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Scaling the students' journey through application of data-driven learning analytics (DDLA): Unlocking the actionable insights acquired and missed in a case study

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ABSTRACT

This research examined the application of data-driven learning analytics in a case study to reveal the actionable insights gained or missed. This was a mixed methods study that used an open, distance and online teaching university as a case study. Data were collected from the learning management platform, and this was supplemented by interviews with the teaching Faculty. The results show that use of learning analytics has improved decision-making that has now become data-driven; enhanced the diagnosis of each student's challenges; boosted the personalization of the learning journey of every learner; revamped our knowledge of the preferred learning styles; nurtured the development of lifelong learning skills, using them as monitoring devices for student learning, improved teaching and learning; revamped the feedback loop through precise, timely, and actionable feedback; and augmented reflections on learning by offering targeted feedback. However, the case under study still needs to do the following: build on how data intersects with human decisions, optimal use of resources to achieve learning outcomes, evaluate the overall effectiveness of the course, use data analysis to adjust or enhance the course, monitor student course activity in real-time, use personal data tracking to support learning, supporting self-directed autonomous learning and optimizing the four processes of data, analysis, reporting, and action. The research concludes that learning analytics improve teaching and learning through the quality of teaching, quality of monitoring, quality of feedback, and quality of data-driven decision-making, among others. However, the institution under study still has a long way to go in many areas as discussed in this paper.

Keywords: *Learning Analytics*

INTRODUCTION

Background to the study

The use of technologies in teaching and learning, has transformed the educational landscape. For example, Lu et al. (2021) speaking in the context of their research that examined the key influencing factors on college students' higher order thinking skills, pointed out that these are being improved and enhanced using the smart classroom environment. This stance is confirmed by Williamson (2016), who posits that the teaching and learning arena has been greatly transformed using digital education governance, the adoption of data visualization, and the application of predictive analytics, among others. On the other hand, Sorensen (2018) in the research on big data in educational administration pointed out that learning analytics (LA) is a key enabling tool that will transform educational provision. This kind of thinking may have taken its time to sink in among the academics and researchers in an open, distance, and e-learning university. This has prompted this study that sought to unveil what academics learn or do not learn from the applications of data-driven learning analytics. It has to be noted that Reinholz, Stone-Johnstone, & Shah (2020) are of the belief that use of classroom analytics supports instructors so that they have the competencies to address implicit bias in teaching.

Kovanovic, Mazziotti & Lodge (2021) in their study on learning analytics for primary and secondary schools, pointed out that we can learn a lot from the applications of data-driven learning analytics. They argued that the learning analytics field harnesses data analysis. This data will then be used to unlock tangible advantages for educators and learners (Kovanovic, Mazziotti & Lodge, 2021). Even though there is evidence of extensive research in the learning analytics literature, geographical disparities in adoption, especially focusing on Sub-Saharan Africa, remain unaddressed, prompting this study. Since the case study is in Sub-Saharan Africa, a region that is still in the developing stage, there is a need to unveil what we learn (do not learn) from the applications of data-driven learning analytics considering that Lu et al. (2021) have pointed out that the use of learning analytics have greatly improved the students' higher order thinking skills because staff will be guided by the analytics to prescribe appropriate targeted instructions.

Kleimola & Leppisaari (2022) have noted that learning analytics is the collection, measurement, analysis, and reporting of data. This data is about learners and their contexts. This view is supported by Cheung, Kwok, Phusavat, & Yang (2021) who added that learning analytics is a process undertaken for the purposes of understanding and optimizing learning and the environments in which learning takes place. Banihashem, & Macfadyen, (2021) also added that learning analytics are defined by the process of leveraging data management systems to efficiently collect learner data objectively and in a timely manner. This view is further supported by Boud & Dawson (2021), who pointed out that learning analytics utilize analytic tools and techniques borrowed from other disciplines to interpret this data. Thus, in the literature, there is a wide range of agreements (Jones, 2019; Ferguson, 2019; Broughan, & Prinsloo 2020; Castro & Tumibay, 2021, Karaoglan, 2021) that learning analytics is the process of collecting and measuring, analysing, and reporting of data that has been generated about learners and the learners' learning contexts. This data was analysed and reported for understanding and optimizing learning and the contexts in which learning takes place.

Although Hilliger, Astudillo & Baier (2023), studied learners' and educators' perceptions of academic workload during the COVID-19 pandemic, their case study findings appear to resonate with this study. For example, data was also collected from the Learning Management Systems. One important finding is that most learning analytics indicators do help to transform teaching practices. Learning analytics allow data-driven decision-making. Data-driven decision-making facilitates greater control (Sorensen, 2018). Institutions that employ data-driven decision-making will gain greater control over the direction of teaching and learning because of the quality of their decisions (Raza, Penuel, Jacobs, & Sumner (2020). Their decisions will be of high quality because they are based on objective data, and concrete evidence (Kwet, & Prinsloo. (2020).

