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Research Article

Enablers and constraints of analytics-supported personalised learning in South African higher education

Mashite Tshidi

Department of Science, Mathematics, and Technology Education, University of Pretoria, Pretoria, South Africa

ABSTRACT
The growing digitisation of teaching and learning in higher education has intensified interest in learning analytics as a means of supporting personalised learning through data-informed pedagogical decision-making. In South African higher education, this interest is shaped by massification, inequality, and pressure to improve student success and completion, positioning learning analytics as a strategic response to structural challenges. Despite institutional investment in analytics platforms and data strategies, personalised learning remains unevenly enacted in practice. This study examines how institutional, technological, and instructional conditions shape analytics-supported personalised learning in a South African higher education institution. Using a qualitative case study design, semi-structured interviews were conducted with seven participants involved in analytics, instructional design, academic support, and teaching. Data were analysed using reflexive thematic analysis. The findings show that personalised learning emerges from the interaction of three interdependent conditions: institutional commitment and governance, technological integration and data coherence, and lecturers' interpretive and ethical capacities to translate analytics into pedagogical action. While leadership support legitimised the use of analytics, fragmented data systems and uneven data literacy constrained coordinated instructional responses. Conceptualising these dynamics as a socio-technical configuration highlights how the design and governance of analytics systems shape pedagogical possibilities for equitable personalised learning.

Keywords Higher education, Learning analytics, Personalised learning, South Africa, Student success

Categories
• **Information systems** → **Information systems applications** → **Decision support systems** → **Data analytics**

Email
Mashite Tshidi – mashite.tshidi@up.ac.za (CORRESPONDING)

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1 INTRODUCTION

The increasing digitisation of teaching and learning in higher education has intensified interest in using data to inform educational decision-making. In particular, learning analytics (LA) has been promoted as a means of leveraging digital trace data better to understand student engagement, progression, and performance, with the promise of enabling responsive and

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personalised learning (PL) experiences (Mougiakou et al., 2023). This promise has gained attraction globally as institutions seek to address massification, diverse student cohorts, and persistent concerns about retention and completion (Brahic et al., 2025). Within such contexts, LA is often positioned as a strategic mechanism for improving student success through targeted data-informed pedagogical action.

These ambitions are salient in South African higher education, where longstanding structural inequalities intersect with contemporary pressures to improve throughput and equity of outcomes. Institutions operate within this landscape shaped by uneven prior schooling preparation, socio-economic disadvantage, and growing reliance on digital learning environments (Dlamini, 2022). As a result, LA has become increasingly visible within institutional strategies aimed at identifying barriers to student success and supporting students in completing their qualifications within the minimum expected timeframe. However, the extent to which analytics-driven insights translate into meaningful PL practices remains uneven (Tsai et al., 2020), raising questions about how such initiatives are enacted in practice rather than how they are envisioned in policy or system design (Khor & Mutthulakshmi, 2024).

Prior research has extensively documented the development of LA tools and techniques, including dashboards, early warning systems, and predictive models. Recently, attention has shifted from technical innovation towards the conditions under which LA is adopted and used within higher education institutions (Márquez et al., 2024). Across the literature, a consistent finding is that institutional, technological, and instructional factors shape the implementation of analytics. Institutional priorities, including leadership support, governance arrangements, and organisational culture, influence whether analytics initiatives are sustained and embedded (Alzahrani et al., 2023). Simultaneously, technological considerations such as data quality, system interoperability, and access to interpretable metrics affect the reliability and usefulness of analytics outputs (Ngulube & Ncube, 2025). This is further mediated by instructional factors on how these analytical insights are interpreted and acted upon in teaching and learning contexts (Li et al., 2025).

Collectively, these studies suggest that the challenges associated with LA are rarely technical alone. Instead, they emerge from how analytics systems are situated within complex institutional environments and integrated into regular instructional decision-making. Despite this recognition, much of the existing research focused on readiness assessments, maturity models, or high-level strategic frameworks, often derived from institutions in the Global North (Tsai et al., 2021). Though such work provides valuable conceptual guidance (Prinsloo & Kaliisa, 2022), it provides limited insight into how analytics-supported PL is actually implemented within contexts characterised by structural inequality, resource variability, and competing institutional demands.

In the South African context, there is a scarcity of empirical studies that examine how institutional arrangements, technological infrastructures, and instructional practices jointly enable or constrain PL supported by analytics. This scarcity is significant because implementation limitations are seldom attributable to a single factor (Macfadyen, 2022); instead, they arise from the interaction of institutional priorities, technological systems, and instructional practices as

they unfold within specific organisational settings (Márquez et al., 2024).

