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Synergies of data-driven learning analytics and the transformation of student learning: The missing piece of the puzzle in a case study

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ABSTRACT

This mixed-methods study examined the missing piece of the puzzle in transforming student learning through data-driven learning analytics. It is a case study of an open, distance, and e-learning institution in Zimbabwe. Data were collected from the analytics generated via the learning management platform, and this was supplemented by interviews with the teaching Faculty. The results show that while learning analytics provide data visualizations on engagement and performance in this institution, there are still many missing pieces of the puzzle that prevent this institution from fully utilizing learning analytics. The results show that this institution is a long way off in building on how data intersects with human decisions, optimal use of resources to achieve learning outcomes, and the improvement of the data infrastructure. The results also showed that the recommendations arising from data analytics were not being implemented. The university was not using data analysis to adjust or enhance student learning and failed to use predictive and prescriptive analytics. Other areas that were found wanting include, monitoring student course activity in real-time, and using personal data tracking to support learning. The research concludes that learning analytics improve teaching and learning, enhances the quality of teaching, quality of monitoring, quality of feedback, and quality of data-driven decision-making, among others. The institution under study is still grappling with the missing piece of the puzzle to tap into the extensive learning data to transform student learning. These areas are discussed in this paper.

Keywords: *Learning analytics, customized interventions, predictive analytics, adaptive learning, and data infrastructure*

INTRODUCTION

Many educational institutions are now using learning analytics. For example, Barba, Kennedy & Ainley (2016) confirm that learning analytics can be used by both teachers and students to predict performance. Dodge, Whitmer & Frazee, (2015) agree and add that learning analytics have improved undergraduate students' achievement, especially in large, blended courses. This is all because of the use of data-driven interventions. According to Kleimola & Leppisaari, (2022), through learning analytics, subject development-related future competencies including self-awareness, reflective competence, self-efficacy, and self-management, are future competencies that can be promoted now through learning analytics. To them, the potential of learning analytics in supporting teaching and learning is great. This study seeks to take the debate further to allow educationists like lecturers and Professors to reflect on their practices that promote learning and competence development. This stance is supported by Virtanen, & Tynjälä, (2019) in their study of higher education students' experiences. They pointed out that learning analytics is considered to promote learning to learn, learning confidence, goal orientation, active engagement, metacognition as well as other factors that explain the learning of generic skills. While this all appears to point to the importance of learning analytics, areas to do with transforming student learning through data-driven learning analytics appear to be thin in the literature. Hence this case study on the missing piece of the puzzle.

This research benefits from the definition by Tsai & Gasevic (2017), who pointed out that learning analytics is the process of measuring, collecting, analysing, and reporting data about learners and their learning contexts. This is done to understand and optimize learning and the environment in which learning occurs. They further add that learning analytics is a discipline that is positioned at the intersection of learning, assessment science, and educational technology. Schneider, Dowell, & Thompson (2021) point out that learning analytics uses the process of computational analysis of learning process data. The main driving force is to better understand and improve learning. They add that this is done through the collection, measurement, analysis, and reporting of data that speaks about learners and their contexts. The purpose is to improve the learning and teaching processes. This is accomplished because of understanding and optimization of the learning and the environment in which learning occurs. In defining learning analytics, Paolucci, et. al. (2024) opine that learning analytics involves the collection, measurement, analysis, and reporting of teaching and learning data that speaks about learners and their learning environment. This process is undertaken to understand and optimize learning and the environments in which learning takes place.

Paolucci, et. al. (2024), think that the use of learning analytics can be a tool that is used to improve educational outcomes. It is because of this that learning analytics is a growing area of research. In their research at the PK-12 level, Paolucci, et. al. (2024), found out that while many see the educational benefits of learning analytics, there are still many in the educational field who remain unconvinced by a lack of evidence of improved outcomes. Mangaroska, & Giannakos (2018) add that learning analytics promote analytics-driven design to enhance learning. They argue that as the field of learning design and learning analytics mature, the convergence and synergies between these two are important concepts for improving teaching and learning. Thus, Mangaroska, & Giannakos (2018) strongly believe that the ongoing design patterns and learning phenomena that are becoming apparent from the synergies in learning analytics and learning design are too important to be ignored in the teaching and learning environments. This is the reason why this research is seeking to transform student engagement through data-driven learning analytics, as a case study of the missing piece of the puzzle in an open, distance, and e-learning institution.

