1

A CRITICAL ANALYSIS OF LEARNING TECHNOLOGIES AND INFORMAL LEARNING IN ONLINE SOCIAL NETWORKS USING LEARNING ANALYTICS

Audu Kafwa **DODO**[1], Ezekiel Uzor **OKIKE**[2]
Department of Computer Science, Taraba State University Jalingo, Nigeria[1], Department of Computer Science, University of Botswana, Gaborone, Botswana[2]
kafwa@tsuniversity.edu.ng[1], euokike@gmail.com[2]

Abstract

Purpose: *This paper presents a critical analysis of the current application of big data in higher education and how Learning Analytics (LA), and Educational Data Mining (EDM) are helping to shape learning in higher education institutions that have applied the concepts successfully.*

Design/Methodology/Approach: *An extensive literature review of Learning Analytics, Educational Data Mining, Learning Management Systems, Informal Learning and Online Social Networks are presented to understand their usage and trends in higher education pedagogy taking advantage of 21st century educational technologies and platforms. The roles of and benefits of these technologies in teaching and learning are critically examined.*

Value/Originality: *Imperatively, this study provides vital information for education stakeholders on the significance of establishing a teaching and learning agenda that takes advantage of today's educational relevant technologies to promote teaching and learning while also acknowledging the difficulties of 21st-century learning. Aside from the roles and benefits of these technologies, the review highlights major challenges and research needs apparent in the use and application of these technologies. It appears that there is lack of research understanding in the challenges and utilization of data effectively for learning analytics, despite the massive educational data generated by high institutions. Also due to the growing importance of LA, there appears to be a serious lack of academic research that explore the application and impact of LA in high institution, especially in the context of informal online social network learning. In addition, high institution managers seem not to understand the emerging trends of LA which could be useful in the running of higher education. Though LA is viewed as a complex and expensive technology that will culturally change the future of high institution, the question that comes to mind is whether the use of LA in relation to informal learning in online social network is really what is expected? A study to analyze and evaluate the elements that influence high usage of OSN is also needed in the African context. It is high time African Universities paid attention to the application and use of these technologies to create a simplified learning approach occasioned by the use of these technologies.*

Keywords: *Learning Analytics, Educational Data Mining, Informal Learning, Online Social Network.*

Paper Type; *Systematic Review of Literature*

Introduction

Learning is essential for obtaining new information and skills in today's ever-changing world, and it does not always take place in traditional educational settings. Most of the student learning, take place informally (Osborne & Dillon, 2007) and technology plays an important role in facilitating these encounters. Although informal learning is not a new concept, social media technologies have opened new possibilities that were previously unavailable and have even "blurred the line between formal and informal learning" (Sergis & Sampson, 2017). Many researchers (Kilis, Gulbhar & Rapp, 2016) , (Siemens & Long, 2011), (Miller & Prior, 2010) stress the social character of informal learning in the digital age since social media technologies have a significant impact on student experiences. For example, as a type of informal learning, today's students utilize instant messaging, browse websites, and use Facebook for chatting, Twitter, Instagram, listen to music, play games, and download

Materials (McAfree, Brynjolfsson, Davenport, Patil & Barton, 2012), and all these practices are important for social interaction. As a result, there has been an increase in the amount of data created from various sources of online social networking sites.

In retrospect between 2014 and 2020, the rate of data growth was anticipated to double every month, according to (Giacalone & Scippacercola, 2007). Higher education has not been spared from the "data flood" age, as it has witnessed a massive increase in data input as well as the introduction and acceptance of new technologies for teaching and learning. However, as compared to other sectors like marketing, finance, health, security, and sport, the primary challenge in the sector has been the inefficient use of this data to create value in a way that satisfies the educational market demand. Furthermore, the popularity of Online Social Networks (OSN) for personal communication and entertainment is driving up demand for OSN-integrated apps. People tend to exchange personal information with linked colleagues in the OSN, whether through games or programs that track one's sports activity. Over the last few years, educational hypermedia has progressed from static systems to dynamic content display and delivery platforms (Bruggeman, 2013). A shift in personal learning is driving the demand for collaborative learning in OSNs. Additional services have recently been incorporated into OSNs, allowing users to search up and debate subjects of interest with other users. Typically, there is no moderator or facilitator to steer the debate. Active and passive triggers can be used to start conversations. The more active option is to start a text-voice or video chat and ask other users to join. Posting messages on one's page and waiting for a response from someone who happens to be looking at it by chance is a passive form of communication. Any user who has been granted access to a post may respond on the person's profile.

The quantity of social media data allows us to better comprehend students' experiences, but it also creates methodological challenges in interpreting social media data for educational purposes. Consider the enormous volume of data, the diversity of Internet slang, the unpredictability of student posting locations and timing, as well as the complexity of students' experiences. Pure manual analysis is unable to cope with the ever-increasing volume of data, while pure automatic algorithms are unable to grasp the data's in-depth significance (Hrabowski & Suess, 2010). Traditionally, educational researchers have collected data about students' learning experiences using methods such as surveys, interviews, focus groups, and classroom activities (Campbell, Deblois & Oblinger, 2007), (Giles, Glonek, Luszcz & Andrews, 2005). Because these procedures are often time-consuming, they cannot be replicated or repeated frequently. The scope of such research is generally constrained as well. Furthermore, when asked about their experiences, students must reflect on what they were thinking and doing in the past, which may have faded with time.

Learning analytics and educational data mining (EDM) are new areas that focus on analyzing structured data from course management systems (CMS), classroom technology usage, or regulated online learning environments to help educators make better decisions (Macfadyen, 2017), (Baker & Yacef, 2009), (Karpinski, 2009). Learning analytics is defined as "the use, assessment, elicitation, and analysis of static and dynamic information about learners and learning environments, for the near real-time modeling, prediction, and optimization of learning processes and learning environments, as well as for educational decision-making" in this study (Ifenthaler & Yau, 2020). Since early 2010, the study of learning analytics has grown tremendously in the fields of education and psychology, as well as computers and data science (Bakhshinategh, Zaiane, Elatia & Ipperciel, 2018). As a result, while learning analytics is a broad concept, it has many conceptual variations, such as school analytics (Barron, 2006), teacher or teaching analytics (Ifenthaler & Schumacher, 2016), academic analytics (Macfadyen, 2017), assessment analytics (Zhou, 2016), social learning analytics (Dawson, Poquet, Colvin, Rogers, Pardo & Gasevic, 2018), or multimodal (Cetintas, Si, Aagard, Bowen & Cordova – Sanchez, 2011).

Predictive models are used in learning analytics to offer actionable data. Data processing, technology-enhanced learning, educational data mining, and visualization are all part of this interdisciplinary approach (Clarke & Nelson, 2013). The goal of LA is to customize educational opportunities to the needs and abilities of each individual learner by intervening with at-risk pupils and giving feedback and instructional content. While LA focuses on the use of established methods and models to address challenges impacting student learning and the organizational learning system, educational data mining focuses on the creation of new computational data analysis approaches (Atman et al, 2010).

There has been considerable criticism that the process of big data mining is driven by higher education management and the economic framework of education (Rushby, 2012), nonetheless, empirical studies have shown that LA may be beneficial for enhancing education. LA heightens learners' and instructors' awareness of their current conditions, allowing them to make better informed decisions and execute their duties more efficiently (Clarke & Nelson, 2013). One of the most common uses of learning analytics is to track and forecast student performance, as well as to detect possible problems and at-risk individuals (Johnson, Adams & Cummins, 2012). Some institutions have already used LA in a variety of courses to help students study more effectively. Purdue University, for example, utilized predictive modeling based on data from its course management system to identify students at danger and intervene. The University of Alabama enhanced student retention by developing a prediction model for at-risk students based on a huge dataset of demographic information. Northern Arizona University, for example, linked resource utilization, risk level, and student success by developing a prediction model to determine which students would benefit from which resource (Nouira, Chenti – Belcadhi & Braham, 2019). These are among the first institutions of higher learning to use LA. Equally, in the UK, the Open University of UK linked the strategic priorities to continues students' enhancement and experience to retention and progression. Nottingham Trent University UK also linked the area of student's retention-less quarter with low average engagement progress of second year students. In the same vein. The Open university of Austria mention that learning analytics is used to drive personalization and adoption of content recommended to individual students as well as provide input and evidence for curriculum redesign. In Edith Cowen University in Austria, they created a probability of retention scores for each undergraduate students to identify most likely students to need support (Papamitsiou & Economides, 2014). While some Higher Education Institutes have had great success in exploiting the benefits of Learning Analytics, many others especially in the African context have yet to do so. This calls for research in LA among African Universities.

