Review of Literature on the Use of Learning Analytics and Learning Analytical Dashboard (LAD) in Improving Student Performance in Higher Education Institutions in Kenya

Mohammed Swaleh Mohammed

Technical University of Mombasa

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ABSTRACT

Purpose – The purpose of the paper is mainly to review the various literature done on Learning Analytics in higher education institutions in Kenya. From the review it aims at identifying the current status of Learning Analytics in Kenya and proposing recommendations for improvement of the same.

Methodology – The paper uses desktop approach to breakdown the various studies done in Kenya on Learning Analytics in higher education institutions in Kenya and identifies any research gaps/ areas for improvement from the review of literature.

Value – The analysis is valuable to Higher Education institutions in Kenya in coming up with a model that will be used to improve student performance in blended learning through use of learning analytics and learning analytics dashboard.

Findings – the findings of the study revealed that there was limited research on learning analytics in Kenya. Moreover, the current study had not used raw data such as the behavioral pattern of students. Therefore, future study can be done using the raw data from Moodle to develop a model for improving student performance.

Keywords: Learning Analytics, Learning Analytics Dashboard, Blended Learning, Higher Education Institutions

INTRODUCTION

Background of the Study

Overview of Interactive Blended Learning, benefits and challenges

Higher education institutions (HEIs) have embraced blended learning as a way to enhance teaching and learning experiences (Ranjan, 2020). Blended learning combines synchronous (face-to-face) and asynchronous (offline learning) learning experiences that combine the conveniences of offline courses while maintaining in-person contact (Ranjan, 2020).

As per Hadullo (2018), Synchronous E-learning refers to the use of real-time tools like chat rooms and webcasts to conduct live e-learning sessions. Web conferencing platforms provide real-time learning,

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replicating the interactive dynamics of in-person classroom sessions.

In his work, Hadullo defines Asynchronous E-learning as a form of learning that allows learners to proceed at their own pace. This includes the ability to download learning materials, complete assignments, and engage with peers at their preferred time. Emails, discussion forums, and blogs exemplify asynchronous approaches of e-learning.

According to Deepika (2021), blended e-learning provides the following range of tools for delivering material and promoting student participation.

1. **Non-interactive (Linear Methods):** These includes audio/ video files such as podcasts, recordings and screencasts which provide easy means of accessing information in multimedia formats. It also includes option of e-textbooks such as portable and searchable electronic books that offer a versatile alternative to conventional textbooks.
2. **Interactive Methods (Collaborative Learning):** this involves the use of virtual classrooms, online group discussions, online blogs, online assessments and simulations after every chapter. The simulations can be in form of virtual labs. These all makes online learning interactive and collaborative through enabling real-time interactions through webcams and chats.

Therefore, Interactive blended learning is an educational approach that combines synchronous (face-to-face) learning with asynchronous (offline) learning of digital media, allowing for a mix of direct instruction and self-paced learning. This methodology leverages the strengths of both in-person and online learning experiences, creating a more integrated educational approach (Ranjan, 2020).

According to Bouilheres et.al (2020), Blended Learning, specifically, enhances students' interactions, communication skills, self-confidence, and self-awareness. It also fosters discussion and collaboration with both lecturers and peers, as well as course materials. This results in an overall positive experience for students, making them more engaged in their learning and creating a more captivating and stimulating learning process. Bouilheres states that this can be achieved by incorporating contemporary technologies and tools to enhance the learning activities in providing courses that align with the preferences of students in the digital era, thereby increasing their willingness to engage and cooperate with others in such activities that promote a constructivist approach.

According to Mayer (2005) the challenge arises in striking a balance between learner-directed and system-controlled approaches. This underscores the importance of providing learners with autonomy while also utilizing technology to support their learning journey. Similarly, Murtaza et al. (2022) informs that personalized e-learning challenges include identifying the most important learner data, providing content in multiple formats, tracking learner comprehension, and continuously collecting and analyzing data. Musumba and Wario (2019) on the other hand, pointed out the shortcomings of the existing adaptive e-learning systems noting that they are difficult to use, expensive to develop, and not always effective for all learners. Additionally, they may not be able to work with other educational systems.