Learning analytics also promote individualized learning, equitable instructions, and enhanced assessment for learning, among others. This was confirmed by Aguilar (2018) who pointed out that, through learning analytics, educational institutions are operating at the nexus of big data. This is an opportunity for these institutions to enhance social justice in education. Reinholz, Stone-Johnstone & Shah (2020), confirm that educators can use classroom analytics as a form of support for their instructors, who in turn will be able to address implicit bias in their teaching and learning tasks. It means, that when other institutions are succeeding in using learning analytics to promote social justice in education, then what is the institution under study missing? This prompted this study. There is a need for all learning institutions to start to speak about the unspoken in learning analytics (Archer & Prinsloo 2019) and start to transform student engagement through data-driven learning analytics.

Learning analytics can be used to design and adapt instruction. According to Williamson (2016), personalization of learning and data-driven education can be promoted using learning analytics. This is a platform that can help many educators in their quest to design and adapt instruction so that they can address the individual needs of every student. This is why Raza, et al. (2020) pointed out that learning analytics have the potential to offer support to educators in the provision of more equitable learning opportunities that include individualized support for learners. Some more common uses in this regard, include addressing learning gaps in prior knowledge. Educators can also use learning analytics to identify learners' preferred learning modalities.

Learning analytics appear indispensable in educational contexts. For example, Tsai & Gasevic (2017), are of the view that learning analytics has many uses in educational contexts. They point out that one of the most common uses of learning analytics is the prediction of student academic success. They further add that educators, parents, and the community can benefit from the identification of those learners who are at risk of failing a course or who are at risk of dropping out of their studies. This view was supported by Tsai & Gasevic (2017); Williamson, (2016), Archer & Prinsloo (2019), and Reinholz, Stone-Johnstone, & Shah (2020). They all agree that there are many productive and potent ways of using analytics to support teaching and learning. They pointed out that learning analytics can be used to support learner development of lifelong learning skills and competencies, they provide personalized and timely feedback to learners to enrich their learning process, and they support the development of critical and useful competencies that include communication, creativity, critical thinking, collaboration and others that are indispensable in the 21st-century learning landscape. Tsai & Gasevic (2017) further add that learning analytics promote the development of learner awareness because they support self-reflection. This will ensure that quality learning and teaching are supported since they provide empirical evidence of the success of pedagogical innovations.

Statement of the problem

Many researchers such as Karaoglan (2021), Ehlers (2020), Dowell, Lin, Godfrey, & Brooks (2020), and Gašević, (2019), report the advantages of using learning analytics that include improvement of teaching quality, data-driven decision-making, management of educational institutions, fostering lifelong and life-wide learning capabilities in students, forecasting, and prediction of risky students, promoting personalized feedback, gaining an informed understanding of how students are progressing, and others that all show that learning analytics are now a necessity in teaching and learning and not a requirement. While many institutions of higher learning are reporting glowingly about learning analytics, studies from the Institution under study appear very thin if any. This means the university is lagging in terms of identifying learners who are at risk of dropping out of their studies, connections to learning sciences, personalized learning that promotes student success, the optimization of learning environments, identifying areas of concern and interest, preventing the risks and barriers that might affect students' success, fostering a culture of quantitative understanding of how teaching and learning data intersects with human decisions, organization of the follow-up actions that can improve teaching and learning quality, and others that put their students at a disadvantage. Hence this study.

Research Questions

What qualitative insights do students and educators provide regarding the missing elements in the synergy of data-driven learning analytics and student transformation at your university?

How do identified gaps in the synergies of data-driven learning analytics quantitatively affect student performance metrics, alongside qualitative experiences shared by students?

METHODOLOGY

This research was a mixed methods study that used an open, distance, and eLearning 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 confirms of the same study. It is the mixture of both qualitative and quantitative research processes in a single study. This is done to enhance the understanding of a research problem. In this case the problem of transforming student learning through data-driven learning analytics.

Research Design

This research employed the concurrent explanatory sequential design for this study. In this case quantitative data was gathered through surveys. These surveys measured key performance indicators such as the use of learning analytics. The perceptions of the academic staff regarding the effectiveness of learning analytics were also sought in a bid to establish a baseline understanding. The interviews were also employed in the study in a bid to provide deeper context to the numerical findings (Patton, 2015). The use of the concurrent explanatory sequential design allowed the integration of the methodologies (Schutt, 2012). This yielded a richer narrative that enhanced a greater understanding of how learning analytics can support transformative educational practices. This problem was confirmed through deficiencies in the utilization of learning analytics to transform teaching and learning in an open, distant, and e-learning university.

