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NEED OF ESTIMATION OF LEARNING IN MOOC COURSES USING LEARNING ANALYTICS: A GAP IDENTIFICATION

Kapil Mohan Garg,
Research Scholar, Galgotia's University, Greater Noida, UP, INDIA.
Postal Address: K B 78/4 Kavinagar, Ghaziabad, INDIA. PIN-201002
E-mail: kapilmohangarg@gmail.com

Dr Adarsh Garg
Professor, Galgotia's University, Greater Noida, UP, INDIA.
E-mail: gargadarsh29@gmail.com

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Abstract

Introduction: *Learning analytics(LA) is an evolving field which utilises analytic tools like BI, social media data analytics, etc., to improve learning and education. It is basically the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs. This process generates lots of data that need to analyzed and put to fruitful use so that learning can be enhanced. Based on literature review, this paper presents the need for learning estimation on MOOC Courses using LA.*

Methodology: *A four stage process is followed to formulate this study as a literature review and gap identifications that concerns Learning Analytics in MOOC. The stages includes extensive search of related literature from reputed national and international academic works, studying the literature and selecting the principal studies, examining and tabulation of various expects of studies, like objectives, analysis tools used, major findings, etc. and reporting the review in form of gap analysis.*

Findings and discussion*: Findings suggests that apart from LA approaches, its implementation in education and learning is more predominant objective. Sophisticated predictive and regression models are applied on gathered data for obtaining better meaningful insights. But no significant study focuses on Management education or Indian Context or both. Findings shows that all online courses are doing traditional evaluation using online assignments, tests etc. to issue certificates. It is found that there are still numerous unexplored areas related to LA and MOOC method to estimate/calculate/ proposes the quantification of learning of students/learners in MOOC courses.*

***Conclusion and recommendations**: In relation to LA and MOOC, it is opined that there is very crucial insight on estimation of learning is required in MOOC for quantification of learning of students/learners for the development of powerful and beneficial learning services.*

1. Introduction

As a field of academic study, according to Lang and Siemens (2017) Learning Analytics has grown remarkably is presently is the fastest and most emerging field of educational research (Lang& Siemens, 2017). It is utilizing e-learning implementations in education and educational data mining, web analytics and statistics. In recent years, increasing numbers of digital tools and MOOC (Massive Open Online Courses) courses for the education, the inclusion of learning analytics comes to some extent, and these tools are now in the early stages of adoption.

There are numerous MOOC course available online like Khan Academy, Courseera, Swayam, etc that are popular in India. The total number of MOOCs that have been announced stands at 9,400 in year 2017, up from 6,850 2016. The top five MOOC providers by registered users are Coursera – 30 million registered Users, edX – 14 million, XuetangX – 9.3 million, Udacity – 8 million and FutureLearn – 7.1 million registered users (Update 10 March, 2018). Shah (2018) estimated that till date, over 800 universities around the world have launched at least one MOOC. MOOC providers are also partnering with companies (mostly tech) to launch courses (Shah, 2018)

1.1. Motivation And Rationale Of The Study

This is nearing to a decade since the start of the "modern" MOOC movement (which traces its birth to late 2011, when the first Stanford MOOCs took off), for the first time, there is a slowdown in the number of new learners being added. The possible reason could be the difference between expected and accrued benefits from the courses or lack of learning among the users.

The final study is expected to contributes to the field of learning analytics from the perspective of estimating the learning score from MOOC courses that helps in quantifying the learning from the courses and in turn will help in creating better learning patterns

1.2. The Research Questions

The main concern of this paper is to present use and need of estimation of learning in online courses based on the gap analysis. Unlike the previous studies, current study makes use of online data values and shall create a predictive model to quantify learning in online educative courses. After comprehensive study of various literatures, prima facie, Elias (2011) suggested the five steps of analytics that is capture, report, predict, act, and refine are resulting in capture of meaningless data which is then reported as information (Elias, 2011). This information is irrelevant in quantifying the learning.

Hence, the researcher tries to address the following research questions, which are differentiated into primary (Generalized: created to accomplish review goals) and secondary (Precise: to improve primary).

