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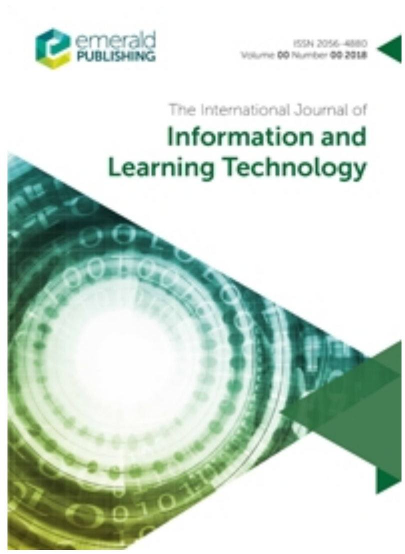

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Abstract.

Purpose: The analysis of data collected from user interactions with educational and information technology has attracted much attention as a promising approach to advancing our understanding of the learning process. This promise motivated the emergence of the field of learning analytics and supported the education sector in moving towards data informed strategic decision-making. Yet, progress to date in embedding such data informed processes has been limited. This paper addresses a commonly posed question asked by educators, managers, administrators, and researchers seeking to implement learning analytics – how do we start institutional adoption of learning analytics?

Approach: A narrative review is performed to synthesize the existing literature on learning analytics adoption in higher education. The synthesis is based on the established models for adoption of business analytics and finding two projects performed in Australia and Europe to develop and evaluate approaches to adoption of learning analytics in higher education.

Findings: The paper first defines learning analytics and touches on lessons learned from some well-known case studies. The paper then reviews the current state of institutional adoption of learning analytics by examining evidence produced in several studies conducted worldwide. The paper next outlines an approach to learning analytics adoption that could aid system-wide institutional transformation. The approach also highlights critical challenges that require close attention in order for learning analytics to make a long-term impact on research and practice of learning and teaching.

Value: The paper proposed approach that can be used by senior leaders, practitioners, and researchers interested in adoption of learning analytics in higher education. The proposed approach highlighta the importance of the socio-technical nature of learning analytics and complexities pertinent to innovation adoption in higher education institutions.

1 Introduction

The modern landscape in higher education is shaped by several critical drivers, including meeting the needs of a diverse group of students, promoting lifelong learning, enhancing student learning experience, and widening access (Davis, 2012; Siemens et al., 2015). The rise of massive open online courses and calls for personalized education have turned the attention of higher education institutions towards new technologies that can provide for greater adaptivity and flexibility. For instance, higher education institutions aiming to scale up educational opportunities while personalizing the student learning experience (e.g. via flipped classroom models) typically turn to technologies as a solution.

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Learning management systems (LMS) and student information systems containing socio-demographic and student enrollment data can be considered as “foundation” technologies for higher education institutions. These technologies typically form the core of a broader suite or a loosely connected ecosystem of technologies.

Higher education institutions are investing in different educational innovation initiatives in which a wide range of technologies plays an important role. Although technologies can aid the design of active learning pedagogies, they may also inadvertently weaken the feedback loops that exist between students and educators (Ali et al., 2012). For instance, many social cues about a student’s engagement are easily picked up by instructors in conventional face-to-face instructional settings. However, through the use of online technologies such social cues are significantly reduced – if not fully eliminated (Dawson, Bakharia, & Heathcote, 2010). Methods that can restore and even enhance such existing feedback loops are necessary steps.

Digital “footprints” (or trace data) about learner interactions with technology have demonstrated significant value for providing novel insights into student learning (Gašević et al., 2015). The access to such data alongside the application of methods drawn from educational data mining for example, has helped to build the field of learning analytics (Siemens, 2013). The results of such analyses are often framed within various learning and cognitive theories commonly associated with educational psychology, cognitive psychology and learning sciences. The Society for Learning Analytics Research (SoLAR) defined learning analytics as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” (Long et al., 2011). It is the second portion of the definition that emphasizes the actionable nature of learning analytics.