Responding to this gap, the present study examines the implementation of analytics-supported PL within a South African higher education institution that explicitly prioritises data-informed approaches to student success. This study seeks to identify the institutional, technological, and instructional factors that shape how analytics is mobilised in support of PL with attention to conditions that enable or constrain its enactment in practice. The following research question guides the study:

> *What institutional, technological, and instructional factors constrain or enable the implementation of analytics-supported personalised learning in a South African higher education institution?*

2 LITERATURE REVIEW

2.1 Learning analytics and the persistent implementation challenge in higher education

LA has developed in response to increasing institutional pressures to improve student success, accountability, and efficiency in higher education (Macfadyen, 2022). Broadly defined as the collection, analysis, and interpretation of data about students and learning contexts to understand and improve learning and educational practice (Mougiakou et al., 2023), LA has been widely promoted as a mechanism for enabling evidence-informed teaching and targeted student support. Advances in digital learning platforms and learning management systems (LMSs) have further intensified expectations that analytics can meaningfully inform pedagogical decision-making at scale (Li et al., 2025).

Despite sustained institutional interest and investment, evidence of durable pedagogical impact remains limited. Numerous studies report a persistent gap between the strategic aspirations associated with LA and its enactment within everyday teaching and learning practices (Sharif & Atif, 2024; Tsai et al., 2020). While institutions have invested in dashboards, predictive models, and reporting systems, these tools frequently remain peripheral to instructional decision-making, operating primarily at managerial or monitoring levels rather than informing curriculum design, assessment, or feedback practices (Li et al., 2025). This enduring "vision–reality gap" has shifted scholarly attention away from questions of technological capability towards implementation-oriented concerns, particularly the reason why the availability of analytics does not translate into meaningful pedagogical change (Gasevic et al., 2019).

A growing body of research suggests that LA implementation challenges are more institutional and instructional than technical in nature. Constraints related to leadership and governance structures, organisational culture, staff capability and analytics literacy, ethical uncertainty, and misalignment with pedagogical practices consistently limit uptake and meaningful

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use (Alzahrani et al., 2023; Prinsloo & Kaliisa, 2025). These findings position LA as a socio-technical practice embedded within complex institutional environments, where technological systems interact with institutional priorities, professional norms, and instructional routines. Consequently, understanding LA implementation requires attention not only to tools and data, but also to the institutional conditions and instructional practices within which analytics is expected to operate.

2.2 Conceptual ambiguity in personalised learning and its implications for analytics

Within this implementation discourse, PL is frequently positioned as the primary pedagogical promise of LA. PL is commonly described as an instructional approach that adapts learning experiences to students' characteristics, needs, interests, or progress. However, the literature reveals substantial variation in how PL is defined and conceptualised, resulting in persistent ambiguity across research and practice (Walkington & Bernacki, 2020). This conceptual plurality has contributed to the conflation of PL with related but distinct approaches, including differentiation, individualisation, and inquiry-based, problem-based, or project-based learning (Major et al., 2021).

Across higher education contexts, definitions of PL emphasise different priorities, such as academic performance, student autonomy, engagement, or equity. In the South African context, PL has been framed as learning experiences tailored to individual students or groups based on learning needs, interests, aspirations, or cultural backgrounds, foregrounding responsiveness and social justice considerations (du Plooy et al., 2024). While such a definition underscores the ethical and pedagogical appeal of PL, it often offers limited guidance on how personalisation is enacted within concrete instructional practices, including curriculum sequencing, assessment design, feedback provision, and pacing decisions (Bernacki et al., 2021).

This lack of operational clarity has direct implications for analytics-supported PL. Although PL is frequently characterised as adaptive and student-centred, empirical studies suggest that personalisation often remains aspirational rather than enacted within lecturers' everyday teaching practices (Walkington & Bernacki, 2020). Bernacki et al. (2021) note that many PL approaches focus narrowly on adapting content, pace, or assessment, while offering little insight into how these adaptations are integrated into lecturers' pedagogical reasoning, workload constraints, or disciplinary norms. As a result, PL risks functioning as a flexible label applied to heterogeneous practices rather than as a coherent instructional strategy that can be systematically supported by analytics.

