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A Transdisciplinary Approach to Enhancing Online Engineering Education through Learning Analytics

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ABSTRACT

In the context of expanding digital education and persistent global disparities in access, this study explores how learning analytics (LA) can enhance teaching effectiveness and student success in open and distance learning (ODeL) environments. Focusing on Mineral Exploitation IA, a first-year engineering module offered in a South African university's Diploma in Mining Engineering program, the study exemplifies the use of data-driven methodologies to address systemic educational challenges such as low pass rates, high dropout rates, and poor learner retention.

This case study employs an interdisciplinary and mixed-methods research design, integrating educational data mining (EDM), behavioral analytics, and comparative analysis to assess student engagement, performance, and demographic context. Drawing on data extracted from the institution's Moodle learning management system, the study examines how students interact with online materials (e.g., video content, discussion forums), complete assessments, and vary in performance across geographic and socioeconomic boundaries.

Findings reveal that students from remote or under-resourced regions—primarily in developing countries—face significant challenges in accessing digital platforms, often due to infrastructural and technological limitations. These constraints negatively impact their participation and performance, highlighting the interdependence of technological, pedagogical, and socio-economic systems in ODeL contexts.

Methodologically, the study aligns with an applied research paradigm, while demonstrating adaptive methodological flexibility. It incorporates a comparative framework that crosses disciplinary boundaries—drawing from education, data science, development studies, and digital communication. In doing so, it situates learning analytics not merely as a technical tool, but as a transdisciplinary research instrument capable of responding to context-specific educational realities.

The study recommends targeted pedagogical interventions, including the integration of low-bandwidth, high-accessibility tools such as WhatsApp-based academic support and e-tutoring. These interventions reflect a culturally and technologically responsive design logic, emphasizing methodological pragmatism rooted in lived student experiences.

By connecting data-informed research, methodological innovation, and context-sensitive teaching practices, this study contributes to the growing field of transdisciplinary education research. It argues for a shift from content-centred instructional design toward learner-responsive, equity-oriented strategies. It demonstrates how the thoughtful use of learning analytics can foster inclusive and effective online learning environments.

Keywords: Learning analytics, Teaching improvement, Educational data mining, Student engagement, At-risk students.

1. INTRODUCTION

The educational field has adopted learning analytics (LA) as a critical concept for processing data to enhance teaching methods and boost student interest and academic achievements. The idea involves data measurement, data collection, analysis, and subsequent reporting of student context data to understand learning environments and optimisation purposes better. Its fundamental components include dashboards, feedback systems, and predictive analytic models that help lecturers understand student data to deliver appropriate educational responses. LA is vital in higher education research because it offers data-driven insights into student behaviour, engagement, and performance. As already stressed, by analysing patterns in digital learning environments, researchers and institutions can identify factors influencing academic success, detect early signs of student struggle, and evaluate the effectiveness of instructional strategies. This evidence-based approach supports more informed decision-making, enabling personalised learning experiences and improved educational outcomes. Ultimately, learning analytics bridges the gap between academic theory and practice by grounding interventions in measurable trends and outcomes.

There are four different types of learning analytics, as stated by [1]: descriptive, diagnostic, predictive, and prescriptive. Predictive Learning Analytics (PLA) creates insights that help identify students facing potential academic downfall and enables educational institutions to intervene early. Diagnostic analytics allow a comprehensive understanding of what has unfolded during a specific learning journey. By examining trends in learner outcomes and overall course performance, the educator can uncover potential issues or identify opportunities for enhancement. Prescriptive analytics provide solutions on what should be done to create the best learning outcomes. This helps to strategically plan for learning interventions, such as a simulation that can be delivered in stages to support learning in a simulated environment. Descriptive analytics is an approach used to search for and summarise data to identify behaviour and/or performance patterns.

Despite its broad adoption in countries such as the USA and Australia, very little is known about the application of learning analytics (LA) in African countries [2], as the field is still emerging, particularly in South Africa. Most research has focused on the Global North and Australia, as emphasised by [3]. This study addresses the gap by applying a transdisciplinary LA framework to Mineral Exploitation IA, a first-year engineering module in the Diploma in Mining Engineering at a South African university.

