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Lecturers' Perspectives on the Benefits and Challenges of Implementing Learning Analytics in South African Higher Education

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Abstract. This study explores lecturers' perspectives on the benefits and challenges of implementing Learning Analytics (LA) in South African higher education institutions. LA offers potential to improve student outcomes, teaching effectiveness, and institutional decision-making through the use of data-driven insights. In the South African context, where universities face persistent challenges related to student retention, performance, and resource constraints, LA could be transformative. However, successful adoption depends heavily on lecturer engagement, digital literacy, and institutional readiness. Using a qualitative case study approach, data were collected through open-ended questionnaire with 41 academic staff across four public institutions of higher education. Thematic analysis of the data revealed that lecturers recognize several key benefits of LA, including early identification of at-risk students, improved academic planning, enhanced student support, and better monitoring of performance. At the same time, they highlighted critical barriers such as lack of awareness, ethical concerns about data use, limited technical infrastructure, inadequate institutional support, and increased workload. These findings underscore the importance of addressing systemic, ethical, and capacity-related issues to ensure the responsible and effective implementation of LA. The study contributes empirical evidence from a developing context and offers practical insights for institutional leaders, policymakers, and educators seeking to leverage LA as a strategic tool for educational transformation in South Africa.

Keywords: Learning Analytics; Artificial Intelligence; Digital Transformation, South Africa, Lecturer, Higher Education

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1. Introduction

Learning analytics (LA) is increasingly recognised as a critical tool for enhancing student outcomes and institutional performance in higher education. In South Africa, universities face persistent challenges: approximately 30% of students do not progress beyond the first year in some institutions, and only ~57% of undergraduate students complete their degrees within the expected timeframe (DHET, 2024). Access to digital devices is uneven, with around 65% of students reporting ownership of a personal computer or laptop, and connectivity remains variable despite SANReN infrastructure (StatsSA, 2023; Czerniewicz & Brown, 2013). Most universities have adopted learning management systems (LMS) such as Blackboard or Moodle; however, their use often remains limited to content distribution rather than interactive or analytics-driven learning (Bozalek et al., 2013). Furthermore, student digital literacy varies significantly, with many proficient in social media but lacking academic ICT skills (Ng, 2012; Mpungose, 2020).

In this context, LA offers a mechanism to address challenges in student retention, throughput, and targeted academic support by enabling early identification of at-risk students, informing curriculum design, and facilitating evidence-based interventions. However, adoption is not straightforward. Prior research in South Africa has often emphasised the technical or theoretical aspects of LA (Hetty & Pather, 2015; Mardiana et al., 2024), while underexploring lecturers' engagement, digital literacy, and perceptions of these tools (Mhlongo et al., 2023; Sithole & Mbukanma, 2024). Concerns about data quality, ethical use, increased workload, and institutional support further shape how lecturers perceive and use LA systems (Soffer & Cohen, 2024).

Lecturers play a pivotal role as mediators of LA insights in the teaching and learning process. While some view LA as an opportunity to enhance student engagement and teaching effectiveness, others question its relevance, reliability, and compatibility with professional autonomy. These tensions are particularly pronounced in developing country contexts, where technological potential often collides with infrastructural limitations, institutional readiness, and socio-cultural dynamics.

Although international studies have examined lecturer perceptions of LA, few have focused on the South African context, where resource constraints, digital divides, and historical inequities create distinctive adoption challenges. Moreover, the recent SoLAR (2025) redefinition of LA emphasises learners and their contexts, underscoring the need for ethically responsible and contextually grounded adoption. This study addresses these gaps by providing an empirical exploration of lecturers' experiences, attitudes, and perceived barriers to LA implementation in South African universities. It contributes a nuanced understanding of how trust, institutional readiness, and contextual constraints interact with technological affordances, thereby informing strategies for sustainable and effective LA integration across the higher education sector.

The study further contributes to participating institutions by offering actionable insights into how LA can be strategically implemented to enhance teaching quality, improve student success, and strengthen institutional decision-making. By analysing lecturers' experiences and perceptions, the findings provide evidence-based recommendations for improving digital capacity, designing targeted professional development programmes, and refining institutional policies to promote responsible and effective LA adoption. In doing so, the research supports institutional efforts to advance quality education through the purposeful integration of technological tools aligned with South Africa's digital transformation agenda in higher education.