Significantly, this conceptual looseness does not merely complicate evaluation; it also obscures implementation. When PL is weakly specified, it becomes difficult to determine what forms of analytics are pedagogically meaningful, how data should inform instructional decisions, or what constitutes effective personalisation in practice (Ning et al., 2025). Consequently, the potential of analytics-supported PL is undermined not only by technical limitations but also by instructional ambiguity and the absence of shared pedagogical frameworks

to guide data-informed action. This study operationalises PL as instructional approaches in which lecturers use student data, including LA metrics, to modify elements of instruction, such as feedback, pacing, or support, in response to students' needs, progress, or prior knowledge.

2.3 Implementing analytics-supported personalised learning as a socio-technical challenge

LA is frequently presented as the mechanism through which PL can be operationalised at scale. By generating insights into student engagement, performance patterns, and learning behaviours, LA is expected to inform adaptive instructional decisions and targeted interventions (Mougiakou et al., 2023). In principle, analytics enables lecturers and institutions to move beyond one-size-fits-all approaches by responding systematically and responsively to student variability.

However, the literature suggests that the relationship between LA and PL is neither automatic nor linear. Translating analytics outputs into personalised pedagogical action requires alignment across institutional structures, technological infrastructures, and instructional practices (Pardo et al., 2022). Studies indicate that when analytics tools are poorly aligned with lecturers' pedagogical goals, disciplinary contexts, or assessment practices, they are challenging to interpret and rarely integrated into teaching decisions (Banihashem et al., 2025; Li et al., 2025). In such cases, analytics outputs are often underutilised or repurposed for institutional monitoring and accountability rather than instructional adaptation.

Technological constraints further complicate this relationship. Issues related to data quality, system interoperability, platform design assumptions, and the fragmentation of institutional data ecosystems limit the instructional usefulness of analytics, particularly in South African higher educational institutions (Ngulube & Ncube, 2025). These technological challenges intersect with instructional realities, including time pressures, curriculum rigidity, and uneven analytics literacy among lecturers (Shibani et al., 2020), shaping how and whether analytics informs PL in practice.

Moreover, the use of LA to support PL introduces ethical and cultural tensions that shape stakeholder trust and acceptance. Ongoing concerns about student consent, data ownership, profiling, and surveillance continue to shape perceptions and use of analytics (Prinsloo & Kaliisa, 2022, 2025). These concerns are especially salient in contexts marked by historical inequities and power asymmetries, where data-driven interventions may unintentionally reinforce deficit framings, exclusionary practices, or institutional control (Brahic et al., 2025; Selwyn, 2019). Consequently, LA functions simultaneously as an enabler and constraint of PL: while analytics can provide actionable insights, its pedagogical value depends on institutional readiness, ethical clarity, analytics literacy, and the extent to which instructional practices are intentionally designed to incorporate data-informed adaptation.

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2.4 Contextualising analytics-supported personalised learning in South African higher education

Recent scholarship increasingly emphasises that analytics-supported PL is inherently context-sensitive. Implementation is shaped by the interaction of institutional, technological, and instructional conditions rather than by tools alone (Alzahrani et al., 2023). However, much of the existing literature is derived from well-resourced institutions in the Global North, where infrastructural stability, platform integration, and staff support structures are often assumed to be in place.

There remains limited empirical work examining how these interacting conditions shape analytics-supported PL within South African higher education. In this context, infrastructural constraints, digital inequalities, legacy systems, and historical legacies of exclusion continue to influence technology adoption and pedagogical practice (Mhlongo et al., 2023). Analytics initiatives are often implemented alongside competing institutional priorities related to access, throughput, and accountability, which can shape how data is mobilised and for what purposes (Brahic et al., 2025). These dynamics position South African higher education not merely as an under-researched context, but as a critical site for examining how LA and PL are negotiated under conditions of constraint, complexity, and inequality.

This study addresses this gap by investigating how analytics-supported PL is enacted within a South African higher education institution. Rather than evaluating a specific analytics tool, the study adopts an implementation-oriented lens to examine the institutional, technological, and instructional conditions that enable or constrain the use of analytics for personalised learning in practice. In doing so, this study seeks to contribute context-sensitive insights into the realities of analytics-supported PL in African higher education and to extend implementation-focused scholarship in LA.

3 METHODOLOGY

3.1 Research approach and design

This study adopted a qualitative approach to investigate how institutional, technological, and instructional conditions shape the implementation of PL strategies supported by LA within a South African higher education institution. Anchored in an interpretivist paradigm, the study foregrounded how LA-supported personalisation is understood, enacted, and constrained in practice by actors across the institution's learning ecosystem, including academic development, learning design, business intelligence, institutional research, academic advising, and teaching. An intepretivist orientation was appropriate given the study's emphasis on participants' meanings, experiences, and sense-making processes, and its recognition that educational practices are socially constructed and inseparable from their institutional contexts (Poquet, 2024).