While there is much interest in learning analytics, the vast majority of institutions are yet to exploit the full use of learner and organizational data to address institutional and educational challenges (Colvin et al., 2015; Tsai, Gašević, et al., 2018; Tsai and Gašević, 2017). This paper addresses a commonly voiced question among educators, and senior managers in higher education – How do we start the process for institutional learning analytics adoption? To this end, the paper starts with a brief narrative review of the existing literature on learning analytics adoption. The review is framed around well-established themes, case studies, and process models in the learning analytics literature (Brown, 2012). The paper then proposes an approach that can aid systemic institutional adoption of learning analytics. The proposed approach draws on a) a well-established approach in business analytics (Barton and Court, 2012); b) evidence documented in the learning analytics literature, and c) two research projects that aimed to provide directions for learning analytics adoption in Australia and Europe (Colvin et al., 2015; Tsai, Gašević, et al., 2018). The paper concludes with several remarks that reinforce the critical points for future work related to the adoption of learning analytics.

2 State of Learning Analytics Adoption

This section outlines the themes commonly explored in learning analytics and reviews the current state of learning analytics adoption in higher education.

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2.1 Common learning analytics themes

Broadly speaking, learning analytics is comprised of three major themes: 1) predictors and indicators, 2) visualisations, and 3) interventions (Brown, 2012). The first theme relates to the analysis of data from an initial learning scenario (e.g. a course) to establish a predictive model. For example, the analysis of LMS and student demographic data to predict student academic performance, attrition or concept understanding (Brooks and Thompson, 2017). Purdue Course Signals is a well-noted example of such an *Early Warning Systems* attempting to detect students at risk of academic failure (Arnold and Pistilli, 2012; Krumm et al., 2014). The intent of these systems is to identify specific correlations between user actions in an online tool and academic performance (Gašević et al., 2016). The provision of this information early in the semester affords more timely opportunity for instructors to implement appropriate support actions. First attempts to establish predictive models were based on broad and often limited data sets (e.g., a single course, LMS data). However, more recently the LA research has rapidly progressed to incorporate methods such as text analysis, process mining, and social network analysis to identify wide ranging outcomes and dispositions including: 21st century skills (Buckingham Shum and Deakin Crick, 2016), self-regulated learning (Roll and Winne, 2015), and learning strategies (Fincham et al., 2018; Jovanović et al., 2017).

The *second* theme of learning analytics deals with research associated with the visualisation and presentation of findings for interpretation by administration personnel, instructors or students (Bodily and Verbert, 2017). Visualisations offer a simpler format to explore and interpret an otherwise complex and confusing set of data. The aim of such visualisations is to prompt the deployment of remediation actions. The use of visualization is established through the development of learning analytics dashboards to offer visual displays of relevant information for key stakeholder groups including students, teaching staff, and administrators.

The *third* category of learning analytic approaches focuses on the deployment of learning *interventions* or how to devise precise actions to shape the learning environment to improve the student experience. These initiatives explore how interventions can be included as an additional element in a learning design and the interaction with the rest of the design components (Lockyer et al., 2013). The recent trend is to provide personalized feedback at scale that combines the power of analytics with pedagogical knowledge to empower the teachers (Pardo et al., 2018). The intended results of any designed intervention is to provide for improvements in student outcomes, and satisfaction (Fincham et al., 2018; Pardo et al., 2019).

2.2 Systemic adoption of learning analytics

Despite the potential of learning analytics for addressing multiple teaching and learning as well as financial challenges confronting the sector there remains a lack of institutional examples demonstrating systemic adoption of learning analytics (Ferguson et al., 2014). In earlier work, Goldstein & Katz (2005) reviewed how higher education institutions make use of data in their decision making noting that out of the 380 US institutions investigated, approximately 70% extracted data for basic reporting, and 8% institutions showed the ability to use data for “what-if” decision support such as scenario building. The remaining institutions analyzed and monitored data for operational performance only. No institutions

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were observed to use predictive modeling & simulation or carry out analytics-informed interventions. Similar results were reported by Yanosky (2009) 5 years after the initial work of Goldstein and Katz. More recently, Yanosky and Arroway (2015) identified the lack of advanced analytics-based projections and proactive responses to analytics results among the US higher education institutions, and claimed that this pattern had not substantially changed since 2012.