It is noted that a report on using learning analytics to predict academic outcomes for first-year students in higher education was also published in the USA [4]. In another study, Wise and Jung (2019) investigated how university instructors use learning analytics dashboards. The authors discovered that the instructors approach LA with curiosity rather than specific questions about dashboard utilisation. The study discussed challenges such as limited technical support and learning management systems (LMS) access. [5] demonstrated how PLA information predicted student performance and helped instructors create adapted intervention methods. The authors examined how providing PLA data to teachers improves student academic results at the university level. This helps to uncover possible obstacles that may hinder learning progress and, by recognising these challenges early, educators can create proactive strategies for timely intervention and personalised support. [7] designed learning analytics-based personalised feedback that helped students develop knowledge while maintaining their emotional state and managing their behaviour during online collaboration, without significantly increasing cognitive stress.

The research conducted is essential; however, there is limited research on using LA at higher education institutions within a South African context. Additionally, comparable studies focusing on using descriptive analytics to enhance teaching effectiveness are scarce, especially in first-year modules with inherent challenges. Some students become discouraged due to the distance, access to technology and limited interaction. These students remain at-risk of failing the module if not identified earlier, and cannot progress with the qualification because the module is a pre-requisite to other modules. Therefore, in addressing this knowledge gap, this study broadens the application of learning analytics within an ODeL institution by employing descriptive analytics to assess a specific Diploma module for first-year students offered at a university. The aim is to explore how LA can enhance teaching for the module and identify at-risk students.

2. LEARNING ANALYTICS AND ITS IMPORTANCE IN EDUCATION ICATIONS

Learning analytics is essential in higher education research because it provides data-driven insights into student behaviour, engagement, and performance. The need for learning analytics has grown within Latin American universities to deliver individualized feedback that supports meaningful assessment of students, teachers, and academic personnel [5]. Their research shows that organized feedback with learning analytics support allows institutions to strengthen student support processes alongside improving teaching effectiveness. Likewise, the study by [6] examined how providing predictive learning analytics (PLA) data to teachers improves student academic results at the university level. PLA technology serves as a tool to recognize struggling students; thus teachers can provide timely interventions and tailored educational methods. Predictive analytics demonstrates its power to help students succeed and enhance educational practices, focusing on mineral exploitation and similar specialized fields. Active learning engagement with video material increases student performance in online learning compared to passive learners [7]. Implementing learning analytics technology for engagement pattern observation enables instructors to discover uninvolved students and create improvement strategies for engagement and results. [8] analyzed learning analytics dashboards and found that cognitive dashboards delivered superior capabilities to increase learners' knowledge of their performance and their ability to evaluate their learning experience and its effects. Mineral exploitation education demands student-led reflective learning because of its challenging nature and knowledge demands.

The research conducted by [8] studied student learning analytics expectations and revealed mixed results due to various expectations about data privacy and service conditions. Flexible and transparent student-oriented learning analytics systems must be designed because of their identified importance. The combination of learning analytics within a support system featuring communication functions, personalization options, and evidence-based decision-making tools delivers value to distance education [5]. The research results support the creation of appropriate learning analytics frameworks to offer live feedback for improved experiences of both students and teachers. The study by [9] showed that students' academic self-efficacy and problem-solving skills improved when they received analytical feedback through flipped models. According to research findings, the inclusion of learning analytics systems in blended learning systems for mineral exploitation enables the simultaneous improvement of theoretical knowledge retention and practical problem-solving capabilities. Data analytics through multiple channels, known as multimodal learning analytics (MMLA), enhances feedback quality and reflection capabilities in educational environments with collaborative learning. The MMLA system received favourable evaluations from teachers and students, yet faced difficulties because of system complexity, data privacy and accessibility obstacles [10]. [8] concluded that by adopting technologies such as artificial intelligence, blockchain, and virtual reality, educational institutions have the potential to instill a culture of perpetual improvement, thereby augmenting resilience and academic outcomes worldwide. The success of implementing programs in specialized educational settings depends on resolving these critical matters.

3. METHODOLOGY

This research adopts a transdisciplinary and mixed-methods research design, integrating educational data mining (EDM), behavioural analytics, and comparative analysis to assess student engagement, performance, and demographic context. The study aligns with an applied research paradigm and incorporates a comparative framework that crosses disciplinary boundaries. In addition, the study adopts an exploratory case study design, aligned with Yin’s (2018) framework, to investigate LA’s role in addressing challenges within a bounded system—the "Mineral Exploitation IA" module. Robert K. Yin’s Case Study Research and Applications: Design and Methods (2018) provides a systematic methodology for conducting case study research, emphasising rigour, structure, and contextual depth. The approach is justified by its ability to provide in-depth, context-rich insights into a real-world educational setting, particularly in under-researched ODeL contexts.