There is a knowledge gap in terms of how Learning Analytics is utilized and what the consequences are in higher education. This paper calls for research to fill this gap. The authors of this paper are currently engaged in research to examine and identify the key factors influencing the use and impact of Learning Analytics and provide a systematic overview of the use and impact of informal online social network learning in higher education institutions. More specifically, this research aims to determine how informal online social networks can effectively use data in the era of Big Data and Learning Analytics as learning tools to influence learning outcomes. This paper therefore serves as input from the various literature reviewed. Although research on the use of LA in higher education institutions has been published in recent years, LA is still a new topic of study. Higher education stakeholders, leaders, administrators, teachers, and course designers must get familiar with LA methodologies and applications (Clarke & Nelson, 2013). The difficulty is that few studies have integrated prior research or offered a comprehensive review of concerns related to the use of LA in higher education.

Statement of Research Problem

Informal online social network learning, according to educators, is inherently disruptive to the learning process. As a result of this belief, many educators have declared it illegal to use electronic devices such as computers or mobile phones in class (Elatia & Ipperciel, 2021). However, online social networking sites such as Facebook, Twitter, Linked In, and others can help students become more academically and socially integrated while also enhancing learning outcomes (Yang, Wang, Woo & Quek, 2011). Most of informal learning processes are implicit, ad hoc, spontaneous, and unnoticed by others (Cross, Cross & Parker, 2010). As a result, this topic poses a fascinating challenge for the field of information systems: capturing and analyzing traces of (social) informal learning in everyday life and the learning environment.

Significance of the Study

This study has the potential to make a significant contribution to the field of learning analytics using an informal online social network, as well as its application and technique being beneficial in the fields of big data, and data mining. This ongoing study stands in stark contrast to the currently prevalent, management-driven training model, which prioritizes formal learning guided by corporate curricular agendas and relies on outside experts and knowledge sources (Lazega, 2003).

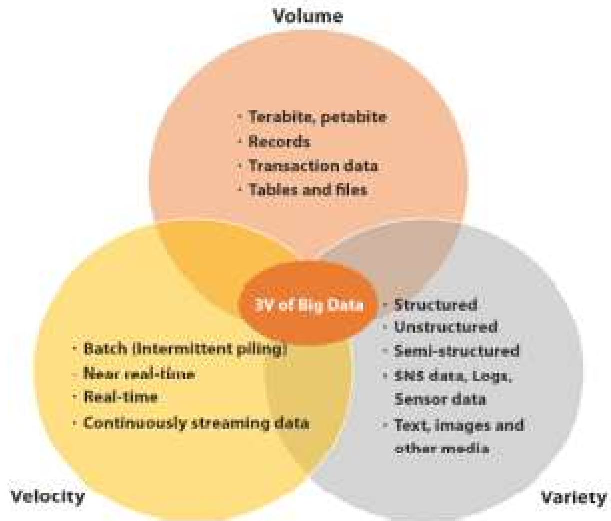
Current Research Effort

Our current research effort is aimed at developing a framework that will be used to utilize learning analytics in higher institution. The study will examine the current status of informal leaning using the online social networks.

RELATED WORK

Big Data

Data is pervasive and has always been important in making decisions. As a result of todays advanced technologies, massive data can be collected quickly, mined, processed and interpreted as explained in. Digital networks, social networking, cellphones, and the World Wide Web are just a handful of the methods used to generate this massive amount of data. These massive datasets are referred to as "Big Data" because they are beyond the capacity of conventional database tools to collect, search, store, transfer, manage, visualize, share, query, analyze, and update them. Nevertheless, depending on the technologies employed and the average amount of datasets connected with the industry, the definition of Big Data may vary from sector to sector, and the present pace of data collection is staggering. Effective data handling and analysis is a significant issue. Formally, Big Data may be defined as collections of datasets whose volume, velocity, or variety is so large that it is difficult to store, manage, process and analyze the data using traditional databases and data processing tools (IBM, 2021). Figure 1 shows the main characteristics of Big Data in terms of volume, velocity and variety.



. Fig. 1. Big Data Characteristics: Source [102].

In recent years, exponential growth in both structured and unstructured data generated by information technology, academia, industry, healthcare, the Internet of Things, and other systems. An estimate by IBM indicate that 2.5 quintillion bytes of data are created every day (Clark, Logan, Luckin, Mee & Oliver, 2009). According to DOMO report (Wagner & Ice, 2021), the estimates of the amount of data generated every minute on popular online platforms can be seen as presented in figure 2.

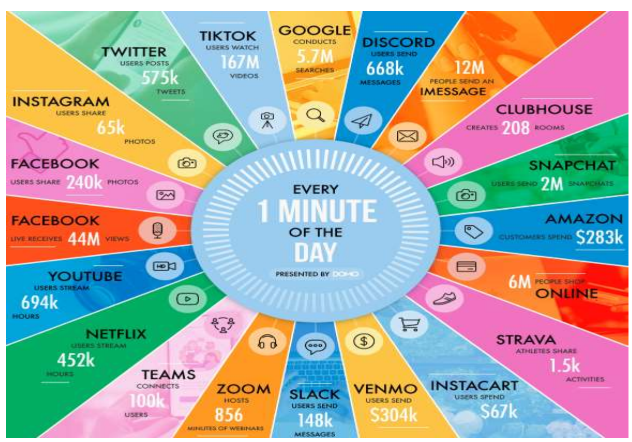


Fig. 2. Data generated every minute by OSNs Source [88]

As of July 2021, the internet reaches 65% of the world's population and now represents 5.17 billion people – a 10% increase from January 2021. Of this total, 92.6% access the internet via mobile devices. According to Statista, the total amount of data consumed globally in 2021 is 79 zettabytes, an annual number projected to grow to over 180 Zettabytes by 2025.

Essentially, Big data is generated from heterogeneous data sources such as email, social media, medical instruments, commercial and scientific sensors, financial transactions, satellite, and traditional databases, etc. in the form of text, image, audio, video, or any combinations of any form of these. Expectedly, organizations will be able to make educated decisions as a result of the massive volume of data being generated (Bagha & Madisetti, 2019). However, because of the diverse nature and scale of big data, managing it is a difficult undertaking.

Big Data Analytics and Educational Data

Recently, Data Mining (DM), Educational Data Mining (EDM), and Learning Analytics (LA) have been employed to handle big homogenous datasets. Traditional data mining approaches, on the other hand, must be updated to process diverse types of data in parallel to handle the heterogeneity of big data. For this reason, some researchers refer to "data mining" as "old big data" and "big data" as "new data mining" (Daniel, 2017), (Burt, 1984). Big data analytics is a technique for analyzing big datasets comprising a range of datasets to find hidden patterns, unknown connections, market trends, consumer preferences, and other relevant business data. Although big data analytics is frequently employed in business to anticipate future trends and consumer behaviors, it is shockingly underused in education. Learners, educators, educational researchers, course developers, learning institutions, and education administrators are the six stakeholders in education. Through learning systems based on big data analytics, learners may receive immediate and thorough feedback on their interactions with the information they are learning. Big data may be utilized to teach pupils about what they have correctly learned and what they have not. Similarly, high-performing students' practices can be shared with other students so that they can adapt their learning by the system. Educators may use big data to assess the overall performance of the class at a macro level, allowing them to plan broad tactics for the class. They can also examine an individual student's performance at a microscopic level to determine his or her strengths and shortcomings. As a result, educators can concentrate on the learner's weak spots to enhance their total performance. Educational researchers may utilize a vast quantity of learner datasets to suggest new learning theories and practices, as well as assess the efficacy of the theories and models offered. Course creators can leverage the rapid availability of numerous online participants, as well as their comments, to create new course materials or alter existing course materials.

