Learning Analytics in Mobile and Ubiquitous Learning Environments

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ABSTRACT
Learning analytics (LA) is one of the promising techniques that has been developed in recent times to effectively utilise the astonishing volume of student data available in higher education. Despite many difficulties in its widespread implementation, it has proved to be a very useful way to support failing learners. An important feature of the literature review of LA is that LA has not provided a significant benefit in terms of learner mobility to date since not much research has been carried out to determine the importance of LA in facilitating or enhancing the learning experience of mobile learners. Therefore, this paper describes the potential advantages of using LA techniques to enhance learning in mobile and ubiquitous learning environments from a theoretical perspective. Furthermore, we describe our simplified Mobile and Ubiquitous Learning Analytics Model (MULAM) for analysing mobile learners' data which is based on Campbell and Oblinger's five-step model of learning analytics. Finally, we answer the question why now might be the most suitable time to consider analysing mobile learners' data.

Author Keywords
Mobile learning , M-learning , Ubiquitous learning , U-learning , Learning Analytics , Mobile Learning Analytics , MLA, Ubiquitous Learning Analytics, ULA.

INTRODUCTION

The wide range of available mobile and communications technology options plays a vital role in extending the use of mobile devices for different purposes instead of merely functioning as phones to make calls and send text messages. More importantly, these different technologies are compatible with almost all handheld devices. This technological facilitation has encouraged educators to utilise mobile technology in education as an instructional tool for learning, which is widely known as mobile learning or m-learning. In addition, it has also encouraged the implementation of ubiquitous computing in education. For example, it provides learners with the context-based learning materials to help them build their own knowledge based on their context and to share it easily with others, without the constraints or limitations of time and place. This is referred to as ubiquitous learning (u-learning) or pervasive learning (p-learning).

Educators who incorporate mobile devices into their learning strategies would derive great benefit from this unprecedented opportunity to engage learners since access to the internet via mobile phones is increasing at a rapid rate. A recent survey found that the percentage of mobile users who access the internet via their mobile devices in the UK is 59%[1], whereas in both the US[2] and Saudi Arabia[3], the percentage of users is 66%. It has been observed that the number of mobile users is continuously increasing; it is estimated that there are over five billion mobile subscriptions around the world (ITU, 2011). Moreover, by 2015, it is estimated that 80% of people will access the internet using their mobile devices (Johnson, Smith, Willis, Levine, & Haywood, 2011). The increasing number of mobile users might play a key role in increasing the volume of data that is produced. A study conducted by the IDC (2008) on the existing volume of digital data found that the rapidly expanding 'digital universe' was expected to grow to 1.2 million PB, or 1.2 zettabytes (ZB), by 2010 and to reach 35 ZB by 2020 (Reinsel et al., 2007).

With the current deluge of data from disparate sources, the potential exists for analytics to increase the value of such data and the understanding of the situations involved. This leads to speculation regarding the sorts of questions that could be answered by analytics. According to the matrix developed by Davenport et al. (2010), six questions can be answered through the effective use of data and analytics, and answering these questions might help many organisations to address many of their problems (see Table 1). The questions are

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[1] http://www.thinkwithgoogle.com/insights/library/studies/our-mobile-planet-United-Kingdom/
[2] http://www.thinkwithgoogle.com/insights/library/studies/our-mobile-planet-us/
[3] http://www.thinkwithgoogle.com/insights/library/studies/our-mobile-planet-Saudi-Arabia/

divided into two groups. The first group concentrates on the effective use of the data. The 'past' information cell reports to the organisation what happened in the past, but it does not involve any analytics. However, by applying the rule of thumb, the organisation can generate alerts in the present. In addition, through the exploration of past patterns, it is possible to create some assumptions about the future. The first group of questions provides informative reports about what is happening rather than why something occurs or how it may recur in the future.

The second group of questions requires advanced analytical tools and methods to carry out comprehensive investigations in order to gather new insights. Using some statistical models and tools, it is possible to gain an insight into the past and thereby highlight possible factors that caused a past occurrence. In addition, it is possible to gain real-time insights which in turn can help an organisation to understand what is happening at the present time and can assist in the formation of recommendations to ameliorate the situation. Finally, future insights can be attained by adhering to predetermined optimisation and simulation techniques that assist in understanding both the past and the present and thereby enable predictions with respect to possible future results. Indeed, the optimal use of data can play an important role in increasing understanding of the past, present and future, improve the accuracy of this understanding and enable smarter decision-making.

