Assessing Institutional Readiness for the Fourth Industrial Revolution: Using Learning Analytics to Improve Student Experiences

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Abstract. The Fourth Industrial Revolution (4IR) brought disruptive technologies, dramatically changing the way businesses operate. Higher education institutions make use of learning management systems (LMS) primarily for teaching, learning and assessment. The COVID-19 pandemic has pushed the use of technology for academic continuity, resulting in institutions using LMS for virtual engagements with students, student collaborations, assessments, and as a repository for resources. Student behaviour on the LMS can be tracked, giving useful learning analytics which may be used to improve student success, retention, experience, and institutional performance. This paper is an exploration of institutional readiness for learning analytics. We adopted a qualitative approach, using purposive sampling to select the institution and initial participants. We used the snowball technique to recruit further participants. The personality traits stated in the Technology Readiness Index model were used to formulate interview questions. The findings show that the institution has systems in place to support students, which were launched to address insights from LMS-based learning analytics. The institution is ready for using learning analytics, with participants innovatively using the LMS, showing enthusiasm, and optimisation of the full potential of learning analytics. We recommend the use of learning analytics to come up with effective student support.

Keywords: Fourth Industrial Revolution (4IR) · Data-Driven · Decision-Support · Higher Education · Learning Analytics · Technology Readiness

1 Introduction

The Fourth Industrial Revolution (4IR) has significantly contributed to the improvement of the quality of education. However, 4IR comes with both challenges and opportunities, according to Elayyan (2021), with some institutions lagging in embracing it. According to the United Nations (UN), attaining inclusive and equitable quality education is necessary for sustainable development, making it a sustainable development goal (SDG)

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(Mori Junior, Fien & Horne 2019). This can only be realised if fair, accountable, and informed decisions are made. Decision-making is at the core of higher education, with decisions made varying on impact. Decisions in higher education are aimed at improving student retention, success and experiences, and overall institutional performance. There is a growing need to make accountable decisions, and additional defined approaches used to make decisions, however, most of the approaches lack fairness and accountability (Bull 2014). Cox et al. (2017), Liu et al. (2017), Kovač & Oreški (2018), Nouri et al. (2019) concur that data-driven decisions are accountable and fair, and often lead to improved institutional performance. Using student learning data is recommended for improving student experience, retention, and chances of success to equip students for the 4IR era.

Learning analytics is an emerging field of study, gaining popularity for its effectiveness in improving institutional performance. Higher education institutions can derive multiple benefits from the use of appropriate data analytics strategies, providing insights that help with decision-making. With the advancement in technology brought about by 4IR, student experiences may be improved through timely decisions, facilitated by real-time analysis and feedback on student learning behaviour (Adams et al. 2020; Elayyan 2021). Artificial intelligence (AI) and machine learning (ML) can optimise and automate several analytics processes, bringing changes to business processes (Elayyan 2021). Studies suggest that learning analytics has the potential of changing higher education (Siemens & Gasevic 2012; Leitner et al. 2017; Wong 2017; Viberg et al. 2018; Sousa et al. 2021). The success of learning analytics in supporting decision-making depends on various factors, which need to be considered and addressed by the institution. With institutions operating differently, it is important to develop a customised framework for learning analytics, instead of using a one-size fits all approach.

Higher education institutions make use of learning management systems (LMS), which are designed to support hybrid teaching and learning (Joo, Kim & Kim2016; Alzahrani et al. 2021). In an LMS, students interact with learning content, resources, and assessments and collaborate in completing academic projects. The use of LMS has grown significantly during the COVID-19 pandemic, supporting remote teaching, learning and assessments by providing virtual engagements, either synchronously or asynchronously (Zhao & Watterston 2021). LMS may be considered the most common source of learning analytics in higher education. As students navigate through an LMS, their behaviour is recorded, leaving a "digital footprint" which may be analysed to give insights on student engagements, predictions on future trends and chances of success and make decisions accordingly, as ascertained by Leitner et al. (2017).