Banihashem, & Macfadyen (2021), in their research on the pedagogical design that can be used to bridge the learning theory and learning analytics, pointed out that learning analytics promote personalized learning. This is the kind of learning that fosters student success. They recommended pedagogical approaches that will help institutions to understand students' needs and challenges. These approaches can be easily promoted by the use of data-driven learning analytics. Blumenstein (2020) earlier added that the use of learning analytics can help institutions of learning to prevent the risks and barriers that might affect their learners' success. In the same vein, Tempelaar, Rienties & Nguyen (2021) added the issue of the contribution of dispositional learning analytics to precision education. They argued that dispositional learning analytics combines learning data with the learners' disposition. The learners' disposition data will have been measured through self-report surveys. For Tempelaar, Rienties & Nguyen (2021), there are some advantages that accrue to the teaching and learning arena when academics use dispositional learning analytics. Some of these include the fact that dispositional learning analytics improves the accuracy of prediction, especially at the early stages in the module. Such usefulness of learning analytics prompted this study so that insights gained can be shared.

Statement of the problem

In contemporary times, there is an increasing reliance on data-driven learning analytics in many educational institutions. Data-driven learning analytics provide unprecedented insights into student learning and student performance. However, literature that has interrogated the underlying assumptions of what we truly learn - or fail to learn - from such practices appear to be thin. The problem statement emerges from the discrepancies between the potential benefits of data driven learning analytics and the pitfalls of ignoring applications that have changed decision making the world over. While quantitative measures may inadequately capture the complexities of human learning, they can be supplemented by qualitative measures so that they anchor decision making in universities especially those that rely on online learning.

The university under study has revolutionized teaching and learning through the provision of flexible learning opportunities. However, the failure to fully leverage data-driven learning analytics, is preventing it from enhancing the educational experiences of the learners. The negligence of the learning analytics means that this university is missing critical actionable insights that could improve the educational outcomes of many learners. Data-driven learning analytics allow the faculty to customize learning pathways, identify trends in student performance, and provide timely interventions for at-risk learners. Without these tools, online universities risk perpetuating a one-size-fits-all model that inadequately addresses diverse learner needs. The universities that ignore this wealth of information will ultimately undermine their capacity for continuous improvement and fail to benefit from evidence-based practices. The lack of responsiveness may not go down well with many of university stakeholders. They will then miss on a transformative opportunity that can enhance educational efficacy. They are also at risk of diminishing the institution's reputation and at the same time erode stakeholder trust. Hence this study.

Purpose of the study

The purpose of study was to examine the application of data-driven learning analytics using a case study, in order to reveal the actionable insights gained or missed.

Research question

What are the actionable insights gained or missed in the application of data-driven learning analytics in your university?

The sub-questions were:

- What were the *actionable insights gained* in the implementation of data-driven learning analytics in your university?
- What were the *actionable insights missed* in the implementation of data-driven learning analytics in your university?

THEORETOCAL FRAMEWORK

The theoretical framework for this study is Biggs (2024), student approaches to learning & studying that focuses on how students learn in institutional settings. This framework also focuses on assessing the quality of learning. Biggs’s approach to teaching is informed by the assumption that teaching decisions should be grounded in our knowledge of how students learn. According to Gibbs, the process should start from formulating the objectives of the study to reporting assessment results.

According to Biggs (2024) student approaches to learning & studying, the learner's approach to learning has two components. These are:

- How the student approaches the task (strategy). In this research, the idea is to look at how learning analytics influence how the student approaches the task (strategy).
- The second component of the theory is that of why the student wants to approach learning (motive). This also means that in this research, the idea is to unravel how learning analytics has influenced the process of why the student wants to approach learning (motive).

Biggs is also of the belief that three common approaches to learning have influenced learners. One such approach to learning is the *surface approach.* The argument in the surface approach is that the learner's motive to learn is that of carrying out the task based on the external positive or negative consequences. This means the motive is external. There are some consequences to be faced. For example, if the learner fails to accomplish given tasks, then life will be unpleasant. On the other hand, when the learner does well in the subject, there are key pleasantries that will accumulate for the learner. According to Biggs (2024), one typical surface strategy is that of rote learning. In the rote learning process the surface-motivated learner will then focus on what appears to be the most important items and memorize them. Since the focus is on memorization, learners do not see interconnections between the meanings and implications of what is learned.

The second most common approach to learning is the *deep approach*. In this deep approach, the motive is based on internal motivation and internal curiosity. When the student is being driven by the deep approach there are signs of a personal commitment to learning. When a learner is driven by a personal commitment to learning, the learner relates the content to personally meaningful contexts. The learner also has the luxury to relate the content being learned to existing prior knowledge. According to Biggs (2024), deep processing involves processes of a higher cognitive level than rote learning. This research, in the process of unveiling what we learn (do not learn) from applications of data-driven learning analytics, seeks to unlock revelations from a case study that shows: how deep processing has been impacted by the applications of learning analytics in a case study. How learning analytics have impacted the processes of a higher cognitive level; and how learning analytics have influenced the use of the processes of a higher cognitive level than rote learning.

The third of the three common approaches to learning that has influenced learners is the *achieving approach*. The achieving motive just like the surface approach, focuses not on learning, but on the product. For example, the learner can focus on attaining an A class or winning an award. The strategy in such a case is to maximize all the opportunities that are available so that one can cease the chances of obtaining a first-class rating. Biggs (2024) agreed that the achievement strategy involves a high level of effort to learn just like in deep learning. However, he argued that the learning in the achievement strategy is merely the means and not the end. In this study, it is the learning analytics that will be examined to see to what extent they are influencing either deep learning, surface learning, or the achievement strategy of learning.

The theoretical framework for this study considers student approaches to learning & studying Biggs (2024) that focus on how students learn in institutional settings, can help to untangle why surface and deep learning appear to be mutually exclusive.