- **RQ1(Primary) -.** To identify the basic research objectives of Learning Analytics (in quantifiable/measurable terms/variables/metrics)
  - **RQ1.1 (Secondary) -** To identify the methods employed to achieve the goals mentioned in primary RQ1.
- **RQ2(Primary) –** Explore the futuristic possible experiments with the Learning Analytics
  - **RQ2.1 (Secondary)** – To Identify the requirement of Quantifying Learning using some predictive model which can be used to lay groundwork for the idea of quantifying learning

2. Research Methodology

Researcher used the below given methodology suggested by Papamitsiou and Economides (2014), to formulate this study, as a literature review and gap identifications that concerns Learning Analytics in MOOC (Papamitsiou& Economides, 2014). For literature review process, researcher followed a four stage process as mentioned: a) Searching the literature for the concerned subject(LA), b) studying the literature and selecting the principal studies, c) examining and tabulation of various expects of studies, like objectives, analysis tools used, major findings, etc. and d) reporting the review in form of gap analysis.

The first stage was primarily about collection of relevant literature. Researcher comprehensively examined international online resources like Google Scholar, Journal of Learning Analytics, web resources of SOLAR (Society for Learning Analytics Research) and other databases of convincing academic resources like Scopus.

The search time frame was primarily within last eight years, that is between 2011 and 2019. This time period was selected as during this period LA was formally recognized and major utilization and growth in LA is during this period only. This collection of literature resulted into 110 relevant papers/articles. While accessing all the relevant articles and after neglecting the papers with duplicate or similar findings, 20 of all the literatures were acknowledged are the one that are more essential to our review and Gap Analysis. Another prominent reason to select this period is that in late 2011, first Stanford MOOCs took off.

In the end, non-statistical approaches were applied for assessment and interpretation of findings of the short listed literatures and the results of short listed literature is tabulated using MS Excel

3. Findings and Results

In this subdivision, we present our results based on the analysis of the collected and short listed literature. No standard statistical tools are utilized to assess or evaluate the collected literature. Rendering to the Research Methodology discussed above, most of the available literature are conceptual and exploratory whereas very few are Experimental and Analytical in nature. Studied literature were quite varied in terms of titles or topics but most of them either focused **on Science and Math or were on the possible application of LA in general.**

Table 1. Classification of Literature on the basis of Research Design

Research Design	Literature Reference (Authors / Years)
Conceptual	Brouns&Firssova, 2017; Elouazizi, 2014; Khalil et al., 2016; Ferguson, 2012; Wise et al., 2018; Sclater et al., 2016; Jørnø&Gynther, 2018; Wise et al., 2016;
Exploratory	Ferguson et al., 2016; Dietze et al., 2016; Bergner, 2017; Liu & Koedinger, 2017; Khalil & Ebner, 2016; Maseleno, 2018; Patwa et al., 2018; O'Connell et al., 2018; Peach et al., 2019;
Analytical	Brooks & Thompson,2017; Nguyen et al., 2018;
Experimental	Mahzoon et al, 2018; Peach et at., 2019;

Source: Developed for this research (paper).

In the studied literatures and according to Brouns and Firssova (2017) , the analysis is mainly focused on variables like Metrics - measures of activity levels, i.e Frequency, proportion of lessons completed, no. of assignments, quizzes completed, materials read or downloaded, frequency of interactions, sequences-patterns of interactions (Brouns&Firssova, 2017). Also, Elouazizi (2014) states that analysis is mainly done on metrics like Instructional practices, Action research, Assessment practices, Learning processes, teaching effectiveness, Teaching evaluation and Similar (Elouazizi, 2014). Authors gathered data from Open data sets or from various literatures, temporal data of online MOOC discussions and many other similar annotations. The data, in different literatures, then applied with various analysis tools and methods to achieve intended results. Table 2 exhibits the selected literatures and the Analysis tools employed. The most widespread process seems to be classification followed by Temporal Data Analysis and Predictive Modelling.

