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Learning Analytics for Educational Innovation: A Systematic Mapping Study of Early Indicators and Success Factors

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Abstract*: Today, theoretical and practical advancements in information and communication technologies (ICT) have proven to be indispensable towards achieving the goals of modern educational institutions including the underlying process models. There is evidence that existing technologies such as learning analytics (LA) can not only be used to understand the users (e.g. learners) and the context in which learning takes place, but also can take educators further in achieving different learning goals and innovation. On the one hand, there is a need for educators to adopt digital technologies in support of different activities that constitute educational processes; ranging from the changing higher institutional labour market to the rapid renovation of information systems and tools used to support learners. Moreover, such a requirement also relates to an educational community that is expected to include more proactive and creative learning strategies and experiences for the said stakeholders (e.g. teachers and students). On the other hand, this study shows that to meet those needs, learning analytics which implies measurement, collection, analysis, and reporting of data about the progress of stakeholders and learning contexts; is of importance. To this end, this paper conducts a systematic mapping study of current literature to determine trends in learning analytical methods and its application over the past decade. We look at how learning analytics has been used to support improved process monitoring and management (e.g. educational process innovation) within different organizational settings and case studies application. Consequently, this paper proposes a Learning Analytics Educational Process Innovation (LAEPI) model that leverages the ever-increasing amount of data that are recorded and stored about different learning activities or digital footprints of users within the educational domain to provide a method that proves to be useful towards maintaining continuous improvement and monitoring of different educational platforms. Thus, the notion of learning analytics for Educational Process Innovation in this paper. Technically, this work illustrates the implication of the method using dataset about online learning activities of university students for its experimentations and analysis.

***Keywords*:** Educational Innovation, Learning Analytics, Process Modelling, Learning Activities, Lifelong Learning, Higher Education.

I. Introduction

Over the past few decades, there have been enormous opportunities and huge benefits of using Learning Analytics (LA) to improve educational processes. Although learning analytical methods are still at a relatively early stage of its development and application especially within modern educational systems; there is convincing evidence from early research that it is capable of improving educational processes and innovation [1], [2]. Moreover, modern educational institutions can consider introducing and adopting suitable (learning) analytical frameworks in their different operational processes.

There are several factors that have spanned research and development within the LA fields. One of them is that different organizations are seeking the best ways on how to make use of learning analytics for educational process innovation. In this study, we highlight the main factors that have led to the increasing need for innovative measures through the results and outcome of the systematic mapping study conducted in this paper (see: section II (*A*)). For instance, we note that higher education institutions (HEIs) have been found to operate in ever-growing competitive and complex environments, including the need to respond to (both international and local) economic, administrative, and social changes that emerge as a result of the LA. Moreover, there also exist policies and requirements by various institutions to increase the number of students that are fully involved or registered in certain areas or fields of study whilst ensuring the relevance and suitability (quality) of learning programs and outcomes respectively [3]. Likewise, rapid trends and revolution of information and communication technologies (that are hypothetically allied to the advancement of new LA platforms such as Challenged-based learning, Flipped Classrooms, Massive Open Online Courses (MOOC's), Self-learning, and Lifelong learning, etc.) [4] are drastically reforming the adopted methods/ways of teaching and learning in the diaspora. Interestingly, Daniel [3] notes that the emerging tools and platforms, new sources of data (or yet, the big data notion), changing learning needs and pedagogy, teaching-learning measures, performance and assessment, etc.; have all inspired and contributed to integrating digital (computer) technologies with educational models for higher education innovation. Apparently, to achieve the aforementioned objectives; a single or specific theoretical and/or technological framework is not enough, rather methods such as LA which integrates the knowledge discovery (KDD) and data mining (DM) approaches have to be employed. Moreover, one of the main benefits of the resultant systems (e.g. hybrid intelligent systems) is the ability to extract useful and meaningful patterns from large volumes of datasets which are stored in the databases of the different systems or processes they are used to support.

Technically, LA methods benefit by drawing upon existing databases, statistics and machine learning, data visualization or pattern recognition, to optimization and high-performance computing [3]. Also, it is important to mention that the need for relatable automation and management of educational processes and learning activities has also led to increasing demand for methods/tools that can be used to support or analyse the accumulative large volumes of data. Besides, those datasets have shown to be extracted from various data sources, stored in different forms, as well as, in diverse granular levels within the different educational organizations [5], [6]. Henceforth, this study believes that those captured datasets can be exploited by educators, process innovators or analysts to understand the behaviours of users (e.g. teachers and students). Certainly, this includes an ample understanding of several users' level of performance and/or achieved learning goals in general.

In theory, a typical example of areas in which this technology (LA) has shown its importance and application in real-time is within Educational Process Mining (EPM)[7]. EPM is an emerging field within the wider context of Business Process Management (BPM) that aims to apply Process Mining (PM) techniques to find out user patterns or models from captured sets of educational data, and then seeks to predict outcomes through further analysis of the discovered models [7], [8]. In other words, EPM refers to the application of process mining techniques within the education domain by taking into account the end to end processes or learning activities as performed in reality [6–10].

Likewise, the work done in this paper leverages such methods that are used to support EPM to demonstrate the real-time application of the LAEPI model (Learning Analytics for Educational Process Innovation) proposed in this paper. In turn, the method shows to be useful towards achieving an efficient and effective analysis and improvement of the different educational processes and innovation.

The rest of this paper is structured as follows; in section II, related works within the area of LA and Educational Innovation are discussed. This includes a systematic analysis of various LA studies conducted from 2009 to 2019. Section III introduces the learning analytics and educational process innovation (LAEPI) model, and consequently, describes the different components that enable its implementation in real-time. In section IV, a case study implementation, experimental analysis, and results of the method are presented. Section V discusses the implications and impact of the learning analytical method towards achieving educational process innovation and then concludes and draws a road map for future works in section VI.

II. Background Information

Every educational institution has an interest in ensuring that learners are learning effectively. On one hand, learning analytics (LA) has been seen as a suitable technology to help address and manage the problem of huge amounts and evolution of students' activities or learning processes [11]. On the other hand, recent studies and practices within the areas of LA and Educational Innovation (EI) have proposed methods to support learning processes, especially in terms of making substantial use of information (datasets) that are constantly generated about the different learning activities, to the provision of innovative models to support lifelong learning strategies.

To note, Ley [12] proposed a learning intervention model that integrates LA and educational innovation strategies to address challenges with institutional change and innovation, new learning environments and practices, teachers and trainers as facilitators of learning, as well as learners´ interaction and cognition [12]. Shibani et al [13] note that although the context in which learning occurs is essentially seen as important for learning outcomes and innovation; the main advantages of LA also implies that through the collection of huge amounts of educational data, educators or process analysts are capable of deriving meaningful insights and decision-making points to impact different stakeholders (e.g. learners) at large. To this effect, the work in [13] proposed a Contextualizable Learning Analytics model that can be flexibly adapted for different learning contexts by pairing learning analytics (LA) and learning design (LD).

Furthermore, another important area of application of LA is that the technique is currently being investigated and applied across different research and education communities to support adaptation and personalization of learning or e-learning contents [14–16]. For instance, Pardo et al. [14] introduced a learning analytics-based method to support instructors in blended learning contexts to provide meaningful feedback to a large student cohort.

Nonetheless, on the one hand, Prieto et al. [17] observe that despite the existing efforts and challenges with LA, the true proof and usefulness of learning analytical frameworks will be their wider usage within research and innovation. Be it either with regards to the main functional and fundamental features of LA methods to the personalized adapted formats, or yet the institutional-driven LA undertakings and innovations.

On the other hand, lessons learned from early studies (see: section II (*A*)) have shown that LA and its methods are capable of improving the quality of teaching, support early identification of constraints/bottlenecks, or students who are struggling to meet with the defined learning processes. In essence, the adoption of LA technologies enables a sufficient level of flexibility as to how, when, and where learning occurs, e.g. by allowing students to take control of their own learning.

Having said that, this work notes some of the implications of the early signals and application of LA methods within the educational settings to include: process innovation and monitoring, recommendation and guidance, personalized and adaptive learning, e-content and curriculum design, etc. Interestingly, Papamitsiou & Economides [2] conducted a systematic review study to analyse empirical evidence for LA and its broader spectrum of educational data mining by examining existing works of literature and case studies between 2008 and 2013. Their work [2] identified around 209 relevant papers within the topic area but goes forward to narrow the findings to 40 most relevant studies based on the extent of perceived innovation, quality of the applied methodologies, and sufficient breakthroughs. Also, Papamitsiou & Economides [2] note some of the strengths, weaknesses, opportunities, and threats to the validity of the different collective research within learning analytics and educational process innovation as outlined in Table 1.

