the University to feed and update their data to support withholding and consulting them). Student satisfaction survey via a questionnaire is conducted, to capture student requirements, understanding their needs, trends, individual learning characteristics and considering their opinion into account, as a main stakeholder.

The investigating of the individual learning characteristics and educational needs, followed through comprehensive surveys, questionnaires, studying university’s documents, brainstorm sessions and face-to-face interviews, to provide significant information and joined strategy formulation for various stakeholders, to support higher quality decision making, tailor educational opportunities to specific students’ prerequisites, future planning and efficiency improvement in the teaching-learning process, addressing LA challenges and enhance utilization of the dynamic and diversity ocean amount of data that available/collected in HEIs building EDW to be a solid foundation for mining knowledge and well understanding of the students’ learning experience and investigating user requirements of target groups in academic background.

BIELA is arises from empirical study, BI initiatives in some modern universities, desktop research, learning analytics modeling review to fill the void in LR, study universities’ documents in Quality

Assurance measures, teaching learning standards and KPI, surveying and interviewing target groups and experts, and by using design and development methods.

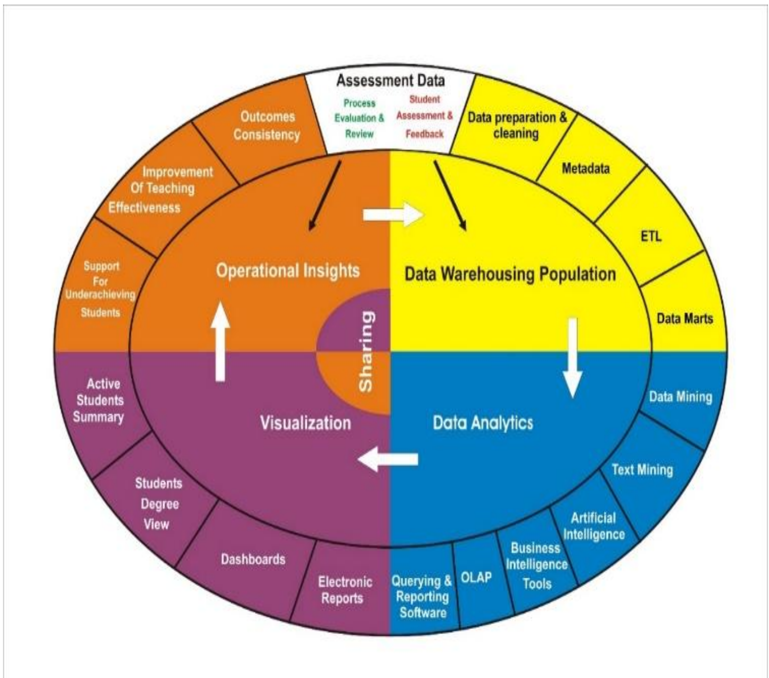

Fig6. *Business Intelligence Enhance Learning Analytics (BIELA) framework*

3.1. Data Preparation (Phase I)

This step concerns manipulating and transforming the raw data gathered into appropriate format that should meet the specific criteria of the quality requirements for visualization, using BI tools.

To better oversee the nature of the data, it also includes checking data redundancy, consistency, completeness, missing values, the credibility of attribute values. Contextual knowledge can be used to lead these instructions.

In addition, for inform knowledge, privacy, ethical consideration and ensuring the quality of data by enforcing constrains and correcting wrong entries, typical examples of manipulation include converting data from manual entry in excel format to attributes in database format, moreover, academic numbers which is the key field, are converted to encrypted/fake numbers using specific code, to anonymize students' personal information for ethical considerations.