Recent studies into systemic institutional adoption of learning analytics report similar findings. For instance, Colvin et al. (2015) scanned the state of learning analytics adoption among 32 (out of 40) Australian universities, noting that collectively the universities could be situated into one of two adoption processes – *solutions oriented* (analytics implemented to address a specific issue) or *process oriented* (analytics implementations fostered through experimentation and innovation). These town trajectories represent the initial Awareness and Experimentation phases of the five phase learning analytics sophistication model previously suggested by Siemens, Dawson, and Lynch (2014). Moreover, the two distinct groups of institutions noted by Colvin et al (2015) were based on the analysis of several contextual dimensions such as leadership, strategy, readiness, conceptualization, and technology. In this instance, the first group of institutions focused primarily on the use of learning analytics to resolve concerns with student retention, whereas the second group stressed the role of learning analytics to help advance understanding of learning and teaching. The former emphasized the acquisition of technical solutions, and the latter was more attended to institutional complexities and the involvement of different stakeholders. The Colvin et al. study recognized the need for institutions to define a strategic vision for learning analytics to achieve long term impact. The emphasis of visionary leadership in systemic adoption of learning analytics aligned with the argument posited by Macfadyen, Dawson, Pardo, & Gasevic (2014) that higher education institutions need to define policies and strategies that address the complexities inherent to their organization, including cultural and social structures and practices.

In answer to the needs identified above, the SHEILA project engaged a wide range of stakeholders among European higher education institutions to develop a framework that can be used to support institutions to develop a context-specific policy and strategy to ensure that learning analytics is deployed effectively and responsibly (Tsai, Gašević, et al., 2018). The SHEILA project reported that 9 out of 51 institutions (across 16 countries) that participated in interviews claimed to have implemented learning analytics throughout their institutions, whereas 2 out of 46 institutions (across 22 countries) that responded to a survey indicated so. The SHEILA project also found that only few institutions had defined strategies or monitoring frameworks to ensure the effectiveness of LA. Moreover, among the few cases that self-reported success of adoption, their achievements tended to be short-term victories, such as experience-gain, cultural change, infrastructural upgrade, and a better understanding of legal and ethical implications. This finding reaffirms the observations of previous studies that the engagement with learning analytics in higher education is predominantly at an exploratory stage and that no evidence has shown organizational or sector transformation (Siemens et al., 2014) due to the adoption of learning analytics.

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3 An Approach for Systemic Adoption

While higher education institutions have long expressed much interest in learning analytics, there continues to be a lack of a data-informed culture in decision making in universities (Macfadyen and Dawson, 2012; Manyika et al., 2012). To bridge the divide between interest and application there are numerous lessons that can be learned from business analytics and organizational change that can be helpful for educational institutions. Specifically, we find the approach developed and used by McKinsey and Company (Barton and Court, 2012) is a promising framework for articulating the directions for learning analytics adoption. The approach consists of three elements – *data*, *model*, and *transformation* – designed to ease communication with organizations (adopters of analytics) and assist senior leaders to grasp the benefits and challenges associated with analytics in organizational decision making. The approach is summarized in Table 1. In the remainder of this section, we make use of this approach to offer directions necessary for systemic adoption of learning analytics by highlighting critical issues specific for education.

Table 1. An approach for systemic adoption of learning analytics in higher education institutions

Data	Model	Transformation
- Development of principles for creative data sourcing - Increasing awareness of data limitations - Securing necessary information technology support	- Following question-driven approaches to the applications of machine learning - Informing the use of machine learning by educational research and practice	- Development of Institutional policy and strategy for learning analytics - Establishing effective leadership models to drive and oversee the implementation - Adopting principles for privacy protection and ethical use of analytics - Implementation of learning analytics tools catering the primary stakeholders - Development of analytics-informed decision making culture

3.1 Data

The data element of the analytics adoption approach includes three key issues:

i) Development principles for creative data sourcing,
ii) Increasing awareness of data limitations, and
iii) Securing necessary information technology (IT) support.