	Past	***Present***	***Future***
Information	What happened? (Reporting)	What is happening now? (Alert)	What will happen? (Extrapolation)
Insight	How and did it happen? (modeling, experimental design)	What's the next best action? (recommendation)	What's the best/worst that can happen? (prediction, optimisation, simulation)

Table 1: Key questions addressed by analytics (Davenport et al., 2010)

The move towards using data to make decisions has been considered in many domains, such as business and medicine, which reflects the value of analytics. In education, analytics is of great importance since it can assist in solving many educational problems, such as student engagement which is anticipated to emerge as a problem owing to the growing complexity and sophistication of higher education research, practice and policy. The issue of student engagement is becoming ever more critical, as it is a process that might enable educators to indicate students' attitudes towards universities and their academic and non-academic activities. Moreover, student engagement identifies the nature of the relationships that exist between students, academics, university resources and academia in general. Identifying these relationships might help to provide insights into the relationship between student engagement and their academic achievement, and the potential for improvement. Consequentially, measuring levels of engagement is of particular importance. It is in light of this issue that the application of analytics could prove to be very useful (Beer, Clark, & Jones, 2010).

For educators, having the ability to analyse the learning activities of mobile learners is likely to be of great value. In the mobile environment, learning materials can be accessed on the move, and the learner does not need to be fixed in one location. Learning on the move requires an understanding of the pattern of communication of learners among themselves and the patterns of the interaction between students and their learning materials. However, in the literature of LA, it is clear that there have been many efforts to make use of non-mobile students' data that is retrieved from different university systems. However, the issue of mobile learners' data has not been addressed sufficiently, and to date only limited research has been conducted in this area. As a result of this gap in the literature, this paper will describe the possible impact of LA on the mobile and ubiquitous learning environment from a theoretical perspective.

This paper is organised as follows: Section 2 briefly describes the concept of learning and academic analytics while Section 3 justifies the significance of Mobile Learning Analytics (MLA). Section 4 discusses the value of Ubiquitous Learning Analytics (ULA) by presenting two possible kinds of learner interaction with computers. In Section 5, we present our suggested MULAM analytical models. Section 6 answers the question why now might be the most suitable time to consider analysing mobile learners' data. Section 7 concludes the paper.

LEARNING AND ACADEMIC ANALYTICS

Higher education is a field where records provide an astonishing amount of data about its participants, such as students and teachers, its facilities and curricula (Campbell & Oblinger, 2007; George Siemens & Phil Long, 2011). With the wide utilisation of communication technologies in learning, the amounts of data about students and their learning activities are accumulating at a rapid pace. Consequently, this utilisation of technologies has played an important role in opening new and unprecedented windows of opportunity to use this available data to measure the students' levels of engagement quantitatively (Beer, Clark, & Jones, 2010), to identify those students who are at risk, assess their progress and help them before it is too late (Barber & Sharkey, 2012), evaluate student dropout rates and improve the rate of student retentions (Lauría, Baron, Devireddy, Sundararaju, & Jayaprakash, 2012). Learning and academic analytics are tow concepts introduced which clarified how students' data might be used and analysed. This section briefly describes the concept of learning analytics and academic analytics along with the difference between them.

LA has been introduced to examine the potential of analytics to improve students' learning. According to 1st International Conference on Learning Analytics and Knowledge[4] , LA is defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs". The focus of learning analytics is on the learners and their academic performance. The data about their academic performance or their learning behaviour can be collected from different resources, such as their interaction with university learning systems. The main goal of this analysis is to identify the learners who might be struggling academically as early as possible, to allow for implementing some early intervention strategies that might help such students to succeed. Johnson, Smith, Willis, Levine, & Haywood (2011) stated that, "The larger promise of learning analytics, however, is that when correctly applied and interpreted, it will enable faculty to more precisely identify student learning needs and tailor instruction appropriately". It is clear that learning analytics focus more on the learning process, which mainly involves students, teachers and learning materials.