This study aims to assess institutional readiness for using learning analytics to support decision-making. There are various decision-support systems in use in higher education, most of which focus on enhancing the student experience and improving institutional performance (Leitner et al. 2017). This paper was done to explore institutional readiness for learning analytics. The paper commences with a review of the literature on decision-making in higher education as well as the challenges thereof. This is followed by a review of decision-making approaches including data-driven decision-making, decision support systems and learner analytics. The paper subsequently proposes the application of the Technology Readiness Index (TRI) and the methodology applied. This is followed by a discussion of the results and concluding remarks.

2 Decision-Making in Higher Education

Higher education institutions collect and generate huge amounts of data intended to advise decision-making and improve institutional performance. Schildkamp & Datnow (2020) posit that vast amounts of data can be overwhelming if not handled and used appropriately, leading to adverse effects. Furthermore, strategies must be implemented to safeguard these data to comply with policies (Nouri et al. 2019). South African universities face several challenges, according to DHET (2019), centred on decision-making. These include lack of accountability, underperformance, and compromised student and staff experiences. Lepri et al. (2018) and Schildkamp et al. (2017) contend that human challenges in decision-making may be overcome by using a data-based approach, of which learning analytics is an example.

In outlining the importance of methodology in strategic decision-making in higher education, Kadoić, Ređep & Divjak (2017) cite the significance of making effective decisions. Their study suggests a data-driven strategic method for decision-making in the context of higher education. Learning analytics data provide valuable insights that may be utilised to support decision-making. In the study carried out by Seale (2015), which focused on capacity building for Deans to ensure effective leadership in South African higher education institutions, the importance of decision-making was emphasised. There is an organisational shift in management and decision-making, which is in line with global trends (Seale 2015). In this vein, it can therefore be argued that efforts should be made to ensure institutional readiness for the use of data to make decisions, in line with global trends. The editorial (Lytras et al. 2018) on learning analysis posits that the use of data to make decisions has received growing attention in recent years. While empirical evidence shows that processing data can be complex and sophisticated, the adoption of emerging technologies in higher education can be optimised [13]. Empirical evidence shows that the availability of data is not enough for decision-making requiring organisational readiness and user adoption of a data-driven decision-making approach (Bouwma-Gearhart & Collins 2015). There is compelling empirical evidence to emphasise the importance of effective decision-making in higher education, with learning analytics recommended for effective student-support decisions (Leitner et al. 2017; Wong 2017).

3 Challenges with Decision-Making

Executives, academics, and admin staff at institutions of higher learning make decisions that impact students. Vanlommel et al. (2020) posit that teachers often rely on intuitive processes to make decisions that affect their pupils' academic and future trajectories. Although intuitive decision-making may save time and provide creative solutions, there are risks involved. Intuitive decision-making may not consider all alternatives, thereby leaving out the best solution (Okoli & Watt 2018). There is a greater risk of making a decision based on incomplete or inaccurate information (Vanlommel et al. 2020).

Although (Okoli 2020) claims that experience and intuitive expertise improve the effectiveness and efficiency of decision-making in times of crisis, empirical evidence shows that intuitive decision-making lack consistency, fairness and equality (Vanlommel et al. 2017; Visscher 2020; Lasater, Bengtson & Albiladi 2021). Therefore, using such an approach at higher learning institutions may compromise student experiences, success, and retention, as well as institutional performance. According to (Cai et al. 2018) data may be used to understand and improve the student experience.

South African higher education is increasingly becoming a regulated sector with political influence (Mngomezulu & Maposa 2017). Policies and regulations are implemented and constantly reviewed, and decision-makers have to comply to ensure inclusion (Dalton et al. 2019). However, such decisions may not be in the best interest of the institution, as (Bull 2014) argues that decisions made in compliance with policies and regulations are often rigid, and accountable, but may not always be effective. Unfortunately, these decisions may be non-negotiable even though their effectiveness may be questionable. It may be argued that some policies are designed for ideal institutions, and may not be applicable in reality (Engelbrecht et al. 2016). The Authority Principle is highly applicable in education (Bull 2014), where decision-making is done by relying on authority figures. These may be experts in a specific field, executives, or heads of departments. This approach shifts ownership and responsibility from the decision maker, and if the desired outcome is not achieved, no one assumes responsibility (Bull 2014; Mngomezulu & Maposa 2017). Furthermore, the importance of ethics cannot be overemphasised. Some decisions may be effective and logical but may not be ethical. Apart from the strategies above, huge amounts of data gathered and generated may be used to make decisions.