	Learning Analytics for Educational Process Innovation	
1.	**Strengths:**	• includes the large volumes of educational data • the ability to use apply the powerful and pre-existing algorithms • the presence of multiple visualisations for the different users activities (e.g. teachers and students) • increase in the innovative models for adaptation and personalisation of the learning process, and • growing insight and methods towards learning strategies and behaviours.
2.	**Weaknesses**	• includes the potential misinterpretation and misconceptions about the different datasets • a lack of coherence or consistency in the absolute variety of the data sources and platforms, and • a lack of significant results from both the qualitative research and overly complex systems and information overload.
3.	**Opportunities**	• include using technologies such as the open linked data and the semantic technologies to help increase compatibility or integration of different datasets across the underlying systems • improving self-reflection and confidence, self-awareness and learning through the intelligent systems, and • the adoption and application of the learning analytics results to other systems or models to help decision making.
4.	**Threats**	• includes ethical issues and data privacy issues, • over-analysis and/or when the results are beyond tractability or comprehension. • lack of generalization of the results and outcomes, and • possibilities for interpretation or misclassification of patterns, and contradictory findings.

*Table 1***.** Strengths, weaknesses, opportunities and threats to validity of the LA methods (Papamitsiou & Economides [2])

A. Systematic Mapping Study of Early Indicators and Success factors within LA as it concerns Educational Process Innovation

This section presents the key composite and targeted aim of conducting the systematic review of existing studies within the area of learning analytics (LA) described in this paper. There are two main drivers for performing the theoretical investigation of the current works. On the one hand, this study seeks to determine trends in LA methods design, development, and application over the past decade. This is because LA is an emerging method that is currently being applied to manage various activities that constitute the different organizations (e.g. the educational processes).

On the other hand, this study looks at how we can leverage learning analytical tools and techniques to support the process of attaining an improved educational process monitoring and management (educational process innovation) across different institutions. Thus, this paper conducts a systematic mapping study of current literature to determine trends and early (success factors) indicators within the field of LA, however, with a focus on its implication for educational process innovation. Moreover, in comparison to other studies that have looked at the impact of the method (LA) within the higher education domain, this study proceeds to highlight the extent (theoretical impact) of the said methodologies, perceived innovation, and breakthroughs over the last decade (between 2009 - 2019).

To do this, we apply the PRISMA methodology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [18] in order to determine the main elements (thematic analysis) of the existing studies in relation to the work done in this paper as reported in Table 2. Henceforth, to achieve the stated objectives; we perform a systematic review of relevant literature within the area of LA as it concerns Education Process Innovation. It is important to mention that the outcome of the review process was grounded on a set of theoretical factors that we have chosen following the PRISMA methodology [18]. This was done in order to allow us to not only determine the early indicators or success factors within this field (LA) but to enable us to draw conclusions and road maps for the future adoption of LA methods and its supported technologies both in theory and in practice.

Search Process: this study performed the search for relevant literature in different academic databases of international quality and indexing. This includes Web of Science, IEEE Xplore Digital Library, and ACM Digital Library. Moreover, searching the stated databases helped retrieve contents from various international journals, conferences, and publishers such as Elsevier, Learning Analytics & Knowledge (LAK), Education Resources Information Center (ERIC), etc. which are deemed relevant to the learning analytics field including overlapping disciplines.

Search Terms: we utilized a combination of keywords to retrieve the papers from the different databases. The chosen keywords are as follows:

"learning analytics" OR "learning design" OR "learning analytics design" OR "learning analytical framework" OR "learning analytical design" OR "learning analytics framework" OR "learning analytical frameworks" OR "learning analytics frameworks" OR "learning analytics model" OR "learning analytical models" OR "learning analytical designs" OR "learning analytics method" OR "learning analytical methods" OR "learning analytics technology" OR "learning analytics technologies" OR "learning analytical technologies" & ranges = 2009_2019_Year

Paper Inclusion and Exclusion Criteria: as represented in Figure 1, the extracted papers were selected based on the following criteria [18], [19]:

1. Is the description or title of the paper related to learning analytics or educational innovation?
2. Is the full text available and does the paper have a digital object identifier (DOI)?
3. Are the methods clearly described in the text?
4. What are the main contributions of the proposed method, mechanisms, or approach to this area of topic?
5. Does the study report some kind of road map or evaluations towards the adoption of the LA techniques for educational process innovation?
6. How substantial is the scope and methodology of the said paper applicable to this study?
7. Can the method or findings be applied to support the proposals and analysis in this paper?
8. Is the paper written in English for generalization purposes or the international audience?
9. Is the study scientifically peer-reviewed (e.g. retrieved from high index database)?
10. Is the publication date between 2009 and 2019?

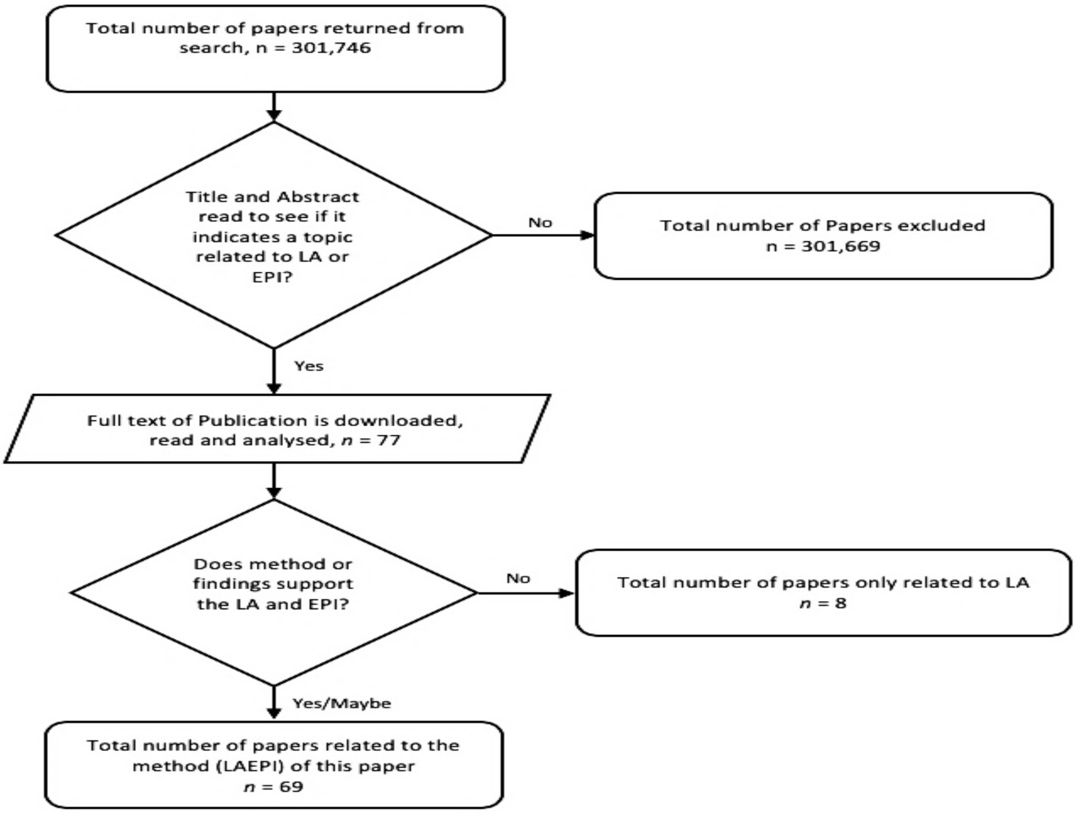

Figure 1. Flowchart representing the incremental search criteria for relevant LA and associated EPI studies.

Results and Outcome of the Review: This study focuses on establishing the trends in the use and application of LA technologies over the past decade. The systematic review shows an emphasis on the early indicators and success factors that have allowed the adoption of the method (LA) within educational settings. This includes the identification of gaps in the current literature that are yet to be addressed. As illustrated in Figure 1, the apriori phase of retrieving the relevant studies based on the target objectives (search criteria) resulted in n = 301,746 papers. Furthermore, we screened the resultant papers based on their perceived suitability (title of the paper, abstract description, domain area of application, availability of full text, peer-reviewed, journal article or conference proceedings, etc.) in order to narrow down the studies. Consequently, this resulted in n = 301,669 papers being excluded. In turn, a total number of n = 77 studies were identified and included in the systematic review; given that the described content matched our search objectives and whether the method or findings were related to LA (n = 8) and/or inclusively educational innovation (n = 69). The results are as shown in the Table 2. Indeed, as presented in Table 2 and subsequently analysed in Figure 2, the selected studies represent the state-of-the-art developments in LA technologies and its application (usage) in the wider spectrum or theoretical concepts. There is evidence (see: Table 2) that learning analytics methods are still in their early stages of adoption especially within the educational domain. Also, the early studies have been centered on describing the usefulness and use of LA techniques in different contexts and/or in practice [1]. This includes a number of studies that have performed empirical studies and review of the LA methods but are not entirely focused on determining its interrelatedness to educational innovation. Thus far, although there has been a significant improvement in the theoretical understanding and application of LA across different fields or domain areas (see: Figure 2 and 3), there appears to be not much work that focuses on determining the implications of the method for educational process innovation [20].