Many institutions, aware of the opportunities for data collection afforded by learning management systems and other technologies, typically opt for the acquisition and/or development of learning analytics systems that are based on trace data about students' views of different web pages. Although there is much promise in the use of trace data, institutions need to be creative in their data sourcing that can enable them to address the questions they are interested in. The major recommendation in the process of finding relevant sources of data is to build on existing principles established in educational research and practice (Gašević et al., 2015, 2017; Wise and Shaffer, 2015). For example, social networks are known to play an important role in a student's learning process and performance (Dawson, 2008), and thus can be a valuable source for understanding and predicting student success. Although commonly used, sources for extraction of social networks are not confined to the use of commercial social media. Social networks can also be extracted from diverse tools such as student information systems that record information about student course enrollments. For instance, Gašević, Zouaq, & Janzen (2013) showed that data extracted from course enrollment records could reveal homophily of networks – common characteristics that connect individuals, such as the inclination of high performance students to take the same course. They argued that insights obtained from this can inform institutions in developing support models for different learning communities.

Awareness of limitations and challenging assumptions related to data commonly used in learning analytics is another critical perspective for successful adoption of learning analytics at a systemic level. For example, data about time spent online an offer some insight into the relevant activities students engaged in and how this is associated with academic performance. There are internal and external threats to validity that can bias the estimation of time online. Internally, many learning management systems do not automatically log students out after some time of inactivity. In such cases, time online estimation may show that a student spent several days continually working on a task. For example, studies conducted by Kovanović and colleagues (2016) found that different strategies resulted in over 20% of absolute difference in explained variability when looking at the association between variables extracted from trace data and academic performance in regression models. However, they could not explain which of the 15 estimation strategies was the most accurate. Externally, there is no reliable way to know whether students were actually engaged in learning when they visit some of the online resources in the learning management system. Few studies have investigated this limitation, though a known approach – Baker Rodrigo Ocumpaugh Monitoring Protocol (BROMP) designed for quantitative field observations of student affect and behavior (Ocumpaugh et al., 2015) – has successfully been used in numerous studies that investigated off-task behavior of students.

Both internal and external threats to validity of time online estimation have practical implications on learning analytics adoption. Transparency in the description of the internal method used for gauging time online is essential to help users of learning analytics understand how to implement results and take actions. This is especially critical when institutions are using learning management systems that provide estimation of time spent online. On the other hand, joint work between developers of learning analytics (technologies) and educational institutions is needed to advance the quality of existing learning analytics solutions to better observe learning that takes place in the online platform.

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The involvement of and support from IT units is essential for systemic institutional adoption and implementation of learning analytics. Without models specifying how existing IT processes and practices can be adopted to support learning analytics, institutions may face problems that can either postpone or even disable implementation of learning analytics processes. For example, a project that supported the development of a learning analytics dashboard in a Canadian university was beset by a challenge related to the availability of established processes and human resources for the IT department hand the required data securely (Beheshitha et al., 2016). Given the complex systems of higher education, a critical recommendation is that institutions need to engage all relevant stakeholders in a timely manner prior to the commencement of any implementation of learning analytics projects (Ferguson et al., 2014; Tsai, Gašević, et al., 2018; Tsai and Gašević, 2017). The involvement needs to go beyond IT units and include other key stakeholders such as students, faculty, student record representatives, security and practice protection officers, learning and teaching units, institutional ethics review boards, and senior leaders. The embedding of learning analytics across an organization cannot be seen as the sole responsibility for an individual unit or leader. The implementation process needs to be seen as a task that requires multidisciplinary teams with active involvement from all relevant stakeholders, as also suggested in the literature (Tsai, Gašević, et al., 2018).

3.2 Model

The use of machine learning methods is widespread in learning analytics. Machine learning generally involves the development of models that can best discover patterns in data, explain associations between variables, predict relevant outcomes, and even reveal causal relationships. To adopt learning analytics, two key aspects need to be considered:

i) Following question-driven approaches to the applications of machine learning, and
ii) Informing the use of machine learning by educational research and practice.