Finally, the study makes distinct theoretical, empirical, and practical contributions. Theoretically, it extends understanding of LA adoption by foregrounding the socio-cultural and contextual factors that influence lecturers' engagement—dimensions often overlooked in previous research. Empirically, it offers a South African perspective in a field largely dominated by studies from well-resourced contexts, providing evidence of how infrastructural limitations, digital divides, and institutional readiness shape adoption.

Practically, it proposes a framework for fostering lecturer trust, capability, and sustained engagement with LA systems, thereby guiding institutional strategies for effective and ethical implementation. Collectively, these contributions distinguish the study from prior work and advance the discourse on contextually grounded learning analytics in higher education.
The study achieves its objectives by addressing the following research questions:
1. What are the benefits that adoption of learning analytics will bring into institutions of higher education?
2. What factors hinder the adoption of learning analytics in institutions of higher education?

2. Literature Review

The literature review provides a critical examination of the key concepts, theoretical foundations, and contextual factors that shape learning analytics (LA) in higher education. It situates LA within broader technological, pedagogical, and institutional landscapes, highlighting both global developments and local challenges. By synthesising research on the evolution of LA, its distinctions from related fields, underlying theoretical frameworks, and South African technological readiness, this review identifies gaps in understanding how LA is perceived, adopted, and operationalised by lecturers in resource-constrained environments. This foundation informs the study's focus on bridging the divide between LA's theoretical promise and its practical implementation in South African universities.

2.1 Defining Learning Analytics: Evolution of the Concept

The field of learning analytics (LA) has evolved considerably since its formal recognition in the early 2010s. The Society for Learning Analytics Research (SoLAR) originally defined LA as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Long & Siemens, 2011). While this foundational definition established the field, SoLAR's recent 2025 redefinition expands on it by placing stronger emphasis on *contextual understanding, ethical responsibility, and the improvement of learning environments through evidence-informed action*. This updated framing acknowledges that learning analytics extends beyond data collection and optimisation—it is also about interpreting data within specific institutional, social, and technological contexts to foster meaningful learning experiences.

Despite this evolution, the literature still tends to conceptualise LA primarily from technical and ethical standpoints, often overlooking the complex institutional and contextual realities that influence its implementation. Scholars have critiqued the earlier definitions for overemphasising data-driven optimisation at the expense of educator agency and contextual nuance (Ferguson, 2012; Gasevic et al., 2015). The socio-technical turn in LA research now recognises that analytics must integrate technical, pedagogical, and ethical dimensions rather than operate as a purely computational process. Clow's (2012) notion of "closing the loop" further highlights that analytics should not merely describe learning patterns but inform actionable interventions. Yet, in many higher education institutions—particularly in developing contexts—this loop remains open due to infrastructural limitations and insufficient institutional readiness (Matsebula & Mnkandla, 2017).

Building on this evolving understanding, the present study addresses a persistent research gap: while LA's conceptual and technical foundations are well established, there is limited empirical insight into how trust, institutional readiness, and contextual constraints affect its implementation in resource-limited higher education systems such as South Africa's. By examining lecturers' perspectives on LA adoption, this study explores the interplay between technological potential and institutional realities in realising LA's transformative promise.

2.2 Distinction Between Learning Analytics, Educational Data Mining and Academic Analytics

The relationship between learning analytics (LA), educational data mining (EDM), and academic analytics (AA) remains contested, with ongoing debates regarding their conceptual boundaries and overlap (Aldowah et al., 2021). EDM, which predates LA, is rooted in computational disciplines and focuses on developing algorithms for pattern discovery and predictive modelling (Baker & Yacef, 2009; Kumar et al., 2024). Its strength lies in methodological rigour and predictive accuracy, yet it often neglects the interpretive and pedagogical dimensions critical to educational practice.

By contrast, LA integrates human judgment and pedagogical theory, emphasising the interpretive use of data for improving learning processes (Siemens & Baker, 2012). However, LA has been criticised for lacking methodological sophistication compared to EDM, relying heavily on descriptive rather than predictive or prescriptive approaches. This has led to calls for methodological convergence that combines EDM's computational depth with LA's pedagogical grounding (Peña-Ayala, 2024).

Academic analytics (AA), meanwhile, operates at an institutional level, using aggregated data for strategic decision-making and performance management (Campbell et al., 2007). While valuable for policy and planning, AA risks reinforcing managerial control and depersonalising the learning process when disconnected from pedagogical concerns. The literature increasingly advocates for integration among these domains, yet such integration is rarely realised in practice, particularly in developing countries where systems, skills, and data governance structures remain fragmented (Matsebula & Mnkandla, 2016).