Ensuring optimal student performance in this blended environment can be challenging to simulate the experiences of classroom learning (Zandvliet, 2020). Nevertheless, Learning Analytics (LA) can be used to address this challenge by analyzing student data from Learning Management System (LMS) logs to gain insights into their learning trends, to provide targeted support and interventions (Duan et al., 2022; Giannakos, 2022; Sušnjak et al., 2022).

Problem Statement

Despite increased use of blended learning in majority of HEIs, students in Kenya's blended learning programs struggle to perform at their best (Hadullo, 2018). One of the reasons cited by various scholars such as Hadullo (2018) is the lack of personalized learning. The traditional blended learning often relies on one-size-fits-all approaches, neglecting individual student needs and learning styles. The other reason is the fact that that the instructors lack clear data on student engagement and progress, making it difficult to provide targeted support. Lastly the students in the traditional blended learning struggle to track their progress, to manage their time, and to stay motivated in blended learning environments.

Study by Macdonald et al (2023) revealed that the Current Learning Management Systems (LMS) provides limited student monitoring capabilities, lack precision and are inadequate for obtaining and evaluating significant data. MackDonald further adds the absence of LA implementation limits Kenyan universities from harnessing its promise for customized learning and enhanced academic results.

The term 'Learning Analytics' (LA) was first mentioned by Long and Siemens in 2011. Despite the global research on LA and its application on eLearning, the research in Kenya on LA for e- Learning is still limited (Kashorda et al., 2007; Oketch, 2013; Kibuku et al., 2020; Ndigirigi, 2012, Kangethe, 2022, Hadullo, et. al. 2017).

Objectives of the study

- To determine the current status of the learning analytics in Kenya
- To understand e-learning enhancement methods
- To provide recommendations for future research

Significance of the study

The findings of the study can help in contributing to the current literature on Learning Analytics. It can also help in identifying the gaps and propose recommendations for future research in the related field.

METHODOLOGY

The paper adopts a desktop research where it focuses on review of current literature on learning analytics and use of learning analytics dashboard in Kenya. The literature is collected basis their relevance and their age related to the topic of learning analytics in higher education institution in Kenya. The materials were later narrowed down using keywords and industry (HEI).

At the end of it the paper aims to come up with recommendation for Kenyan higher education institution to adopt and propose areas for future research to be done.

DISCUSSION OF FINDINGS

Below are the discussion and findings of the current status of study of Learning Analytics in Higher Education Institutions (HEI) in Kenya

Status of Learning Analytics in Kenya

In Kenya, there are few studies done on using LA to improve student performance. For instance the study by Kangethe (2022); Mwalumbwe and Mtebe (2017). Kangethe (2022) developed a model for evaluating efficacy of e-Learning at Higher Educational Institutions (HEIs); Mwalumbe and Mtebe (2017) on the other hand used linear regression analysis to identify the relationship between LMS usage and student performance respectively. The limitations for the two studies is that both study did not capture inputs from blended learning to determine student performance. Secondly there is no framework used for improving student performance. Thirdly, For Mwalumbe, the study used linear regression in determining the relationship between the variables without considering the accuracy of the other modeling techniques.

Another study on using LA for e-Learning is that of Araka et al. (2021). Araka developed a model to use data from the LMS to enhance personalization and strengthen learning and teaching. The study focused on skills that help students learn on their own (self-regulated learning) and how to measure those skills. However, Araka did not create a model to measure how the data they collected can improve student performance.

E-learning Enhancement Methods

According to Kangethe, G. N. (2022), the methods that are used to enhance the e-learning experience, is by introducing adaptive and personalized eLearning systems:

- Personalized (Learner-directed approach) e-learning: The learner sets their own goals and chooses the learning content and activities.
- Adaptive (System-controlled approaches) e-learning: The system selects the learning content and activities based on the learner's performance and assessment results.
- Self-Regulated Learning (SRL) is a theoretical framework that outlines the necessary skills and attributes learners need in order to effectively manage and direct their own learning process (Araka 2021).

Kangethe reports the challenge arises in striking a balance between learner-directed and system-controlled approaches. This underscores the importance of providing learners with autonomy while also utilizing technology to support their learning journey. Similarly, Murtaza et al. (2022) informs that personalized e-learning challenges include identifying the most important learner data, providing content in multiple formats, tracking learner comprehension, and continuously collecting and analyzing data. Musumba and Wario (2019) on the other hand, pointed out the shortcomings of the existing adaptive e-learning systems noting that they are difficult to use, expensive to develop, and not always effective for all learners. Additionally, they may not be able to work with other educational systems.