Analysis of large educational datasets can be done by using the combination of two techniques, namely, educational data mining (EDM) and learning analytics (LA). These techniques develop a capacity for quantitative research in response to the growing need for evidence-based analysis related to education policy and practice (Vogot, Erstad, Dede & Mishra, 2013). As Big data is being used to evaluate the rationality and effectiveness of training programs at universities (Yang, Wang, Woo &Quek, 2011), evidence from (Thille, Schneider, Kizilcec, Piech, Halawa & Greene, 2014) which studied three different online learning environments: Open Learning Initiative (OLI) at Stanford University and Carnegie Mellon University, Code Webs Project, and massive open online courses (MOOC), suggest that learners and instructors both can benefit from big data. Big data assists instructors in the assessment process by enabling the continuous diagnosis of learners' knowledge and related states and by promoting learning through targeted feedback. Data-enhanced assessment can provide feedback to instructors in designing teaching and assessment strategies in online and offline learning environments. The influence of technology can be seen in many aspects of education from student engagement in learning and content creation to helping teachers provide personalized content and improving student outcomes (Wellings & Levine, 2009). One may argue that educational data is not Big Data when studying big data in education. Is educational data characterized by the three Big Data characteristics of volume, velocity and variety? Data collected within a MOOC is high in velocity and volume but low in variety unless deliberate efforts are made to increase variety. Demographic information such as (gender, ethnicity, etc.) and previous knowledge assessments can be included in educational data (prior college enrolments, high school grades, standardized test scores, etc.). However, these variables are not collected automatically in MOOCs (Lai, 2011). Also, when comparing the volume of educational data to other industry data such as web data, retail, and health care data, learning analytics may fall short on volume. Volume, speed, and variety are the major distinctions between Big Data and Analytics (McAfree, Brynjolfsson, Davenport, Patil & Barton, 2012). Despite these variations, many research projects are looking into the use of learning analytics and educational data, as significant quantities of data are generated every day via eLearning tools that might provide valuable insight into students' performance, attentiveness, and habits (Lai, 2008).

Big Data and Learning Analytics

Big Data is at the heart of both learning analytics and business analytics and provides data sources for generating insights through analytics. Big Data has a lot of value and may have a lot of influence, but it's all predicated on Learning Analytics and Business Analytics. Big Data may be extremely valuable and impactful, but companies must utilize analytics to make sense of it (Hofstein & Rosenfeld, 1996). Some individuals use the terms "Big Data Analytics" and "Business Analytics" interchangeably. Analytics in business is referred to as Business Analytics, while Analytics in high education is referred to as Learning Analytics. According to (Macfadyen, 2017), Big Data encompasses the emerging field of Learning Analytics, which is now an emerging field in education. Reports in (Dawson, Gasevic, Siemens & Joksimovic, 2014) have highlighted the use of Big Data in Higher Education, claiming that technical advancements have facilitated the shift to greater use of analytics in high education.

In addition, Big Data in higher education implies an understanding of a wide range of administrative and operational data collected procedures aimed at examining institutional performance and improvement to predict future performance and identify potential challenges related to research, academic programming, teaching, and learning , (Picciano, 2014), (Lai, Khaddage & Knezek, 2013). In a similar vein, (Erevelles, Fukawa & Swayne, 2016) claims that most of the current work on analytics in higher education comes from interdisciplinary research, which includes educational technology, statistics, math, computer and information science, and data mining is a key component of the current work on analytics in education.

Big Data is now well-positioned to begin tackling some of the major problems now confronting high education using today's technologies. With these technologies, organizations (including educational institutions) get superior perspectives from data at previously unattainable levels of complexity, speed, and accuracy. Students, systems, and computer applications (Boud & Hager, 2012), (Laat, Lally, Lipponen & Simons, 2007). Learning Analytics (LA) therefore, is a fundamental instrument for learning change in education that provides evidence on which to build a better perspective and make learned rather than inherent choices (Greenhow & Burton, 2011). Formally defined, Learning Analytics is the process of gathering, analyzing, and reporting educational Big Data because of business intelligence and data mining (Reyes, 2015). As a growing field of study, it provides students, instructors, and other stakeholders with a better knowledge of how they learn (Dawson, Poquet, Colvin, Rogers, Pardo & Gasevic, 2018), (Dabbagh & Kistanas, 2012). Other key benefits of Big data and LA include student course performance prediction, identifying risk of abrasion, interactive visualization and reporting of data, smart feedback, course commendations, approximation of skill development, identification of group-based collaborative feedback, and schedule management (Pattern, 2016). The idea is extended to smart learning environments and interactive educational systems in order to sustain active learning and therefore a general development for learning and engagement (Hammad & Ludlow, 2016), (Sclater, Peasgood & Mullan, 2016). With the current shift in educational settings to blended and online learning, as well as the introduction of Learning Management Systems (LMSs) like Moodle and Blackboard, it is unsurprising that Big Data has made its way into education and is expected to be widely used in high institutions as these platforms generate massive educational data sets over a period of time.

Learning Analytics and Educational Data Mining

Data produced by and accessible in higher education (HE) provide the basis for conducting research and analysis in understanding and improving teaching and learning. The sources of these data are not only from teaching and learning but also include all data units of a university such as finance, human resources, the registrar's office, maintenance and faculties, internet usage, admission, program development, libraries, and research. As a result, HE has been paying careful attention to utilizing technologies made accessible by advancements in big data analysis, with employability and graduate skills at the forefront of many institutional initiatives to harness the usefulness of educational data. For teaching, learning and services provided to students, it seems that both Educational Data Mining (EDM) and Learning Analytics (LA) can become optimal tools to guide universities in adapting to changes and addressing specific needs for the future. EDM has grown into its own discipline, using data mining methods in educational settings. EDM includes a wide range of techniques and applications that may be divided into two groups. On the one hand, EDM may be utilized to achieve practical research goals like improving learning quality. On the other hand, it may be utilized as a tool for pure research purposes, such as improving our knowledge of how people learn (Romero & Ventura, 2020). EDM provides a variety of options for analyzing and directing learning in a multidimensional environment where data comes from many sources and in various formats (Lazer et al, 2009). These methods are eclectic in character, combining qualitative and quantitative approaches. They also let researchers examine large amounts of data that are influenced by a variety of unknown factors. Hence, analysis of observational datasets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owners is a critical (Shirky, 2010). Data mining as a multidisciplinary field also involves methods at the intersection of artificial intelligence, machine learning, statistics, and database systems as shown in fig. 3.

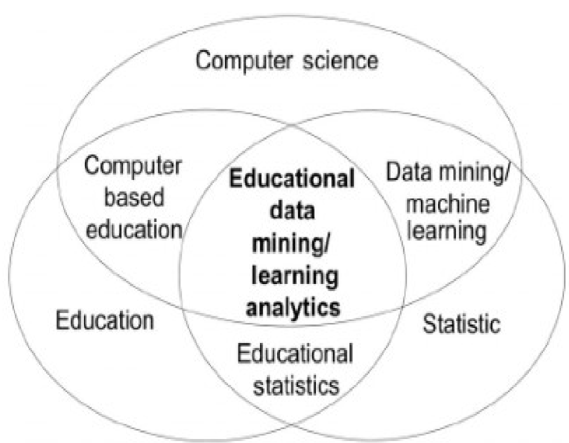


Fig. 3. Areas related to EDM and LA: Source (Zhou, 2016)

Data analytics in the context of learning and education (Learning Analytics) entails gathering information on student actions and behaviors, as well as educational settings and situations, and then utilizing statistics and data mining methods to uncover important patterns that show how learning occurs. LA may be used to report learning activity measurements and patterns or optimize learning methods and settings.

Because of the enormous quantities of data becoming accessible from the increasing number of courses offered in e-learning and hybrid settings, the educational applications of EDM and LA in higher education are new and developing trends. They are a great tool for methodically analyzing the massive amounts of data generated by higher institutions.