Research Participants

The population of this study was 253 academics. The sample size for the study was 43. The 43 participants provided both qualitative and quantitative information for this study. Further quantitative information was obtained from the learning management system.

The participants in this research were chosen through purposive sampling. According to Patton (2015), purposive sampling is the purposeful identification and selection of information-rich cases for a study. This is confirmed by Babbie (2010) who opined that purposeful sampling is used in qualitative research studies to select a specified group of individuals or units for a research study. Purposive sampling is seen by Babbie (2010) as an appropriate method that is used when the researcher has a clear idea of the characteristics or attributes as was the case in this study. In this study, a sample that appeared to be representative of the characteristics and attributes that could inform learner transformation through learning analytics was selected. This selection process was supported by the work of Denscombe (2011), who pointed out that purposive sampling is used primarily as a way of identifying specific trends, insights, or characteristics resident within a targeted subset of a population.

This research utilized a concurrent explanatory sequential design. As a mixed methods research the research integrated both quantitative and qualitative data. Initially, quantitative data was gathered through the learning management system. This was done to establish a statistical foundation for the study and for providing a broad understanding of the research problem. Thereafter, qualitative data was collected through interviews. This enabled the study to examine and explore the underlying reasons behind the quantitative findings. The sequenced approach enhanced the richness of the results to be discussed below. The sequencing also allowed the study to triangulate data and achieve a better understanding of this complex phenomena.

Quantitative data was analysed using simple descriptive statistics while content analysis was used to analyse the qualitative data. In this case, the research extracted objective content from the interview texts. According to Patton (2015), this is done to examine meanings and come up with relevant themes and patterns that may be manifest or latent in a particular text. The content analysis allowed the research to go further and provided a platform where the researchers could understand social reality in a subjective but scientific manner (Babbie, 2010). Thus, following this process, the study was able to quantify and analyse the meanings, and the relationships of the words, the themes, and the concepts from the end users of learning analytics.

In summary, the data for this research was collected from the learning management platform. The data collected was varied. It included data that covered issues like assessment scores for both summative and formative assessments, course completion rates, time spent on courses, and 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 qualitative interviews with 43 participants from the teaching Faculty.

RESULTS AND DISCUSSION

Results

The findings of this study are presented below showing what the academics at the university under study saw as the missing pieces of the puzzle in the process of transforming student learning through data-driven learning analytics. Table 1 below shows some relevant learning analytics from the Learning Management System

Table 1: *The Missing Piece of the Puzzle in Use of Learning Analytics at the Institution*

	Frequency	**%**
Course completion rate	**79**	**86**
Course marking rates by tutors	**92**	**100**
Time spent on a course (1 hour and more)	**47**	**51**
Student attendance	**92**	**100**
Log in frequency (per week)	**92**	**100**
Students struggling with a specific course/assignment	**63**	**68**

Table 1 displays the analytics that were obtained from the learning management system of the university under study. These analytics highlight trends and patterns of student behaviour. The results show that all tutors (100%) mark their assignments for the students under study. All students visit the LMS at least once a week as shown by the attendance figures and the log in frequency. It also shows that 86% of the students under study completed their courses.

While the data in Table 1 was useful, it fell short on addressing the qualitative insights. Such insights are necessary for understanding the missing links in the synergy of data-driven learning analytics. These qualitative insights are captured in Table 2 below (N=43).

Table 2: *Perceptions of Academics - The Missing Piece of the Puzzle in Transforming Student Learning through Learning Analytics at the Institution*

	Frequency	**%**
Shaping future-ready learning environments	**21**	**49**
Learning ecosystems that integrate personalized learning and smart learning	**18**	**42**
Designing learner-centric environments	**23**	**53**
Improving data infrastructure	**26**	**60**
Ethical considerations essential for safeguarding student privacy	**20**	**47**
Predicting future learning trends	**17**	**40**
Developing customized interventions	**24**	**56**
Developing adaptive learning pathways	**19**	**44**

Table 2 shows what academics in the university under study perceived as the missing piece of the puzzle in the process of transforming student learning through data-driven learning analytics.

DISCUSSION

This section discusses the findings. The themes from the findings will form the basis of the discussions. The themes below address issues to do with the “missing piece of the puzzle” in the process of transforming student learning through data-driven learning analytics. While we all face challenges, our situations differ. Hence, individual circumstances importantly influence our ability to navigate them.