Academic institutions build reputations based on several factors (Yadufashije 2017), including student success rate, research output, and contribution to addressing skills needs, among others. Decision-making is a process of evaluating and identifying the best option or course of action, based on the values and objectives of the organisation (University of Massachusetts 2018). Moreover, while different approaches may be used for decision-making, many lack consistency and accountability (Lepri et al. 2018). Decisions on instruction and intervention are particularly important for teaching and learning experiences, and therefore directly impact throughput rate (Kovač & Oreški 2018), student experiences, and institutional performance. It is therefore recommended to make such decisions based on student learning data.

4 Decision-Making Approaches

Decision-making involves choosing a course of action, from identifying the decision to be made, gathering information, weighing the alternatives and finally making a choice (University of Massachusetts 2018). The urgency of the decision to be made, as well as the impact it will likely have, are the most crucial factors to consider before making a decision (Batteux, Ferguson & Tunney 2019). There are several approaches used for making decisions, and in most cases, a combination of approaches is used. These approaches include careful consideration of both internal and external factors. According to (Bull 2014), some decisions are made based on what is currently trending. Personal preferences, convenience, intuition, tradition, and indifference are some of the strategies that lack consistency, fairness, and accountability.

4.1 Data-Driven Decision-Making

There are several types of data that institutions gather and use to inform their improvement plans, including demographic, school processes, and student-learning data (Prenger & Schildkamp 2018). Decisions made based on data are considered fair, consistent, and accountable (Lepri et al. 2018). Such data may be collected from stakeholders, generated by algorithms and other intelligent systems including learning analytics or as a result of research (Liu et al. 2017; Kovač & Oreški 2018; Nouri et al. 2019). Data are necessary to make strategic decisions and measure organisational performance concerning student throughput, retention, and staff turnover, among others. Organisations face challenges in adopting a data-driven approach to decision-making. Schildkamp et al. (2017) posit that organisational data use depends on the characteristics of the data, the user motivation levels, and the organisation at large.

Data-driven decision-making is increasingly becoming popular in education and other sectors where accountability is expected. This approach is used for university admittance, as well as for making predictions on the probability of success of students (Asif, Merceron & Pathan 2014) in certain courses. Kovač & Oreški (2018) ascertain that there is a need to use data at all levels of education to develop systems that help improve the chances of student success. This is further supported by the findings of Nouri et al. (2019), who conclude that despite a lack of policies and national guidelines, data-driven systems have improved teaching and learning experiences in Europe. Institutions are more likely to succeed in the adoption and successful use of data-driven approaches if teams get support, as concluded by Schildkamp & Datnow (2020).

4.2 Decision-Support Systems

According to (Kashada, Li & Kashadah 2016) decision support systems refer to anything that can be used to provide rational and measurable scientific data on which decisions may be based. Such systems can be manual, hybrid, or specialised computer software. Manual decision support systems have been in use for decades, including SWOT analysis, cost-benefit analysis, Pareto analysis and decision matrixes, among others (Abdel-Basset, Mohamed & Smarandache 2018; Leiber, Stensaker & Harvey 2018). Due to the huge amount of data and the advent of new technologies, hybrid systems and specialised software are becoming popular. The 4IR brought a new era of technology and innovation, enhancing human-computer relationships, making data capturing and processing easy (Ramlall 2020). Technology has the capability of analysing huge amounts of data in a short time, making them more efficient and effective (Cid-López et al. 2015; Francis & Babu 2019). However, these systems have not been fully adopted in most developing countries (Kashada, Li & Kashadah 2016), including the South African Higher Education System. Kashada, Li & Kashadah (2016) posit that user awareness, among other factors, greatly influences the adoption of new technology by individuals. Some of these factors may be explained using models and theories for technology acceptance and adoption. Organisational readiness is of utmost importance in the adoption and use of any new technology and innovation (Nusir, Law & Aldabbas 2012; Kaushik & Agrawal 2021). Readiness may be measured quantitatively using the technology readiness index (Parasuraman 2000; Mufidah, Husaini & Caesaron 2022), and qualitatively by assessing organisational capabilities including the availability of resources, human capacity with skills and knowledge, weighing individual awareness, motivations and inhibitors (Christensen & Knezek 2017; Alzahrani et al. 2021; Kaushik & Agrawal 2021).