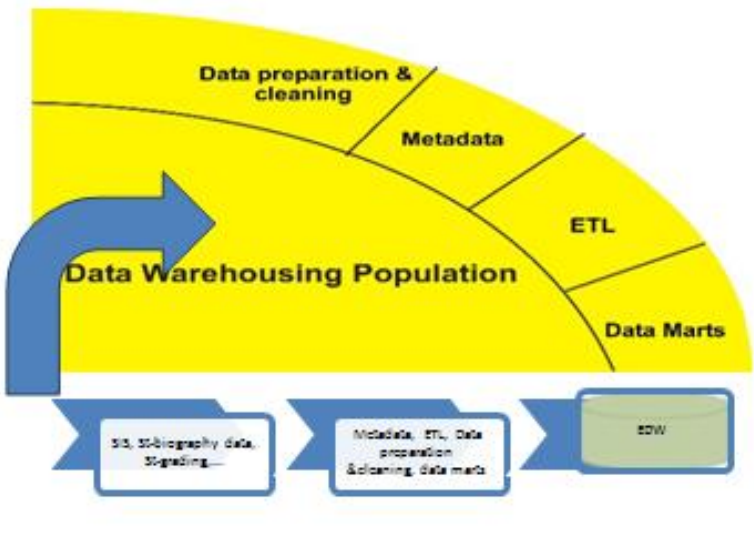

Fig7. *1st phase in BIELA*

3.2. Analyzing Knowledge (Phase II)

At this point, BI software tools, Tableau, which considered the dominant tool in data visualization that has great desire, fast and broad adoption in practice [24], and topping the Gartner lists for many years. , that is why we applied to extract useful knowledge from preprocessed data. Tableau is the powerful technology that can collect spread and dissimilar data in an intelligent way that will be suitable for decision support and strategic organization, this usually comprises the standardization of the factors to the optimal values.

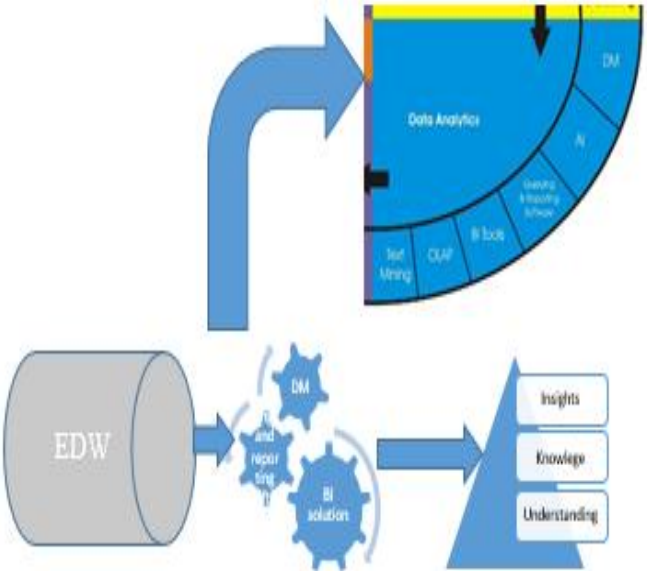

Fig8. *2^{nd} phase in BIELA framework*

3.3. Visualization (PhaseIII)

Visualization are vital tools of the communication, sharing and customizing of information which provide users with the information required to monitor and controlling deliverable outcomes to make intelligent, real-time decisions, that's why it should be prepared very carefully. The well designed dashboards let managers make well-informed and suitable decisions that help achieve institutional goals,

The ideal visualizing system would tell managers all they want to know and only those things. Although no such ready-made system exists for every application.