A case study focuses on students enrolled in the Mineral Exploitation IA module. These students are first-year students, most of whom are at the lower level of the mining industry. Due to their level, they spend most of the time in operations. The module is an introduction module at the undergraduate level and a prerequisite for other modules to proceed to the next level. The concepts covered are the foundation on which all the subsequent modules in studying Mining Engineering are built. This study uses the LMS and student information system to gather data for predictive analysis. The population under study comprises 315 students enrolled for the academic year at the university. Out of the initial population count, only 250 students were recorded as having taken at least one assessment for the module. Demographic data, such as names, gender and location, were anonymised.

The course site is a web-based learning platform containing all the study materials. The appearance of the course site is shown in Figure 1, captured from the Moodle site. The site allows students to interact and engage with the module content.

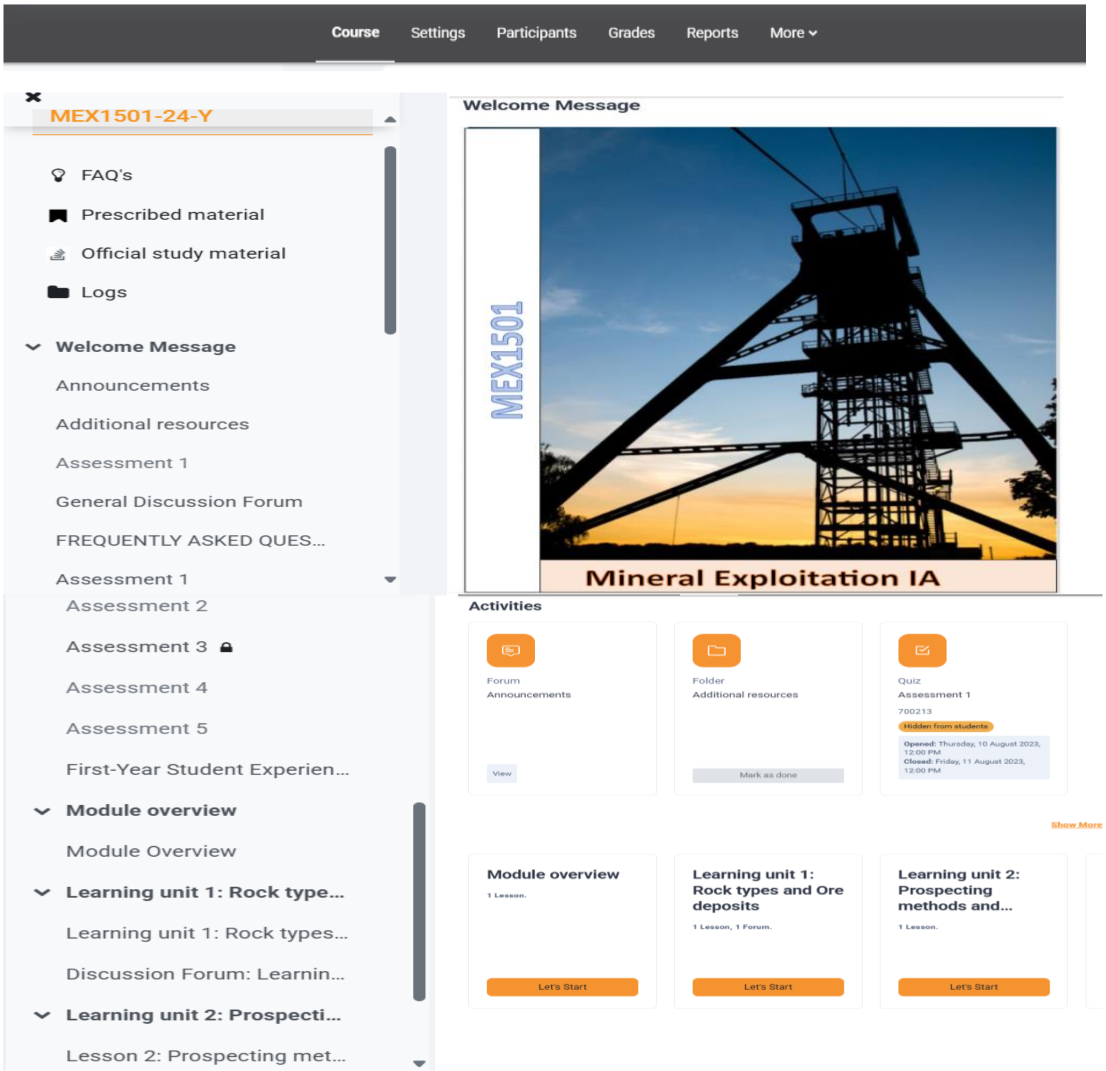

Figure 1. Module site showing activities.

The engagement metrics, occurrence logins, forum posts, participation and resource download or access were extracted from the LMS. The record of assessment performance, i.e. quiz scores and assessment grades, was obtained from the student system (SIS) or XMO reports. Data was anonymised and aggregated to protect student privacy. Institutional approval was obtained, adhering to university research ethics guidelines.

4. RESULTS AND DISCUSSION

Data was analysed and descriptive analytics techniques were employed: the trend analysis to visualise engagement metrics and performance distributions, and the comparative analysis to quantify relationships between engagement metrics and assessment outcomes. The results from a university in South Africa were compared to those from a university in Spain. The comparison was conducted between Bachelor's degree students registered for a more technical module from a developed country and Diploma students registered for a less technical module with no laboratory work from a developing country. The rationale of the comparison was to evaluate the impact of limited access or technology challenges on teaching improvement.

The recorded student enrolment started at 250, and only 228 students remained active in the system as they had completed at least one activity during the academic year in 2024. As part of their learning experience, students are expected to navigate the course menu as shown in Figure 1. They need to start by reading the welcome message, which introduces the subject and offers links to all the subsequent sub-menus. Apart from taking note of the announcements, students were expected to read the module overview, which provides the module outline, before accessing and progressing to the lessons.