Despite growing theoretical convergence among LA, EDM, and AA, there is insufficient empirical research examining how higher education institutions, especially in the Global South, navigate these overlapping domains in practice. This study situates itself at this intersection, exploring how lecturers perceive the potential and limitations of LA amidst institutional and infrastructural constraints.

2.3 Theoretical Underpinnings

Learning analytics draws from multiple theoretical traditions, resulting in what Knight et al. (2022) describe as theoretical pluralism. This interdisciplinarity enriches the field but also creates fragmentation and ambiguity in theoretical grounding. Early frameworks drew heavily from behaviourism and cognitivism, focusing on measurable indicators of performance (Zimmerman & Schunk, 2011; Winnie et al., 2013; Sedrakyan, et al., 2020). More recent approaches incorporate sociocultural and constructivist perspectives, viewing learning as contextual, social, and dynamic (Kaliisa et al., 2022).

Several theoretical perspectives have been used to underpin LA research. These include the Activity Theory (Engeström, 1987), which conceptualises learning as a mediated, goal-oriented activity influenced by tools, community, and rules; the Technology Acceptance Model (TAM) (Davis, 1989), which explains user adoption based on perceived usefulness and ease of use; and the Sociotechnical Systems Theory (Trist & Bamforth, 1951), which emphasises the interdependence of social and technological subsystems in organisational change. Other commonly applied frameworks include the Self-Regulated Learning Theory (Zimmerman, 2000), which focuses on learners’ metacognitive and behavioural control over learning processes, and the Institutional Theory (Scott, 2001), which explores how institutional norms and structures influence technology adoption and use. These theories collectively illustrate the diversity of conceptual lenses through which LA is studied and implemented.

In developing contexts, however, many institutions still adopt imported models without adequate adaptation to local realities. Matsebula et al. (2025) argue that frameworks for LA in resource-constrained environments must integrate socio-technical and institutional theories to account for factors such as digital inequality, leadership readiness, and organisational culture. This perspective highlights the importance of context-sensitive theoretical grounding that captures both the human and structural dimensions of LA adoption.

A major theoretical debate concerns the balance between automation and agency. While AI and machine learning enhance scalability and predictive accuracy, they also risk diminishing educator autonomy and transparency in decision-making. The challenge, therefore, lies in designing explainable learning analytics systems that preserve interpretability and ethical accountability while supporting evidence-based pedagogical decisions.

Guided by these perspectives, this study adopts a socio-technical theoretical framework that integrates Institutional Theory and Sociotechnical Systems Theory as its core underpinning. This framework acknowledges that LA implementation is not merely a technical process but one that is shaped by organisational structures, human agency, cultural norms, and institutional readiness. It enables an exploration of how lecturers engage with LA tools within their institutional ecosystems and how factors such as trust, policy support, and infrastructure influence their adoption behaviours. By grounding the analysis in this integrated framework, the study situates lecturers' perceptions within the broader institutional and socio-technical context, contributing to the development of contextually responsive and sustainable models of LA adoption in South African higher education.

2.4 South African Technological and Digital Readiness

Technological readiness across South African HEIs remains uneven, shaped by historical inequities and divergent resource allocations (Brown & Czerniewicz, 2010). While leading universities maintain world-class ICT infrastructure, many historically disadvantaged institutions still struggle with connectivity, hardware reliability, and staff capacity. Although initiatives like SANReN have expanded bandwidth access, disparities persist in speed, stability, and affordability (Czerniewicz & Brown, 2013). The COVID-19 pandemic further exposed these inequalities, revealing that access to devices, data, and electricity remains a major barrier to equitable learning (Dube, 2020; Mpungose, 2020).

Despite widespread LMS adoption (Bozalek et al., 2013), many academics still use these systems primarily for administrative rather than interactive or analytics-driven teaching. This limited pedagogical integration reflects broader gaps in digital literacy, institutional policy, and training support (Ng, 2012). Mobile learning initiatives show promise in leveraging South Africa's high mobile penetration (Traxler & Wishart, 2011), yet sustainability remains constrained by inconsistent institutional strategies and the ongoing impact of load shedding (Adebayo, 2021).

South Africa's digital readiness narrative is often framed in infrastructural terms, yet the more profound challenge lies in *institutional culture and trust in technology*. Many universities adopt technology reactively rather than strategically, leading to fragmented and short-lived initiatives. Additionally, dependence on imported platforms raises concerns around data sovereignty and localisation (Kshetri, 2013). While existing studies document infrastructural disparities, few explore how these material and cultural conditions influence educators' trust and acceptance of LA. This study contributes by analysing how lecturers lived experiences within these digital ecosystems shape their perceptions of LA adoption feasibility and institutional readiness.