Table 2. Classification of Literature on the basis of Data Analysis Approaches and Tools

Data Analysis Approaches and Tools	Literature Reference (Authors / Years)
Classification and Research Feedback or Author(s)'s Experiential learning	Bergner, 2017; Jørnø&Gynther, 2018; Wise et al., 2018; Sclater et al., 2016; Brouns, et al., 2017; Ferguson et al.,2016; Dietze, et al.,2016; Ferguson, 2012; Peach et al., 2019;
Temporal Data Analysis	Nguyen et al.,2018; Mahzoon et al, 2018; Peach et at., 2019; Wise et al., 2016.
Predictive Modelling	Brooks & Thompson, 2017; Khalil & Ebner, 2016;
Cognitive Modeling and Data Mining	Liu & Koedinger,2017; Khalil et al., 2016;
Visualization	Khalil & Ebner, 2016; Peach et al., 2019; Brouns&Firssova, 2017;
Descriptive Statistics / Regression	Maseleno, 2018; Patwa et al., 2018; O'Connell et al., 2018; Peach et al., 2019;
Discovery with models	Elouazizi, 2014;

Source: Developed for this research (paper).

Table 3 exhibits the Literature cataloguing on the basis of Exploration goals or Research Objectives. The mainstream of Literature throws light on LA Approaches in teaching and learnings followed by its implementation in education and futuristic exploitation.

Table 3. Classification of Literature on the basis of Objectives

Objectives of Research	Literature Reference (Authors / Years)
LA Approaches in teaching and Learnings	Brouns&Firssova, 2017; Khalil et al., 2016; Ferguson, 2012; Sclater et al., 2016; Maseleno et al., 2018; Friend Wise et al., 2016; Patwa et al., 2018;
LA Implementation in Education, Learning	Elouazizi, 2014; Ferguson et al.,2016; Brooks & Thompson,2017; Liu & Koedinger,2017; Ferguson,2012; Nguyen, et al.,2018; Friend Wise et al., 2016; Patwa et al., 2018;
Future Challenge, Trends and Exploitation	Ferguson et al.,2016; Khalil Mohammad, et al., 2016; Bergner, 2017; Liu & Koedinger,2017; Mahzoon, et al, 2018; Wise et al., 2018; Sclater et al., 2016; O'Connell et al., 2018;
Potential Analysis	Khalil Mohammad, et al., 2016; Brooks & Thompson,2017; Wise et al., 2018; O'Connell et al., 2018; Friend Wise et al., 2016;
Behavior analysis and performance estimation	Bergner, 2017; Nguyen, et al.,2018; Mahzoon, et al, 2018; Brooks & Thompson,2017; Khalil & Ebner, 2016; Maseleno et al., 2018; O'Connell et al., 2018; Peach et at., 2019; Patwa et al., 2018;
Retention in MOOC Courses	Mahzoon, et al, 2018; Khalil & Ebner, 2016; Sclater et al., 2016; Patwa et al., 2018;
Reference of Resources	Dietze, et al.,2016; Ferguson,2012; Jørnø&Gynther, 2018;

Source: Developed for this research (paper).

3.1. Answer To Key Rsearch Questions Of The Study

This segment is focused on key research questions in the form of findings and answers to the research questions RQ1 and RQ1.1. The other primary question that is RQ2 and its secondary RQ2.1 are being answered in next section along with possible gaps and new research prospects and opportunities.

RQ1(Primary) -. *To identify the basic research objectives of Learning Analytics (in quantifiable/measurable terms/variables/metrics)*

As we can see from Table 3, the basic research objective is to identify LA Approaches in teaching and Learnings. Table 3 suggest that apart from LA approaches, its implementation in education and learning is more predominant objective along with LA implementation in learning and education. Behavior analysis and performance estimation is another important objective in addition to retention in MOOC, behaviour analysis of stake holders and analysis of potential of LA in MOOCs. There are very few reviewed literatures that emphasized on reference of resources.