The module comprises five learning units, of which the first two are presented in the format of Moodle lessons and the other three are uploaded as PDF files under the sub-menu “Additional resources”. Another lesson to access was made of the Frequently

Asked Questions (FAQs), to guide the students on key learning points. Table 1 focuses on students’ activities from 2024, where the module has the highest enrolment. Only 28 of 228 students completed their module overview, which is a significant concern as this platform provides students with all the relevant information required to manoeuvre around the module. Within the 28 students, only 15 completed the first year experience survey, which is another challenge, as it shows students have little understanding of their learning system. This is evident with only 18 students passing the overall, having participated in the module overview.

Table 1. Student activities

Module overview	1st year survey	Performance
28	15	18 passed 10 failed

Students are expected to take five assessments planned between the lessons continuously. The assessment, numbered 1 to 5, was accessible from the course site, as seen in Figure 1. Two of the five assessments are considered minor tests or assignments. The first assessment is the Multiple Choice Question quiz, and the second is a written assignment. Three assessments are timed tests named major tests, similar to an examination. The majors were taken on a platform identical to myModules, called myExams. In Table 2, the focus is on students' performance from their five assessments in 2024. It was noted that students who did not write all assessments or only wrote 1-2 have failed the module. Also, some students who wrote three assessments failed, while others passed. A total of 37% of students failed, thus delaying completion of the qualification in record time due to not fully participating in all assessments.

Table 2. Student engagement

Assessments Completed	No. of Students	Performance
1 or 2	70	Fail
3	15	Fail
3	19	Pass
4 or 5	124	Pass

As a first-year module, the students' enrolment fluctuates, as shown in Figure 2 for the qualification over the past five years. As much as student enrolment started at a low number and fluctuated, so did the student success pass rate, with a great start of 100% pass rate in 2020 to 60% pass rate in 2024. The trend observed from student engagement in different activities indicates that there is involvement that can be compared to the performance of the students. Some students are highly involved, while others are less involved or show no active interest.