Authors	**Year**	**Method/Tool Used or Proposed**	**Findings/Main Contribution**	**Scope related to Educational Innovation?**	**Is Method/Results applicable for Research design/purpose?**	**Source (DOI)**	**Domain/Area of Application**
Aguilar et al [21]	2019	Autonomic cycle concept that supports Semantic Mining, Text Mining, Data Mining etc.	Monitoring student's interaction (learning styles) e.g. Felder and Silverman model and recommendation of learning activities.	Yes, SLA technologies to analyse external data from the web and social networks to build knowledge models. Thus, incorporates SLA in a smart classroom	Yes, applies a SLA method to discover patterns of interaction and behaviour.	https://doi.org/10.1080/10494820.2019.1651745	Teaching-Learning process, Learning Design
Aldowah et al[19]	2019	Review and Synthesis study of EDM and LA tools/methods	The study found that specific EDM and LA techniques could offer the best means of solving certain learning problems.	Yes, studies EDM and LA methods from four main dimensions: computer-supported LA (CSLA), CS predictive analytics (CSPA), CS behavioural analytics (CSBA), and CS visualization analytics (CSVA).	Yes, Adoption of LA by the educators for continuous improvement (CI) purposes.	https://doi.org/10.1016/j.tele.2019.01.007	Learning Analytics Implementation
Aljohani et al [22]	2019	Framework: AMBA Prototype with famous Learning Management Systems. Conducts a MANOVA test for its analysis	Empirical study focused on learners' ecosystem with value added learning services.	Yes, exploitation of big volume learning data is a critical challenge for designing personalized curricula and experiences.	Yes, leveraging the big data for learning process improvement	https://doi.org/10.1016/j.chb.2018.03.035	Learning Design, Hybrid modelling
Alonso-Fernández et al [23][24]	2019	Case studies review: applying game learning analytics data with serious games	Highlights lessons learned in use of game learning analytics in the context of serious games to improve their design, evaluation and deployment processes.	Maybe, review of 3 case studies using serious games with different goals, targets and uses.	Maybe, general use of LA form the educational perspective	https://doi.org/10.1016/j.chb.2019.05.036	Learning Design, Intervention Design
		Systematic Review study	General LA (GLA) data used to validate serious game design e.g. through student profiling	Yes, use of data science techniques can permit both teachers and institutions to make evidence-based decisions.	Yes, a systematic mapping approach	https://doi.org/10.1016/j.compedu.2019.103612	Learning Analytics, Learning Design
Aristizábal [25]	2018	Measures of Academic Progress (MAP) Growth: a CAT (Computer Adaptive Testing) platform and Tableau as the tool for LA.	Viable solution for an enhanced data integration and mining through a methodological model aligned with fundamental principles of LA.	Yes, some useful guidelines/question that can help Educators to have a deeper insight as to what to do with educational data	Yes, integrates both LA and Visualization Analytics (VA) to draw road map for Educators to dive into the world of EDM and LA.	https://doi.org/10.26817/16925777.434	Learning Analytics, CLT adoption
Atkisson & Wiley [26]	2011	Westerman's key arguments and interpretive enquiries to the practice of LA in educational interventions.	Method for making observational data in virtual environments concrete through nested models.	Yes, idea of educational intervention to detect e.g. learning occurrences, behaviours, or sense data.	Yes	https://doi.org/10.1145/2090116.2090133	LA frameworks, Cognitive processing
Bader-Natal & Lotze [27]	2011	Query-based analysis by applying item response theory (IRT) and use of online analytic processing (OLAP)	Automated LA system designed to add flexibility and scalability to understanding learning process (data)	Yes, creating a pipeline for advanced analysis can be a significant boon for learning about students' behaviour and performance.	Yes, data-focused analysis	https://doi.org/10.1145/2090116.2090146	Interface design, LA development
Bakharia et al [28]	2016	Literature review, Interviews and user scenarios applied to grasp the implication of LA designs in five dimensions	Learning analytics conceptual framework that supports enquiry-based evaluation of learning designs.	Yes, use of analytical tools in evaluating learning activities in relation to pedagogical intent.	Yes	https://doi.org/10.1145/2883851.2883944	Affective Computing
Benkwitz et al [29]	2019	Focus group and interview data analysis allied to the PRISMA methodology using a humanistic approach.	Student engagement data can assist in supporting the student transition into higher stages of learning.	Yes, small scale externally funded innovation projects can have significant institution-wide impact, in contrast to innovative deployment of IT projects.	Maybe, learning data to draw conclusions.	https://doi.org/10.1016/j.jhlste.2019.100202	Human-Centered Computing, Collaboration
Blikstein [30]	2013	Review of multimodal learning analytics with some examples	Presentation of some examples of multimodal learning analytics	Yes	Yes	https://doi.org/10.1145/2460296.2460316	EDM, LAKS
Bodily et al [31]	2018	Systematic review comparing open learners models (OLMs) and learning analytics dashboards (LADs) allied to PRISMA methodology.	Suggests ways to bridge between OLMs and LADs.	Yes	Yes, personalization of teaching or recommendation models.	https://doi.org/10.1145/3170358.3170409	Metacognition, Learning Analytics design

Bronnimann et al [32]	2018	Case study related to the broader concept of student success using LA.	LA for teaching-learning process, as well as, exploring pedagogical questions with existing big data methods.	Yes	Yes, data collection triggered by LA concepts and its application for educational process management.	https://doi.org/10.1007/s10755-018-9431-5	Learning Analytics, Educational Innovation
Clow [33]	2012	Campbell and Oblinger's five-step model, Kolb and Schön theories, theoretically-grounded LA Cycle.	LA strategies that considers the stakeholders will help close the loop with LA methods.	Maybe, learning theories which can be applied for improvement of learning analytics projects.	Yes	https://doi.org/10.1145/2330601.2330636	Learning Analytics, students assessment
Dawson et al [34]	2018	Coded data analysed with latent class analysis using a mixed method analytical framework.	Application of complexity leadership theory (CLT) within the education domain.	Yes, LA for scaling up (emerging) innovation within the educational institutions	Yes	https://doi.org/10.1145/3170358.3170375	EDM, Content analysis
Dollinger & Lodge [35]	2018	Theoretical study focused on current LA Issues and potential of Co-creation in LA	Issues and barriers and how co-creation strategies can help address many of the LA challenges.	Yes, collaborative approach to improve usability, usefulness, and draw insights from LA interventions.	Yes, process modelling and monitoring procedures	https://doi.org/10.1145/3170358.3170372	Student engagement
Drachsler & Greller [36]	2012	Use of surveys to collect data on stakeholder understanding and expectations of LA.	Results showed so many uncertainties about LA among stakeholders	Yes	Yes	https://doi.org/10.1145/2330601.2330634	Learning Analytics review
Du et al [37]	2019	Systematic meta-review of learning analytics	Most publications focused on LA concepts or frameworks and conducting proof-of-concept analysis rather than conducting actual data analysis.	Yes	Yes, literature review and analysis of state-of-the-art	https://doi.org/10.1080/0144929X.2019.1669712	Instructional science
Er et al [38]	2019	A mixed-methods research aligning learning design (LD) and learning analytics (LA)	Two predictive models: LD-specific model (based on LD and pedagogical intentions), and a generic model (not informed by LD).	No	Maybe	https://doi.org/10.1080/10494820.2019.1610455	LA implementation, personalisation
Ferguson & Clow [39]	2016	Weighs the LACE evidence hub with other existing hubs	Describes functionality of the LACE hub and quantitative and thematic content to date.	Yes, Research on LA designed to provide answers to teaching-learning practices.	Yes	https://doi.org/10.1145/2883851.2883878	Educational technology, LA development
Ferguson & Shum [40]	2012	Case study Iterative approach to analytics by reviewing key drivers to social learning.	Recommendation and users response to the outcome of LA technologies.	Maybe, innovation depends on social connection taking into account both formal and informal educational environments	Maybe	https://doi.org/10.1145/2330601.2330616	Deep learning analytics
Ferguson et al [41][42]	2014	Case studies and tools through a framework called ROMA (RAPID Outcome Mapping Approach)	Offers a step-by-step approach to the institutional implementation of LA	Yes	Yes, LA implementation procedures.	https://doi.org/10.18608/jla.2014.13.7	Autonomous, self-regulated learning
	2015	Panel discussion organized by Europe's Learning Analytics Community Exchange (LACE) project examining trends in LA.	List of major area of interest and shift of attention of LA from the North America towards Europe.	Maybe, paper notes that learning science research can improve as the quantity of data increases.	Maybe, how the stakeholders (researchers, practitioners) can benefit from LA research	https://doi.org/10.1145/2723576.2723637	Predictive modelling, Performance assessment
Filvà et al [43]	2019	LA to detect student behaviour and feedback mechanism	Functional solution to categorize and understand students' learning behaviour based in Scratch	Yes	Yes	https://doi.org/10.1016/j.future.2018.10.057	Learning Analytics, personalisation
Gedrimiene et al [44]	2019	Systematic Literature review study using a PRISMA checklist.	LA for knowledge transfer and integration between the classroom and workplace.	Yes, impact of LA technologies and development in higher education settings	Yes, systematic review following PRISMA methodology	https://doi.org/10.1080/00313831.2019.1649718	EDM, Learning Analytics
Gibson & Kitto [45]	2015	Anomaly Recontextualisation (AR) method for identification of anomalies in datasets through a supervised approach	AR process information and usage through affective nature and learner focus.	Yes, potential of detecting students with learning constraints or bottlenecks	Yes	https://doi.org/10.1145/2723576.2723635	Cognitive computing, Pattern discovery
Gibson et al [46]	2014	Uses Bloom's taxonomy in a flexible structure way to implement cognitive operations in education.	Framework called COPA that provides basis for mapping levels of cognitive operation in LA systems.	Yes, LA framework which can be used to support Curriculum design	Yes	https://doi.org/10.1145/2567574.2567610	Data visualisation
Grover et al [47]	2017	Empirical study (evidenced-centered design - ECD) using a combination of statistical and process modelling techniques	A framework that formalizes users' learning process using a hypothesis-driven approach grounded on ECD and data-driven LA.	Yes, framework to better interpret student actions and processes in captured log data.	Yes, data-driven LA approach	https://doi.org/10.1145/3105910	Learning Analytics Dashboards
Hernández-García et al [48]	2018	Team-level indicator model that leverages the CTMTC methodology.	Predictive model using a set of log data-based indicators to facilitate group assessment.	Yes	Maybe, LA in collaborative learning contexts.	https://doi.org/10.1016/j.chb.2018.07.016	LA, formative assessments