Many educational institutions have tried to outsource analytics work to consulting organizations that have specialized expertise (Colvin et al., 2015). This is especially beneficial to educational institutions that do not have the internal capacity and experience to implement learning analytics. However, the lack of understanding in what can be achieved with analytics at a strategic level and the failure to define initial questions or challenges to address through the use of analytics often limit the outputs of the collaboration with external analytics consultants. This (data-driven) process has been proven as ineffective in business analytics (Barton and Court, 2012). On the contrary, existing cases showed that learning analytics solutions that were developed based on clear questions and priorities identified by institutions could effectively address institutional needs (Campbell, 2007; Wright et al., 2014). It is important to note that special care needs to be taken when acting upon analytics results or instituting new support structures and changes. Macfadyen et al. (2014) remind that the complexities of educational systems often pose challenges that can impede the uptake of learning analytics. Similarly, Tsai, Gašević et al. (2018) highlighted the needs for a comprehensive policy, user-centered implementation of learning analytics, and effective communications with primary stakeholders as three important areas of work in addition to tool development.

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Existing studies suggest that learning analytics need to be informed by educational research and practice in order to produce actionable insights (Gašević et al., 2015, 2017). The lack of theory informed learning analytics can lead to (failed) attempts to replicate results without adequately accounting for contextual factors under which original results of analytics use were generated (Joksimović et al., 2016; Wise and Shaffer, 2015). As education is a rich and broad discipline, relevant experience from practice and results derived from the literature needs to be first identified in order to inform the development and use of specific learning analytics.

To address the limitations of data-driven approaches to learning analytics, several authors emphasize theory informed use of learning analytics (Gašević et al., 2015; Wise and Shaffer, 2015). For example, Gašević et al. (2015) build on a model of self-regulated learning to account for external (e.g., instructional design) and internal (e.g., study skills, prior knowledge, and motivation) conditions when developing, interpreting, and acting on learning analytics. Consistent with Rogers and his colleagues' proposition to account for external conditions, Lockyer, Heathcote, and Dawson (2013) posit that learning analytics needs to be first informed by documenting the pedagogical intent through detailed learning designs. Similarly, the study by Gašević et al. (2016) found that predictive models of student performance and retention built on trace data could not offer sufficient actionable insight of relevance for practice in specific courses. Course specific predictive models however overcame this problem and identified variables of significance for teaching practice in accordance to course specific learning designs. Another example is the study by Kovanović, Gašević, Joksimović, Hatala, & Adesope (2015), which challenged the common assumption that time spent on learning is positively associated with academic performance (Fritz, 2011). Based on principles of communities of inquiry, Kovanović, Gašević, Joksimović, et al. (2015) found that students who spent the highest amount of time would be highly inefficient in their learning and would not have the highest academic performance, whereas the amount of time online and activities attempted for the group of most successful students was mostly below the class average due to good prior knowledge and strong study skills.

3.3 Transformation

The transformation involves a systemic adoption of learning analytics to address key institutional priorities. The transformation entails consideration of several critical dimensions:

i) Building the institutional policy and strategy for learning analytics,
ii) Establishing effective leadership models to drive and oversee the implementation,
iii) Defining principles for privacy protection and ethical use of analytics,
iv) Implementation of learning analytics tools catering the primary stakeholders; and
v) Development of analytics-informed decision-making culture.

Building institutional policy and strategy is an essential step towards for systemic adoption of learning analytics (Colvin et al., 2015; Ferguson et al., 2014; Macfadyen et al., 2014). A growing trend has been noted in the development of learning analytics in higher education institutions around the world[1]. The

[1] Collection of representative institutional policies: http://sheilaproject.eu/la-policies/

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SHEILA framework is a general approach to the development of learning analytics policy and strategy that recognizes the critical importance of contextual factors and stakeholder involvement. Upon defining the purpose of learning analytics policy and/or strategy, the SHEILA framework suggests the consideration of six dimensions that can be executed without any strict order: i) mapping of the political context; ii) identification of key stakeholders; iii) identification of desired behavioral change; iv) development of engagement strategy; v) analysis of internal capacity to effect change; and vi) establish the monitoring and learning frameworks. The SHEILA framework have already been used to inform the development of policies and strategies for learning analytics at numerous higher education institutions such as the University of Edinburgh and Universidad Carlos III de Madrid.