4.3 Learning Analytics

Learning analytics refers to the analysis and reporting of measured and collected learner data about learning, as defined by Siemens & Gasevic (2012). The purpose of learning analytics is to understand and optimise learning and learning environments to enhance student experiences and improve success and retention rates. Wong (2017) ascertain that the use of computational techniques and artificial intelligence offers new opportunities for dealing robustly with huge amounts of data that are collected and generated by institutions. Research has shown that learning analytics is crucial for academic planning, lifelong learning skills and strategies, learning resource allocation, curriculum renewal and supporting quality teaching and learning through analysis of the impact of different pedagogical innovations (Siemens & Gasevic 2012; Leitner et al. 2017; Wong 2017; Viberg et al. 2018; Jalil & Wong 2021). Provision of timely, personalised feedback to learners and supporting 21st-century skills such as critical thinking, communication creativity and collaboration makes learning analytics practical and significant in higher education today.

Researchers and data analysts often categorise learning analytics into three categories, depending on how they are used. While predictive analytics uses collected data to establish trends and predict possible future outcomes (Liu et al. 2017; Kovač & Oreški 2018), prescriptive analytics goes deeper, giving potential outcomes of different actions by combining the power of algorithms, machine learning, computational modelling, and business rules to recommend decision choices, leading to possible autonomous systems (Liu et al. 2017). Further from these two, descriptive analytics provides insight into the past by using data mining and aggregation techniques. This past data may be used to reflect on past practices and improve in future. For instance, student feedback surveys may be used to improve pedagogy. Diagnostic analytics is often used to find cause and effect (Asif, Merceron & Pathan 2014; Kovač & Oreški 2018; Alyahyan & Düştegör 2020; Sousa et al. 2021).

Learning management systems (LMS) have tools to track learner behaviour. Analytics from an LMS can be used to design strategies to improve learner engagement, and quality of teaching and learning, offer appropriate intervention, and provide timely feedback to students (Joo, Kim & Kim 2016; Mufidah, Husaini & Caesaron 2022), thereby improving chances of success and retention. Without learning analytics, such decisions are made without any evidence, and their effectiveness is questionable (Kovač & Oreški 2018). Research proved that decisions made on data are fair, accountable, and effective. With the rate at which LMS learning analytics may be generated, the feedback loop can be closed quickly, offering students timely, actionable feedback which is personalised and precise. All institutional stakeholders stand to benefit from the use of learning analytics, especially students, academics, curriculum developers, instructional designers, and student support services personnel.

5 Theoretical Framework

Institutional readiness for learning analytics depends on various factors based on both individuals and the institution. There are many models and theories to predict the likelihood of technology acceptance, including the Technology Acceptance Model in its various forms (TAM, TAM-2, e-TAM), the Theory of Reasoned Action (TRA), and the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT 2), among others. While these models and theories are useful and have been extensively used to study technology domestication (Lai 2017; Putra Kusuma 2019; Nugrahani & Wahid 2021), they fall short on assessing the readiness to adopt new technology. Parasuraman developed the Technology Readiness Index, which is a paradigm that focuses on personality dimensions to assess the ability to accept and use new technology (Parasuraman 2000).