The term academic analytics was firstly introduced by Goldstein and and Katz: "the term academic analytics is our imperfect equivalent for business intelligence. We use it to describe the intersection of technology, information, management culture, and the application of information to manage the academic enterprise" (Goldstein and Katz, 2005) .There are many different opinions about what academic analytics means. For instance , (Arnold, 2010) reports that "Academic analytics helps address the public's desire for institutional accountability with regard to student success, given the widespread concern over the cost of higher education and the difficult economic and budgetary conditions prevailing worldwide.". In addition, some researchers consider academic analytics as a new way of applying business intelligence in an academic setting to provide data with the emphasis being on institutional, regional, and international levels (George Siemens and Phil Long, 2011). In addition, it was stated that "analytics marries large data sets, statistical techniques, and predictive modelling. It could be thought as the practice of mining institutional data to produce actionable intelligence" (John P. Campbell, 2007).

Generally, the focus of the academic analytics is on the institutional data which can be used at the administrative level, which in turn helps build a better understanding that can be used to determine the prospective universities' educational and administration strategies, for example. It helps in building a predictive model which allows admissions offices for example to know what to expect in terms of the size and composition of a prospective entering class. It is worthy of note that administrative departments, such as admissions and fundraising are believed to be the most common users and beneficiaries of analytics in higher education today (George Siemens and Phil Long, 2011). To summarize the main difference between them , it can be said that academic analytics clarifies the role of data analytics at the institutional, administrative and policy making levels. The scope of learning analytics on the other hand is not as broad as academic analytics as it focuses more on the role of data analytics at the learning process level.

There are many successful examples that show the role of analysing the students' data in enhancing their learning. For instance, Macfadyen & Dawson (2010) developed an early warning system, which revealed the relationship between the students' online participation and their academic status. One of the more well-known examples of how student data has been used to enhance learning is the 'Course Signals' application, which was developed at Purdue University. Course Signals is a student success system that identifies academic and behavioural issues early and notifies students and instructors in sufficient time that a recommended course of action can be provided to help students achieve their full potential in a course and also help minimise course failure (Arnold, 2010).

MOBILE LEARNING ANALYTICS (MLA)

MLA focuses mainly on the collection, analysis and reporting of the data of mobile learners, which can be collected from the mobile interactions between learners, mobile devices and available learning materials; it is also supported by the preregistered data about learners in different university systems.

In mobile learning environment, the nature of interaction between learner and mobile device takes the explicit form of interactions (Aljohani, Davis, & Loke, 2012). Based on this form of explicit interaction, the role of

[4] https://tekri.athabascau.ca/analytics/

MLA might be realized by analysing the mobile learners' data resulted in tow main interactions activities. The first one is the interaction between learner and available learning materials; this is called Explicit Learner-to-Learning Materials Interaction. Second, the interaction among learners, this is called here Explicit Learner-to Learner Interaction.

Explicit Learner-to Learner Interaction

Learning on the move is the foundation of the mobile learning environment. Since learners are not required to remain in a specific location, learning activities can occur without the normal physical constraints and greater learning flexibility is possible. Thus the learning interaction with learners can take place as long as learners carry their mobile devices. MLA can assist in developing knowledge regarding the way in which explicit mobile interactions with learners might improve learning. Analysing mobile learners' data generated as a result of this explicit interaction between students might provide useful information and lead to an understanding of the pattern of interaction between learners. Beyond the mobile learning environment, a useful tool known as Social Networks Adapting Pedagogical Practice (SNAPP) provides a visual representation of the interaction between students in relation to their activities on discussion forums. It enables teachers to identify which students are participating in discussions. SNAPP also illustrates comprehensively how interactions between students can be analysed (Dawson, Bakharia, &Heathcote, 2010).

Explicit Learner-to-Learning Materials Interaction

MLA might offer teachers the opportunity to understand the pattern of the explicit interactions between mobile learners and their learning material. One of the advantages of utilising MLA in the mobile learning environment is the possibility of evaluating whether the interaction between the learner and their learning materials is proving successful in the achievement of the designated learning objectives. In this context, mobile devices are used by learners to specifically study certain topics. The utilisation of MLA may provide a greater understanding of the efficacy and the quality of the learning process as it occurs in the interactions between learners, the educator and the curriculum. MLA may also offer the possibility of developing learning in the mobile environment through an analysis of the time spent by learners on specific activities, their preferred learning styles, their preferred learning times and the frequency of their access. This could allow for the provision of more customised learning materials for learners. Moreover, educators and students may acquire better knowledge of academic progress. Zoodles [5] is a good example of the value of implementing MLA. Zoodles has many features which provide a safe learning environment for young learners. The most important feature in the context of this paper is the dashboard which shows parents the learning activities that children have completed based for each subject, e.g. maths, reading, science, along with snapshot of their sketching.