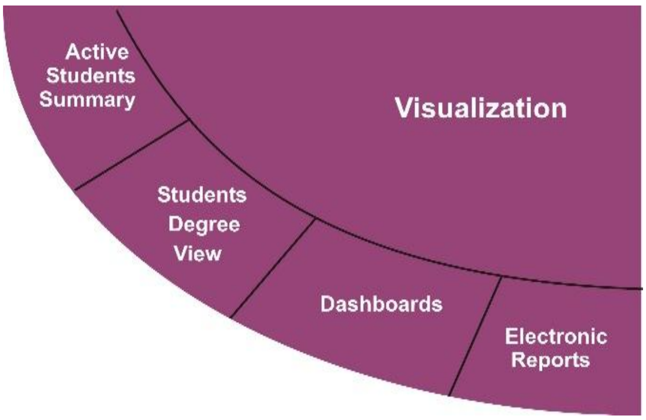

Fig9. *Phase III in BIELA*

Only approved models are retained for the next step, otherwise the process is revised to identify which data entry could be corrected to validate the results (e.g., writing wrong input name, getting different data). The researcher assessed the results carefully through case study and expert corporation and thus gain confidence as to whether or not they are qualified. Researcher exploring documents of QA in teaching learning standards in HEIs and gather ideas about specific quality indicators to evaluate the effects of learning analytics technique.

Deliver away to regulate the assessment of learning analytics tools. In addition, the academic context experts support.

3.4. Operational Insights (PhaseIV)

This final phase, that an important aspect of the overall effort consists of predicting how and where to put the final discovered knowledge into realistic activities and decisions. The fundamental elements of this phase are derived from awareness and the lessons learned from all the previous processes.

Fig10. *Phase IV in BIELA*

3.5. Assessment Data

The evaluation stage serves to help ensure that the discovered knowledge meets the original research objectives and extracting real valued knowledge before moving further. Researcher used evaluation techniques like interviews, surveys and /case study, with feedback from main stakeholder and decision makers.

4. Discussion of the Result

BIELA framework, differs from previous models, in its fourth and fifth phases addition, which is insightful, assessment data and feedback, BIELA framework also differ in fundamental elements that characterize the five Stages. BIELA framework is distinct because verified and proved its success and hypothesis using real dataset for more than one thousand university students, rather than the greatest of the research in the field of LA, which has been applied on the Online/blended/survey/eye tracking etc. [23].

5. Conclusion

BIELA is arises from empirical study, review LA construction and modeling , studying BI initiatives in some modern universities, desktop research, study universities' documents in QA measures, teaching learning standards and KPI, surveying and interviewing target groups and experts, and by using design and development methods (CRISP- data mining method, Monkey survey and Corel Draw).

This research article identifies five main phases of this integrated framework: Data warehouse population, Data analytics, Visualization, Operational insights and assessment data phase. Each stage involves of several key fundamentals.

References

[1] J. Bichsel, "Analytics in Higher Education: Benefits, Barriers, Progress, and Recommendations," Educ. Cent. Appl. Res., pp. 1–31, 2012.

[2] T. Elias, "Learning Analytics : Definitions, Processes and Potential," Learning, vol. 23, pp. 134–148, 2011.

[3] Y. Lu, S. Zhang, Z. Zhang, W. Xiao, and S. Yu, "A Framework for Learning Analytics Using Commodity Wearable Devices," Sensors, vol. 17, no. 6, p. 1382, 2017.

[4] M. Jantti and J. Heath, "What role for libraries in learning analytics?," Perform. Meas. Metrics, vol. 17, no. 2, pp. 203–210, 2016.

[5] M. A. Chatti, A. L. Dyckhoff, U. Schroeder, and H. Thüs, "A reference model for learning analytics," Int. J. Technol. Enhanc. Learn., vol. 4, no. 5/6, p. 318, 2012.

[6] N. R. Aljohani, A. Daud, R. A. Abbasi, J. S. Alowibdi, M. Basheri, and M. A. Aslam, "An integrated framework for course adapted student learning analytics dashboard," Comput. Human Behav., 2018.

[7] S. P. Atkinson, "Using learning design to unleash the power of learning analytics," Aust. Soc. Comput. tearning Tert. Educ., no. June, pp. 358–362, 2015.

[8] B. Rienties, A. Boroowa, S. Cross, C. Kubiak, K. Mayles, and S. Murphy, "Analytics4Action Evaluation Framework: A Review of Evidence-Based Learning Analytics Interventions at the Open University UK," J. Learn. Anal., vol. 1, no. 1, pp. 75–87, 2016.