Hernandez-Lara et al [49]	2019	Combination of LA and data mining techniques using a business simulation game	Use of LA tools to gain a more wide and holistic view of the learning process of students.	Yes	Yes, discovery of new aspects that affect learning.	https://doi.org/10.1016/j.chb.2018.03.001	LA implementation, evaluation
Herodotou et al [50][51]	2019	Advanced predictive learning analytics system, OU Analyse (OUA), and evidence-based case study and evaluation.	Benefits of predictive LA and intervention for better performance	Yes	Yes	https://doi.org/10.1111/bjet.12853	Analysis of Learning Analytics
		Semi-structured Interviews in understanding how teachers use the LA system.	Teachers can positively affect students' performance when engaged with PLA	Yes	Yes	https://doi.org/10.1007/s11423-019-09685-0	LA, Learning Design
Holmes et al [52]	2019	Novel LA for Learning Design (LD) methodology applied in an online distance learning context.	Applying LA to LD might, in a virtuous circle, contribute to validity and effectiveness of both.	Yes	Maybe	https://doi.org/10.1080/01587919.2019.1637716	Human Learning Process, AI
Hundhausen et al [53]	2017	IDE-based LA through review of key design dimensions	Process model for IDE-based learning data analytics in computing education.	Maybe, LA tools design and delivery of interventions.	Maybe, predictive modelling.	https://doi.org/10.1145/3105759	LA implementation
Jin et al [54]	2019	Use of a generative adversarial network (GAN)-based approach to study learning behaviours.	LA system to facilitate teaching.	Yes	No	https://doi.org/10.1080/10494820.2019.1636827	Learning Analytics Ethics and Practice
Jones [55]	2019	Privacy in LA and Big Data practices and challenge.	Platform for Privacy Preferences (P3P) technology considering existing norms and values.	Yes	No	https://doi.org/10.1186/s41239-019-0155-0	Behavioural studies, Performance indicators
Kitto & Knight [56]	2019	Use of case studies to discuss ethics in LA	Pilot open database for an informed LA practice.	Yes	Yes, ethics and practice	https://doi.org/10.1111/bjet.12868	LA, Flipped classroom
Kitto et al [57]	2015	Application Programming Interface (API) for learning data extraction.	Connected LA (CLA) toolkit that uses a Learning Record Store (LRS) to enable data extraction.	Maybe, privacy and ethical considerations can be detriment to innovation.	Maybe, LA design and modelling strategies	https://doi.org/10.1145/2723576.2723627	Game LA (GLA), Data Science
Klein et al [58]	2019	Case study, Focus groups and interviews on adoption of LA tools in higher education.	Organizational context and factors that can affect adoption of LA tools	No	Yes, factors for adopting LA	https://doi.org/10.1353/rhe.2019.0007	Game LA (GLA), Serious games
Knight et al [59]	2013	LA approaches to determine relationships between epistemology, pedagogy, and assessment.	Alternative LA for epistemic beliefs which are applicable to other areas of interest.	Yes, LA to support educational assessment	Yes	https://doi.org/10.1145/2460296.2460312	LA, Learning Design
Kurilovas [60]	2019	Method to personalise learning using LA and decision strategies	LA methods can be used to personalise learning	Yes	Yes	https://doi.org/10.1080/0144929X.2018.1539517	Performance Improvement and Feedback
Lacave et al [61]	2018	Bayesian networks (BNs) and Classifiers, K2 Algorithms	Determining the suitable classifiers for prediction e.g. using hybrid models	Yes, educational process-related decision making and strategies	Yes, application of hybrid method to predict student profiles and patterns	https://doi.org/10.1080/0144929X.2018.1485053	EDM, Learning Analytics
Liñán et al [62]	2015	Review of existing EDM and LA methods	Commonly used EDM-LA methods	Yes	Yes, review work, and possibility of extracting valuable information from learning data.	http://dx.doi.org/10.7238/rusc.v12i3.2515	Students interaction, Pattern prediction
Lockyer & Dawson [63]	2012	A summary of a workshop on LA and learning design	N/A	Yes	No. workshop description, not the actual publications	https://doi.org/10.1145/2330601.2330609	Predictive modelling, Team assessment, LMS
Mangaroska & Giannakos [64]	2019	Systematic review of empirical evidence on LA for LD following Campbell and Oblinger's five-step model.	Research on LA and LD should consider developing a framework on how to capture and systematize LD data grounded in LD and learning theory.	Yes, LD choices made by educators can consequently influence learning activities and performances over time.	Yes	https://doi.org/10.1109/TLT.2018.2868673	Learning Analytics in Higher Education
McNely et al [65]	2012	Systematic qualitative case study methodology conducted with ethnographic methods of field research in writing scenarios.	System to visualize and edit real time contribution and history of collaboratively written documents.	Yes, users of LA tools can leverage LA as formative assessment to foster metacognition and improve final deliverables.	Yes	https://doi.org/10.1145/2330601.2330654	Multimodal Learning Analytics
Nkhoma et al [66]	2019	Text analytics and Topic modelling techniques for unstructured data from a descriptive content and semantic network analysis perspective.	Guidelines on risk detection and effective text analytics technique for extracting insights from student data.	Yes	Yes	https://doi.org/10.1080/0144929X.2019.1617349	Visual Learning Analytics, Process monitoring
Noroozi et al [67]	2019	Use and analysis of rich multimodal data recorded	Data visualisation and processing for the users	Yes	Yes	https://doi.org/10.1016/j.	LA Services implementation