These are areas in which research participants feel they were not yet ready to benefit from learning analytics.

Shaping future-ready learning environments

Some 29 (49%) of the participants in this research posited that their learning analytics are failing to shape future-ready learning environments. This was mentioned as an area where participants in this research felt they were lagging. One participant pointed out that:

> *"Learning analytics has the potential to transform the teaching and learning contexts. Learning analytics just like artificial intelligence can turn the teaching and learning industry from a fact-memorizing system into a transformation system whose actual package helps learners to learn essential skills. It is the true transformative power of learning analytics that will unlock the learners' full potential, using customized learning."*

Another participant supported the issue of shaping future-ready learning environments by adding that:

> *"Learning analytics can shape the future-ready environment. This is because when analysing data on teaching and learning activities, teacher performance, learning assessment, and student feedback, among others, can transform the teaching and learning landscape. This also helps to identify niche areas for professional growth in line with future trends and effective teaching practices that can lead to improved teaching quality, learning outcomes, and student engagement."*

While another participant added:

> *"Our learning management system produces learning analytics that includes time spent on a course, course completion rate, assignment submission, feedback from tutors, and others. The use of learning analytics to track our learners' progress data, performance, and engagement, is useful for supporting teaching and learning. We can use that information to provide not only personalized and adaptive learning experiences but also to shape future-ready learning environments."*

In terms of shaping the future-ready learning environment, Cheung et al. (2021), pointed out that learning analytics can transform various pedagogical and technological innovations. This transformation process can lead to brand new learning environments created to optimize learners' ability to learn. They called them "smart learning environments" which can best delineate future learning environments (Cheung et al. 2021). To them, the process is made possible by many of these applications that support learning analytics to transform the future learning environment. Cheung, et al. (2021) noted that some of these embrace a variety of concepts that include flexible learning, mobile learning, personalized learning, blended learning, and adaptive learning, among others.

According to Hwang & Fu (2020), the smart learning environment should be given more attention in any discussions addressing the future-ready learning environment. It is an environment that will pay attention to the individual needs of learners. Hwang & Fu (2020) pointed out that such a future smart learning environment will be seen as a learning system that can facilitate efficient personalized learning. They also added the issue of adaptive learning in their debate for the future-ready learning environment. They argued that adaptive learning will provide methodological and technical support for personalized learning. Thus, they saw both personalized learning and adaptive learning, leading to personalized adaptive learning in the future. To them, the starting point is learning analytics. The analytics in Table one show that 68% of the learners, struggle with some courses. This confirms that learning analytics was a missing piece of the puzzle in this study.

According to Hwang & Fu (2020), personalized adaptive learning will make adaptive adjustments that are a result of the individual characteristics of learners obtained through learning analytics. This will transform teaching and learning by promoting the individualized development of students. Cheung et al. (2021) also added their voices by arguing that intelligent technologies and smart devices that are used in a smart learning environment can lead to the promotion of the development of personalized learning and adaptive learning for learners. Learning analytics that are used in conjunction with the smart learning environment do have the potential to effectively promote the development of both adaptive learning and personalized learning (Peng, Ma & Spector, cited in Cheung et al. 2021).

Learning ecosystems that integrate personalized learning and smart learning

Student attendance in this study was 100%. However, the completion rate was 85%. This may show the need for personalised learning. The learning ecosystems that integrate personalized learning and smart learning were mentioned by 18 (42%) of the participants in this study. One staunch supporter of the concept of learning ecosystems that integrate personalized learning and smart learning for the future noted that:

> *"I see our university as lagging in terms of the learning ecosystems that integrate personalized learning and smart learning. For example, learning analytics should be used in conjunction with elements that include cloud computing, artificial intelligence, and big data to come up with a, learning ecosystems that integrate personalized learning and smart learning. Such innovative means can then become integrated into traditional learning. Such a learning ecosystem will certainly enrich learning experiences for all learners leading to enhanced learning effectiveness."*

A second, equally enthusiastic advocate of the learning ecosystems that integrate personalized learning and smart learning, added that:

> *"Our future will be defined by a learning ecosystem that integrates personalized learning and smart learning. Such a learning ecosystem will be enabled by various technological innovations supported by current pedagogical practices. This will lead to brand-new learning environments that optimize the use of learning analytics to support the students' ability to learn."*