UBIQUITOUS LEARNING ANALYTICS (ULA)

Following the development of sensing technologies it is now more possible to attain contextual data, such as times and locations, regarding the learners' use of various technologies, for example WiFI, GPS and RFID. This is the most significant aspect which distinguishes the ubiquitous learning environment from the mobile learning environment. The use of learner contextual data can assist in enhancing the interaction between learners, mobile devices and learning environments. The ubiquitous learning application retrieves contextual data about learners to improve the interaction between the mobile device and learner. The necessary learning materials are then provided to the learner implicitly based on the collected contextual information, allowing the learner to interact explicitly. The required contextual data is retrieved on an on-going basis to facilitate the explicit interaction through mobile devices (Aljohani, Davis, & Loke, 2012). Collecting the contextual data in this environment is useful in assisting learners to concentrate more on necessary tasks and allows for time to be saved on considering how a task can be performed.

ULA is concerned with the retrieval, analysis and reporting of the data of mobile learners along with their contextual information. This data might be retrieved from the mobile interactions between learners, mobile, learning environments and the provided context-based learning materials. This can be supplemented by existing data regarding learners from different university systems.

The effectiveness of this environment is derived from the utilisation of integrated sensing technologies of modern mobile devices. However, even though this is the case, little research has been carried out regarding the potential of LA in this learning environment. The implantation of ULA in this environment could offer a better understanding of the manner in which learning occurs in this heterogeneous learning environment. This could provide a good insight into the different requirements of each learner. Moreover, this might be of significant value in developing more functional educational software which would be more effective to deal

[5] http://www.zoodles.com/en/home/marketing

with the special features of the ubiquitous learning environment. In this section, the value of ULA is discussed by considering two possible kinds of interactions. The first is the interaction between learners and their contexts, referred to as Implicit Learners-to-Context Interaction. The second is the interaction between learners and context-based learning materials, referred to as Implicit/Explicit Learner-to-Context-Based Learning Materials Interaction.

Implicit Learners-to-Context Interaction

Analysing implicit contextual information has the potential to improve knowledge of the patterns of interactions of students with their context. The contextual information about a learner, e.g. location and time, is collected automatically by the mobile application using different sensing technologies, e.g. RFID, GPS and WiFi. The collection of this contextual information does not necessarily require any direct intervention from learners, however the use of such data could make learning more effective. For instance, the System for Capturing and Reminding of Learning Log (SCROLL) is an ubiquitous learning log system which has been developed by Mengmeng, Ogata, Bin, Uosaki and Yano (2012). This system can be considered as a good example of the potential that analysing the interactions between learners and their context provides. SCROLL utilises past retrieved collected contextual data about learners which in turn offers learners the potential to benefit from the context-based logs: when learners are in the place where the log was written, it can assist them in remembering what they learnt.

The RunKeeper[6] mobile application is also a good example of the successful utilisation of the analysis of the implicit interaction between a user and their collected contextual data, however this example is not derived from within the formal learning environment. RunKeeper utilises GPS to track the running locations of its users which is thus considered to be implicit collected contextual information. This data allows RunKeeper to provide users with, for example, the opportunity to track their fitness or health history. These statistics are displayed to users on their personal dashboard which can be accessed using their mobile. Most importantly, by analysing the users' collected location information, RunKeeper allows users to compare workout information from the locations they have visited. Also, it provides users with the ability to share fitness and health data with other users in their network.