It will also be used to argue that even if the surface approach and the deep approach are mutually exclusive, the achievement approach is in many cases linked to both.

Research Methodology

This is a mixed methods study that used an open, distance and online teaching university as a case study. According to Denscombe (2011), mixed-methods research is a research approach in which researchers collect and analyse both quantitative and qualitative data within the same study.

The data for this research were collected from academics who use analytics from the learning management platform. The data collected was varied. It included the views of the academics regarding the analytics that covered issues like assessment scores for both summative and formative assessments, course completion rates, time spent on courses, among others that can benefit the teaching and learning environment. This process was undertaken because it helped streamline the data collection process. It also helped in the process of ensuring data accuracy. The quantitative data collected from the learning management system was supplemented by interviews with the teaching Faculty. The interviews were undertaken with a purposive sample of 31 academics. According to Patton (2015), qualitative research is crucial if it is used in the context of improvements. This is because qualitative research provides in-depth understanding of processes, contexts, and experiences that, in the context of this study, can enable the academics to address complex issues and tailor instruction to individual need.

FINDINGS

The findings of this study are presented below in two sections. The first section presents data on what the institution under study is gaining from the use of learning analytics. The second part looks at what actionable insights, the academics at the institution under study are (not) learning from learning analytics.

The actionable insights gained in the implementation of data-driven learning analytics

This first of the two sections presents findings regarding the actionable insights gained in the implementation of data-driven learning analytics in the university under study.

DISCUSSION OF FINDINGS

Table 1 shows what academics in the case study saw as the actionable insights gained in the implementation of data-driven learning analytics (N=31). This section discusses the findings. The themes from the findings in regard to research sub-question one, are shown in Table 1 below, and will form the basis of the discussion

Table 1: *Actionable Insights Gained*

Actionable insights gained in the implementation of data-driven learning analytics	**Frequency**	**%**
Data-driven decision-making	27	87
Personalization of the learning journey	23	74
Learning style preferences	18	58
Nurturing lifelong learning skills	21	68
Forecasting, predicting, detecting, and tracking students at risk	28	90
Promoting targeted, real-time, individualized, and actionable feedback	23	74
The use of engagement metrics	19	0

Actionable insights gained in the implementation of data-driven learning analytics

Data-driven decision making

The participants in this research opined that they use learning analytics to promote data-driven decision-making. One of the participants pointed out that:

> *"Learning analytics have improved decision-making that has now become data-driven in our university. In my faculty, learning analytics has found its niche in the provision of actionable insights that help all faculty to make sense of student learning and student engagement data"*

Another participant added that:

> *"I vouch that learning analytics has greatly enhanced decision-making in my work and the work of my colleagues. Through learning analytics, I have managed to transform raw data into valuable insights that I can use for making informed decisions. The analyzed data reveals trends, patterns, and opportunities that have all along been hidden from many of us"*

Dowell, Lin, Godfrey, & Brooks, (2020) appear to agree with the research participants. They pointed out that learning analytics will ensure that those in decision-making can master the tools and techniques that are useful in creating a culture of informed and effective decision-making. They added that learning analytics will empower teachers, professors, and decision-makers so that they can leverage statistical analysis and predictive models in what they do in educational institutions. These views are also supported by Mangaroska, & Giannakos (2018) who pointed out that through the use of learning analytics, decision-makers can foster a culture of evidence-based decision-making and evidence-informed strategic planning.

In the context of utilizing learning analytics, Karaoglan (2021) noted the utility of learning analytics in supporting students' problem-solving capabilities, and academic self-efficacy. Through this process academics can see patterns, and predict how students will perform in their classes, virtual or face-to-face. For Karaoglan (2021), most important, educators provide feedback that is targeted and specific to each student's needs. This is made possible by the use of statistical models, advanced algorithms, and data visualization tools (Karaoglan, 2021).

Personalization of the learning journey

One area that was subscribed to by many of the research participants in this study is that of the personalization of the learning journey. One of the participants pointed out that:

> *"I have benefited very much from the use of learning analytics. For example, I have used them to promote personalized learning. In this regard, I customize my students' learning. In this process, I take into consideration each student's unique needs, strengths, competencies, skills, weaknesses, and interests when I plan my lessons. This has helped in many ways. This is because I provide each student with an individualized learning plan that is customized to what they know and how they learn best"*

The idea of customized learning was supported by Virtanen & Tynjälä, (2019) who pointed out that through learning analytics, educators will make use of adaptive technology, data-driven approaches, and differentiated instruction methods to create customized learning pathways. This was also supported by Schneider, Dowell, & Thompson (2021) who examined what they called collaboration analytics in their study. They found that the current state and potential future of customized learning nurtured through learning analytics is great. To them, learning analytics have the potential to promote personalization frameworks where both educators and their students can engage with real-world case studies, thereby designing actionable learning pathways that can be applied to diverse educational settings. In support, Ehlers (2020) earlier added that the focus of a personalized learning framework is to address unique needs, foster learner autonomy, and enhance outcomes by reshaping traditional pedagogies. Thus, educators in this study, through learning analytics were equipped with insights and cutting-edge tools that can transform their teaching practices by maximizing their students' potential through personalized learning driven by learning analytics. This then could nurture their unique learning journey (Ehlers, 2020).