		from collaborative learning situations using SLAM-KIT.	through a Graphical User Interface (GUI) known as SLAM-KIT.			chb.2018.12 .019	
Owolabi et al [68]	2018	Descriptive analysis of data about student performance and regression model	Learning process assessment and feedback	No	No	https://doi.org/10.1016/j.dib.2018.06.078	LA, Learning Intervention
Papamitsiou & Economides [69]	2019	Learning data for measuring autonomous interactions, and effects of four self-regulated learning (SRL) strategies on users choices.	Exploratory study on learners' goal-setting and time-management regulation.	Yes	No	https://doi.org/10.1111/bjet.12747	User-centric design, LA dashboard
Papamitsiou et al [70]	2014	Simplified and modified version of LAERS assessment environment to determine and predict assessment and performance.	Temporal data for development of more personalized and fully automated systems for accurately predicting users performance.	Yes, temporal interpretation of students' activities to predict their progress.	Yes, process modelling and monitoring	https://doi.org/10.1145/2567574.2567609	Human-Computer Interaction, Higher Education
Pardo et al [14]	2019	Empirical evidence on use of LA to provide personalised feedback at scale.	LA method in blended learning contexts to provide meaningful feedback to large student cohorts	Yes, generating learning feedback	No	https://doi.org/10.1111/bjet.12592	Risk assessment, personalisation
Passalis & Tefas [71]	2019	Overview of two deep learning analytics: unsupervised and supervised techniques	N/A. Chapter gives the techniques for data extraction	Yes	No, reference resource	https://doi.org/10.1007/978-3-319-94030-4_13	Risk assessment, personalisation
Prinsloo & Slade [72]	2017	Dialogical case study methodology	Moral and legal basis for the obligation to act on LA application and analyses of student data.	Yes, deontological or rule-based response to LA in higher education context.	Yes	https://doi.org/10.1145/3027385.3027406	Learning design
Prinsloo et al [73]	2012	A case study to reveal the challenges, opportunities and paradoxes of LA.	Highlights challenges, opportunities and paradoxes of LA.	Yes	Yes	http://dx.doi.org/doi:10.1145/2330601.2330635	LA implementation
Quincey et al [74]	2019	User-centered design, development and evaluation of LA tools and dashboard using an inetrview technique called laddering.	Approach that produces forms of LA representation, recommendation and interaction design that go beyond those used in current similar systems.	Yes, in that LA dashboards can help inform decisions on learning	Yes, guideline on developing LA dashboard and user motivation.	https://doi.org/10.1145/3303772.3303793	Learning theories, Learning Analytics cycle
Riquelme et al [75]	2019	Used ReSpeaker devices to capture speech data using multidirectional microphones, and social network analysis techniques.	Develop a computational environment to both analyse and visualize collaborative student discussion groups.	Yes	Yes, innovative ways to assess students participating in group work	https://doi.org/10.1007/s10209-019-00683-w	Social Learning Analytics, Educational assessment
Rubio-Fernández et al [76]	2019	Flipped classroom using a set of recommended actions	Development of tool to support the methodology	No	No	https://doi.org/10.1002/cae.22144	General Impact of Learning Analytics
Sharma et al [77]	2016	Observational research method using visual LA	Theoretical framework for conducting gaze-based LA in context of MOOCs.	Yes, tool designed to improve With-me-ness (measurement of attention levels) by observing users behaviour.	Yes	https://doi.org/10.1145/2883851.2883902	Learning Analytics platforms
Shibani et al [13]	2019	Co-design methodology: conceptual model for Contextualizable Learning Analytics Design (CLAD)	Effective use of LA tools by users have to be integrated with pedagogical approaches and the learning design.	Yes, the context in which learning occurs is important for educational innovations to impact student learning.	Yes, impact of LA in understanding and driving learners performance	https://doi.org/10.1145/3303772.3303785	Social Learning Analytics
Siemens [78]	2012	Holistic and Integrated Research method	Integrated and holistic vision for advancing LA as a research discipline.	Yes, draws a road map on impact of LA on teaching, learning, and education system.	Yes	https://doi.org/10.1145/2330601.2330605	LA in Education, Performance evaluation
Siemens & Baker [79]	2012	Comparative study between Educational Data Mining (EDM) and Learning Analytics and Knowledge (LAK).	Shows how EDM and LAK are used to address and provide solutions to data and analytics problems in educational domain.	Yes, a formal relationship between stakeholders of EDM and LAKS can help formalize approaches for dissemination of research and enacting cross-community ties.	Yes	https://doi.org/10.1145/2330601.2330661	EDM, Learning analytics
Simanca et al [80]	2019	Development of a sensor called AnalyTIC which uses a risk assessment matrix to identify learning bottlenecks.	AnalyTIC can identify students at risk and the teacher can then intervene to prevent drop out or failure	Yes	Yes, practical results and implementation strategies for LA development.	http://dx.doi.org/10.3390/app9030448	Adoption of Learning Analytics
Slade & Galpin [81]	2012	Workshop discussion and outline	Workshop that focuses on determining to what extent LA fulfil its promise to make its usage and institutions more accessible and appropriate.	Yes, vast potential of LA in student support cannot be denied especially in terms of personalization, although ethical issues cannot be neglected.	Yes	https://doi.org/10.1145/2330601.2330610	Privacy in Learning Analytics
Sønderlund et al [18]	2019	Systematic review and quality assessment of studies on use of LA in higher	Identifies studies that evaluates effectiveness of interventions based on LA	No	Yes, effect of learning interventions and review methodology	https://doi.org/10.1111/bjet.12720	Data-driven Learning Analytics,

		education using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines	and potential of such interventions, but the research was moderate, and left several important questions unanswered				Process assessment
Spikol et al [82]	2017	Workshop discussions that frames emerging interest in Multimodal LA (MMLA)	Opportunity for scientists to develop and use multimodal datasets and future-looking MMLA challenges and concepts.	No	Maybe, use of LA tools to support captured data analysis	http://dx.doi.org/10.1145/3027385.3029437	Interpretive enquiry, Educational Intervention
Starčič [83]	2019	Collection of empirical studies discussing current applications of AI as it affects pedagogical practices	Considers what we might learn from developing AI by exploring the human learning process.	Maybe, application of LA methods within the educational context	Maybe, road map to a plethora of tools which can be applied in LA context	https://doi.org/10.1111/bjet.12879	Computer for Education
Sun et al [84]	2019	Sequential analysis to establish differences between learning achievements and engagement considering cognitive styles.	Identifies "evaluate" and "analyze" as the two most frequent behaviours in Bloom's Taxonomy	No	Yes, can be applied to datasets to better understand users performance	https://doi.org/10.1080/10494820.2019.1660996	Review of Learning Analytics
Suthers & Verbert [85]	2013	Introduction to proceedings of the 3rd International Learning Analytics & Knowledge Conference	Identifies emerging themes and advocates a multidisciplinary approach to LA.	Yes	Yes, to find out the state-of-the-art in LA	https://doi.org/10.1145/2460296.2460298	Risk assessment, Prediction and Personalisation
Tempelaar et al [86]	2013	Instance of Shum and Crick's theoretical framework through self-report of learning data and visual analytics.	Practical application of LA infrastructure focused on combining learning and learner data.	Yes, leveraging data from learning platforms to support formative assessment and learning design.	Yes	https://doi.org/10.1145/2460296.2460337	Learning Analytics review
Verbert et al [85]	2013	Use of dashboard applications which could be small mobile applications or large public displays	Overview of existing LA dashboards and several research issues for development and evaluation of dashboards for learning.	Yes	Yes, setting up dashboards	https://doi.org/10.1007/s00779-013-0751-2	Data Analytics, Computing Education
Viberg et al [87]	2018	Review study on Learning Analytics in Higher Education published between 2012 and 2018.	Little evidence was found that LA are deployed widely and are used ethically.	Yes, data from previous publications showing improvement in understanding the students' learning experiences	Yes, literature review study.	https://doi.org/10.1016/j.chb.2018.07.027	Learning technologies, Learner models
Whitelock-Wainwright et al [88]	2019	Student Expectations of Learning Analytics Questionnaire (SELAQ)	Development of a descriptive instrument to measure student expectations (ideal and predicted) of learning analytics services.	Yes, helps improve student engagement, which is necessary for educational innovation	Maybe, including stakeholders in LA studies to help inform decision the expectations and implementation	https://doi.org/10.1111/jcal.12366	Computer-assisted instruction (CAI) and LAD
Wise et al [89]	2013	Embedded and Extraction Analytics through Visual LA and querying tools	Guidelines for integrated and reflective metacognitive activity	Yes, parity in LA may not seem as important for the users e.g. students.	Yes, value of pedagogical models and student-teacher dialogue around the analytics.	https://doi.org/10.1145/2460296.2460308	Performance evaluation
Xing et al [90]	2019	Task model to characterize the Learning design process so that the data features can be associated with the abstract design phases. Uses Radial Basis Function based Support Vector Machines for prediction to identify learning patterns.	Use of LA to build performance prediction models. A two-stage feature selection method is proposed to address the data sparsity and high dimensionality problems.	Yes	Yes	https://doi.org/10.1080/10494820.2019.1680391	Social Learning Analytics
Yu & Jo [91]	2014	Multiple linear regression analysis of web log data from a Moodle LMS	Model for predicting students' academic achievement based on their learning behaviours and patterns in LMS.	Yes	Yes	https://doi.org/10.1145/2567574.2567594	Learning Analytics, Visual Data Mining
Zhang et al [92]	2018	Mapping Study (bibliometric and visualisation methods)	Behavioural analysis of multiple data in education domain divided into four main parts; content analytics, discourse analytics, social LA and disposition analysis.	Yes, educational innovation under technological development	Yes, development process of LA methods e.g. by analysing data about students' behavior for prediction of performance and personalization.	https://doi.org/10.1080/0144929X.2018.1529198	Learning Assessment and Intervention

*Table 2***.** Systematic Mapping Study of Learning Analytics for Educational Process Innovation based on PRISMA methodology (Literatures between 2009 - 2019).