Kwet & Prinslo (2020) appear to support the issue of learning ecosystems that integrate personalized learning and smart learning. They pointed out that a smart learning environment should be integrated into different scenarios so that the future of teaching and learning is built on the data-centric smart learning ecosystem. This will provide students with a seamless learning experience (Lu, Yang, Shi, & Wang, 2021) that nurtures personalized and customized services for the learners. Lu, Yang, Shi, & Wang, (2021) further opined that there is a need to collect and use the learning data responsibly through observing relevant data protection principles and guidelines. Thus, to them, a learning ecosystem that integrates personalized learning and smart learning could be used to process learning data that will be used in monitoring learning progress and providing feedback to the students, the teachers, and the teaching and learning system. The focus should be on the applications of learning analytics to transform teaching and learning from the pedagogical perspectives (Peng, Ma, & Spector, 2019).

Tempelaar, Rienties & Nguyen, (2021) argued that there is a need to create learning ecosystems that enable learners to thrive, grow, and experience immersive learning experiences that nurture their full participation and involvement in the learning process. This can strengthen and transform student learning. This is made possible by nurturing connected learning ecosystems that are connected to the individual learner, the family, the schools, the classroom, and the community. Such a learning ecosystem not only integrates personalized learning and smart learning but also transforms teaching and learning in an environment where learners face the crisis of belonging and the crisis of connection.

Designing learner-centric environments

The data in Table 1 shows that the log-in frequency was 100% per week, suggesting the need for a learner centric environment. Some 23 (53%) of the participants in this research pointed to the learner-centric environment as the future of learning analytics. They thought that their use of learning analytics was limited because they fell short of the learner-centric environment that they saw as the piece of the puzzle in the transformation of the learning and teaching environment for the future. One participant elaborated by pointing out that:

> *"The learner-centric environment is what learning analytics should lead us to. We should have designed the learner-centric environments using advanced analytics that we get from learning analysis. These environments are needed because they are designed for the active construction of knowledge. This construction of knowledge is by and for learners. In a learner-centric environment, it is what the learners bring to the learning environment and what they are learning and not what they are taught that is central to the teaching and learning context."*

The issue of the learner-centric environment was also supported by Broughan & Prinsloo (2020). They opined that learners in a learner-centric environment play a more active role in their learning. This means that using learning analytics, teachers, tutors, and other educators should customize learning paths for individual students. This customization should be informed by learning analytics and should also be based on learner needs. On the other hand, Lu et al. (2021) appear to support this view. They claim that in a learner-centric learning environment, teachers, tutors, and other educationists should design ways that will help them uncover the skills, knowledge, attitudes, interests, and beliefs of every learner. This is done to show that learners are not blank slates. It is what they bring with them to the learning arena that leads to a conceptual understanding, or misunderstanding.

Kwet & Prinsloo, (2020) also added their voices to the learner-centric teaching and learning environments. They argued that people's thoughts and beliefs are often tacitly held. They also added that the learner's understanding of any subject matter is based on what they bring with them to the teaching and learning arena. This may include the students' cultural and social experiences and traditions. In such situations, learning analytics will help educators as they work to create unlimited opportunities to draw those beliefs to the surface. By so doing, they make their learners visible. When learners are visible, it makes the work of the educator easier in creating a learner-centric environment. It is easier to work with visible learners because one can use such an opportunity to build upon what the student already knows and can do.

Peng, Ma, & Spector, (2019), added the issue of students being encouraged, and not forced, to share their positive and negative experiences. These experiences can be modest or grand. In support, Tempelaar, Rienties, & Nguyen, (2021) bring to the debate on learner-centric environments the issue of collaborative learning strategies such as whole-class circle discussions and small-group literature circle discussions, among others. Such learner-centric environments were a missing piece of the puzzle in the university under study.

Improving Data Infrastructure

Some of the research participants in this study (26 or 60%), were of the view that they are not benefiting fully from learning analytics owing to deplorable data infrastructures. They saw state-of-the-art data infrastructures as part of the missing piece of the puzzle. In support of this view, one participant pointed out that:

> *"It is the entire data landscape that needs to be revamped if we are to increase our benefits from data analytics in this institution. I believe that we need to improve the data infrastructure. For me, this includes data capture, data analysis, data visualization, and others that illuminate the analytics that we are going to use."*

In support of the issue of data infrastructure issues, another research participant pointed out the need for data infrastructure modernization. Pointing out that:

> *"When the data infrastructure is modernised, then our benefits will increase. This means we need to look at the whole process where we can transform and optimize the large volumes of data that are accumulated by this university. This data should be more accessible, and more usable than it is in its current form. We need more servers, storage systems, software, and networks that can be used to enhance our abilities to benefit from learning analytics. With such data infrastructures, we can enhance our abilities to drive meaningful insights when the data is invaluable form."*

Another participant added that:

> *"There is a need for data management optimization, the use of modern data storage solutions, benefit from data security measures that are difficult to breach, and data consolidation among others. This entails the improvement of data infrastructure that includes data capture, data analysis, and the use of visualisations in data presentation."*

The importance of data infrastructures is ably captured by Ness (2024) who pointed out that data infrastructure is the architecture and the technologies that allow the storage, management, and processing of any accumulated data. To them, data infrastructure consists of the hardware, the software, the servers, the storage devices, the database infrastructure, and the analytical and business intelligence tools that are used in data collection, analysis, and storage (Ness, 2024). It also includes networking resources that are deployed in support of data storage, data processing, and data analysis. Data infrastructure enables organizations like universities to then have a centralized view of data. Such practices were seen as missing in this study, yet they make it easy for every learning institution to collaborate and share data insights. Blumenstein, (2020) concurred and added that there is a need for the data to remain secure and compliant.

According to Ness (2024); Karaoglan (2021), and Ehlers (2020), with adequate data infrastructures, decisions are made quickly and more accurately when they are using accurate and up-to-date information. The time spent on data acquisition and analysis is also important for decision-making because it will be readily available on demand. Organizations can leverage their modernized data infrastructures to retain a competitive advantage when analysing market trends. According to Ness (2024), big data infrastructure is indispensable in the modern data-driven world, because it is custom-built to the needs and requirements of the organization. This is why they added that big data is an enabler for innovation and customer experiences. However, it requires monitoring, security, maintenance, and optimization regularly (Ness, 2024).

Ethical considerations essential for safeguarding privacy

The abundant availability of learning data in the institution under study was seen as an excellent opportunity for improving learning outcomes for all learners. However, 20 (47%) of the participants in this study were concerned with the ethical issue that may arise from the use of learning data to improve teaching and learning.

One participant was of the view that:

> *"There is a need to ensure that the data collected and analysed is used appropriately. I am concerned that I have seen many instances where the potential misuse, of the data collected appears to be rampant. I also fear the issue of hacking. This may lead to the exposure of personal information*."

Another one who was also concerned had this to say:

> *"I am worried that if the use of data in learning analytics is not controlled, then it means my information and that of my students can be collected, monitored, and analysed without explicit consent from us."*

According to Pargman & McGrath (2021), the issue of ethics is now a prominent topic in learning analytics. However, they pinpointed many knowledge gaps in the literature regarding ethical practices in learning analytics. Cormack (2016) appeared to be concerned with the issue of learning analytics when pointing out that individual students lose control of the data that has been harvested about them once the data is made available to all. The worry was further confirmed by a participant who bemoaned that:

> *"My students are unable to screen who has access to the data that has been collected and analysed about them. They are not able to specify for what purpose their learning analytics will be used. In some instances, there is a risk of unfair and unjustified discrimination against some social groups, especially minority groups."*

Ferguson (2019) also added to the issue of ethics in learning analytics by arguing that there are ethical issues that should not be ignored when dealing with learning analytics. Some of them include prominent ethical principles such as the privacy of the students, anonymity issues, and consent issues that emerge in the learning analytics arena. In support of this same stance, Jones (2019) added some ethical principles that include ownership and control of the data, anonymity, non-maleficence, and beneficence, and issues like data management and security, among others.

According to Kitto & Knight (2019), in their research on the practical ethics for building credible learning analytics, student privacy should be respected and those who work with student data should ensure that the potential harm is avoided. Thus, in their research, Kitto & Knight (2019) recommended that there is a need to provide a middle space. This is the space where technical builders of systems could find time to deeply interface with those concerned with ethics in their attempt to promote learning analytics that encourage human flourishing across a lifetime of learning (Kitto & Knight (2019). In this study, this was seen as a missing piece of the puzzle.