Benefits of LA and EDM

Papamitsiou and Economides performed a comprehensive systematic literature evaluation of empirical evidence on the advantages of LA as well as the related area of educational data mining (EDM). They categorized the approaches into case studies that focused on student behavior modeling, performance prediction, increased self-reflection and self-awareness, dropout prediction, and retention. Their results indicate that vast amounts of educational data as well as the use of pre-existing algorithmic techniques were accessible. Furthermore, LA allows for the creation of accurate learner models that may be used to guide adaptive and customized treatments. Other advantages of LA include the detection of key learning moments, learning methods, navigation behaviors, and learning patterns (Cormode & Krishnamurthy, 2008). A separate systematic review on LA. Was done in (Bienkowski, Feng & Means, 2012). The authors suggest that, in order to effectively assist learning processes, logs of students' data activity should be supplemented with extra information (e.g. actual time spent learning, semantic-rich information). As a result, extensive data on students' attempts and performance, as well as precise information about psychological, behavioral, and emotional states, are required for LA to promote study success. There is a lot of overlap between these two areas of study. Despite this, there are several divergences view in the literature. Notwithstanding, the aim of EDM and LA is the same: to improve education quality by analyzing massive quantities of data and extracting valuable information for stakeholders. Companies in other industries, such as finance, and healthcare, have already used statistical, machine-learning, and data-mining methods to improve performance via data-driven choices. Figure 4 shows the evolution of EDM and LA

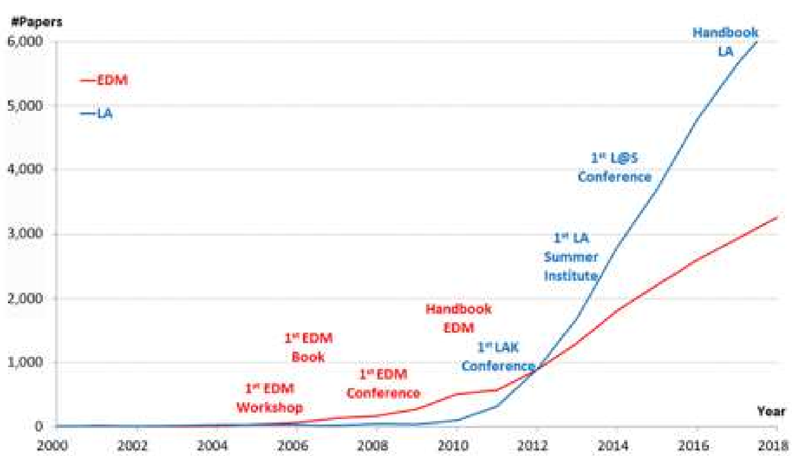


Fig. 4. Evolution of EDM and LA Source (Zhou, 2016)

Although EDM research began a few years earlier, the popularity of EDM and LA areas of study has been on the increase since the early 2010s (Figure 4). Due to the potential advantages (for students, instructors, administrators, researchers, and society in general) and the relevance of current Big Data research, these areas are anticipated to continue to grow (Dron & Anderson, 2017).

Incorporating Social Systems into Learning Analytics

The complex social networks that facilitate the flow of adoption processes are part of the broad social system settings that are engaged in higher education (Kozieski, Gibson & Hynds, 2012). The existing conceptual models of learning analytics adoption in higher education, as recently pointed out by (Livingstone, 2000), fail to operationalize how key dimensions interact to inform the realities of the implementation process, necessitating a need to rethink learning analytics adoption through complexity leadership theory and to develop systems understanding at leadership levels to enable the movement of boutique analytics projects into the enterprise. Learning analytics adoption is frequently hampered by a lack of resources, obstacles requiring many stakeholders' buy-in, and worries and anxiety about big data ethics as well as privacy concerns in higher education (Centre Domo, 2021), (Haythornthwaite & De Laat, 2012). To meet these difficulties, leaders must be flexible, sensitive to environmental forces, adept at handling disputes, and able to harness complex social networks for change (Gibson, 2000).

One of the most promising techniques for investigating the complexity of social impact, multilayer hierarchies, and relationship development is network analysis. In (Greenhow & Robelia, 2009) network techniques were used to describe the spread and diversity of behaviors, forecast the pattern of dissemination of innovations, analyze educational phenomena, and identify opinion leaders and followers in order to better comprehend information flows (Pattern, 2016). Epistemic network analysis is noteworthy in the context of learning analytics.

Conceptualizing Informal Learning and Online Social Network

The study of asynchronous discussion forums dominated previous work on online informal learning analysis, with an emphasis on finding successful learning and knowledge-building processes through content analysis (Han, Kamber & Mining, 2006) (Kiser & Porter, 2011). In social contexts, learning is defined as a collection of processes through which a learner builds meaning, and new ideas based on prior experiences. This implies that evidence of learners' online interactions, like chats, may be used to identify cognitive and social processes that learners participate in to give meaning to their new concepts.

a. Informal Learning

Informal learning is more difficult to describe due to many conceptual and methodological problems (Eshach, 2007) (Rost, Barkhuus, Cramer & Brown, 2014). In terms of learning context location, informal learning refers only to learning that occurs outside of the classroom (Kerka, 2000), (Greenhow, Robelia & Hughes, 2009). Other research, such as (Hrabowski III, 2011), examines informal learning in terms of structure and technique, as well as teacher-student interaction. It is viewed as a self-directed, purposeful activity from this perspective. Another perspective emphasizes the goal of learning, describing informal learning as learning that occurs inadvertently, spontaneously, and without attention, and is typically associated with leisure activities (Kvartalnyi, 2020). Learning is a continuous process in which the learner's capacity to arrange, classify, and evaluate knowledge determines the degree of formality or informality. As described in (Furlong & Davies, 2012), it is about "the degree of control teachers and learners have over the selection, organization, and timing of knowledge transmitted and absorbed." When a student has more control over learning possibilities, as well as the flexibility to select what to study and how learning is assessed, learning becomes more informal. As stated in (Laurillard, 2009) informal learning gives the learner the focal point of control. Laurillard (Clark et al, 2008) argues that there is no instructor, no specified curriculum topic or concept, and no external evaluation. The informal learner chooses their own 'teacher,' who may or may not be a person; they determine their curriculum, or what they wish to learn about, and they choose whether to submit to external evaluation. If informal learning experiences are beneficial, how can these experiences be transferred from one context to another to create "seamless learning" informal learning settings?

Furthermore, there is a growing understanding that formal and informal learning have a pragmatic connection. While students learn differently in school and out of school contexts, learning may occur across boundaries, and what is acquired outside of school can help shape what is taught in school (Ifenthaler, Gibson & Dobozy, 2018). What children learn in school, on the other hand, might encourage them to learn outside of school (Callan, Cervantes & Loomis, 2011). Students' informal learning has been demonstrated to be prompted by their schoolwork in (Merceron, Blikstein & Siemens, 2015). While learners will utilize the kinds of learning that they have already mastered in formal settings, in informal learning circumstances, they will also use techniques that are not often used in schools identified as "informal learning methods" (Furlong & Davies, 2012)

It appears there is a gap in how learners utilize technology in formal and informal learning. In school, technology is utilized to accomplish curricular work in public areas in an organized, supervised, guided, and most individual way. Learners, on the other hand, use technology in chaotic, unsupervised ways at home and in other informal settings, socially and cooperatively, to pursue interests in private places. Learners have established habits and expectations of how electronic devices should be used in informal contexts, and because schools do not encourage these practices, it has resulted in what some observers have dubbed "digital dissonance" (Clow, 2013). As a result, teachers and institutions are frightened of the disruptive social potentials of the disputed technologies, and do not identify or comprehend the expanded repertory of practices available to learners in their interaction with them. At the same time, most students are ignorant of these materials' broader educational potential. Leveraging in online social networks could turn learning into a seamless aspect of daily life to the point that it is no longer recognized as learning challenge (Sefton – Green, 2004)

b. Online Social Network

Through interactions people establish networks of connections that allow them to access resources like jobs, information, and materials, goods, and services. The concepts and cross-disciplinary potential of network principles derived from graph theory are currently gaining significant attention across fields, for example, in bringing together ideas small-world structures from physics to bear on the social results embodied in the idea of "six degrees of separation" (Haythornthwaite & De Laat, 2010). Thus, a more cross-disciplinary approach that is becoming known as "network science" has been born. Our focus here is on maintaining the social network viewpoint, which, as pointed out in (Blikstein & Worsley, 2016) has a long history and a strong empirical and theoretical foundation. Figure 5 illustrates the basics of social network.