Dietze, Siemens, Taibi and Dressler (2016) suggests references to Data sets and data that arises from actual learning processes in any domain that is used within research and practice (Dietze, Siemens, Taibi& Dressler, 2016); Jørnø and Gynther (2018) provide an overall indication of how actionable insights are conceptualized and operationalized (Jørnø&Gynther 2018). Precisely stating, the implementation of suitable learning analytics is quite complex. The metrics in learning analytics are connected to goals of the learning activities. MOOCs have different categories of learners who differ in their level of engagement with the course materials and learning activities to meet their personal learning goal. Maseleno (2018) highlights the framework of learning analytics in order to improve personalized learning (Maseleno, 2018). Brouns and Firssova (2017) states that Learning analytics should take that into account and support the learning goal of that particular category (Brouns&Firssova, 2017). Khalil, Taraghi and Ebner (2016) states the principles of engaging Learning Analytics in Massive Open Online Courses (MOOCs) and discussed the capabilities (the good), the dilemmas (the bad) and the out of the bound situations (the ugly) related to LA in MOOCs (Khalil, Taraghi & Ebner, 2016). Sclater, Peasgood and Mullanet (2016) suggest about the LA contributions. According to them, LA could be used as a tool for quality assurance and quality improvement (Sclater, Peasgood&Mullanet, 2016). Patwa, Seetharaman, Sreekumar and Phani (2018) suggests that with the help of learning analytics, there will be increase in learner retention (Patwa, Seetharaman, Sreekumar &Phani, 2018). Finally, Wise, Vytasek, Hausknecht and Zhao (2016) has reviewed the challenges for students' learning analytics use and presented the Student Tuning Model as a concept by which students use learning analytics as part of a self-regulatory cycle (Wise, Vytasek, Hausknecht& Zhao, 2016).

RQ1.1 (Secondary) - *To identify the methods employed to achieve the goals mentioned in primary RQ1.*

Ferguson (2012) identify and states that four significant challenges of LA must be addressed: integrating experience from the learning sciences, working with a wider range of datasets, engaging with learner perspectives and developing a set of ethical guidelines (Ferguson, 2012). Khalil, Taraghi and Ebner (2016) states that Learning Analytics provides various tools and to optimize learning (Khalil, Taraghi & Ebner, 2016). Brooks andThompson (2017) states the Computational and statistical methods are good for predictive modelling have been made available for educational researchers to apply to teaching and learning data and Beyond performance measures, predictive models have been used in teaching and learning (Brooks & Thompson, 2017). Bergner (2017) states that Predictive modelling is one of the most prominent methodological approaches in educational data mining where as an explanatory model can be used to make predictions (Bergner, 2017). Sclater, Peasgood and Mullanet (2016) suggests that LA can act as a tool for boosting retention rates (Sclater, Peasgood&Mullanet, 2016). Further, O'Connell, Wostl, Crosslin, Berry and Grover (2018) suggest the Indicators of evaluation like students' past performance, experience, including GPA and no. of accumulated credit hours, best predict student success (O'Connell, Wostl, Crosslin, Berry & Grover, 2018).

3.2. New Research Prospects and Opportunities

Intakes of previous segment and results of key research questions in the form of findings and answers to the research questions RQ1 and RQ1.1. states that LA is playing very pivotal role in education and learning. Educational exploration by researchers in the field of LA has started applying sophisticated predictive and regression models on gathered data for obtaining better meaningful insights. However, these findings are not completely independent and noteworthy connections helps and could only constitute inadequacies that may not infer futuristic value of findings.

RQ2(Primary) *–Explore the futuristic possible experiments with the Learning Analytics*

Liu and Koedinger (2017) states that design of educational data modelling efforts can yield more explanatory models (Liu & Koedinger, 2017). Through the study of Mahzoon, Maher, Eltayeby, Dou and Grace (2018), it is learnt that prediction of success or failure in a degree program can be based on sequence patterns of grades and activities across multiple semesters (Mahzoon, Maher, Eltayeby, Dou & Grace, 2018). Wise, Knight and Ochoa (2018) suggest that Learning Analytics should include and embrace considerations of time (temporal data) as a way to produce more relevant and impactful results (Wise, Knight & Ochoa, 2018). Patwa, Seetharaman, Sreekumar and Phani (2018) suggests that with the help of learning analytics, learners can keep an eye on their progress and it is also helpful for learners to realize what should get improved to get better learning outcomes (Patwa, Seetharaman, Sreekumar &Phani, 2018).

Also, Wise, Vytasek, Hausknecht and Zhao (2016) proposed the Align Design Framework which enacted in an implementation with validation evidence about how the four principles of Integration, Agency, Reference Frame, and Dialogue/Audience which comprise the framework support and/or hinder students' engagement (Wise, Vytasek, Hausknecht& Zhao, 2016). Very recently, Peach, Yaliraki, Lefevre and Barahona (2019) talks about clusters of learners where cluster analysis can be engaged with statistically distinct patterns, from distributed to massed learning, with different levels of regularity, adherence to pre-planned course structure and task completion (Peach, Yaliraki, Lefevre & Barahona, 2019).