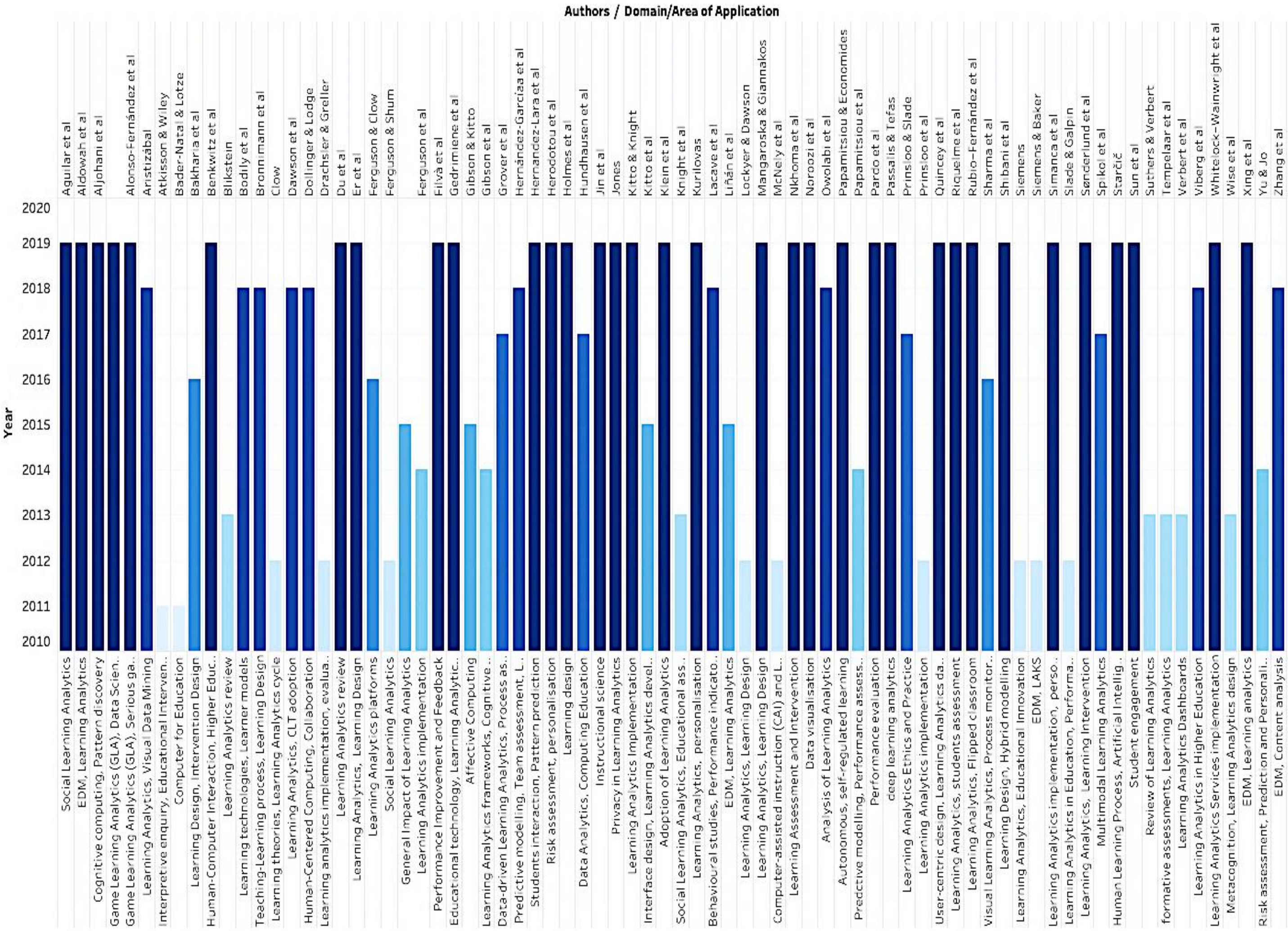

Figure 2. Representation of studies according to years and domain areas/application.

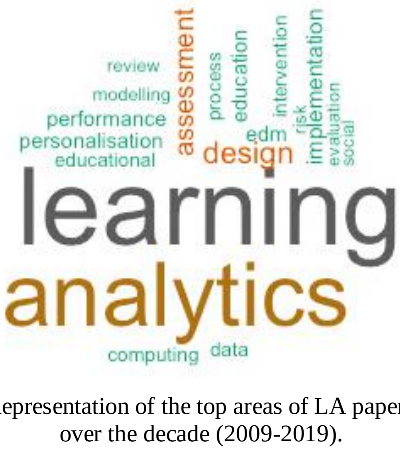

Figure 3. Representation of the top areas of LA papers and focus over the decade (2009-2019).

Interestingly, although the early methods which support LA and are driving the development of the different supported technologies have mainly originated and is shifting from the American marketplace to the European perspective [1][42]. Ferguson [1] notes that future lines of research within the field of LA and the overlapping areas (such as EDM, Online learning, Data-driven analytics, etc.) do not only benefit the direct consumers or stakeholders (e.g. educational communities, developers, IT experts, etc.). They also benefit the different learning analytics groups that participate in sharing and development of the supported technologies, regulations and policies, as well as their practices across the national boundaries by extending the focus beyond North America, Western Europe, and Australia (Figure 4).

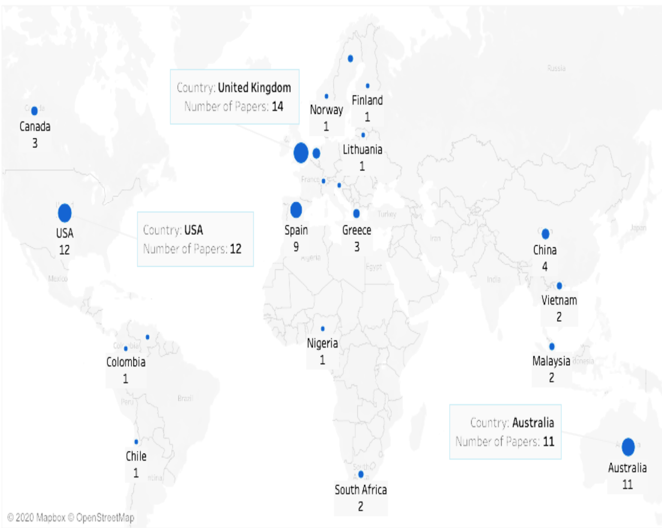

Figure 4. Demographic distribution of the main LA studies by country and number of studies.

Overall, we note that there has been a significant progress in the number of studies carried out, and perhaps, adoption of LA field and its supporting technologies over the past decade. Moreover, a majority of those works were recently recorded (conducted) as represented in Figure 5.

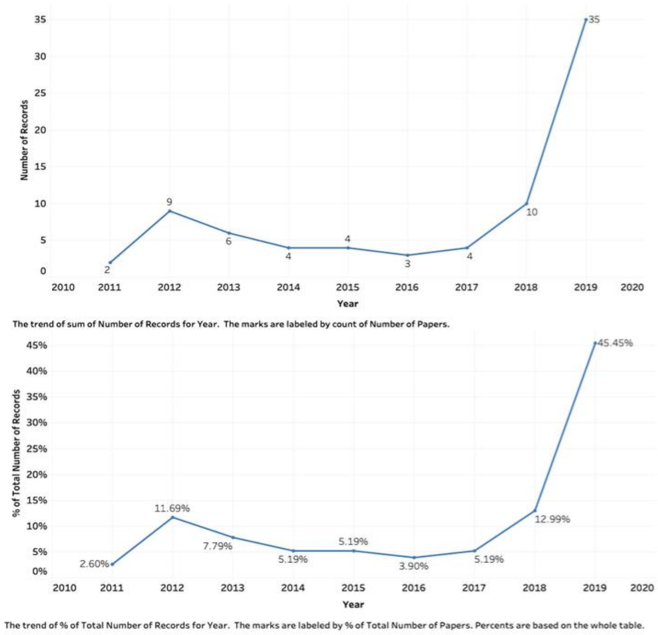

Figure 5. Trends in LA publications over the decade (between 2009-2019).

In summary, learning analytics (LA) and its related technologies are still at relatively early stages of development and application especially in terms of educational process innovation. However, the process of mounting its utilization, validity, and reliability of discoveries is rapidly evolving as shown in Figures 2 to 5.

However, there is also convincing evidence that the technology (LA) would not only help to develop a more student-focused provision for higher education models and curriculum [1] [17]. But can be used to enable technology-focused educational practices and infrastructures across the national boundaries [1]. For example, such technological advancement may constitute the process of leveraging the various sources of educational data through the LA methods for the purpose of supporting or providing continuous improvement of the educational sector. Thus, the motivation or notion of the Learning Analytics for Educational Process Innovation (LAEPI) model introduced in this study (see: section III).

Having examined the literature to determine the trends in LA in the past decade, we turn our attention to a case study to demonstrate how the method can be applied for educational innovation. The resultant model (see: Figure 6) seeks to respond to both the need for theoretical and real-time application of LA methods within educational settings by filling the aforementioned-gaps identified in the literature.

III. Case Study and Proposed LAEPI Model

This section introduces the LAEPI model which we proposed for the implementation of the learning analytics method and case study analysis in this paper. Fundamentally, the LAEPI model integrates the key elements and technologies which are used to enable a more functional and automated analysis and improvement of educational processes (data) as shown in Figure 6. Moreover, the resulting framework can be applied to any given process or domain provided there is some form of data extracted or stored (recorded) about the processes in question.