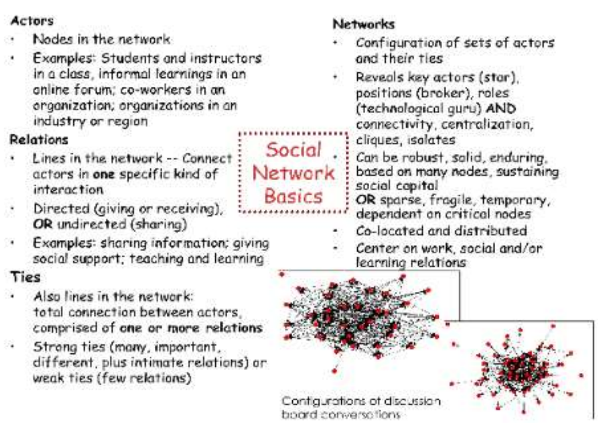


Fig 5. Social network basic; Source: (Williams, 2010)

The nodes or actors in the network, as well as the connections between them are the building elements of social networks. Students, instructors, informal learners in an online forum, coworkers in a company, colleagues on a research team, industries or regions, and academic disciplines are all examples. Individuals, organizations, communities, and other types of collectives can all be actors. However, there is little research using social network analysis to incorporate objects at this point and interpreting the social elements of networks that contain mixed and/or inanimate items. Our current study focuses on person-to-person contact and the application of contemporary network theory to learning networks.

Relations in the network refer to the relationships that exist between actors. Actors may have one or more ties, which can range from impersonal to intimate, rare or regular, and elective or mandatory. Actors are linked when they retain at least one type of relationship. Such relationships might be weak when contacts are few, insignificant, or incidental, or strong when interactions are based on numerous types of exchanges, reciprocity in the relationship, and self-disclosure. The actors and the relationships that bind them together constitute networks, which are patterns of connections between members of a certain group of people, such as students in a class, project team members, or instructors in a school. Networks can be drawn based on any relationship between individuals, such as by asking each member of a group of people a broad question such as "who do you talk to?" Networks can also be created using more specific inquiries, such as "with whom do you discuss significant issues? “Who have you worked with this week?" (Henri, 1992).

To investigate changing network dynamics, (Borgatti, 2009) proposed an integrated multi-method and temporal methodology. By integrating questions like "who talks to whom?" with "what are they talking about?" and "why are they talking the way they do?" this technique seeks to provide a more comprehensive view of the processes and behaviors involved in networked learning. Learners now have more choices over what, how, and with whom they learn in a wide range of settings: classrooms, after-school programs, home-school, formal online learning, and so on. These changes impact constructs for learning, teaching, and future research (Merceron, Blikstein & Siemens, 2015). Increasing learners' educational attainment, science and math learning, technological fluencies, communication skills, civic engagement, and preparation for the twenty-first-century workplace are some of the most pressing issues facing education today (BUREAU, 2007), (De Laat, 2006).

Learners prefer to use the online social network while they are not in school, during their free time, and among peers of all ages, ethnicities, and socioeconomic levels (Czerkawski & Hernandez, 2013). Essentially, we provide some basic definitions. Formally, social network sites are collections of Web-based services that allow individuals to establish a public or semi-public profile inside the system's limits, to give a list of other users with whom they are connecting, and to monitor and roll over the list of connections (Tankovska, 2021). Hence, social network websites are online communication platforms for individuals who have common interests and activities (Warschauer & Matuchniak, 2010). Users may interact with one another via several means on websites, including chat, messaging, and e-mail. Online social network software are Internet-based programs that enable users to build and manage virtual social networks.

In (Scearce, Kasper & Grant, 2010), a study of trends among non-profits, foundations, and socially responsible businesses was conducted. The result suggests that facilitation of human relationships and connections via social media has the potential to gather significant organizational advantages, such as weaving community; encouraging greater openness and transparency; accelerating information-sharing; accessing more diverse perspectives; and mobilizing a workforce. There are also disadvantages of using social media to facilitate relational practices. These include the fact that "half-baked" ideas are made public, and those trying to manage workflows and processes must deal with concerns about brand and message control, privacy concerns, dealing with information overload, and learning the language. range of technology options and leveraging the right social media for one’s purposes (Scearce, Kasper & Grant, 2010). Some important questions are:

- How should we think about these broader trends with thinking about learning, teaching, and the incorporation of social media into education? To advance this conversation, it is good to synthesize what the educational research currently says about learning and social network, the dominant form of social media used by learners. The goal is to inform educational leaders, apprehensive or cautiously optimistic about learners’ media-using practices.
- What are learners' purposes and practices with social network sites, and are they doing anything of educational value?
- How might these understandings help us to design for wider civic participation, increasingly sophisticated interactions, and accomplishments, and deal with potential dangers?
- Are existing social networking technologies and attendant practices appropriated and/or re-envisioned and re-worked to produce improvements in areas of educational priority such as educational attainment, the development of science, math, and technology literacies, communication and twenty-first-century skills, and preparation for future work lives?

Two insights related to these questions are generated from a review of the educational literature (Merceron, Blikstein & Siemens, 2015), from explorations of learners (ages 16-24) use of the social network sites MySpace and Facebook (Callanan, Cervantes & Loomis, 2011), (Rideout, Foehr & Roberts, 2010), (Merceron, Blikstein & Siemens, 2015) and an ongoing investigation of learners use of an open-source social networking application, implemented within Facebook, and designed for informal science learning and civic action. At the end of the investigation, it was found that learners would adapt the spaces they frequent for their educational-related purposes, as well as school-related activities. What is surprising is the presence of these behaviors and beliefs even among most of our students, a group understudied in the educational technology literature and presumably experiencing more barriers to (but potentially more to gain from) participating in social network sites where such social media are typically blocked-in schools and public libraries (Merceron, Blikstein & Siemens, 2015).

Furthermore, where such informal sharing, peer validation and feedback, alumni support, and spontaneous help with school-related tasks has typically occurred offline, pre-dating the internet, these social processes, moved online into social network sites, can now be archived and tracked with social graphing software. In theory, we should be able to begin to identify what learning resources exactly are moving through the network, to and from whom, and with what impacts over time (Okike & Mogorosi). Moreover, educational designers might think about how some of the socio-technical features most utilized in naturally occurring, learners social network sites, like Myspace (e.g., multimedia identity-posting capabilities, frequent updating, and sharing of micro content, social search, linking users with content contributions, annotation, ranking, recommendation systems) could be incorporated into the personalized learning systems touted in the Educational Technology Plan of the institution.

Empirical Study of Online Social Networks

In everyday life, we make informal observations of the people and things around us, and use these observations as basis for making decisions (Scheffel, Drachsler, Stoyanov & Specht, 2014). In educational institutions for example, a teacher might observe that his or her students seem bored and decide to switch to a livelier instructional activity. A study in (De Laat & Schreurs, 2013) on informal learning networks in the workplace and their impact on professional growth was done. In this study, it was noted that most of the participants (school leaders) in the study had limited knowledge of what instructors daily study entail. This implies the need for raising awareness about the value of informal learning. Another study in (Homan, 2006) also underscores the need for n facilitating informal professional development networks and the need for creating a framework on it. The study noted that informal organizations support and activities are critical to effective organizational transformation and innovation. An innovative approach in (Homan, 2006) created the change mirror research technique to identify informal networks and reflect their voices and views of the company. Using social networks analysis (SNA) the approach first raises awareness of the presence of the informal networks. Second, utilizing group discussion software, the technique elicits information about what the networks are all about, and by combining the two stages it significantly simplifies the understanding of change process in companies.

In the context of networked learning, the change mirror method in an organization was used to examine how well it fits with the goal of detecting informal professional development networks. Using a multi-method framework (fig 6) the goal was to get a better understanding of networked learning processes in a realistic environment (Borgatti, Mehra, Brass & Labianca 2009), (Kizilcec & Brooks, 2017). The multi-method framework triangulates SNA to find out "who is talking to whom," content analysis (CA) to find out "what they are talking about," and contextual analysis (CxA), focusing on the context of the organization the participants are working in to find out "why they are talking as they do."