From this perspective, LA-supported personalisation was not approached as a neutral or purely technical intervention. Instead, it was conceptualised as a socio-technical practice

emerging through interactions between institutional policies, digital infrastructures, and instructional decision-making. Therefore, an interpretive stance enabled a closer look at how analytics data, pedagogical intentions, and contextual constraints are negotiated in practice to shape what personalisation becomes rather than what it is intended to achieve in theory.

To capture these dynamics, the study employed a single-case study research design, enabling an in-depth, context-sensitive examination of analytics-supported PL within a bounded institutional setting. The case was defined as a single South African higher education institution that explicitly prioritises data, research, and innovation to identify barriers to student success and support completion within the minimum expected timeframe. These institutional commitments provided a policy and cultural context for examining the implementation of LA-supported personalisation.

3.2 Participant selection

A purposive sampling strategy was used to recruit participants whose professional roles intersected with LA, PL, and data-informed pedagogical practices within the institution. Seven participants were selected to capture perspectives across institutional, technical, and instructional domains, including individuals involved in analytics governance and strategy (n = 2), institutional data and analytics infrastructure (n = 2), and pedagogical or student-support roles such as lecturers, instructional designers, and academic advising (n = 3). The sample size was intentionally small to support analytical depth, consistent with qualitative case study research where contextual insight is prioritised over representativeness (Poquet, 2024). Sample adequacy was assessed based on the dataset's conceptual sufficiency, as participants' complementary yet overlapping roles enabled the study to capture how analytics-supported PL is shaped across institutional layers of policy and system design, instructional enactment and student-facing support. Semi-structured interviews were conducted with each participant and lasted between 45 and 60 minutes. Participants were assigned pseudonyms to protect confidentiality and to encourage reflection on institutional practices.

3.3 Data collection and analysis

Data was generated through semi-structured interviews designed to elicit participants' experiences of engaging with LA in support of PL. Interview questions focused on how analytics data was accessed, interpreted, and applied in practice; how personalisation was conceptualised and operationalised; and how institutional, technological, and pedagogical factors shaped these processes. Particular attention was given to moments of ambiguity, tension, or constraint, as these instances offered insights into the practical limits and trade-offs of analytics-supported PL. These interviews were conducted online, recorded with participants' consent, and transcribed verbatim to preserve the integrity and nuance of participants' accounts.

The interview data were analysed using reflexive thematic analysis, which offers a flexible yet systematic approach to identifying patterns across qualitative datasets while acknow-

ledging the researcher's interpretive role (Braun & Clarke, 2021). This study was derived as part of a broader doctoral thesis. At the time of research, the researcher had approximately four years of professional experience in South African higher education, including two years in educational technology and two years as an adjunct lecturer with direct exposure to LA at the course and institutional levels. This positioning provided familiarity with LA literature, LMS and the types of behavioural data used to inform student engagement and performance.

Simultaneously, this familiarity and involvement with analytics introduced a potential for bias that leaned towards viewing it as pedagogically beneficial. To mitigate this bias, reflexive practices were employed through the analysis, including iterative engagement with the data, critical examinations of assumptions and careful alignment of interpretations with participants' accounts, rather than prior expectations. Analysis commenced with repeated readings of the interview transcripts to achieve immersion and familiarisation. Initial coding was conducted inductively, after which codes were iteratively refined and clustered into three thematic domains: institutional, technological, and instructional. Within each domain, coded data were interpreted to determine whether specific conditions enabled or constrained the enactment of analytics-supported PL. Themes were refined through iterative comparison with the dataset to ensure they remained grounded in participants' accounts.

4 FINDINGS

The findings are presented thematically, drawing on patterns that emerged through iterative engagement with the interview data. Analysis combined inductive interpretation of participants' accounts with attention to institutional, technological, and instructional conditions shaping practice. The themes are reported in a narrative form to preserve the contextual integrity of participants' experiences and to reflect how analytics-supported PL is enacted in practice.