Learning style preferences

An area of utility of learning analytics that was unearthed in this study is that of learning style preferences. One participant pointed out that:

> *"I have discovered over the years that learning styles influence how students learn. They also influence how teachers teach. I also discovered that every student in my class was brought up with certain tendencies toward particular styles. However, all this information is now readily available when using learning analytics. I am now able to know more about inherent characteristics that are influenced by personal experiences, cultural exposure, and maturity levels among others"*

The issue of learning style preference was supported by another research participant who pointed out that:

> *"My students prefer different learning styles. This is because I have discovered that their overall academic performance is greatly influenced by their learning style. Some of my students exhibited high pragmatist scores. Through learning analytics, I now know that such students perform well in my courses that have a large practical component"*

Saad (2017) added a commanding voice to learning style preferences among students. In his analysis of Gender and Ethnicity, it was noted that Interactive response systems appear to increase learner engagement. They can also improve learning outcomes. The purpose of Saad's study was to determine whether student learning style plays a role in gender and ethnicity environments, and the findings indicated that it is important for educators to respect the learning style of each learner. According to Saad (2017), learning outcomes can be measured through comprehending the subject knowledge, critical thinking abilities and capabilities, and effective decision-making capabilities. This information is hidden from many educators. It is learning analytics that have the potential to unmask all these abilities and capabilities that will enhance students' learning and learning outcomes.

Raza, Penuel, Jacobs, & Sumner, (2020), in their study on supporting equity in schools, discovered that by using visual learning analytics they could understand learners' learning preferences, classroom experiences, and their learning styles among others. They pointed to diagnostic analytics that they carried out in their study when compiling data. Their data analysis revealed a strong relationship between students' learning styles, experiences, and learning preferences. The students in their study exhibited varying learning styles that were revealed through the use of learning analytics.

Nurturing lifelong learning skills

The participants in this study pointed to nurturing lifelong learning skills through learning analytics. One of the research participants shared the view that:

> *"I am one of those who have benefited from learning analytics. For example, my students, have lifelong learning skills that include abilities that they can use to help them continue to seek information and expand their knowledge no matter their age. Many of them are now committed to lifelong learning because I have seen that they are more likely to pursue promotions. They are also more inclined to gain professional opportunities due to their increasing skill set"*

According to Kanuru, & Priyaadharshini 2020), competency skills like critical thinking skills, problem-solving skills, and innovative thinking competencies are analysed using learning analytics strategies. These skills promote lifelong learning capabilities and competencies in learners. The performances of the learners in a study by Kanuru, & Priyaadharshini (2020) were broadly categorized based on metrics like analytical, conceptual, logical, and conceptual thinking, among others. The results showed that this kind of analysis benefitted the students in enhancing their lifelong learning competencies and capabilities. It also promoted their time management skills and commitment to learning.

The study by Kanuru, & Priyaadharshini (2020) further revealed that implementing Artificial Intelligence concepts through learning analytics provides the results that can aid in creating the most suitable teaching-learning environment. They also pointed out the best outcome for disruptive engineering education, and concluded that learning analytics is indispensable because it provides an understanding and optimization of learning and competency skills to be acquired by the learners (Kanuru, & Priyaadharshini, 2020). These researchers saw learning analytics helping to improve the teaching-learning process wherein, teachers can build a lasting foundation for students to be lifelong learners (Kanuru, & Priyaadharshini, 2020).

Shum and Crick (2016) in support of learning analytics and lifelong learning, argued for educational institutions shifting their teaching and learning towards equipping students with knowledge, skills, and dispositions that prepare them for lifelong learning, in a complex and uncertain world.

According to Shum & Crick (2016), learning analytics (LA) as an approach to teaching and learning offers many kinds of computational support. This computational support can be used by teachers to track learner behaviour, manage educational data, and visualize patterns that will provide indispensable feedback to both educators and learners. They pointed to the diverse range of learning analytics techniques and tools that can be deployed in the service of nurturing and promoting 21st-century competencies that are the building blocks for lifelong learning.

Forecasting, predicting, detecting, and tracking students at risk

The participants in this research pointed to forecasting, predicting, detecting, and tracking students at risk using learning analytics. In open-ended responses, one of the participants pointed out that:

> *"Learning analytics is being used in my department for the provision of comprehensive insights that are being used by the department for forecasting, detecting, predicting, and tracking at-risk learners"*

Another participant agreed and added:

> *"We have some of the best Mathematicians in our department. These help us to unravel meaning in the figures that we get from the learning management system. For example, recently these same guys used statistical models, advanced algorithms, and data visualization tools to forecast, predict, detect, and track at-risk students"*

According to Albassam (2019), educationists can use learning analytics to detect students at risk. First, they have to learn how to interpret any given data patterns so that they make sense of these data patterns. There is also a need to integrate predictive models and implement some form of a monitoring system that can be used to support student success. Albassam (2019), added that by helping at-risk students, institutions of higher learning will be able to promote retention, enhance students' ability to obtain better results, analyse diverse students' analytics, and help both tutors and students to succeed in what they are doing.

In the context of forecasting, predicting, detecting, and tracking students at risk using learning analytics, Aguilar (2018) argued that learning analytics can be used at the nexus of big data, social justice, and digital innovation. He pointed to what he termed predictive analytics which can be used to analyse student data in a bid to predict future performance. The same predictive analytics can also be used to identify potential issues that could hinder learning (Baig, Shuib, & Yadegaridehkordi, 2020). Both Aguilar, (2018) and Albassam (2019) appeared to agree with the process that is followed in predictive analytics. They all follow a process that begins with the collection of data. This data includes students' grades, students' attendance patterns, and students' online activities, among others (Baig, Shuib, & Yadegaridehkordi, 2020).