The change mirror method with a three-step research design is described as follows:

Fig 6: Multi-method research framework for studying networked learning; source: (Veletsianos & Navarrete, 2012)

Step 1—SNA (Social Network Analysis): This is used to determine who is talking to whom about an issue. This phase visualizes existing informal networks where experts cooperate on a specific issue and illustrates how linked (or not) they are throughout the whole organization. This is accomplished via the use of an online survey.

Step 2—CA (Content Analysis): The next stage is to figure out what these networks are talking about, as well as their opinions and views regarding the issue. Synthetron, a group discussion tool, is used for this. Everyone takes part in an asynchronous online conversation where they may share and discuss their thoughts and experiences with this work-related issue. The application allows you to analyze the whole conversation as well as the logged data.

Step 3—CxA (Contextual Analysis): This phase is to figure out how and why these networks act the way they do in their informal settings. CxA is based on focus groups, interviews, which may assist in understanding the impact that certain networks may have on the organization and give weight to the "voices" that exist inside these networks. We can create a clear picture of the possibility for networks to start working together or sharing information and resources by integrating the findings of the survey and the Synthetron conversation with the input from the research teams. Such findings suggest that after identifying informal networks (Step 1), there may be a desire to link the networks (Steps 2 and 3). The important characters in these networks may be seen as latent connections (Roreger & Schmidt, 2012), bridging the gap between the organization's presently disconnected networks. The ability to link these spontaneous informal learning networks will improve knowledge sharing and productive learning across the business. Despite believing in the potential of informal professional development networks, the study team observed that the visualization process and attempts to bring these networks closer together were time-consuming. They also discovered that local management at the participating schools misinterpreted their job as a member of the study team, as well as their motivations for doing so. They discovered that school leaders struggled to grasp what informal networks are and how they support professional growth in discussions with local management.

Conclusion

This paper provided a comprehensive review of Learning Analytics (LA), Educational Data Mining (EDM) and Online Social Networks (OSN) and some interesting current best practices. Imperatively, this kind of study goes a long way in informing education stakeholders on the significance of establishing a teaching and learning agenda that takes advantage of today’s educational relevant technologies to promote learning while also acknowledging the difficulties of 21st-century learning. From the extensive reviews, it appears that there is lack of research understanding in the challenges and utilization of data effectively for learning analytics, despite the massive educational data generated by high institutions. Also due to the growing importance of LA, there appears to be a serious lack of academic research that explore the application and impact of LA in high institution, especially in the context of informal online social network learning. In addition, high institution managers seem not to understand the emerging trends of LA which could be useful in the running of higher education. Though LA is viewed as a complex and expensive technology that will culturally change the future of high institution, the question that comes to mind is whether the use of LA in relation to informal learning in online social network is really what is expected? A study to analyze and evaluate the elements that influence high usage of OSN is also needed in the African context. It is high time African Universities paid attention to the application and use of these technologies to create a simplified learning approach occasioned by the use of these technologies.

References

1. A. BAGHA and V. Madisetti, Big Data Analytics: A Hands-On Approach. USA: Arshdeep Bahga & Vijay Madisetti, 2019.
2. A. G. Picciano, ‘The evolution of big data and learning analytics in American higher education.’, Journal of asynchronous learning networks, vol. 16, no. 3, pp. 9–20, 2012.
3. A. Hofstein and S. Rosenfeld, ‘Bridging the gap between formal and informal science learning’, 1996.
4. A. IBM, ‘Big data analytics’, IBM, 2021. https://www.ibm.com/analytics/hadoop/big-data-analytics (accessed Oct. 19, 2021).
5. A. I. Kiser and T. Porter, ‘Social networking: Integrating students and university professor utilization’, in Global Conference on Business and Finance Proceedings, 2011, vol. 6, no. 6, pp. 191–196.
6. A. Karpinski, ‘Media sensationalization of social science research: Social networking insites’, Teachers College Record, 2009.

7. A. McAfee, E. Brynjolfsson, T. H. Davenport, D. J. Patil, and D. Barton, 'Big data: the management revolution', Harvard business review, vol. 90, no. 10, pp. 60–68, 2012.
8. A. Merceron, P. Blikstein, and G. Siemens, 'Learning analytics: From big data to meaningful data', Journal of Learning Analytics, vol. 2, no. 3, pp. 4–8, 2015.
9. A. Nouira, L. Cheniti-Belcadhi, and R. Braham, 'An ontology-based framework of assessment analytics for massive learning', Computer Applications in Engineering Education, vol. 27, no. 6, pp. 1343–1360, 2019
10. B. Bakhshinategh, O. R. Zaiane, S. ElAtia, and D. Ipperciel, 'Educational data mining applications and tasks: A survey of the last 10 years', Education and Information Technologies, vol. 23, no. 1, pp. 537–553, 2018.
11. B. Barron, 'Interest and self-sustained learning as catalysts of development: A learning ecology perspective', Human development, vol. 49, no. 4, pp. 193–224, 2006.
12. B. Czerkawski and J. N. Hernández, 'Formal, non-formal, and informal e-learning experiences with emerging technologies: a case study of a Graduate Educational Technology Program', in Cases on formal and informal e-learning environments: Opportunities and practices, IGI Global, 2013, pp. 337–355.
13. B. K. Daniel, 'Big data in higher education: The big picture', in Big data and learning analytics in higher education, Springer, 2017, pp. 19–28.
14. C. Greenhow and B. Robelia, 'Informal learning and identity formation in online social networks', Learning, media and technology, vol. 34, no. 2, pp. 119–140, 2009.
15. C. Greenhow, B. Robelia, and J. E. Hughes, 'Learning, teaching, and scholarship in a digital age: Web 2.0 and classroom research: What path should we take now?', Educational researcher, vol. 38, no. 4, pp. 246–259, 2009.
16. C. Greenhow and L. Burton, 'Help from my "friends": Social capital in the social network sites of low-income students', Journal of Educational Computing Research, vol. 45, no. 2, pp. 223–245, 2011.
17. C. Haythornthwaite, 'Strong, weak, and latent ties and the impact of new media', The information society, vol. 18, no. 5, pp. 385–401, 2002.
18. C. Haythornthwaite and M. De Laat, 'Social networks and learning networks: Using social network perspectives to understand social learning', in Proceedings of the 7th international conference on networked learning, 2010, pp. 183–190.
19. C. J. Atman et al., 'Enabling engineering student success: The final report for the Center for the Advancement of Engineering Education', San Rafael, CA: Morgan & Claypool Publishers, 2010.
20. C. Romero and S. Ventura, 'Educational data mining and learning analytics: An updated survey', Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, vol. 10, no. 3, p. e1355, 2020.
21. C. Shirky, Cognitive surplus: Creativity and generosity in a connected age. Penguin UK, 2010.
22. C. Steinfield, N. B. Ellison, C. Lampe, and J. Vitak, 'Online social network sites and the concept of social capital', in Frontiers in new media research, Routledge, 2013, pp. 122–138.
23. C. Thille, E. Schneider, R. F. Kizilcec, C. Piech, S. A. Halawa, and D. K. Greene, The future of data-enriched assessment. Research & Practice in Assessment, 9 (2), 5–16. 2014.
24. D. A. Erlandson, E. L. Harris, B. L. Skipper, and S. D. Allen, Doing naturalistic inquiry: A guide to methods. Sage, 1993.
25. D. Boud and P. Hager, 'Re-thinking continuing professional development through changing metaphors and location in professional practices', Studies in continuing education, vol. 34, no. 1, pp. 17–30, 2012.
26. D. Clow, 'An overview of learning analytics', Teaching in Higher Education, vol. 18, no. 6, pp. 683–695, 2013.
27. D. Ifenthaler, Designing effective digital learning environments: toward learning analytics design. Springer, 2017.
28. D. Ifenthaler and C. Schumacher, 'Student perceptions of privacy principles for learning analytics', Educational Technology Research and Development, vol. 64, no. 5, pp. 923–938, 2016.
29. D. Ifenthaler, D. Gibson, and E. Dobozy, 'Informing learning design through analytics: Applying network graph analysis', Australasian Journal of Educational Technology, vol. 34, no. 2, 2018.
30. D. Ifenthaler and J. Y.-K. Yau, 'Utilising learning analytics to support study success in higher education: a systematic review', Educational Technology Research and Development, vol. 68, no. 4, pp. 1961–1990, 2020.
31. D. Lazer et al., 'Social science. Computational social science.', Science (New York, NY), vol. 323, no. 5915, pp. 721–723, 2009.
32. D. R. Garrison, T. Anderson, and W. Archer, 'Critical thinking, cognitive presence, and