4.1 Institutional conditions shaping analytics-supported personalised learning

Participants described PL as embedded within broader institutional conditions that both enabled and constrained its enactment. At an enabling level, PL was firmly anchored in the institution's strategic commitment to student success. LA was not positioned purely as a technical innovation, but as a mechanism aligned with the academic project and equity-oriented outcomes. As Participant 5 noted, *"student success is the ultimate priority … all the structures we have put in place support the academic project."* In participants' accounts, this framing ensured that analytics initiatives were justified not only in technical terms but also as part of the institution's responsibility to improve student outcomes. As a result, analytics-informed interventions were understood as purposeful responses to patterns in student engagement and performance rather than as isolated technological experiments.

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This strategic orientation was reinforced by a growing institutional culture that treated data as a shared asset. Participants spoke of a shift toward collective ownership of data practices, in which responsibility for data quality, interpretation, and use was distributed across institutional units. Participant 7 explained that *"if data is an asset, then all of us involved in producing and using it need to ensure we look after it."* In practice, this orientation translated into collaborative data practices and the development of analytic tools designed to support teaching. For example, participants described institutional reports that provide lecturers with contextual information about their students, including prior academic performance, language background, and diagnostic assessment results. Access to these insights before teaching begins enables lecturers to anticipate potential learning challenges and adjust their instructional planning accordingly.

Leadership buy-in emerged as a critical institutional enabler. Executive endorsement legitimised LA initiatives and unlocked access to financial, human, and technological resources. Participants emphasised that once senior leadership supported these initiatives, engagement at the faculty and departmental levels became feasible. As Participant 3 observed, *"once leadership buys into the project … lower-level staff will follow the executive's lead."* Leadership advocacy also ensured that analytics initiatives were discussed in formal decision-making forums, including Senate and faculty structures, thereby reinforcing their relevance to institutional teaching and learning priorities.

Closely connected to leadership support was sustained investment in staff development. Participants described targeted professional development as central to enabling staff to move beyond awareness toward pedagogical action. Training initiatives focused on helping lecturers interpret analytics indicators, identify students who may be disengaging from course activities, and design timely interventions. As Participant 1 explained, *"it becomes more than important simply identifying students at risk … we need to intervene."* In practical terms, this meant encouraging lecturers to respond to analytics signals, for example, when large numbers of students fail to submit assignments or disengage from online activities, by implementing targeted support strategies. These initiatives were complemented by efforts to strengthen data literacy and ethical awareness, encouraging lecturers to use analytics insights responsibly while maintaining sensitivity to student circumstances.

Despite these enabling conditions, institutional constraints limited the scale and consistency of PL. Large class sizes, cross-campus alignment requirements, and a shortage of specialised analytics expertise restricted lecturers' ability to personalise learning at scale. Participant 2 captured this tension succinctly: *"It becomes very tricky to personalise unless you have a bunch of tutors."* Participants explained that while analytics tools could identify patterns of disengagement across large cohorts, the capacity to respond meaningfully often depended on the availability of additional teaching support. Collectively, these findings demonstrate how institutional structures simultaneously make LA-supported personalisation feasible while setting clear boundaries on its practical reach.

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4.2 Technological conditions mediating analytics-supported personalised learning

Participants portrayed technology as a decisive mediator between institutional intent and the practical realisation of analytics-supported PL. Although analytics-enabled personalisation was widely considered to depend on digital systems, its effectiveness was shaped by the quality, integration, and limitations of the institution's technological infrastructure. Thus, technology functioned simultaneously as an enabler of insight and a constraint on what personalisation could realistically achieve.

Early experiences with the institution's former learning management system (LMS), Sakai, underscored these constraints. Participants described how limited data extraction and weak interoperability restricted both teaching innovation and research. Participant 4 recalled that despite strong expertise and international collaboration, *"the problem was that the learning management did not allow for that data to be extracted … it was not a people or a knowledge issue. It was a technological issue."* Engagement data was reduced mainly to surface metrics such as logins and submissions, providing limited insight into learning processes. These limitations were compounded by fragmented institutional systems, where academic, administrative, and support data were siloed: *"when you look at a student's data, you do not see the whole picture because some of it sits elsewhere."* As a result, analytics-informed personalisation remained constrained in scope and depth.

The transition to the Canvas LMS marked a turning point. Participants described the new LMS as the digital backbone of PL, enabling institution-wide data capture and near-universal adoption. Participant 1 noted that LMS use increased dramatically, reaching *"98% in terms of adoption,"* which created the conditions for reliable analytics at scale. The Canvas LMS's mobile affordances further extended access, with one participant emphasising that *"everyone has a mobile phone… so one intervention was to leverage these mobile platforms."* This shift transformed analytics from a peripheral activity into an embedded feature of everyday teaching and learning.