Paolucci et. al. (2024) also reviewed the opportunities and challenges that are brought about by learning analytics. In that study, they concluded that the power of learning analytics can be used to address teaching and learning challenges. Some of the challenges that they cited include issues like diverse students' characteristics, early detection of those students that are at risk, and proactive interventions applied with minimal effort. They further added that predictive learning analytics provides valuable insights into individual weaknesses that can threaten learning outcomes, individual strengths that can be capitalized on by the teacher, and weaknesses that should be addressed promptly before they get out of hand. With this information, educators are guided in the selection of appropriate instructional materials, appropriate pacing, and the use of appropriate differentiation strategies that can meet diverse student needs.

Promoting targeted, real-time, individualized, and actionable feedback

The participants in this research were of the view that learning analytics is used in promoting targeted, real-time, individualized, and actionable feedback. One of the research participants had this to share with others:

> *"One area that has benefited my students greatly is the use of learning analytics to improve my feedback to students. For example, learning analytics helps me in that the feedback that I use is not only real-time and individualized feedback, but also redirects and then refocuses my students' actions to achieve a goal. This is done through aligning effort and activity with an outcome"*

Another participant also supported feedback being important to learning analytics by pointing out that:

> *"My feedback is no longer the same since I started to employ learning analytics with the help of statisticians. I am now able to use feedback in promoting targeted and actionable feedback. To my students, the targeted feedback that I provide is an opportunity for them to learn new ideas, competencies, and skills and an opportunity for growth and development"*

Thus, it is clear that the use of learning analytics has helped in promoting targeted, real-time, individualized, and actionable feedback. This is supported by Banihashem et al. (2022) in their study where they reviewed the role of learning analytics in enhancing feedback practices in higher education. They pointed out that feedback has long been acknowledged as a powerful tool for learning, and they also saw feedback playing a crucial role in student competencies, attitudes, and skill acquisition. They further cited issues such as an important factor that influences student motivation. To them, quality teaching is not enough if feedback is not factored into this process. Thus, Banihashem et al. (2022) are of a strong view that high-quality feedback is a contributory factor to what they called 'authentic learning', and the promotion of student metacognitive skills that can significantly improve both learning processes and outcomes.

According to Banihashem, & Macfadyen, (2021), feedback is very important in the teaching and learning arena because it is one of the most powerful teaching and learning tools that can be used to improve learning and increase achievement. They also pointed out that feedback when used in conjunction with learning analytics can provide clear indicators of performance and also indicate those areas that may need further improvement. These views were also expressed by Blumenstein, (2020) in a study on the synergies that can be built between learning analytics and learning design. This research pointed out that the synergy between learning analytics and feedback will lead to timely and insightful feedback. More so, when feedback is timely, it can alert both tutors and their students on issues to do with their learning progress. Such information can then be used to improve the students' learning and self-regulation.

Amiryousefi & Geld (2021) took the debate on the synergy between learning analytics and feedback further by adding the role of automated feedback in students' performance. They argued that the effectiveness of feedback depends not only on the quality of that feedback but more importantly on the timeliness of the feedback. It is this timeliness that is enhanced by the use of learning analytics. Broos, cited in Banihashem, & Macfadyen, (2021) agreed with the issue of timeliness of the feedback that is given, but further added the issue of the dashboards that can provide actionable feedback for improving learning skills. Thus, learning analytics should be an essential component of timely and actionable feedback that is designed in a data-rich environment.

The use of engagement metrics

An area where learning analytics has improved the teaching and learning process in the university under study is that of using engagement metrics. This was confirmed by the participants in this study. One of them pointed out that:

> *"Learning analytics has helped me in using engagement metrics. There are many areas of engagement metrics that I am being assisted with using learning analytics. Some good examples include course completion rates, the login frequency of the learners, the participation of the students in the discussion forum, the assessment scores, and the progress being experienced by the learners"*

Another participant agreed that engagement metrics were useful for the department, adding that:

> *"The use of learning analytics in the engagement process has greatly improved my work. I now understand that learner engagement is an essential component of the quality of my teaching. In this regard, I use some key metrics that include course time expenditure, course completion rates, and participation in real-time discussions. I do all this so that I can track learner engagement, especially in real time"*

The use of engagement metrics that came out of this study is also supported in the literature. For example, Boud & Dawson (2021), think that engagement metrics can provide insight into whether the content that is being used in the learning process is engaging enough. This is because some content can even leave students feeling unmotivated or they may become confused. Such unengaging content may cause learners to drop out of the course. Thus, Boud & Dawson (2021) noted that engagement metrics help the tutors to identify issues that need to be addressed. They also pointed out that engagement metrics will give insights into what learner interests and preferences are because they allow them to identify those areas that may need improvement in the user experience.

The issue of the use of engagement metrics is further supported by Castro & Tumibay (2021) who expressed the view that engagement is a key concept in the teaching and learning arena. This is because it is used as a measure of the quality and relevance of content. For example, they pointed at issues like reflecting on how well the content is resonating with users. Thus, they contend that there is a need for educators to track engagement rates that will allow them to make sense of learner behaviour, learner attitudes, and learner progress in their classes. Every teacher should know how every learner is interacting with their content so that they can identify trends that can be key in making decisions that will unlock value in the teaching and learning environment.