The TRI gives optimism, innovativeness, discomfort, and insecurity as the four personality traits that influence an individual's technology use (Parasuraman 2000; Mwapwele et al. 2019). These personality traits do not focus on knowledge and skills, but rather on the individual's beliefs and state of mind. Optimism refers to an individual's belief that technology has positive benefits, while innovativeness is an inherent tendency to explore and experiment with technology. These two constructs are motivators for technology use. Discomfort and Insecurity are inhibitors of technology use. Discomfort is the perceived fear of being overwhelmed by technology and lack of control thereof, while insecurity refers to the perception that the technology may not work as expected and may result in adverse effects (Parasuraman 2000; Mwapwele et al. 2019; Shonhe 2019; Warden et al. 2020; Kaushik & Agrawal 2021; Mufidah, Husaini & Caesaron 2022). An individual can have both motivators and inhibitors. However, motivators should overcome inhibitors for one to be ready to use technology.

The TRI is mostly used quantitatively by using Likert scale surveys. However, in this study, we decided to use it qualitatively to explore institutional readiness based on staff optimism, innovativeness, discomfort, and insecurities about learning analytics.

6 Methodology

6.1 Participants

The sample was drawn from a preselected institution using purposive sampling. The institution was selected for convenience since it is among many other institutions that fit the selection criteria. Purposive sampling ensures that data is collected from all key stakeholders. Initial participants were identified by their positions at the institution and approached for consent. The Snowball method was then used to select more participants. The sample represented academic, support, and administrative staff as well as executive management.

Bryman (2012) posits that interpretivism holds that reality is subjective, socially constructed, and a composite of multiple perspectives. Interpretivism enables a deep understanding and exploration of lived experiences of a complex world from the perspectives of those who live in it (Saunders, Leweis & Thornhill 2009). In this study, adopting an interpretivist approach enables us to explore, interrogate and understand the perceived benefits of learning analytics by stakeholders in the higher education sector. Intepretivism is characterized by subjective deviations, and as such, should be considered in interpreting the findings of this study as well as for future research.

6.2 Procedure

The study was approved by the institutional Social Sciences Research Ethics Committee, and institutional permission was granted to collect data. Two initial semi-structured interviews were carried out first with data analysts/architects. The purpose of this interview was to identify the status of learning analytics; finding out what systems are in place, how learning data is analysed and who has access to what data. A total of 24 participants were interviewed using semi-structured interviews. The duration of the interviews was significantly different- ranging from a minimum of 23 min to a maximum of close to 1 h 30 min. Interviews with Data Analysts (or related) and directors were much longer compared to Admin staff (secretaries) and academics. Data saturation was reached after 19 participants, after which a further 5 interviews were conducted to ensure that no new data emerge.

Interviews were conducted virtually and recorded. Subsequently, thematic analysis was used to analyse the responses. Interviews were transcribed and coded using open-coding. The codes were then grouped into categories, which were then used to come up with themes. Interview questions were guided by literature on technology acceptance models and the technology index model (TRI), which states that an individual's personality influences their potential acceptance of technology, citing optimism, innovativeness, discomfort, and insecurity as the four personality traits that impact acceptance of new technology (Parasuraman 2000). We were interested in identifying optimism through responses with a positive belief of the capabilities of technology, knowledge of systems in place and their perceived potential; innovation by how one's understanding of how learning analytics systems work, how they experiment, navigate and explore learning analytics. Discomfort and insecurity were identified through one's fears of using learning analytics, lack of knowledge of systems in place at the institution, and uncertainty of how to analyse and interpret learning data (Table 1).

Table 1. Participants' breakdown

Position	Number of people
Data Specialist (Analyst, Instructional Designer or related)	8
Managers/Directors	4
Academics	7
Admin/Other Support	4

7 Results and Discussion

Successful adoption and use of any new technology or innovation depend on individuals' beliefs and perspectives, as well as organisational support. Several systems are in place at the institution, and learning analytics is an active source of data that is used to support decision-making for enhancing the student experience and institutional performance. Access to data is provided to authorised stakeholders. However, this came up as a challenge due to the need for privacy in compliance with policies and legislation.