3. Methodology

This study adopted a positivist stance as it aimed to determine perspectives on learning analytics (LA) implementation in higher education institutions (HEIs) without the researcher influencing the existing context of adoption. A qualitative method of inquiry was employed to address the research questions, and a deductive approach guided the study design. Purposeful sampling was used to select participants, and a survey research strategy was followed to capture lecturers' perceptions of LA.

Four public HEIs in South Africa were selected based on their demonstrated engagement with or potential value from LA implementation. Data were collected through open-ended questionnaires distributed via email. To ensure instrument validity and reliability, the questionnaire was developed based on constructs derived from prior empirical studies on technology adoption and learning analytics frameworks. The instrument was reviewed by two experts in educational technology and piloted with three lecturers to confirm clarity, relevance, and alignment with the research objectives.

Qualitative data from the open-ended responses were transcribed and analysed using NVivo 12 to support systematic coding and theme development. A hybrid approach combining inductive and deductive thematic analysis was followed, guided by Braun and Clarke's six-phase framework: (1) familiarization with the data, (2) generation of initial codes, (3) identification of themes, (4) reviewing and refining themes, (5) defining and naming themes, and (6) producing the final report. Both theory-driven and data-driven codes were applied to ensure a balanced interpretation between existing theoretical constructs and emergent insights from participants.

To enhance the credibility of findings, themes were verified through peer debriefing and cross-checking of coded data by an independent qualitative researcher. Dependability was ensured through a clear audit trail documenting coding decisions and theme refinement, while confirmability was strengthened by maintaining reflective notes that captured analytical decisions and researcher assumptions throughout the process. This structured and transparent procedure enhanced the overall trustworthiness of the qualitative findings.

Ethical approval for the study was obtained from the Institutional Research Ethics Committee of the participating university. Participation was voluntary, and informed consent was secured from all respondents prior to data collection. Participants were assured of confidentiality and anonymity, with no identifying information disclosed in any part of the analysis or reporting. All data were securely stored and used exclusively for academic purposes in accordance with institutional and national research ethics guidelines.

Table 1 presents the demographic distribution of the 41 lecturers who participated, categorized according to their years of experience in higher education.

Table 1: Lecturer Demographics

Years of Experience			
Years of Experience	**Frequency**	**%**	**Cumulative %**
0-2 Years	6	14,6	14,6
10+ Years	21	51,2	65,9
2-5 Years	4	9,8	75,6
5-10 Years	10	24,4	100,0
Total	41	100,0	

The table summarises the distribution of participants based on their years of experience. Among the respondents, the largest group (51.2%) had more than 10 years of experience, followed by 24.4% with 5-10 years of experience. A smaller proportion had 0-2 years (14.6%) or 2-5 years (9.8%) of experience. The cumulative percentage indicates that 65.9% of respondents had more than 2 years of experience, and 100% are accounted for by the inclusion of all experience categories. This distribution suggests most experienced participants in the dataset, with a significant representation from highly experienced individuals (10+ years).

3.1 Findings

This section presents a detailed data analysis by highlighting the main themes and subthemes from the study as illustrated in Table 2 and Table 3.

3.1.1 The benefits that adoption of learning analytics will bring into institutions of higher education

Learning analytics (LA) presents significant opportunities for improving higher education outcomes in the South African context. Based on lecturers' qualitative responses, the following themes capture perceived benefits of LA, drawn directly from their insights and aligned with broader institutional goals. These themes reflect both individual and systemic advantages, highlighting a strong belief among lecturers in the transformative potential of LA when ethically and strategically implemented.

Table 2: Thematic Summary of Lecturer Perspective on Learning Analytics (Benefits)