With richer digital traces available, analytics tools became central to student support and instructional decision-making. Dashboards enabled lecturers and tutors to identify disengagement patterns and intervene early. As Participant 7 explained, analytics allowed them to reach out directly: *"I noticed that you have not logged in for the last two weeks… let us have a chat and see how we can help you."* These practices framed analytics as a form of care rather than surveillance, supporting timely, personalised engagement.

Simultaneously, participants remained aware of technological blind spots. Participant 1 observed that offline interactions, informal learning, and student experiences beyond the LMS were often invisible: *"We also understand there is a significant amount of data that's not captured."* This recognition tempered confidence in purely data-driven personalisation and reinforced the need to interpret analytics contextually. Overall, the findings show that technological advances substantially expanded the possibilities of PL; infrastructure constraints and data gaps continued to shape and limit what analytics could meaningfully support in practice.

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4.3 Pedagogical factors shaping analytics-supported personalised learning

Pedagogical reasoning emerged as the critical layer through which institutional priorities and technological affordances were translated into PL practices. Participants emphasised that access to analytics alone was insufficient; what mattered was lecturers' capacity to interpret data meaningfully and act on it pedagogically. In this sense, LA functioned less as a prescriptive tool and more as an interpretive resource that shaped instructional judgement.

Several enabling practices illustrated how analytics informed pedagogical decision-making. Participants described using engagement and performance data to model student progress, identify learning risks, and coordinate timely support. Participant 6 noted that analytics enabled lecturers to *"predict whether a student will complete a course … and also use clustering to group students based on their learning patterns, so that you can personalise their instruction."* In practice, such predictive approaches were linked to institutional support mechanisms. According to Participant 5, lists of students identified through analytics were often shared with academic advising units, who then contacted students directly to provide support: *"We would send lists of students of concern to advising, and they would then follow up directly."* These practices illustrate how analytics enabled anticipatory rather than reactive pedagogy, allowing lecturers and support units to intervene when early signs of disengagement emerged.

Course design was central to this process. Participants stressed that well-structured, self-paced courses not only supported diverse student needs but also generated meaningful data that could inform instructional adjustments. As Participant 7 explained, lecturers were encouraged to design courses around *"multiple student scenarios or profiles,"* recognising that students enter courses with different needs, motivations, and constraints. In practice, this meant designing alternative learning pathways or resources that could support different learner profiles, for example, providing additional visual materials or alternative explanations for students requiring additional support, while offering extended resources for highly motivated learners. Analytics fed back into this design logic by revealing how students interacted with course materials, allowing lecturers to refine content, pacing, and assessment structures over time.

Pedagogical personalisation was further strengthened through diverse teaching approaches that promoted student agency. Participants described combining acquisition, inquiry, collaboration, and practice as complementary modes of engagement within courses. For example, Participant 6 noted that "*students might first encounter content through lecturer-led presentations (acquisition), explore supplementary materials such as external videos or resources (inquiry), discuss interpretations with peers (collaboration), and then test their understanding through low-stakes assessments (practice).*" Participant 1 observed that adaptive tools allowed lecturers to *"identify students who are struggling with a particular concept"* and provide targeted resources or referrals. These approaches supported differentiated learning experiences while maintaining curricular coherence. As Participant 2 reflected, student agency was particularly visible in case-based and problem-based approaches, where students could *"pick a case from a whole corpus,"* allowing them to engage with problems aligned to their interests, goals, or professional contexts.

Alongside these enabling practices, pedagogical constraints remained evident. Resistance to data-informed teaching persisted, particularly where analytics challenged established teach-

ing practices. Participants noted that some lecturers questioned the reliability or relevance of analytics data and chose not to incorporate it into their instructional decision-making. As one participant explained, lecturers sometimes dismissed analytics insights by arguing that the data were incomplete or unreliable, stating that *"they may not buy the data and say, 'we are just going to keep doing what we are doing.'"* In other cases, analytics use remained superficial. Participant 1 noted that some lecturers treated the learning management system as *"a dumping site,"* uploading static resources without designing interactive learning activities that could generate meaningful engagement data. In such cases, the absence of intentional pedagogical design limited the value of analytics for informing teaching.

Limited data literacy further constrained pedagogical uptake. Even where lecturers were willing to engage with analytics, interpreting dashboard data and translating it into pedagogical action proved difficult. Participants noted that many lecturers were subject-matter specialists rather than data analysts, which made it challenging to interpret engagement indicators or identify appropriate instructional responses. As a result, analytics insights were sometimes acknowledged but not translated into concrete teaching adjustments.