7.1 Personal Beliefs and Perspectives

All participants agree that there is a need to regularly analyse, review, and reflect on how students are performing, and make decisions on intervention, assessment, resource allocation, curriculum renewal and level of support needed, among others. While some participants admit that they cannot analyse data on their own, they highlight that they are willing to get training that will enable them to use data to support decision-making. Participants acknowledge the importance of data-driven decision-support systems but are only willing to undergo training that will enhance their performance and simplify their work. There is optimism that learning analytics will improve the student experience, retention, and success rate, with all participants acknowledging the need to understand and use learning analytics effectively except for some support staff. Two of the support staff interviewed claim that they do make decisions on their own, but rather take instructions from their line managers. All academics claim that they often *"…click around and explore…" student learning data, "…especially access to resources and assessment marks…"* to establish relationships between performance and engagement with resources. Data analysts claim they are *"…fascinated by data and its meaning…"*, and always engage with student learning data, among others.

One therefore may conclude that there is great optimism for the potential of learning analytics, and stakeholders are innovative and enthusiastic about learning analytics. The level of discomfort and insecurity is very low, arising mainly from a lack of sufficient knowledge and skills to analyse data. It is important therefore for training to be offered regularly to stakeholders so that the power of learning analytics may be fully realised.

7.2 Institutional Capabilities/Readiness – Systems in Place

Technology Availability
The institution has a Sakai platform LMS in please, which is branded as iKamva at the institution. Findings show that the platform is well known, well communicated, and utilised by the relevant stakeholders. Academic staff use the LMS for teaching, learning and assessments. Participants highlight that iKamva is very effective and easy to use, and enable them to remotely engage with students, allow students to collaborate, and access resources easily.

The LMS have various functionalities that generate student learning behaviour. Participants use LMS-based learning analytics for decision support. What only differs is the decisions and type of data they use. For example, academic staff highlight that they are most interested in real-time analytics which enables them to give timely feedback, and planned intervention. Data analysts, instructional designers, institutional planners, and directors use real-time, predictive, and summative analytics for broader decisions, leading to equitable resource allocation, appropriate curriculum renewal, and student support services, among other services. However, the LMS alone does not provide enough insights for all decisions to be made, and for that reason, the institution has other decision-support systems in place.

Participants realise the importance of learning analytics in advising student support strategies and acknowledge its potential in improving student success and retention. Participant P1, an academic, said, *"I use iKamva daily since lockdown. I don't know all its functions, but I know what I want, and it works for me. I can see how they[students] perform and give feedback accordingly"*. Similar sentiments being aired by other participants, indicating the levels of optimism and innovativeness among staff.

Further to the LMS, the institution is in the process of developing a central data warehouse, which all institutional systems will draw data from. This level of innovation indicates readiness and commitment to data-driven decision support from the institution. For students, these data will include, among others, learning data and biographical information. A centralised database allows sharing of ideas among analysts, higher level of security, enhances data integrity and reduces data redundancy. These efforts are evidence that the system is ready for data-driven decision-support, which includes using learning analytics to enhance student experiences, and improve chances of student success and institutional performance. While some stakeholders did not know about this move, they all unanimously agree that a central database will improve data-sharing and the use of data to support decision-making.

Staff Availability
Snowballing led to interviews with professionals in the data analytics field. The institution has several staff members who are Data Analysts, Data Architects, Instructional Designers, and Teaching and Learning Specialists, among other Information and Communication Technology specialists. They are responsible for various aspects of ICT systems, including decision support systems. In addition, academic staff and administrators are trained to effectively use the LMS for their day-to-day needs without t the need of a specialised professional. For example, participant P2 highlights that he *"…can*

track student progress and identify those at risk timeously…". It is therefore clear that the institution has adequate staff capabilities to use learning analytics effectively.

Analysing and making sense of data is often a challenge for stakeholders. Academics interviewed pointed out that they can *"understand the data they get from iKamva"* concerning student behaviour. However, they highlighted that they would prefer data to be analysed for them and provided with a summary and recommendations. This was also echoed by all other stakeholders except data specialists, who claim they can extract, analyse, and interpret the data for themselves. For successful use of learning analytics, stakeholders need to be able to understand the data at their disposal, as concluded by Leitner et al. (2017), Tsai & …, (2017). Having data professionals giving support to other institutional stakeholders by giving reports and recommendations from learning analytics shows that the institution has the sufficient human capacity to effectively use learning analytics for decision-support.