Theme	Refined Keywords	Description (with Lecturer Insights)
Student Learning and Improvement	Early identification, at-risk students, personalized support, learning outcomes, predictive analytics	Lecturers believe that learning analytics enable early identification of students who are at risk and allow for timely, tailored interventions to improve learning outcomes. One lecturer explained, *"When analytics show a pattern of low engagement or declining grades, I can intervene before the student disengages completely. It helps us act early rather than waiting for failure."* This highlights LA's role in shifting teaching from reactive to proactive support.
Institutional Improvement	Teaching quality, institutional effectiveness, strategic planning, performance enhancement, data-driven improvement	LA is viewed as instrumental in improving institutional effectiveness and teaching quality through data-informed planning. A participant stated, *"When departments use analytics to review performance trends, they can refine teaching models and resource allocation to enhance overall academic quality."* This perspective underscores LA's potential to drive continuous improvement at institutional level.
Decision-Making and Support	Data-informed decisions, academic support, student wellbeing, evidence-based management, empowerment	Lecturers emphasized the importance of LA in strengthening decision-making processes across academic and support structures. One noted, *"Analytics empower us to make decisions that genuinely serve students' wellbeing and academic success because those decisions are grounded in evidence, not assumptions."* This demonstrates how LA fosters more responsive and equitable academic support.
Academic Enhancement and Trust	Trust, data reliability, confidence, transparency, evidence-based teaching, system credibility	Trust emerged as a critical factor in lecturers' willingness to engage with LA. Participants highlighted that confidence in data accuracy strengthens acceptance and effectiveness. One lecturer said, *"When the system produces reliable and consistent data, I can trust it to guide my teaching decisions. Without that trust, the whole process feels uncertain."* This underscores the link between trust, data reliability, and academic enhancement.
Student Performance and Intervention	Performance tracking, behavioural insight, early intervention, learning behaviour, proactive teaching	Lecturers view LA as a tool for understanding student performance and initiating timely interventions. A respondent explained, *"By analysing patterns in attendance and assessment performance, we can step in before a student fails. It helps us identify who needs help and when."* This reflects LA's role in enabling

		data-driven, preventative academic support.
Student Success and Monitoring	Progress monitoring, student success, completion rates, retention, academic guidance	LA is perceived as vital in supporting continuous monitoring of student progress and promoting academic success. One lecturer shared, *"Analytics allow me to track how students are progressing throughout the semester, so I can ensure no one falls through the cracks before graduation."* This highlights LA's contribution to sustained student engagement and institutional retention efforts.

These perspectives reveal a strong alignment between lecturers' expectations and the potential impact of LA on student success and institutional performance. The themes emphasize that learning analytics is not merely a technological tool, but a strategic asset for South African higher education when deployed with sensitivity to context, ethics, and capacity.

3.1.2 The factors hinder the adoption of learning analytics in institutions of higher education.

Table 3: Thematic Summary of Lecturer Perspective on Learning Analytics (Challenges)

Theme	**Keywords**	**Description (with Lecturer Insights)**
Lack of Awareness and Interest	Lack, matter, willingness, privacy, right, regard, budget, plan, institution, online	A lack of institutional awareness and staff interest undermines LA uptake. One lecturer remarked, "*Many academics don't even know what learning analytics is or why it matters.*"
Ethical Use of Data	Analytic, concern, learn, staff, change, datum, lack, ethical, data, student	Ethical concerns about data privacy and student rights are prominent. A lecturer asked, "*Do we even have consent from students to use their learning data in these systems?*"
Resource Constraints and Capacity Issues	Capacity, resource, software, load, datum, office, low, human, planning, institutional	Institutions face systemic limitations in infrastructure and funding. One explained, "*We don't have the tools, or even the people, to use analytics meaningfully at our institution.*"
Data Ownership and Development Challenges	Datum, academic, ownership, development, especially, workload, relentless, slow, new, adoption	Concerns over data control and slow system development stall progress. A participant noted, "*We're not even sure who owns the data, and developing anything new is painfully slow.*"
Lack of Training and Support	Training, support, staff, faculty, understand, benefit, process, policy, university, analytic	Without training, lecturers feel unprepared to engage with LA. One said, "*There is no structured training on how to use the data or understand its implications.*"

Staff Shortage and Workload	Lack, staff, academic, load, student, interest, analytic, shed, support, data	Overburdened staff struggle to engage with new technologies. A lecturer shared, "*We are already overloaded – there's no room to add something new like learning analytics on top of everything else.*"

These challenges point to the need for a holistic and institutionally supported approach to learning analytics implementation. Without addressing foundational issues such as training, staffing, ethics, and infrastructure South African institutions of higher education risk underutilizing a tool that could transform student success and institutional performanceDo not end a section with an indented quotation. Always conclude with the relevant concluding sentence.

4. Findings: Interpretation of Findings

Figures and tables must be introduced before they are presented. Generally, the discussion of the contents will follow the figure or table; however, the discussion may also precede the figure or table, depending on where best to position the figure or table.