RQ2.1 (Secondary) –*To Identify the requirement of Quantifying Learning using some predictive model which can be used to lay groundwork for the idea of quantifying learning*
Correspondingly, the literature survey discovered a number of new possibilities related to LA and learning in MOOCs.

According to Liu and Koedinger (2017), the relationships between the fields of educational data mining, learning theory and the practice of education could be greatly strengthened with increased attention to explanatory power of models and their ability to influence future learning outcomes (Liu & Koedinger, 2017). Sclater, Peasgood and Mullanet (2016) proposed LA as a tool for assessing and acting upon differential outcomes among the student population and work as an enabler for the development and introduction of adaptive learning (Sclater, Peasgood&Mullanet, 2016).

Nguyen, Huptych and Rienties (2018) revealed in their findings that there is a mismatch between how instructors designed for learning and how students study (Nguyen, Huptych&Rienties, 2018). Students spent less time studying the assigned materials compared to the number of hours recommended by instructors. Also, High-performing students spent more time studying in advance, while low-performing students spent a higher proportion of their time on catching-up activities. Through, Brouns and Firssova (2017), it is also learnt that time spent on task is often considered to be a measure of learning (Brouns&Firssova, 2017). Also, Khalil and Ebner (2016) extracted an algorithm and propose a LA-MOOCs scheme that employ principles such as awareness and feedback for the purposes of predicting student at-risk and notify them beforehand by using an algorithm in order to increase retention rate, improve learning and study their behavior (Khalil & Ebner, 2016) whereas O'Connell et al. (2018) that overall final grades are representative of performance and the amount of time spent working on assignments led to improved grade outcomes (O'Connell et al., 2018). Further, O'Connell et al. (2018) states that these baseline data, lays foundation for interventions that can increase rates of student success in future courses (O'Connell et al., 2018). Very recently, Peach et al. (2019) shows that high performing learners are spread across clusters with diverse temporal engagement, low performers are located significantly in the massed learning cluster, and unsupervised clustering identifies low performers more accurately (Peach et al., 2019)

4. Aftermaths, Gaps and Suggested Recommendations

Above analysis of various literatures, their classifications on basis of Research Design, Data Analysis Approaches and Tools and objectives, some important points that revealed quite a few unmapped issues in this rapidly grown domain. Few of these are:

- Studied literature were quite varied in terms of titles or topics but most of them either focused on Science andMaths or were on the possible application of LA in education / learning. Almost none of the literature mentioned is focused specifically on Management Education.

- At the time of writing this paper, researcher was unable to locate any study related to MOOC and LA in Indian context.
- Most of the studies were focused on student retention, performance improvement or measurement, temporal data analysis and its implementation. At the time of writing this paper, author was unable to locate any studies or researchers that were focused on estimation of learning. However, there are some studies according to which time spent on task is often considered to be a measure of learning.
- All online courses are doing traditional evaluation using online assignments, tests or examinations to issue the certificates.

After studying various literature(s) analysis and measuring gaps, it is found out that there are still many unexplored areas related to LA and MOOC, as mentioned above. There are no known research that proposed any theoretical, mathematical, statistical or predictive models, formulae or strategy to quantify the learning of students or learners in online education. No known research or studies are found by the researcher (till writing this statement) that suggest any method to estimate/calculate/ proposes the quantification of learning of students/learners in MOOC courses. We believe that this active research area can provide lots of future scope and will continue contributing with valuable pieces of work towards the development of powerful and beneficial learning services for researchers and community as a whole.

5. Conclusions

The current paper presents a methodical evaluation of Literature evidence of LA and related research work. We searched the research work and collected established and highly-cited papers and case studies from the dominion of LA and MOOCs, combined. The examination of selected research literature suggests the methodologies and propagation in the mentioned subject matter and discovered the potential and future scope of this emerging field. Along with this, we also synthesized a number of gaps that need the thoughtfulness of researchers working in the area of LA and MOOC. Finally, this paper also recommends a study that shall be objected towards proposing an embryonic model giving an insight on estimation of learning.

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