[9] F. Martin and J. C. Whitmer, "Applying Learning Analytics to Investigate Timed Release in Online Learning," Technol. Knowl. Learn., vol. 21, no. 1, pp. 59–74, 2016.

[10] D. Ifenthaler and C. Widanapathirana, "Development and validation of a learning analytics framework: Two case studies using support vector machines," Technol. Knowl. Learn., vol. 19, no. 1–2, pp. 221–240, 2014.

[11] W. Greller and H. Drachsler, "Translating Learning into Numbers : A Generic Framework for Learning Analytics Author contact details :," Educ. Technol. Soc., vol. 15, no. 3, pp. 42 – 57, 2012.

[12] Bogarín, R. Cerezo, and C. Romero, "Discovering learning processes using Inductive Miner: A case study with Learning Management Systems (LMSs)," Psicothema, vol. Vol. 30, no. No. 3, pp. 322–329, 2018.

[13] F. Martin, A. Ndoye, and P. Wilkins, "Using Learning Analytics to Enhance Student Learning in Online Courses Based on Quality Matters Standards," J. Educ. Technol. Syst., vol. 45, no. 2, pp. 165–187, 2016.

[14] P. Murnion, "LEARING ANALYTICS EVALUATION: AN EXAMINATION OF PRACTICE," in International workshop on IT Artefact Design & Workpractice Improvement, 2014.

[15] R. Ferguson, "Learning analytics: drivers, developments and challenges," Int. J. Technol. Enhanc. Learn., vol. 4, no. 5/6, p. 304, 2012.

[16] Abdul Aziz, J. Aida Jusoh, H. Hassan, W. Mohd Rizhan Wan Idris, A. Putra Zulkifli, and S. Anuwar Mohamed Yusof, "A framework for educational data warehouse using business intelligence technologies," J. Theor. Appl. Inf. Technol., vol. 69, no. 1, pp. 50–58, 2014.

[17] M. Bienkowski, M. Feng, and B. Means, "Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics: An Issue Brief," 2012.

[18] Z. Z. Papamitsiou and A. A. Economides, "Learning Analytics and Educational Data Mining in Practice: A Systematic Literature Review of Empirical Evidence.," Educ. Technol. Soc., vol. 17, no. 4, pp. 49–64, 2014.

[19] J. Martin, "Why now ? The occasion for learning analytics," in Learning Analytics, 2016, pp. 1–12.

[20] P. Murnion and M. Helfert, "Academic Analytics in quality assurance using organisational analytical capabilities," UK Acad. Inf. Syst. Conf. Proc. 2013, 2013.

[21] R. Ferguson et al., "Learning analytics," Proc. 5th Int. Conf. Learn. Anal. Knowl. - LAK '15, pp. 69–72, 2015.

[22] Klašnja-Milićević, M. Ivanović, and Z. Budimac, "Data science in education: Big data and learning analytics," Comput. Appl. Eng. Educ., vol. 25, no. May, pp. 1066–1078, 2017.

[23] N. Nistor and Á. H. García, "What Types of Data Are Used in Learning Analytics? An Overview of Six Cases," Comput. Human Behav., 2018.

[24] S. Mamonov, R. Misra, and R. Jain, "Business Analytics in Practice and in Education : A Competency-based Perspective," Inf. Syst. Educ. J., vol. 13, no. January, pp. 1–10, 2014.

[25] M. Goyal and R. Vohra, "Applications of Data Mining in Higher Education," Int. J. Comput. Sci. Issues, vol. 9, no. 2, No 1, 2012.

[26] G. Siemens et al., "Open Learning Analytics: an integrated & modularized platform Proposal to design, implement and evaluate an open platform to integrate heterogeneous learning analytics techniques Project Overview," Educ. Rev., vol. 42, no. 4, pp. 53–54, 2011.

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