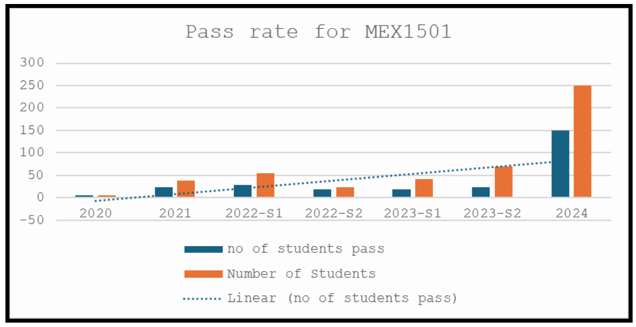

Figure 2: Enrolment of students and success rate

Generally, the number of female registered students in Engineering modules is lower than that of male students. The total number of female students who participated in the course during the academic year was 96, representing 42% of the student population. The female students achieved a higher pass rate of 66% compared to the males at 55%, as shown in Table 3. While the observed pass rate for females (66%) is higher than that of the males (55%), the difference is not statistically significant based on the sample. Therefore, it cannot be established that females were more active than males.

Table 3: Success rate according to the gender

Gender	Number	Percentage (%)	Passed	Pass rate (%)
F	96	42	63	66%
M	131	58	72	55%
Total	227	100	135	59%

UNISA, as a distance learning institution, offers online learning, thus one can study from anywhere in the world. In Figure 3, we can see our students' locations, with most coming from mining towns or where UNISA has regional offices.

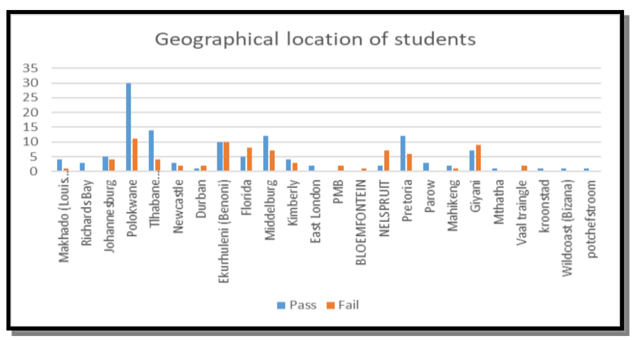

Figure 3. Correlation between student activity and geographic location

Since the inception of the qualification in the academic year 2020, the observed trend of pass rates has been downward, and the average pass rate over the past five academic periods is sitting at 62%. As with other first-year subjects in engineering at the University level, this module faces recurring challenges, including low pass rates, high dropout rates, and poor retention, which impact the overall throughput of the qualification. The study shows that LA can reveal learning challenges. This was observed in a few or fewer student logs in student activities, resulting in a poor success rate. Continuous engagement initiated by the lecturer encouraged more students' participation, which resulted in more students accessing the system when new information was communicated. The value of data-driven strategies for improving teaching effectiveness and student outcomes in the ODeL context is noted in the case study.

The study explored challenges such as limited technical support and learning management systems (LMS) access. In the developing countries, access to technology is still a challenge. It can therefore be put down to predictive analytics. Comparable studies using descriptive analytics to enhance teaching effectiveness, especially in first-year modules with inherent challenges, are scarce. To broaden the use of learning analytics within an ODeL institution, this initial study in the field of engineering has been carried out using a case-study approach that may offer valuable insights and interventions for lecturers.

5. CONCLUSIONS

The evaluation and analysis in Learning analytics revealed the challenges students face that result in poor performance. In the previous studies, learning management systems provided learning trends of students after the students had enrolled on the module. Early detection of students at-risk can be identified in their behaviour and engagement with the module. Access to technology and data for internet connection is critical for students' engagement. Some students who are not very active are affected mainly by access to technology, especially those in remote areas. Another group of students who are less active or inactive in the module are not planning sufficient time for their studies due to their employment responsibilities. The Mineral Exploitation IA module students are beginners in the mining industry and spend most of their time working in the open-pit or underground operations.

Learning analytics can assist in the improvement of teaching strategies. These strategies and applications of data analytics enhance academic outcomes, focusing on the impacts of artificial intelligence on students and lecturers in Education 5.0. The study highlighted the role of data analytics in improving educational processes and outcomes by providing insights into student performance and learning patterns. It is not enough to have insights only, but intervention strategies are critical for teaching improvement. Teaching strategies such as e-tutoring, including frequently and easily accessible platforms or applications such as WhatsApp, will improve teaching and enhance student engagement. The authors conclude that leveraging data analytics can lead to more personalised and effective teaching methods, ultimately benefiting students and educators.

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