Predicting Future Learning Trends

The data in Table 1 shows that 51% of the students in this study spent at least an hour on a course. These practices can be used to predict future learning trends. Shouting from the touchline, 17 (40%) of the participants in this research pointed to the use of learning analytics to predict future learning trends as an area that is missing from their list of benefits accruing from the use of learning analytics. To support this stance, one of the participants elaborated by pointing out that:

> *"Our use of learning analytics to predict future learning trends appears to be questionable. For example, many of us just stop at the use of predictive analytics to come up with engagement metrics. Yes, this is good because we can identify at-risk students through such practices. I am concerned with the future learning trends such as customized learning, generative artificial intelligence, micro learning, and others where we are lagging behind others."*

In support of the capacity to predict future learning trends using learning analytics, another participant added that:

> *"I am happy that we can use learning analytics to intervene early and then provide individualized support to our learners. However, the future of learning is changing. We need to use learning analytics to deliver bite-sized pieces of information to our learners. This is not the case right now."*

Another participant added to the debate on predicting the future of learning using learning analytics by arguing that:

> *"Teaching and learning are a moving target. We should be seen to be moving with the times using big data and learning analytics. For example, we should be embracing those strategies that are humanizing such as design thinking. However, what I see are practitioners who are clinging to the teach-by-telling strategies even though they are exhaustive and ineffective. Learning analytics should lead us to fully embrace emerging technologies such as virtual reality. In such instances, we will be promoting the learn-by-doing approaches."*

Baig, Shuib, & Yadegaridehkordi, (2020) proffered that the future of learning is driven by big data in education. To them, even future research directions should take this into account. This future, among other things, should also focus on the need for increased focus on inclusion, equity, and diversity. This will help in nurturing stronger talent with better ideas and increased creativity and problem-solving capabilities.

Sorensen (2018) also researched big data in the context of educational administration in a bid to use learning analytics to predict school dropout risk. Some of the recommendations are that school administrators should increasingly focus on ensuring that all voices are heard. They should also focus on ensuring that all perspectives are considered and respected. This means the future of education is pointing at nurturing diversity and inclusion. For this reason, learning analytics should promote these aspects of the future of education. If the views of the participants in this research are anything to go by, then predicting the future of learning is a missing piece of the puzzle in the use of learning analytics.

Baig, Shuib, & Yadegaridehkordi, (2020) in their argument noted that the future of learning is driven by big data, and added that future focus should be aimed at reducing seat time. To them, the use of micro learning strategies can increase the efficiency and effectiveness of education. There is a need to leverage the brevity and engagement of micro learning (Baig, Shuib, & Yadegaridehkordi, 2020). Thus, learning analytics should help predict the future of learning yet this was not the case in the institution in this study.

Developing Customized Interventions

Of the participants in this study, 24 (56%) contended that while they are benefiting immensely from the use of learning analytics, they are falling short in terms of customized learning. To them, personalized learning and customized learning should be enhanced using learning analytics. They believed that when they needed to provide learning material with proper content and context based on the data that they could generate through learning analytics. They argued that the best way for the learner is for the teacher to use the existing knowledge that they have for their students to develop them. One of the participants argued that:

> *"I feel that our use of learning analytics falls short when it comes to customized learning. This is because we are short-changing our students. After all, customized or personalized learning allows the learners to learn at their own pace. That focused learning will be enhanced by focused guidance that is informed by learning analytics. I, as the teacher, can also use updated learning plans that can be used to assist learners in targeting the topics and skills that they need more help with. I have seen before that such practices have the potential to build students' confidence and self-efficacy."*

Customized learning is supported in the literature. For example, Kleimola & Leppisaari (2022) in their research on learning analytics that can be used to develop future competencies in higher education found that the way to go is to use personalized learning that is customized to the needs and circumstances of the individual learner. In further support of the customized learning mantra, Virtanen & Tynjälä (2019) studied the factors explaining the learning of generic skills. In their findings, they concluded that the use of customized learning, personalized to a particular student, will increase student motivation since they know that their felt needs are being met. They also pointed out that learners are not only motivated, but they are more engaged in their learning. They even take responsibility for their learning.

While the participants in this research did not see any distinction between personalized learning and customized learning, because they used them interchangeably, Schneider, Dowell, & Thompson (2021) did not agree. In their research on collaboration analytics where they examined the current state and potential futures, they saw the potential in customized learning more than in personalised learning though the two complement each other. To Schneider, Dowell & Thompson, (2021) the personalization of learning is about tailoring an experience for the learner while the customization of learning is seen as the process of giving the learner control over the learning experiences. To the participants in this study, customisation of the learning experiences that will empower the learner to take charge of the learning experiences was a missing piece of the puzzle in the institution under study.