Concerns about misinterpretation and ethics also shaped pedagogical uptake. Participant 3 cautioned that engagement metrics did not necessarily indicate meaningful learning, noting that *"just because a student has viewed a document, it does not mean they comprehended it."* This scepticism prompted some lecturers to triangulate analytics with assessment evidence or practice activities to verify student understanding. Ethical tensions were especially apparent in how analytics-informed feedback was communicated to students, with concerns that predictive messages about performance could be discouraging or demotivating. Overall, these findings demonstrate that pedagogical personalisation depended not only on data availability but also on lecturers' interpretive capacity, ethical judgement, and willingness to reconfigure teaching practices in response to analytics.

5 DISCUSSION

This study examined the institutional, technological, and instructional factors that shape the implementation of analytics-supported PL within a South African higher education institution. The findings show that personalisation does not arise from analytics infrastructure alone but from the interaction between institutional readiness, technological integration, and lecturers' interpretive and pedagogical capacities. In this sense, LA-supported personalisation operates as a socio-technical system in which institutional priorities, digital infrastructures, and instructional practices together shape how student data become meaningful for pedagogical decision-making.

At the institutional level, an explicit discourse emphasising student success, equity, and data-informed decision-making legitimised the use of analytics to support teaching and learning. Leadership commitment, formal governance structures, and targeted professional development created an enabling environment for analytics-informed practices. These dynamics correspond with international scholarship identifying leadership support and institutional cul-

ture as critical conditions for sustainable LA adoption (Macfadyen, 2022; Tsai et al., 2020). However, strategic commitment did not automatically translate into coherent implementation. Uneven staff capacity, fragmented ownership of data responsibilities, and tensions between personalised pedagogies and institutional standardisation constrained coordinated action. Similar dynamics are reported globally, where analytics initiatives often advance more rapidly at the policy level than in everyday pedagogical practice (Alzahrani et al., 2023; Macfadyen, 2022). These findings suggest that leadership intent must be accompanied by distributed institutional capability spanning organisational, technical, and pedagogical domains.

Technological conditions also shaped the feasibility of analytics-supported PL. The migration to the Canvas LMS enhanced analytical capacity through dashboards that provided lecturers with insights into student engagement and performance, reflecting global trends in which LMS platforms function as the primary infrastructure for LA deployment (Veluvali & Surisetti, 2022). From an information systems perspective, such dashboards operate as sense-making artefacts that translate large volumes of clickstream and assessment data into interpretable indicators of engagement and risk. However, the pedagogical value of these tools depended on the coherence of the broader data ecosystem. Limited interoperability, persistent data silos, the absence of integrated case-management systems, and gaps in multimodal engagement data restricted the development of holistic student profiles. International literature similarly notes that fragmented data environments constrain the pedagogical potential of analytics even when advanced dashboards or predictive models are available (Ning et al., 2025). Therefore, the findings reinforce the view that the effectiveness of LA depends less on individual tools than on the integration and interoperability of institutional data infrastructures that connect LMS data, student information systems, and support services.

Instructional engagement with analytics proved equally decisive. Participants described varied uses of analytics, ranging from adaptive and anticipatory practices that informed course design and targeted student support to more cautious engagement shaped by limited data literacy, interpretive uncertainty, ethical concerns, and workload pressures. These patterns reflect what international research describes as a "visibility–action gap," in which analytics reveal engagement patterns but do not necessarily translate into pedagogical intervention (Li et al., 2025). The challenges identified in this study, particularly difficulties in interpreting dashboards and concerns about fairness in communicating analytics insights, support growing calls for systems that provide interpretive and communicative scaffolding, such as personalised feedback mechanisms, rather than relying solely on visual dashboards (Pardo et al., 2022). In this sense, the findings highlight that dashboards alone rarely produce PL; rather, personalisation emerges when analytics outputs are translated into pedagogically meaningful interactions between lecturers and students.

Furthermore, ethical considerations shaped lecturers' engagement with analytics. Although formal governance guidelines were in place, participants expressed uncertainty about how to communicate analytics insights to students without reinforcing deficit narratives or perceptions of surveillance. These concerns resonate with international debates that conceptualise responsible LA as a relational and contextual practice grounded in trust, care, and institu-

tional accountability rather than compliance alone (Prinsloo & Slade, 2018; Selwyn, 2019). Therefore, ethical maturity in analytics appears to develop through ongoing engagement with lecturers and students rather than through policy frameworks alone. Significantly, these ethical concerns intersect with the equity ambitions of PL, as the interpretation of analytics signals can determine whether student data are used to support learners or inadvertently classify them as deficient or disengaged.