Implicit/Explicit Learner-to-Context-Based Learning Materials Interaction

The collection of contextual information on learners has facilitated the enhancement of learning, especially in outdoor activities (Hui-Chun & Gwo-Jen, 2010; Shu-Chen et al., 2010). This can helps learners to concentrate more on learning and the relevant material. However, in certain cases, further research and analysis into the interaction between learners and provided context-based learning materials is required. ULA could help develop an understanding of the patterns of interaction between learning and the context-based learning materials. The potential use of ULA might depend on the collection of data and suitable analysis of the interactions between learners and context-based learning materials. ULA could be used with the assistance of analytical methods such as data mining and social network analysis, providing further understanding of learner and context-based learning materials interaction. The ULA report may provide details such as the amount of time spent on learning, preferred contextual objects for interaction, preferred times of context-based learning and learning styles. This information would help to categorise students with similar learning features and needs. Additionally, it could help identify those learners who are not participating effectively on learning to a desired standard. The collection of the aforementioned information in this section might be of great use in tracking the progress of learners and assisting them effectively during the learning experience.

MOBILE AND UBIQUITOUS LEARNING ANALYTICS MODEL (MULAM)

There are many suggested models for learning analytics, one of which is the Campbell and Oblinger five-step model of learning analytics namely Capture, Report, Predict, Act and Refine (Campbell & Oblinger, 2007). This model provides a useful understanding of how learning analytics can be applied. In the spirit of this model, we propose our simplified model, which will be followed in our investigation in the m-learning and p-learning environments (see Figure 1).

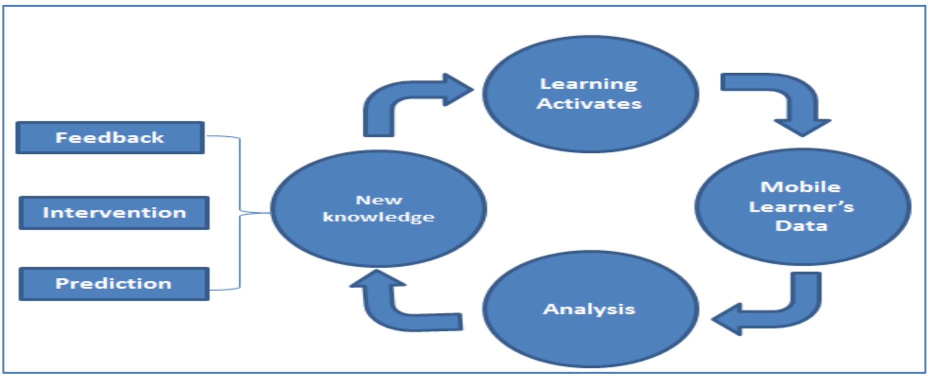

Figure 1: Mobile and Ubiquitous Learning Analytics Model (MULAM)

Learning Activities

The model starts with the specification of the learning activities as the core requirement that needs to be understood before conducting the analytics. Specifying the targeted learning activities plays a key role in increasing the accuracy of the collected data, meaning that it helps to answer the question, “which data could provide useful insights” (Campbell & Oblinger, 2007). In addition, specifying the learning activities might limit the number of required data which might turns to decrease the degree of seriousness or the challenges of analytics.

Mobile Learners’ Data

Upon successfully specifying the learning objectives of the learning activities, the needed learners’ data can be collected. In the literature, it is noticeable that some of the LA research has collected a high volume of data from different systems; however, a large portion of this data was not used as it was not relevant to the investigation.

Analysis

The analysis of data is the most important step and helps to make sense of the collected data and to make sure that the planned learning objectives of the specific learning activities have been met. Furthermore, it provides an insight into the learning difficulties that students might suffer from in the early stages, which will give the teacher the information needed to assist students before it is too late. There are many methods of analysing the collected data; these are generally based on the desirable outcome and how fast this outcome is needed. For instance, it can be done using statistical methods such as mean, standard deviation. In addition, data mining techniques can be used; data mining has two famous objectives, which are predictive and descriptive objectives. The predictive objectives of data mining, such as classification and regression, can be achieved using part of the available variables to predict one or more of the other variables. On the other hand, the descriptive objectives of data mining, such as clustering and association rule discovery, can be achieved by identifying the patterns that describe the data. This approach has the advantage of being easily understood by the user (Han, Kamber, & Pei, 2011). Analysis can also be done by using the social network analysis methods in which the interactions between students can be understood (Siemens & Baker, 2012).

New Knowledge

Upon successful completion of the analysis phase, it is likely that new knowledge or tacit knowledge will be found. Based on our model, this new knowledge can be used in three ways. First, it can be fed back to the learners in their personal dashboard, which will serve to increase their awareness of their performance, especially if there is a comparison between each student’s academic achievement with his/her peers. Second, it can be used to develop suitable intervention strategies that can be applied to solving the learning problems that have been encountered. Third, the new knowledge helps in building a predictive model, which, for example, allows teachers to know what to expect in terms of the number of students who might be able to complete the class or might leave. These three ways can be used separately, or together.