According to Karaoglan (2021), learning analytics can be used to support the students' problem-solving capabilities and academic self-efficacy. Karaoglan went on to give an example of using AI-powered personalized learning experiences. Karaoglan (2021) believed that artificial intelligence can be used to leverage customized learning paths for individual learners. Such practices will enhance student engagement and the effectiveness of the teaching and learning processes. This was not noted in this case study where customised learning appears to be one of the missing pieces of the puzzle.

Developing Adaptive Learning Pathways

Of the participants in this research, 19 (44%) agreed that learning analytics are increasingly becoming important especially for higher education institutions because they help these institutions measure student progress, engagement, and performance (Hershkovitz, Knight, Dawson, Jovanović & Gašević, 2016). They noted that learning analytics is the process of collecting, analysing, and reporting data about learners and their contexts. While the participants agree that in the institution under study, learning analytics promoted learning optimisation and the environments in which it occurs, they questioned the promotion of adaptive learning pathways using learning analytics. One of the participants had this to share:

> *"Learning analytics have transformed the way we teach but we have not reached a stage where we need to create adaptive learning pathways. These will allow us to customize the content that we teach, the methods that we use, and the assessments that we administer so that they match the learner's pathway. When we use learning analytics, we can configure a learning path that provides an individualized learning experience based on the learner's analytics."*

Another participant concurred and added that:

> *"Our teaching has gone a step ahead using learning analytics. For example, we now can obtain valuable insights that benefit both faculty and students from the analytics. However, some areas may need to be improved. For instance, there is a need to use learning analytics to dynamically adapt learning content and activities so that these conform to the unique individual characteristics of each learner."*

According to Schneider, Dowell & Thompson (2021), adaptive learning pathways enabled the delivery of personalized learning at a large scale. They added that adaptive learning pathways reduce cheating because the content and assessments can vary for each student. In support of the adaptive learning pathways, Sorensen (2018), added that an adaptable teacher can quickly and easily adjust his/her teaching tactics and teaching methodologies to meet the needs of all their students through adaptive learning practices. Sorensen (2018) further opined that the adaptive learning pathways can promote improved student participation, motivation, and engagement. Then this will lead to better student outcomes for the benefit of all the educational stakeholders like teachers, parents, and the community at large.

The issue of adaptive learning pathways was taken further by Hershkovitz et al. (2016), who pointed out that learners get real-time feedback using adaptive learning pathways. Learners can also do their work on their schedule while the faculty can obtain insights into student needs via data generated through learning analytics. Hwang & Fu (2020) also added to the discourse on the issue of adaptive learning pathways by arguing that the use of adaptive learning can lead to a decreased risk of students falling behind because by using adaptive learning, the faculty and their learners engage in highly productive interactions.

CONCLUSION

This research analyzed the synergies of data-driven learning analytics and the transformation of student learning. The research concluded that while the institution under study employs strategies that benefit from data-driven insights and proactively plan and adapt to changes with real-time data analysis, many pieces of the puzzle restrict its benefits. While they can redefine the teaching and learning process by using learning analytics to shape future learning spaces, to foster student engagement and collaboration, they are unable to reshape pedagogical approaches using learning analytics and provide learning ecosystems that integrate personalized learning and smart learning. Their students cannot immerse themselves in dynamic interactive simulations because they are failing to design learner-centric environments. They appear not to be developing customized interventions, yet this is a powerful bridge that promotes equity and inclusivity and narrows educational attainment gaps. They appear to be short of developing adaptive learning pathways.

This often restricts collaborative learning and interactivity for their learners. They appear to be failing to build an ideal, equitable learning environment, because of limitations in predicting future learning trends. Thus, the conclusion is that the synergies of data-driven learning analytics and the transformation of student learning are being compromised by the missing pieces of the puzzle.

Recommendations

The findings of this research have resulted in the following recommendations:

- There is a need to use learning analytics so that the institution can easily adapt to pedagogical advancements.
- They must use learning analytics as a departure from static teaching methods and promote personalized learning experiences that are tailored to student's individual learning needs and preferences.
- There is a need to redefine learning spaces to scale up sustainability, accessibility, and adaptability
- There is a need to use learning analytics to create a more collaborative and dynamic learning environment that is anchored on the development of customized interventions
- Improving data infrastructure is a collective responsibility that fosters a comprehensive solution that seamlessly integrates adaptable hardware and software. This means that policymakers, educators, and other key stakeholders must collaborate to reshape a sustainable technologically enriched future for all learners.
- There is a need to create a personalized learning analytics framework that is tailored to the specific needs of their students.

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