computer conferencing in distance education', American Journal of distance education, vol. 15, no. 1, pp. 7–23, 2001.
33. D. Laurillard, 'The pedagogical challenges to collaborative technologies', International Journal of Computer-Supported Collaborative Learning, vol. 4, no. 1, pp. 5–20, 2009.
34. D. M. Boyd and N. B. Ellison, 'Social network sites: Definition, history, and scholarship', Journal of computer-mediated Communication, vol. 13, no. 1, pp. 210–230, 2007.
35. D. Scearce, G. Kasper, and H. M. Grant, 'Working wikily', Standford Social Innovation Review, vol. 8, no. 3, pp. 30–37, 2010.
36. D. W. Livingstone, 'Researching expanded notions of learning and work and underemployment: Findings of the first Canadian survey of informal learning practices', International Review of Education, vol. 46, no. 6, pp. 491–514, 2000.
37. E. B. Kozleski, D. Gibson, and A. Hynds, 'Transforming complex educational systems: Grounding systems issues in equity and social justice', Defining social justice leadership in a global context, pp. 263–286, 2012.
38. E. Lazega, 'Rationalité, discipline sociale et structure', Revue française de sociologie, vol. 44, no. 2, pp. 305–329, 2003.
39. E. Wagner and P. Ice, 'Data changes everything: Delivering on the promise of learning analytics in higher education.', Educause Review, vol. 47, no. 4, p. 32, 2012.
40. F. A. Hrabowski III, Boosting minorities in science. American Association for the Advancement of Science, 2011.
41. F. A. Hrabowski III and J. Suess, 'Reclaiming the lead: higher education's future and implications for technology', UMBC Office of the Vice President of Information Technology, 2010.
42. F. Henri, 'Computer conferencing and content analysis', in Collaborative learning through computer conferencing, Springer, 1992, pp. 117–136.
43. G. Cormode and B. Krishnamurthy, 'Key differences between Web 1.0 and Web 2.0', First Monday, 2008.
44. G. Siemens, 'How data and analytics can improve education, July 2011', Retrieved on August, vol. 8, 2011.
45. G. Siemens and P. Long, 'Penetrating the fog: Analytics in learning and education.', EDUCAUSE review, vol. 46, no. 5, p. 30, 2011.
46. G. Veletsianos and C. Navarrete, 'Online social networks as formal learning environments: Learner experiences and activities', The International Review of Research in Open and Distributed Learning, vol. 13, no. 1, pp. 144–166, 2012.
47. H. Chen, R. H. Chiang, and V. C. Storey, 'Business intelligence and analytics: From big data to big impact', MIS quarterly, pp. 1165–1188, 2012.
48. H. Eshach, 'Bridging in-school and out-of-school learning: Formal, non-formal, and informal education', Journal of science education and technology, vol. 16, no. 2, pp. 171–190, 2007.
49. H. Roreger and T. C. Schmidt, 'Socialize online learning: Why we should integrate learning content management with Online Social Networks', in 2012 IEEE International Conference on Pervasive Computing and Communications Workshops, 2012, pp. 685–690.
50. H. Tankovska, Social media-Statistics & Facts. Statista. Com. https://www. statista. com/topics/1164/social-networks, 2021. Last Accessed 2021/09/15
51. J. A. Reyes, 'The skinny on big data in education: Learning analytics simplified', TechTrends, vol. 59, no. 2, pp. 75–80, 2015.
52. J. Bruggeman, Social networks: An introduction. Routledge, 2013.
53. J. Clarke and K. Nelson, 'Perspectives on learning analytics: issues and challenges. Observations from Shane Dawson and Phil Long', The International Journal of the First Year in Higher Education, vol. 4, no. 1, pp. 1–8, 2013.
54. J. Dron and T. Anderson, Teaching crowds: Learning and social media. Athabasca University Press, 2014.
55. J. Furlong and C. Davies, 'Young people, new technologies and learning at home: Taking context seriously', Oxford Review of Education, vol. 38, no. 1, pp. 45–62, 2012.
56. J. Han, M. Kamber, and D. Mining, 'Concepts and techniques', Morgan Kaufmann, vol. 340, pp. 94104–3205, 2006.
57. J. Osborne and J. Dillon, Research on learning in informal contexts: Advancing the field? Taylor & Francis, 2007.
58. J. P. Campbell, P. B. DeBlois, and D. G. Oblinger, 'Academic analytics: A new tool for a new era', EDUCAUSE review, vol. 42, no. 4, p. 40, 2007.
59. J. Sefton-Green, 'Literature review in informal learning with technology outside school', 2004.
60. J. Voogt, O. Erstad, C. Dede, and P. Mishra, 'Challenges to learning and schooling in the digital networked world of the 21st century', Journal of

computer assisted learning, vol. 29, no. 5, pp. 403–413, 2013.
61. J. Wellings and M. H. Levine, 'The digital promise: Transforming learning with innovative uses of technology', 2009.
62. J. Williams, 'Social networking applications in health care: threats to the privacy and security of health information', in Proceedings of the 2010 ICSE workshop on software engineering in health care, 2010, pp. 39–49.
63. K. Gibson, 'The moral basis of stakeholder theory', Journal of business ethics, pp. 245–257, 2000.
64. K. J. Cios, W. Pedrycz, R. W. Swiniarski, and L. A. Kurgan, Data mining: a knowledge discovery approach. Springer Science & Business Media, 2007.
65. K.-W. Lai, 'Digital technology and the culture of teaching and learning in higher education', Australasian Journal of Educational Technology, vol. 27, no. 8, 2011.
66. K.-W. Lai, 'ICT supporting the learning process: The premise, reality, and promise', in International handbook of information technology in primary and secondary education, Springer, 2008, pp. 215–230.
67. K.-W. Lai, F. Khaddage, and G. Knezek, 'Blending student technology experiences in formal and informal learning', Journal of computer assisted learning, vol. 29, no. 5, pp. 414–425, 2013.
68. L. C. Giles, G. F. Glonek, M. A. Luszcz, and G. R. Andrews, 'Effect of social networks on 10 year survival in very old Australians: the Australian longitudinal study of aging', Journal of Epidemiology & Community Health, vol. 59, no. 7, pp. 574–579, 2005.
69. L. Hamilton, What Facebook users share: Lower grandes. Time. 2009.
70. L. Johnson, S. Adams, and M. Cummins, Technology outlook for Australian tertiary education 2012-2017: An NMC Horizon Report regional analysis. The New Media Consortium, 2012.
71. L. M. Miller and D. D. Prior, 'Online social networks and friending behaviour: A self-determination theory perspective', in Proceedings of the Australia and New Zealand Marketing Academy Annual Conference, Christchurch, New Zealand, 2010, pp. 1–9.
72. L. Naismith, P. Lonsdale, G. Vavoula, and M. Sharples, 'Literature Review in Mobile. 5', RESULTADOS Technologies and Learning, 2004.
73. L. P. Macfadyen, 'Overcoming barriers to educational analytics: How systems thinking and pragmatism can help', Educational Technology, pp. 31–39, 2017.
74. M. Bienkowski, M. Feng, and B. Means, 'Enhancing Teaching and Learning through Educational Data Mining and Learning Analytics: An Issue Brief.', Office of Educational Technology, US Department of Education, 2012.
75. M. Callanan, C. Cervantes, and M. Loomis, 'Informal learning', Wiley Interdisciplinary Reviews: Cognitive Science, vol. 2, no. 6, pp. 646–655, 2011.
76. M. Clark et al., 'Academic pathways study: Processes and realities', in 2008 Annual Conference & Exposition, 2008, p. 13.137. 1-13.137. 23.
77. M. De Laat, 'Networked learning', 2006.
78. M. De Laat and B. Schreurs, 'Visualizing informal professional development networks: Building a case for learning analytics in the workplace', American Behavioral Scientist, vol. 57, no. 10, pp. 1421–1438, 2013T. H. Homan, Wolkenridders: over de binnenkant van organisatieverandering. Open Universiteit Nederland, 2006.
79. M. De Laat, V. Lally, L. Lipponen, and R.-J. Simons, 'Online teaching in networked learning communities: A multi-method approach to studying the role of the teacher', Instructional Science, vol. 35, no. 3, pp. 257–286, 2007.
80. M. Giacalone and S. Scippacercola, 'BIG DATA: ISSUES AND AN OVERVIEW IN SOME STRATEGIC SECTORS.', Journal of Applied Quantitative Methods, vol. 11, no. 3, 2016.
81. M. Patten, Questionnaire research: A practical guide. Routledge, 2016.
82. M. Rost, L. Barkhuus, H. Cramer, and B. Brown, 'Representation and communication: Challenges in interpreting large social media datasets', in Proceedings of the 2013 conference on Computer supported cooperative work, 2013, pp. 357–362.
83. M. Warschauer and T. Matuchniak, 'New technology and digital worlds: Analyzing evidence of equity in access, use, and outcomes', Review of research in education, vol. 34, no. 1, pp. 179–225, 2010.
84. N. Carr, 'Is Google making us stupid: What the Internet is doing to our brains', 2008.
85. N. Dabbagh and A. Kitsantas, 'Personal Learning Environments, social media, and self-regulated learning: A natural formula for connecting formal and informal learning', The Internet and higher education, vol. 15, no. 1, pp. 3–8, 2012.