ACTIONABLE INSIGHTS MISSED IN THE IMPLEMENTATION OF DATA-DRIVEN LEARNING ANALYTICS

Research sub-question two sought to unearth the actionable insights that could have been missed in the university under study, regarding the implementation of DDLA. Data-driven learning analytics (DDLA) has the potential to transform educational practices by leveraging data to improve student outcomes. In this section some of the actionable insights that were missed are identified.

The data in Table 2 below show what academics in the case study saw as the actionable insights missed in the implementation of data-driven learning analytics (N=31).

Table 2: *Issues Raised by Academics*

Issue raised	Frequency	%
Robust Learning Management Systems (LMSs) infrastructure	24	77
Visibility of African DDLA Scholars' best practices	18	58
Stakeholder involvement and collaboration in DDLA	21	68
Predictive learning analytics	19	61
Proactive interventions	26	84
Data Visualization:	17	55

Robust Learning Management Systems (LMSs) infrastructure

The participants 24 (77%) in this study pointed out that their implementation of DDLA is being hampered by the lack of robust learning management system infrastructure. This means that in the university under study, several areas of DDLA remain underutilized or entirely absent. One significant challenge is the limited access to a robust Learning Management System (LMS). This discrepancy appears to hinder the collection and analysis of essential learning data.

One of the research participants pointed out that:

> *"We lack robust learning management systems that will help us in collecting and analysing data that can be used for decision making"*

Another participant concurred, and added that:

> *"It is not only LMS infrastructure that we are missing. There is also the issue of the scarcity of technical experts that are readily available to support these systems. Such shortage of experts further exacerbates the implementation of DDLA"*

The issue of infrastructure is key as higher education institutions seek to implement robust and effective analytics strategies (Benke & Widger, 2023). Without robust LMS infrastructure, universities cannot effectively track student performance or engagement metrics. Broughan & Prinsloo, (2020) opined that data-driven learning analytics is increasingly recognized in many higher education institutions. This is because it is seen as a transformative approach in education. Its transformative nature emanates from its ability to enable these higher education institutions to enhance student outcomes. It also helps them to optimize teaching methodologies. Ness (2024) agreed with these views on the efficacy of data-driven learning analytics, maintaining that the efficacy of such systems hinges significantly on robust infrastructure. The main points from that argument are that without adequate technological frameworks, the potential benefits of data-driven analytics remain unrealized. These sentiments appear to underscore the crucial role that infrastructure plays in this educational paradigm shift (Gros, 2016).

According to Broughan & Prinsloo (2020) a strong infrastructure will ensure that higher education institutions can collect and manage vast amounts of data effectively. The efficacy of data-driven learning analytics hinges on the ability to collect and manage vast amounts of data. This means that the higher education institutions should have the ability and capabilities to manage real-time data from diverse sources. What this means for the case study approach in this study is that its inadequate technological foundation is a handicap. This handicap can lead to challenges such as data silos (Ness, 2024). It may also lead to further challenges such as inconsistencies in information gathering (Gros, 2016). Such silos and inconsistencies will mean that the institution is making decisions based on compromised analytics. In such a case, Broughan & Prinsloo (2020) noted that the reliability and accuracy of the insights derived from this compromised data cannot be relied on. The case study approach in this study should therefore invest in comprehensive data infrastructure that are essential for fostering an environment where meaningful analysis can occur.

Visibility of African DDLA Scholars' best practices

An area that participants 18 (58%) in this study saw as compromising the implementation of data-driven learning analytics is the visibility of African scholars so that institutions can learn from best practices from the African continent.

A participant in this study pointed out that:

> *"In our institution, I have observed that there is a notable lack of research and visibility regarding our African scholars in the field of learning analytics. I stand corrected, because I see this lack of visibility as a limiting factor in the implementation of DDLA. To me, this absence limits our opportunities for collaboration and partnerships"*

According to Chiome (2025), knowledge sharing and collaborations are a rare opportunity that can enhance DDLA practices within Zimbabwe (Chiome, 2025). There are also few studies conducted on the continent (Chiome, 2025). These studies are predominantly originating from South Africa (Chiome, 2025). This leaves a significant gap regarding localized applications and interventions tailored to African contexts. What this means is that the university under study is missing out on valuable insights such as best practices that could inform their own analytical frameworks.

Stakeholder involvement and collaboration in DDLA

In the context of data-driven learning analytics, there are key stakeholders who matter regarding the success of its implementation. According to Lee, Cheung, & Kwok (2020), some of the key stakeholders are the educators, the students, the administrators, and IT staff. Their contributions to the success of the implementation of data-driven learning analytics has been mentioned by the participants 21 (68%) in this research as lacking. One of these participants had this to say:

> *"My view regarding the missing insights is that stakeholder involvement is an albatross in the development and implementation of data-driven learning analytics. This is so in our institution"*

A second participant appears to concur with these sentiments regarding the absence of collaborations from key stakeholders.

> *"From where I am standing, effective and robust learning analytics are possible through collaborations among key stakeholders. In our case these key stakeholders are the administrators, the ICT staff, the faculty and the students"*

An approach where stakeholder involvement and collaboration in DDLA is lacking, compromises the issue of inclusivity (Benke & Widger, 2023). Broughan & Prinsloo (2020), appear to concur with the participants in this study. They argued that by neglecting key stakeholder perspectives in data-driven decision-making processes, the higher education institutions may compromise on critical factors that can influence favourable student outcomes. This means, for the institution under study and other like-minded higher education institutions, there is a need to address these gaps. Such a move will be essential for maximizing the benefits of data-driven learning analytics in the context of higher education (Archer & Prinsloo, 2019).