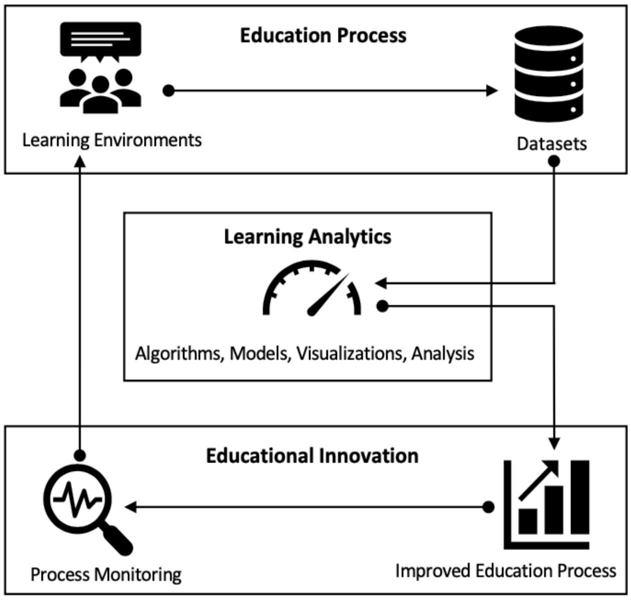

Figure 6. The Learning Analytics and Educational Process Innovation (LAEPI) model.

As shown in Figure 6, the LAEPI model constitutes three main phases or components for its application in real-time as follows:

- Education process (learning environments and classrooms, educational data, and learning activities, etc.): describes the different data and activities that make up the educational process which are leveraged to provide an improved process for the users.
- Learning analytical tools and methods (procedures and algorithms, process models discoveries, visualizations and mappings, contextual and conceptual-based analysis, etc.): defined as the link between the Educational process and Educational Innovation.
- Educational process innovation (improved learning process and innovations, monitoring and recommendation, personalized and adaptive learning, etc.): represented as the by-product of the learning analytics which are also referenced or utilized for the purpose of monitoring of the several learning environments.

By definition, the LAEPI model makes use of data from the educational processes or domains to create a method for data-driven analysis (learning analytical tool) used to provide useful information that can be adopted to improve the educational processes and learning activities.

IV. Data Analysis and Experiments

To demonstrate the real-world application of the learning analytics method through the LAEPI model described in this paper; this study makes use of the Massive Open Online Course (MOOC's) learning data (see: Figure 7 to 11) recorded about 333 students who undertake and are enrolled in a Conventional, Clean Energies and their Technology program offered by Tecnologico de Monterrey edX online [93] in 2017. Typically, the recorded data consist of different attributes (learning concepts) about the students' learning process and outcomes which the paper references for its analysis. Essentially, the datasets consist of a number of attributes that we referenced to perform the analysis. This includes the students' ID that was represented as the conceptsName or Case ID, current Grade (of both the Not Attempted and Completed students) and Final Exam scores of the completed students used to represent the different events and activities, and other attributes such as the Evaluación del tema 1 to Evaluación del tema 6 (i.e. the evaluation stages), total Average mark of the different evaluation stages, Practical, and Exercises that were all assigned as custom variables for the purpose of the analysis. Also, the work notes that for students to be awarded a certificate in the course (measured as interval values between 0 to 1, i.e., representing 0% -100% pass mark), the students have to complete the required evaluation stages and final exam respectively. Therefore, we assume that a variety of different learning scenarios and problems are represented in the data. Moreover, the available data consists of the minimum requirements for any learning process mining method and analysis [8] as described in this paper to be performed.

Practically, this study applies the Inductive Visual Miner (IvM) algorithm [94], [95] in ProM (Process Mining Framework) [96], [97] in order to discover the models and analyse the different activities in the events log. Technically, not only is the IvM one of the process exploration algorithms that have proved useful towards discovering worthwhile process models from the readily available event logs or datasets but are also useful to detect potential bottlenecks or constraints [98], [99] in the models. Thus far, this study applies the IvM method to analyse data about the online course for university students by doing the following:

- determine the distribution of the student's current grade and the different process instances or classes.
- establish the distribution of the students who completed the course/final exam.
- expound on the concepts (process instance) classes to determine the instances that did not attempt or complete the course and model visualizations.
- determine the bottlenecks and deviations in terms of the different grades and scores for further process improvement and decision-making purposes.

In turn, the following figures (Figure 7 to 11) represent the learning process events log distribution and lifecycle transitions, process models discovery and visualizations, and the model alignments and deviations, respectively. Whereas Figure 7 represents the statistical results (absolute and relative occurrences) or distribution of the different process instances (classes), including the attempted or not attempted scores (i.e. final exam grades) measured in terms of 0 -100% pass marks, i.e., 0 to 1 scale as contained in the dataset. Figure 8 shows the frequency of the different classes or instances where: the ConceptName is used to define the student IDs and the Events Name and Lifecycle transition are used to represent the related exam scores or grades.

Event classes defined by (Event Name AND Lifecycle transition)
All events

Total number of classes: 12

Class	Occurrences (absolute)	Occurrences (relative)
Not Attempted+complete	173	51.952%
1+complete	65	19.52%
0.93+complete	45	13.514%
0.87+complete	22	6.607%
0.8+complete	15	4.505%
0.07+complete	3	0.901%
0.73+complete	3	0.901%
0.67+complete	2	0.601%
0+complete	2	0.601%
0.4+complete	1	0.3%
0.6+complete	1	0.3%
0.53+complete	1	0.3%

Figure 7. Distribution of process instances considering the students' grades in the Events logs.

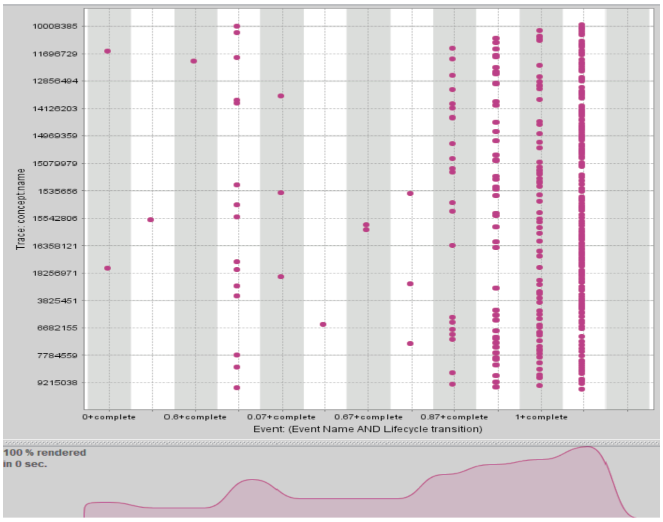

Figure. 8. Frequency of distribution of the process instances in terms of the exam grades.

Indeed, as gathered in the figures (Figure 7 and 8), although the proportion of students that have not attempted the final exam 51.592% (173 out of 333) (see: Figure 7) appears to be the highest number of recorded occurrences, the results of the analysis in Figure 8 shows that there has been a consistent and positively impacting progression in the learning style or patterns of the students from start to finish of the course (i.e. from the initial process of enrolling in the course to the final exams scores). Moreover, there also exists evidence from the analysis (see: Figure 2) that a greater proportion of the students who completed the course, i.e., 160 students (333 minus 173) have achieved a 100% pass mark (65 occurrences) with 0.93 (93% mark) at the second place (45 occurrences), etc. Also, although the analysis in Figure 8 shows a consistent improvement in the learning patterns or behaviours of the students, there have been settings where the map shows a flat frequency or line which perhaps may suggest the presence of some bottlenecks or constraints during the learning process or across the dataset. To this end, the work further expounds on the results (see: Figure 9 to 11) to not only discover the learning process trees or individual traces within the model [94][95], as well as to visualize the different paths the process instances follow in terms of the grades and exam scores of the students; but also to determine points at which the deviations or bottleneck may have occurred in the resultant model.