Within the African context, these findings reflect broader continental patterns. Across Africa, LA adoption remains uneven and often characterised by technological ambition outpacing institutional or pedagogical readiness (Prinsloo & Kaliisa, 2022). Consistent with continental reviews, LMS-based analytics served as the primary data source, while limited interoperability restricted visibility into student engagement beyond clickstream activity. Even in relatively well-resourced institutions, such constraints mirror those reported across East, West, and Southern Africa (Ngulube & Ncube, 2025). As a result, analytics systems often produce partial representations of student activity, which can limit the extent to which data-informed personalisation captures the broader learning conditions shaping student success.

In the South African context, these dynamics are intensified by massification, persistent inequality, and the legacy of apartheid. National imperatives to improve student success and reduce dropout rates have stimulated interest in early-warning systems and data-informed interventions (Cele, 2021). However, structural disparities in digital access, device quality, and bandwidth continue to shape the production and interpretation of student data. Under these conditions, analytics may risk interpreting structural disadvantage as disengagement or academic risk, thereby reinforcing deficit narratives rather than addressing systemic inequities. This has significant implications for equity-oriented PL: the effectiveness and fairness of analytics-supported interventions depend not only on predictive accuracy but also on how institutional systems account for unequal access to digital resources that shape students' data traces. Moreover, the limited representation of emotional and relational dimensions of student engagement highlights the constraints of current analytics infrastructures in contexts where belonging, care, and psychosocial support remain central to student success (Otu et al., 2023).

6 CONCLUSION

This study examined how institutional, technological, and pedagogical conditions shape the implementation of analytics-supported PL in a South African higher education institution. The findings indicate that PL arises from the alignment between institutional readiness, integrated information systems, and lecturers' interpretive and pedagogical judgment. As such, the study contributes an empirical socio-technical perspective on LA implementation, demonstrating that the educational impact of analytics systems depends on technological functionality and the institutional and instructional contexts within which they operate.

At the institutional level, leadership commitment and governance frameworks legitimised the use of analytics to support student success; however, their influence remained uneven in the absence of distributed capacity and coordinated ownership across academic, technical,

and support units. These institutional conditions shaped the technological environment in which analytics systems operated. Although the migration to the Canvas LMS expanded the availability of engagement and performance data, limited interoperability with institutional information systems, persistent data silos, and the absence of a case-management infrastructure constrained longitudinal analysis and coordinated intervention. From an information systems perspective, consistent with prior literature, these findings underscore the significance of analytics infrastructures that extend beyond isolated dashboards towards integrated data ecosystems capable of transforming educational data into interpretable and actionable insights (Macfadyen, 2022). In this context, dashboards enabled lecturers to identify engagement patterns and potential risks. However, the lack of integrated data architectures limited the translation of these insights into coordinated institutional responses, confining analytics largely to course-level visibility rather than institution-wide student support processes.

In turn, these technological conditions shaped pedagogical engagement with analytics. PL was most evident where lecturers possessed sufficient data literacy, ethical confidence, and pedagogical autonomy to translate analytics indicators into instructional decisions and targeted support. Where such interpretive capacity was limited, analytics was either underutilised or treated cautiously, reinforcing a persistent visibility-action gap in which engagement data were available but did not lead to pedagogical intervention. These findings underscore that analytics-supported PL depends on access to data and on lecturers' ability to contextualise analytical insights within disciplinary knowledge, students' circumstances, and ethical considerations.

The study also has implications for analytics governance and system design. Effective analytics infrastructure requires integrated architectures that enable interoperability among LMS platforms, student information systems, and advising tools, enabling institutions to construct holistic representations of student engagement and progression. In addition, analytics systems must incorporate mechanisms that support interpretive scaffolding and responsible communication of analytics insights to students.

The study is limited by its focus on a single institution and a small group of participants, which constrains transferability. The institution's relatively advanced digital infrastructure also means the findings may not fully reflect conditions in less-resourced contexts. In addition, the study centred on staff perspectives; student experiences of analytics-informed interventions warrant further investigation. Future research should examine Analytics-supported PL across multiple institutions, comparing how different information system architectures, governance arrangements, and pedagogical cultures influence implementation. Longitudinal studies are also needed to explore how analytics practices evolve and how multimodal data sources can be responsibly integrated to support context-sensitive and equitable personalisation.

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