Chiome (2025) is of the belief that key stakeholders are important in the implementation journey of data-driven learning analytics considering that this can enhance the diagnosis of each student's challenges. This can also, in many ways, boost the personalization of the learning journey of every learner. Benke & Widger (2023) concurred by pointing out that key stakeholders can help educational institutions to revamp their knowledge of the preferred learning styles. They also added that the key stakeholders have the capabilities to nurture the development of lifelong learning skills, using them as monitoring devices for student learning, improved teaching and learning. These revelations appear to point out that the institution under study can build on how data intersects with human decisions using key stakeholders. These key stakeholders will help in the optimal use of resources to achieve favourable learning outcomes. They will also have a hand in the improvement of data infrastructure (Chiome, 2025).

According to Yang & Li (2020), there is a need to foster long lasting and impactful collaboration among diverse groups. Such collaborations and partnerships will ensure that higher education institutions can leverage their collective wisdom, knowledge, and competencies to develop more effective strategies that will ensure robust implementation of learning analytics in support of student success. This means that for the institution in this case study, there is a need for collaborative efforts among all stakeholders. These collaborative efforts are key to ensuring that data-driven learning analytics becomes both functional and aligned with educational initiatives.

Predictive learning analytics

Participants in this study 19 (61%) felt that data that was provided from the learning management system fell short of the predictive learning analytics form. For example, one of the participants in this research opined:

> *"We want to use the data from the learning management system to identify our students who are at risk of failing. We are failing to do this. We expect our learning management system to analyse student performance data. This is not happening. The system should identify the students who are struggling and are likely to fail a course"*

Another participant added:

> *"At the end of the end of a course, we are surprised to find out that some able students did not make it. It is our system that is falling short here. We expect the system to predict course completion rates so that we are not surprised at the end of the day. All this should be based on historical data"*

According to Mustapha (2023), Predictive Learning Analytics (PLA) has emerged as a significant component of data-driven learning analytics, particularly in higher education. The systematic review by Sghir et al. (2022) highlighted that PLA employs machine and deep learning to enhance student outcomes such as retention and performance. This advancement is crucial as educational institutions strive to utilize data for informed decision-making. However, the implementation of PLA is not without challenges, including the need for optimal model characteristics and effective evaluation metrics. Thus, while PLA holds promise for improving educational experiences, it necessitates careful consideration and rigorous evaluation to maximize its potential.

Ramaswami, Susnjak, & Mathrani (2023) noted that despite the benefits of predictive analytics in Learning Analytics Dashboards (LADs there are significant limitations in their current application, also noted by Umer et al. (2021). Most LADs primarily focus on identifying at-risk students rather than providing comprehensive insights into student behaviour or performance trends. Furthermore, the lack of interpretability in predictive models restricts their usefulness for educators seeking actionable insights. Without robust evaluations of these dashboards' impact on student outcomes, stakeholders may remain sceptical about their effectiveness. Therefore, enhancing the design and functionality of LADs is essential to ensure that they serve as effective tools for fostering improved educational environments.

Recent research conducted by Mustapha (2023) underscores the necessity of employing advanced machine learning techniques for predicting academic performance more accurately. By comparing traditional methods with state-of-the-art approaches, this study illustrates how incorporating data mining techniques can significantly enhance prediction accuracy using readily available data from Learning Management Systems (LMS). As educators increasingly rely on these analytics to inform teaching strategies and interventions, ongoing research must focus on refining prediction methodologies to better support learners' diverse needs within a rapidly evolving educational landscape.

Proactive interventions

The participants in this study believed they had missed actionable insights regarding proactive interventions 26 (84%). Their understanding is that data-driven learning analytics should be able to allow for proactive interventions.

One of the participants put it this way:

> *“I think our system is short-changing us. For example, it is my view that data-driven learning analytics should lead to the identification of the students at risk early. Once we can identify such students, we will be able to help them using proactive strategies”*

Another participant appears to agree as seen in her views that

> *“Early identification of the students who are struggling in my course is important. I want this information so that it can enable me to put into place targeted support. This means that I have to adjust my teaching strategies so that I can accommodate the personalised needs of those students who are at risk of being left behind by the whole class”*

Chiome (2025) has noted the potential of predictive models. He pointed out that these models can be used to identify at-risk students. This important information allows higher education institutions to intervene before academic issues escalate. The early identification is crucial because it can be used by educators to mount comprehensive personalized support strategies that are tailored to individual student needs and challenges that they face.

Herodotou et al(2020), provided evidence from the Open University UK that confirms that there are many tangible benefits of proactive motivational interventions that are guided by predictive analytics. In their research, they used randomized control trial. The results showed significantly improved retention rates among students receiving supportive communications compared to those who did not (Herodotou et al. 2020). We learn from these findings that the university under study is missing an important element of data-driven learning analytics, that is, predictive interventions. The findings from the Open University UK underscore the importance of implementing data-driven strategies. These strategies help in enhancing academic success. They also help in fostering a supportive educational environment.

Herodotou, et al. (2020) noted that for predictive interventions to work well, there is a need for early identification of struggling students. This can be obtained from analysed student data. The academic, educators or teachers can then use the analysis to identify students who might be falling behind or struggling with specific concepts before their performance significantly declines.