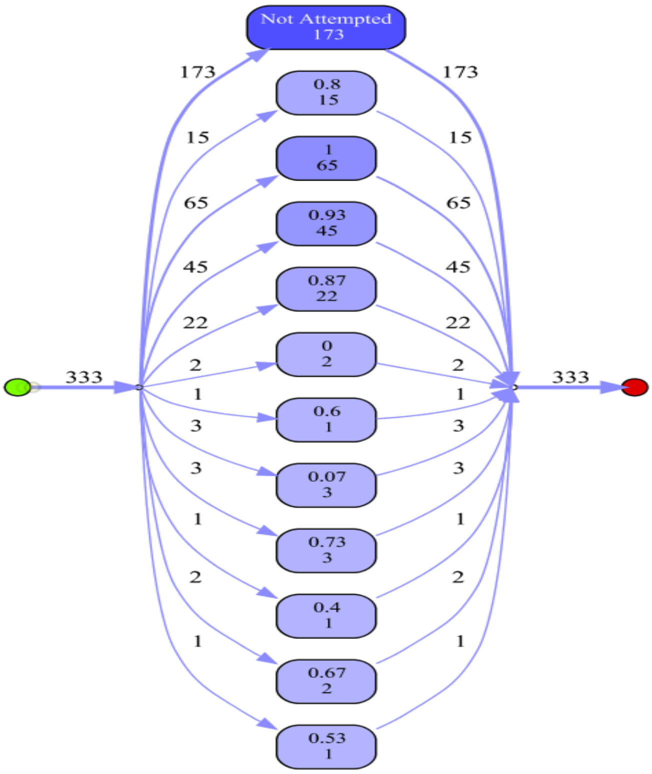

Figure 9. IvM process model showing occurrences and frequencies of the process instances (students) and final grades.

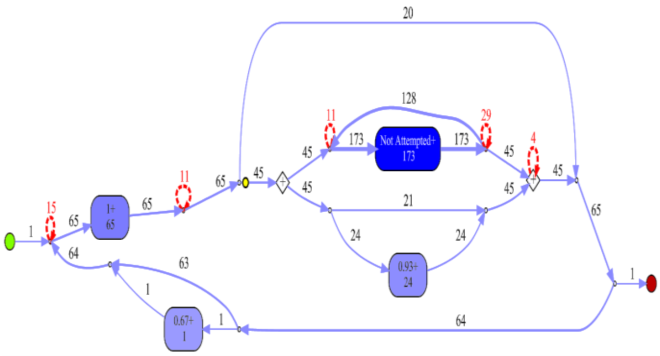

Figure 10. IvM model showing the deviations or bottlenecks for the final exam grades.

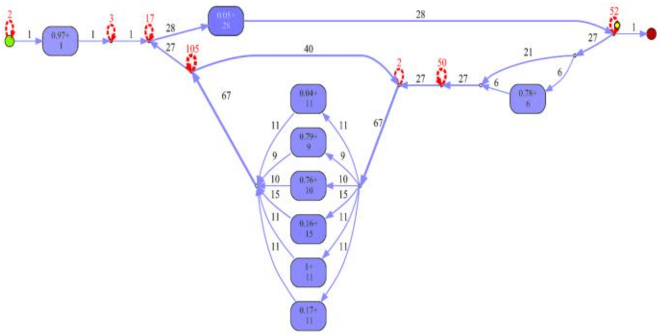

Figure 11. IvM model for the current grades of the students with bottlenecks/deviations.

As gathered in the figures (Figure 9 to 11), the work notes that most of the bottlenecks/deviations have been observed or directed towards the process instances that have not attempted the final exam (see: Figure 10). Moreover, when considering the current grades of the students as shown in Figure 11, the work notes that although the highest number of bottlenecks (105) has collectively been observed for the students whose current grades are 0.04+, 0.97+, 0.96+, 0.16+, 1+, 0.17. However, the students with current grades of 0.05+ appear to be the most frequently observed outcome or effect with an occurrence of 52 loops in total (see: Figure 11). Generally, the purpose of the experimentations, otherwise allied to the educational process mining approach as illustrated in this section of the paper is to (i) define a learning analytics method which provides the process analysts or educators with dependable and insightful knowledge about the different activities or events that underlie the said educational processes, and (ii) in turn, can be leveraged for ample monitoring of potential bottlenecks, recommendation of contents and/or personalization of learning and experiences for the users based on the discovered educational process models.

V. Discussion

In higher educational settings, students are leaving an unprecedented huge amount of data or digital footprints behind with regards to the different courses in which they undertake or study. Apparently, those footprints (which today are recorded and stored as educational data within the various IT systems) can tell us about the learning patterns and experiences of the students during and after the time of their study at the institutions. Indeed, the work done in this paper has shown that the educators or process innovators can make use of the readily available datasets to understand how the students learn and to provide support if needed to enhance the students' experience. This is called Learning Analytics [100].

On the one hand, there has been an ever-increasing interest and research within the educational domain in using new information derived from the LA methods to provide personalized and adaptive learning, support formative and performance assessments or measurements, or yet, provide a data-driven and decision-making strategies for learning, curriculum design and management [101].

On the other hand, LA has shown to be useful for enhancement of teaching and its practices across national boundaries [42] at a time when the quality of teaching in the different HEIs is becoming competitive and increasingly being scrutinized. Perhaps, as demonstrated in this paper, datasets captured about stakeholders (e.g. individual students' learning activities or behaviours, course, grades, etc.) have become a potential tool or asset to not only measure how well teachers or students are performing. But also can be utilized to measure and support the operational processes of the said institutions and the decision making strategies at large [102]. This is called Learning Analytics for Educational Innovations [20].

In the wider spectrum of scientific research, the learning analytical methods and its outcomes can be allied to the notion of Business Intelligence (BI), the broader term used to describe the business process management (BPM) methods that are used for process enactment and analysis. In theory, the BI methods allow most organizations to gather a wide range of information or data about the operations of the company, determine the state-of-the-art and performance of the businesses and operations over a period of time, and consequently, apply the insights derived from analyzing the datasets for decision-making purposes or process monitoring strategies. In short, the said existing datasets are utilized by the different organizations for the enactment of business intelligence, analytical and decision-making purposes, etc.

[102]. Moreover, according to Sharma et al. [102], data has become the mainstay of each of those decisions, and the performance of the said organizations (e.g. educational institutions) is contingent upon the optimality of the operations carried out on the available data as well as its design mechanisms. Whereas, Zaim [103] notes that the evaluation of data about the users by the institutions in question (e.g. the educators) can be a way to improve/ensure the performance, experiences, and satisfaction levels of the stakeholders (e.g. the learners). Besides, when this is done, the institutions can be less assured of the usability, content adequacy, and reliability of the several services or operational processes in general [103].

Likewise, a lot of time the results of the LA methods includes amongst the many benefits; visualization (mapping) of the complex datasets collected about the processes which they are used to support. And, allowing the process owners or analysts to clearly make or take effective business-related decisions about the different organizations/processes. Therefore, LA methods just like the BI's can be applied to analyze the different activities and determine the performance of the business processes and models (e.g. the educational process). The method (LA) can also be used to identify and provide adequate ways of monitoring and improvement of the existing processes. Interestingly, the systematic mapping study (see: Table 2) that was conducted in this paper shows that there has been a significant improvement in the use of LA methods to support the different organizations and processes across the decade. Although, the process of its full adoption and proposals/testing of the theoretical methodologies or models is still at its early stages and is consistently improving over the years (see: Figure 5).

VI. Conclusion

This study shows that learning analytics (LA) is not only used to provide a better understanding of the different datasets collected about users (e.g. the learners), and how their effective usage can help provide educational institutions with a competitive advantage in the rapidly growing global economy. But at the same time, LA can help provide technological advantage and support towards an informed strategic business-related decision making for the organizations. For example, the resultant models or frameworks can be used to continually enhance the student experiences and retain a competitive edge across the higher education community.
Therefore, LA can be described as the bridge between an enhanced user's (e.g. student learning) experiences, the educational process innovation and growth and vice versa. For this purpose, this paper proposed the Learning Analytics and Educational Process Innovation (LAEPI) model to not only support the adoption of LA methodologies in theory but also to illustrate the implications and impact of the resultant methods in real-world settings or applications.

Practically, this work applies the LAEPI model on a case study of the online course (data) for university students in order to demonstrate the usefulness of the method. Evidently, the outcomes of the series of experimentations show that the LA methods can be used to foster personalization and adaptation of learning contents according to individual students' needs or learning patterns. Besides, the method can be applied to identify and monitor bottlenecks or constraints that the student may encounter during the learning process, and in turn, used to provide recommendations for future learning and/or curriculum or e-content design.

Having said that, the implication of the LA methods, such as the LAEPI model introduced in this paper, can be perceived from the two main drivers or perspectives as follows: (i) student-focused analytics, and (ii) institutional-focused analytics. In essence, for the first affirmation, LA can help identify struggling students and support the early provision of interventions through analysis of the apriori or known information (data) about the students in advance. For the later, LA has inadvertently created a broader institutional analytics mindset across the different educational institutions by increasingly basing the decision-making processes on evidence that are drawn from results of the method (learning analytics) rather than just some kind of predefined or static business strategies.

Although a number of the LA methods are relatively still in their early stages of development and are not yet fully applied across the education sectors, there is convincing evidence that the technique will help to develop a more student-focused learning, continuous process improvement, and provision of lifelong learning strategies and innovations in the HEIs, as drawn from the results of the systematic mapping study and educational process mining and analysis in this paper.

Future works can apply the learning analytics for educational process innovation model or the real-time case studies and application in this paper; by adopting the methodology and analysis that has already been performed in this paper, or yet, re-construction of the resultant model to include further areas that may have not been addressed in this paper.

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