Learning Analytics-Based Projects

The institution hosts some projects based on learning analytics. These projects vary in scope, depending on whether they are based on predictive, real-time, and summative. However, one can conclude that running such programs illustrate the high level of readiness for using learning analytics that the institution is at.

The Siyaphumelela project was launched in 2020. Siyaphumelela is an IsiXhosa word meaning "We Succeed". This project focuses on using learning analytics to enhance student support. The project has been launched due to student retention and success challenges faced, identified using learning analytics. Participant P3, a Data Analyst, who is part of the Siyaphumelela projects outlined how learning analytics are used to provide improve student experience through curriculum development, and academic and psychosocial support. According to P3, Siyaphumelela is *"… all about using data to make informed decisions that will lead to student success…."*. P3 further posits that the project was launched after some time of using learning and other data analytics for research into student success and challenges. In essence, the Siyaphumelela project is mainly focused on students who need support to succeed.

Data analytics, including learning analytics, in higher education, focuses on identifying gaps in learning and supporting learning at different levels. This may include supporting students academically, psychosocially, or even guiding and preparing them for workplaces. To support and recognise academically high-performing students, the institution runs the Accelerated and Excellence Project (AEP). AEP focuses on supporting high-performing students with their academics as well as equipping them with essential skills required for the workplace.

Further to Siyaphumelela and AEP, the institution is working on a student success and retention framework, aimed at addressing the low undergraduate throughput rate and curbing the high dropout rate. Using data analytics, academic, well-being and financial need have been identified as key factors contributing to student dropout. The framework aims to address such challenges by advising, mentoring, and supporting students throughout their academic journey. The framework relies heavily on learning analytics, identifying students' deficiencies and needs, and referring them to the services that may ensure an improved experience.

Learning analytics is important in identifying students at risk and coming up with strategies to mitigate the risk timeously. A participant, P4 from student support services claims that students often struggle academically due to language (and accent), pace, and low confidence levels. According to P4 *"…[some students]are scared to ask questions from their lecturers for fear of the reaction from other students"*, and others find it *"…hard to acclimatise themselves to the different accents and pronunciations…"* by their lecturers. The institution runs a Tutor Enhancement Program (TEP), which has been designed to offer peer support to such students. Tracking their progress has proved that they significantly improve their academic performance and chances of success, which is in line with empirical evidence from other studies (Morano & Riccomini 2017; Pugatch & Wilson 2018; Arco-Tirado, Fernández-Martín & Hervás-Torres 2019).

8 Conclusion, Limitations and Recommendations

There are several studies on technology readiness, but few on learning analytics. Furthermore, technology readiness has been broadly studied quantitatively, without a deeper exploration of the meanings attached to the indices provided. To complement quantitative studies and contribute to the body of knowledge, this study qualitatively interrogates readiness from a different perspective, by exploring the systems in place and identifying key uses of learning analytics. This study, therefore, contributes to both theory and practice by enabling policymakers, institutional planners, and curriculum designers to better understand innovative ways of using and improving learning analytics to improve student success, retention, and experience. Furthermore, it contributes to the body of knowledge by providing institutional insights, which may help other institutions in adopting a learning analytics-based decision-support approach to improving institutional performance.

This research should be interpreted with its limitations. This paper is part of a broader study on decision-support systems, and limited questions were focusing directly on learning analytics. This was done to reduce the length of the interviews. However, learning analytics-specific follow-up interviews were conducted with a few individuals which provided deeper insight into the use of learning analytics. Furthermore, to have a full picture of institutional readiness, a survey should be carried out with all stakeholders, including students, to triangulate the qualitative data reported herein. We recommend a quantitative study that includes students, who are also part of the university community. Being an interpretive study, subjective deviations are thus inherent in this study. This should be considered on interpreting the findings.

Our findings show that the institution is ready for learning analytics. However, we cannot ascertain its impact on student success, retention and experience since those aspects are out of the scope of our study. The conclusion that the institution is ready for learning analytics has been reached after the analysis of responses from participants, who all show enthusiasm for using data to make an informed decision, and are optimistic about its potential to simplify their work, improve their performance, enhance their experience, improve student retention, success, experience and consequently improve institutional performance.

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