86. N. Khan et al., ‘Big data: survey, technologies, opportunities, and challenges’, The scientific world journal, vol. 2014, 2014.
87. N. Kvartalnyi, Impact of big data on education: history, benefits and examples. 2020.
88. N. Rushby, ‘An agenda for mobile learning.’, British Journal of Educational Technology, vol. 43, no. 3, pp. 355–356, 2012.
89. N. Sclater, A. Peasgood, and J. Mullan, Learning analytics in higher education: A review of UK and international practice Full report, Educause 39 (2016).
90. Okike, E. U., & Mogorosi, M. (n.d.). Educational Data Mining for Monitoring and Improving Academic Performance at University Levels. Environments, 4, 5.
91. O. L. S. BUREAU, ‘US department of Labor’, College Enrollment and Work Activity of 2013 High School Graduates, 2007.
92. P. Blikstein and M. Worsley, ‘Multimodal learning analytics and education data mining: Using computational technologies to measure complex learning tasks’, Journal of Learning Analytics, vol. 3, no. 2, pp. 220–238, 2016.
93. P. J. Piety, D. T. Hickey, and M. J. Bishop, ‘Educational data sciences: Framing emergent practices for analytics of learning, organizations, and systems’, in Proceedings of the fourth international conference on learning analytics and knowledge, 2014, pp. 193–202.
94. P. Mahajan, ‘Use of social networking in a linguistically and culturally rich India’, The International Information & Library Review, vol. 41, no. 3, pp. 129–136, 2009.
95. R. Besbes and S. Besbes, ‘Cognitive dashboard for teachers professional development’, in Qatar Foundation Annual Research Conference Proceedings Volume 2016 Issue 1, 2016, vol. 2016, no. 1, p. ICTPP2984.
96. R. centre Domo, ‘Data Never Sleeps 9.0’, Domo, 2021.
97. R. F. Kizilcec and C. Brooks, ‘Diverse big data and randomized field experiments in massive open online courses: Opportunities for advancing learning research’, G. siemens & c. lang (eds.), handbook on learning analytics & educational data mining, 2017.
98. R. Hammad and D. Ludlow, ‘Towards a smart learning environment for smart city governance’, in Proceedings of the 9th international conference on utility and cloud computing, 2016, pp. 185–190.
99. R. L. Cross, R. L. Cross, and A. Parker, The hidden power of social networks: Understanding how work really gets done in organizations. Harvard Business Press, 2004. https://www.domo.com/learn/infographic/data-never-sleeps-9 (accessed Oct. 19, 2021).
100. R. S. Baker and K. Yacef, ‘The state of educational data mining in 2009: A review and future visions’, Journal of educational data mining, vol. 1, no. 1, pp. 3–17, 2009.
101. R. S. Burt, ‘Network items and the general social survey’, Social networks, vol. 6, no. 4, pp. 293–339, 1984.
102. R. Zhou, ‘Education web information retrieval and classification with big data analysis’, Creative Education, vol. 7, no. 18, p. 2868, 2016.
103. S. B. Shum and R. Ferguson, ‘Social learning analytics’, Journal of educational technology & society, vol. 15, no. 3, pp. 3–26, 2012.
104. S. Cetintas, L. Si, H. P. Aagard, K. Bowen, and M. Cordova-Sanchez, ‘Microblogging in a classroom: Classifying students’ relevant and irrelevant questions in a microblogging-supported classroom’, IEEE Transactions on Learning Technologies, vol. 4, no. 4, pp. 292–300, 2011.
105. S. Dawson, O. Poquet, C. Colvin, T. Rogers, A. Pardo, and D. Gasevic, ‘Rethinking learning analytics adoption through complexity leadership theory’, in Proceedings of the 8th international conference on learning analytics and knowledge, 2018, pp. 236–244.
106. S. Dawson, D. Gašević, G. Siemens, and S. Joksimovic, ‘Current state and future trends: A citation network analysis of the learning analytics field’, in Proceedings of the fourth international conference on learning analytics and knowledge, 2014, pp. 231–240.
107. S. ElAtia and D. Ipperciel, ‘Learning Analytics and Education Data Mining in Higher Education’, in Advancing the Power of Learning Analytics and Big Data in Education, IGI Global, 2021, pp. 108–126.S. Sergis and D. G. Sampson, ‘Teaching and learning analytics to support teacher inquiry: A systematic literature review’, Learning analytics: Fundaments, applications, and trends, pp. 25–63, 2017.
108. S. Kerka, ‘Incidental Learning. Trends and Issues Alert No. 18.’, 2000.
109. S. Kilis, Y. Gülbahar, and C. Rapp, ‘Exploration of teaching preferences of instructors’ use of social media’, European Journal of Open, Distance and E-learning, vol. 19, no. 1, 2016.

110. S. P. Borgatti, A. Mehra, D. J. Brass, and G. Labianca, ‘Network analysis in the social sciences’, science, vol. 323, no. 5916, pp. 892–895, 2009.
111. S. Sergis, D. G. Sampson, and L. Pelliccione, ‘Investigating the impact of Flipped Classroom on students’ learning experiences: A Self-Determination Theory approach’, Computers in Human Behavior, vol. 78, pp. 368–378, 2018.
112. V. J. Rideout, U. G. Foehr, and D. F. Roberts, ‘Generation m 2: Media in the lives of 8-to 18-year-olds.’, Henry J. Kaiser Family Foundation, 2010.
113. W. Clark, K. Logan, R. Luckin, A. Mee, and M. Oliver, ‘Beyond Web 2.0: Mapping the technology landscapes of young learners’, Journal of computer assisted learning, vol. 25, no. 1, pp. 56–69, 2009.
114. Y. Yang, Q. Wang, H. L. Woo, and C. L. Quek, ‘Using Facebook for teaching and learning: a review of the literature’, International Journal of Continuing Engineering Education and Life Long Learning, vol. 21, no. 1, pp. 72–86, 2011.
115. Z.-H. Zhou, ‘Learnware: on the future of machine learning.’, Frontiers Comput. Sci., vol. 10, no. 4, pp. 589–590, 2016.
116. Z. K. Papamitsiou and A. A. Economides, ‘Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence.’, J. Educ. Technol. Soc., vol. 17, no. 4, pp. 49–64, 2014.