THE RIGHT TIME FOR MLA AND ULA

The present is the best time to introduce MLA and ULA in order to enhance academic achievements as well as solve the academic problems that students might face. Firstly, as previously mentioned, there has been a noticeable increase in the number of mobile users. In addition and most importantly, there is clear technical support for the building of applications for handheld devices. Building applications for small devices used to be constrained by small file sizes, low memory, display and power capacity. However, currently, there are many programming languages and technologies which play a key role in increasing the possibility of creating applications for constrained devices. These programming languages take into consideration the obstacles from which small devices suffer. This section reviews a selection of these promising technologies that support application building for mobile devices. It is important to clarify the difference between native and mobile web applications as a contextual prelude to a discussion in this regard. A native mobile application is an application that has been developed using a specific language to be utilised on a specific platform. For instance, the iPhone platform requires the mobile application to be written in objective C programming language. However, mobile web applications have not been developed to work in specific mobile devices.

Html 5 support

The continuous improvement of HTML5 open new windows of opportunity to build a mobile application that can be used across all platforms and plays a key role in overcoming the problem of platform dependency. This was not possible a few years ago; it was difficult to develop mobile applications that worked across all platforms. Even though some might prefer a native application as it makes use of all available device features, HTML5 holds great potential for the future of learning through mobile devices (Levy, 2011).

jQuery Mobile
It is HTML5-based user interface system .It provides broad level of support for the design of interfaces for different mobile platforms and therefore plays a role in overcoming the problem of platform dependences.

Phonegap
It is a cross platform native development framework that enables one to write native applications for seven different platforms, such as IPhone, Android and Symbian, using HTML, JavaScript and CSS. It allows you to convert the web application written using HTML, JavaScript and CSS to a native application based on the targeted platform. In addition, it allows one to use some of the device's specific features, such as Accelerometer and Geolocation. For instance, it converts an HTML5 mobile website to objective C to work in iPhone and iPad devices.

Highchart
Highchart is a very good JavaScript library that allows the data of lightweight devices to be visualized. Not only does it work perfectly with HTML5, but it provides different kinds of charting ranging from a simple pie chart to a more advance dynamic chart. Highchart is a very useful tool that can be used to visualise the data generated by MLA and ULA.

Dreamwehver CS6 and ASP.net MVC4
Dreamweaver CS6 incorporates the stable jQuery Mobile version, HTML5, CSS and JavaScript frameworks which are designed to create an optimised mobile website. Also, it provides the multiple views feature which is very useful in that it allows the user to see how the mobile website will look based on the targeted device sizes, such as an iPhone versus an iPad. ASP.net MVC4 has built-in support to build mobile websites as well.

CONCLUSION

Learning analytics is a landmark technique which has been developed in recent times and which can be utilised to process large volumes of university students' data. Although there are obstacles with its widespread implementation, it has been shown to be a useful method for supporting students who struggle academically as well as students with good academic performance.

Two notions have been introduced in this paper: Mobile Learning Analytics (MLA) and Ubiquitous Learning Analytics (ULA). In terms of MLA, the major source of data comes from mobile learners' data. Non-mobile learner data, which already exists in different university systems, could also provide value in this area. ULA also analyses the data of mobile learners but goes a step further by analysing collected contextual mobile learners' data. In addition, ULA supports its analyses by using existing data about non-mobile learners in various university systems as well. In this respect, ULA can be considered more comprehensive than MLA.

This paper offered an understanding of the importance of MLA by discussing the two possible kinds of explicit interactions between learners, mobile devices and learning material in the mobile learning (m-learning) environment. Furthermore, it provided an overview of the significance of ULA by considering the implicit and explicit modes of interaction between learners, mobile devices, learners' context and the context-based learning materials in the ubiquitous learning (u-learning) environment. In addition, it proposed a Mobile and Ubiquitous Learning Analytics Model (MULAM). Finally, it outlined some of the most important technological developments that could facilitate the move towards the implementation of MLA and ULA techniques for the analysis of mobile learners' data.

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