The process of embedding learning analytics requires a transition from the technical to social systems. The generation of models and presentation of data and analyses are basic technical requirements. In contrast, the acceptance of and action on such information requires adoption within the social system of an organisation (Dawson et al., 2018). This is where effective leadership is required. Uhl-Bien and colleagues (2007)described this model of leadership as complexity leadership. In short, this requires leaders to broker and foster networks of influence where tensions arise. For instance, the presentation of students at risk may lead to increased workload for teaching staff. Effective leaders work with staff to identify novel solutions that can address the cause of friction. That is, working in the primary area of concern that would prevent or impede uptake. Leadership in learning analytics requires a strong propensity and ability to work in and between organisational silos to translate challenges into workable solutions.

Ethics and privacy protection are key enables for successful adoption and impact of learning analytics (Ferguson et al., 2016; Tsai, Gašević, et al., 2018). The SHEILA project identified – through a group concept mapping study involving experts in learning analytics – that addressing questions related to privacy and ethics should be the first task institutions should complete before committing to technical implementation of learning analytics (Tsai, Gašević, et al., 2018). Today, institutions have many guidelines and frameworks that can be used to inform institutional principles for privacy protection and ethical use of learning analytics. Notable guidelines that have been developed to ensure responsible adoption of learning analytics are the Jisc code of practice for learning analytics (Sclater and Bailey, 2015), the DELICATE framework for privacy protection (Drachsler and Greller, 2016), data de-identification methods (Khalil and Ebner, 2016), the development of student agency in connection to data privacy (Prinsloo and Slade, 2016), and a learning analytics policy and strategy framework (Tsai, Moreno-Marcos, et al., 2018).

The development of a data-informed culture in decision making is probably the most profound step that educational institutions must take in order to enable institutional transformation, as also shown in the study by Tsai et al. (2018). This process needs a recognition of limitations of data and analytics in order to make use of the benefits afforded by learning analytics and avoid possible detrimental effects of inadequate use. Importantly, any adoption of learning analytics should avoid simplistic measures in order to circumvent the unintended organizational consequences described by Goodhart's law (Elton, 2004). The development of data literacy, strategic capabilities, and overall institutional capacity in

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connection to learning analytics are key milestones for institutions on their journey of systemic learning analytics adoption.

The tools for primary stakeholders should be created to help them most effectively answer their key questions with analytics and optimize learning and learning environments. To date, higher education institutions have demonstrated much interest in learning analytics dashboards, typically dashboards developed by learning management vendors and/or educational institutions (Bodily and Verbert, 2017). There are however no empirically validated and widely accepted principles for design and evaluation of learning analytics dashboards. This may impede the acceptance by end-users and the performance of learning analytics dashboards. For example, in some cases, learning analytics dashboards are found to be negatively associated with academic performance and intrinsic motivation, to be misunderstood by students, and to evoke negative emotions and offer little educational guidance (Gašević et al., 2017). Much more promising results are recently reported by deploying analytics-based tools that support provision of personalized feedback at scale through email messages with platforms such as OnTask and SRES (Liu et al., 2017; Pardo et al., 2018). Existing research shows that the introduction of analytics-based personalized feedback at scale is positively associated with the perceived value of feedback, learning outcomes, and learning strategy (Fincham et al., 2018; Pardo et al., 2019).

4 Concluding Remarks

This paper aimed to outline some of the current state and key directions for learning analytics. The main recommendation for systemic adoption of learning analytics is that institutions need to embrace the complexity of educational systems (Macfadyen et al., 2014) along with internal and external factors established in the literature to shape operation of and experience in educational institutions. Adoption of learning analytics cannot be deemed as a simple fix to address the challenges of contemporary education. Rather, learning analytics must be considered in a broader context of interconnected organizational, social, and political structures that form modern educational institutions. Effective adoption and impact of learning analytics can only be achieved if multidisciplinary teams responsible for and representative of all relevant stakeholder groups are formed and charged with implementation.

The approach presented in this paper is based on the narrative review and previous projects completed by the authors. This may have inherently induced some unintended omissions in the coverage of the literature and other approaches present. Future research should attempt to undertake studies that will evaluate the existing literature around the proposed learning analytics adoption approach by conducting a systematic literature review. Such a review may result in changes of the approach and will provide a comprehensive accounts of the existing evidence and practices in learning analytics adoption.

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