Al-Zahrani & Alasmari (2023) added the issue of personalized support and interventions resulting from predictive interventions. They pointed out that once the learners at risk are identified, interventions that are data-driven can be implemented. These interventions will then provide targeted support to the learners. They gave examples of targeted support as small group sessions, one-on-one tutoring, and access to additional learning resources.

Herodotou, et al. (2020) claimed in their studies that the use of proactive interventions is important. To them, data can inform the adjustments to curriculum and teaching methods. They went further to state that data can also reveal that a particular topic is consistently causing difficulties for students. What this means is that educators can then think of proactive ways that will enable the students to learn this topic better. In such a case, academic staff can re-evaluate the teaching approach that they are using. In some instances, they can think of providing more in-depth instruction on the topic that is causing challenges to the learners.

Al-Zahrani & Alasmari (2023) in the context of proactive interventions, brought to this debate the issue of the improved student outcomes. Their argument being that when one is implementing proactive interventions based on data, they should be helping struggling students. This help to the struggling students will improve their learning and performance, leading to better overall student outcomes.

Data Visualization:

The actionable insights missed were mentioned by 17 (55%) of the participants in this study. One of the participants claimed that:

> *"While we are doing well in many respects concerning data-driven learning analytics, I think we are not doing enough regarding data that should be presented in a clear and accessible way, especially using visualizations. This is because to me, visualisations can make it easier for me and my colleagues to understand and act upon the insights that are presented through visualisations"*

Another research participant added that:

> *"It is my view that statistical graphics presented using visualization are a critical component of data-driven learning analytics. We may not be doing enough on these, yet they should be serving as a bridge between actionable insights and complex datasets"*

According to Wen & Wang (2020) effective data visualization techniques are essential for data-driven learning analytics. This is because through data visualisation, it is easier to interpret large volumes of information generated by a learning management system. Wen & Wang (2020) further pointed out that some methods like word cloud may provide basic insights. They also mentioned advanced techniques that include interactive visualizations and dynamic dashboards. To them these advanced techniques offer deeper engagement with the data. This research has shown that such sophisticated tools have been missed in this case study. Yet the tools enable academics to discern patterns that inform their teaching methods, assessment techniques and instructional decisions (Archer & Prinsloo, 2019).

Vieira, Parsons, & Byrd, (2018) noted the centrality of visualization in learning analytics. To them, the important role of visualisations cannot be overstated. This is because visualisations play a pivotal role in transforming raw data into understandable formats. These forms can influence teaching strategies and assessment practices (Wen & Wang, 2020). The findings of these studies also add that visualisations can be used in the creation of diverse representations of student performance metrics. To them, the versatility of visualisations allowed for nuanced analyses that go beyond mere averages or mere totals that are used in descriptive statistics. Visualisations have the power, the capability and the ability to facilitate a more comprehensive understanding of student achievement and student engagement. This means that the academics in this study were correct that visualisations are a missed opportunity that could have helped the academics to visualize trends over time. This is why both Wen & Wang (2020) and Vieira, Parsons, & Byrd (2018) agreed that through visualisations, academics can compare different cohorts where they use visualisations to enrich the narrative around students' learning journeys. This is why the two authors concurred that there is a need to harness the power of data-driven learning analytics through creating more advanced visualizations that not only present data, but also align with pedagogical principles (Vieira, Parsons, & Byrd 2018). The alignment will then ultimately improve both student outcomes and teaching effectiveness.

CONCLUSION

Through learning analytics, academics at the university in this case study can analyse various types of educational data to identify patterns and trends that inform teaching methods and learning processes within diverse classrooms. They can design innovative solutions that have the potential to address complex educational challenges. They do this by synthesising learning analytics insights with pedagogical theory and practice.

The academics in the study are still to learn about implementing robust data visualization, actionable proactive analytics, stakeholder involvement, and the use of a modern Learning Management System (LMS) infrastructure. These areas are putting the institution at a significant disadvantage. They also need assistance in predicting future trends and assessing the effectiveness of learning analytics interventions, where they use evidence-based practices to refine and optimise educational outcomes continually. What is evident from the findings is that the absence of these critical elements of data-driven learning analytics undermines the potential for informed decision-making. The absence further inhibits and erodes the potential of the institution to respond effectively to the needs of students.

RECOMMENDATIONS

Academics at the institution under study need to move with the times by leveraging expert insights that are supported by cutting-edge research to optimize the use of learning analytics. They should ensure that learning analytics empowers them to become change agents in their various endeavours. The university should ensure that all academics are equipped with the skills to craft actionable plans for harnessing the potential of learning analytics. This will enable them to ultimately drive educational innovation and enhance student outcomes. There is a need to ensure clarity that can promote transparency in learning processes. There is also a need for nurturing and fostering a culture of data-informed decision-making.

The use of visualization techniques is recommended as an outcome of this research because the institution under study is risking alienating key stakeholders who may not possess advanced analytical skills, yet these stakeholders require actionable insights into student performance metrics. There is a need to inculcate forward-thinking capabilities in the institution under study because this culture can enhance student retention rates and improve overall academic performance. Promoting collaboration, fostering a sense of ownership, investing in modern LMS infrastructure, developing advanced analytics capabilities, and access to real-time insights, should be prioritized. This research has shown that they are fundamental aspects of data-driven learning analytics. Without them, the institution under study risk falling behind in an environment of technological transformation.

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