Summarized Research Gaps

The above research findings and gaps can be summarized in the below table:

Study Findings and Gaps	Reference (Author)
Despite the global research on LA, still Kenyan research on LA for eLearning is limited	Kibuku et al., (2020); Kangethe (2022); Hadullo, et. al. (2018); Macdonald et al. (2023).
Most studies in Kenya are focused on adoption of eLearning platforms (e-learning readiness)	Kingori (2018); Kibuku et. al. (2020); Omulando and Osabwa (2021); Omieno, (2022); Makhaya and Ogange (2019); Macdonald et al. (2023); Osakwe et al. (2022).
A study on students' performance based on student academic records but did not analyze the raw data from eLearning systems	Ogwoka et al. (2015)
Studies about LMS usage and student performance obtained through surveys (Questionnaire), results are highly subjective	Gitonga and Wambua (2020); Hadullo, et. al. (2018)

A Study on LA: developing a model for evaluating efficacy of eLearning at Higher Educational Institutions (HEI's) without capturing input from blended learning A study on using linear regression analysis to identify a relationship between LMS usage and student performance respectively, without considering accuracy of the other modeling techniques **Research Gap:** Both study did not capture inputs from blended learning to determine student performance. No framework was used for improving student performance	Kangethe (2022), Mwalumbwe, and Mtebe, (2017)
Developing a model using data from the LMS to enhance personalization and strengthen learning and teaching. The study focused on skills that help students learn on their own (self-regulated learning) and how to measure those skills. However, the study did not create a model to measure how the data they collected improved the student performance	Araka et al. (2021),
Proposed to design an adaptive e-learning model that uses AI to create a personalized learning path for each learner based on their prior concepts and misconceptions. The author proposed to design the Adaptive Personalized Learning Systems noting that there is not much happening on adaptive learning systems in Kenya	Musumba and Wario (2019); Murtaza et. al (2022),
The author proposed to develop a learner analytic dashboard but the inputs were manually inputted and not generated from the system	Chege, L. M. (2017).

CONCLUSION

Summary and Conclusion

The paper addressed the fact that blended learning is gaining increasing awareness in Kenya and is implemented in all HEI. The challenge arises in striking a balance between learner-directed and system-controlled approaches. This underscores the importance of providing learners with autonomy while also utilizing technology to support their learning journey. Similarly, Murtaza et al. (2022) informs that personalized e-learning challenges include identifying the most important learner data, providing content in multiple formats, tracking learner comprehension, and continuously collecting and analyzing data. Ensuring optimal student performance in this blended environment can be challenging to simulate the experiences of classroom learning (Zandvliet, 2020).

Therefore, Learning Analytics (LA) can be used to address this challenge by analyzing student data from Learning Management System (LMS) logs to gain insights into their learning trends, to provide targeted support and interventions (Duan et al., 2022; Giannakos, 2022; Sušnjak et al., 2022).

In addition, it has been established from related studies, although there has been increased research in LA globally, there is still limited research in Kenya on how LA can improve student performance in blended learning

In Kenya, the existing studies relating LMS usage to student performance have mainly used academic records, primary sources rather than raw LMS data to predict student performance. A number of other studies have focused only on online learning without considering blended learning inputs. Furthermore, neither the framework nor the methodology of analyzing LMS log files has been tested with data from LMS.

Also, significant research gaps still exist around utilizing educational data mining to provide students and lecturers with actionable feedback through the use of Learning Analytics Dashboards (LAD) (Duan et. al. 2022)

Limitations and future Research

The above is merely desktop research and does not carry out quantitative analysis on the actual raw data. Thus, future research can use the raw data using the Learning Management Systems (LMS) such as Moodle to come up with framework for improving performance.

Also study by Love (2021), proposed the design of Learning Analytics Dashboard (LAD) to which the same is yet to be done in Kenya. Student-centric learning analytics dashboards aim to improve learning outcomes by offering students practical insights derived from their own and their peers' engagement in a course. These dashboards are more common and are now regarded as standard in specific Learning Management Systems (LMSs) such as Blackboard and Moodle. However, the extent to which these technologies assist or hinder learning surpasses our understanding of effective design and progress in their development (Love, 2021). Considering this, Love (2021) proposed to create an LAD for students.

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