4.1 Benefits of Learning Analytics: Lecturer Perspectives

The analysis revealed six distinct themes representing the perceived benefits of learning analytics adoption in South African higher education institutions. These themes demonstrate lecturers' sophisticated understanding of learning analytics as both a pedagogical tool and institutional asset.

4.1.1 Student Learning and Improvement

Lecturers consistently emphasized learning analytics' potential for early identification and intervention with at-risk students. This theme aligns with established early warning systems literature (Macfadyen & Dawson, 2010; Arnold & Pistilli, 2012) while providing empirical validation in a developing country context. The emphasis on proactive rather than reactive support suggests lecturers understand analytics as a transformative rather than merely descriptive tool.

4.1.2 Institutional Improvement

Participants recognized learning analytics' capacity to enhance institutional effectiveness beyond individual student outcomes. This finding extends Campbell and Oblinger's (2007) academic analytics framework to include teaching quality improvement and organizational learning. Lecturers demonstrated systems thinking by connecting data insights to institutional performance improvements.

4.1.3 Decision-Making and Support

The emphasis on data-informed decision-making reflects alignment with evidence-based practice principles (Bryk et al., 2015). Lecturers particularly valued analytics' potential to support student wellbeing decisions, indicating understanding of learning analytics as a human-cantered rather than purely technical endeavour.

4.1.4 Academic Enhancement and Trust
Participants linked system reliability to trust and effectiveness, introducing trust as a mediating factor in learning analytics success. This finding extends technology acceptance models (Davis, 1989) by highlighting how data quality perceptions influence user confidence and system adoption.

4.1.5 Student Performance and Intervention
Lecturers demonstrated understanding of predictive analytics' actionable potential, connecting data insights to intervention strategies. This theme bridges predictive modelling literature (Baker & Inventado, 2014) with practical pedagogical applications, showing how theoretical models translate into educational practice.

4.1.6 Student Success and Monitoring
The focus on continuous monitoring for retention reflects sophisticated understanding of student persistence theories (Tinto, 1993) applied through digital means. Lecturers recognized analytics' potential to operationalize theoretical models of student success through systematic support systems.

4.2 Challenges of Learning Analytics Implementation
Six themes emerged representing barriers to learning analytics adoption, revealing complex implementation challenges beyond technical infrastructure limitations.

4.2.1 Lack of Awareness and Interest
Fundamental knowledge gaps emerged as primary adoption barriers, supporting innovation diffusion theory (Rogers, 2003) by demonstrating that awareness precedes acceptance. These finding challenges assumptions that technical barriers are primary impediments to learning analytics adoption in developing contexts.

4.2.2 Ethical Use of Data
Participants expressed sophisticated ethical concerns regarding data privacy and student consent, reflecting awareness of privacy rights and data protection principles. These concerns represent practical barriers rather than merely theoretical considerations, extending educational data ethics literature (Slade & Prinsloo, 2013) to implementation contexts.

4.2.3 Resource Constraints and Capacity Issues
Resource limitations extended beyond technical infrastructure to encompass human capital and institutional capacity constraints. This multidimensional understanding of resource barriers contributes to digital divide literature (Warschauer, 2003) by highlighting capacity building needs in developing country contexts.

4.2.4 Data Ownership and Development Challenges
Unclear data governance structures and slow development processes created implementation barriers. Participants' concerns about data ownership reflect sophisticated understanding of governance principles while highlighting practical obstacles to analytics adoption.

4.2.5 Lack of Training and Support
Professional development deficits emerged as significant barriers, demonstrating that technical infrastructure alone is insufficient for successful implementation. This finding extends faculty development literature by showing specialized competency requirements for learning analytics adoption.

4.2.6 Staff Shortage and Workload
Systemic capacity constraints created competitive pressures between learning analytics adoption and existing academic responsibilities. This theme contributes to academic labor literature (Berg & Seeber, 2016) by showing how work intensification affects educational innovation adoption decisions.

5. Discussion

5.1 Synthesis of Key Findings

The findings reveal a central paradox in South African higher education's engagement with learning analytics (LA): while lecturers possess a deep understanding of LA's transformative potential, systemic barriers impede effective implementation. This aligns with Muntongoza (2025), who observed that transformation is constrained by historical inequalities, limited funding, institutional cultures, leadership weaknesses, global pressures, and socio-political dynamics. This paradox reflects the broader tension between aspiration and capacity that often characterises educational innovation in developing contexts (Oke & Fernandes, 2020).

5.2 The Recognition-Implementation Gap

The contrast between recognition of LA's benefits and practical implementation challenges highlights a "recognition-implementation gap." Stakeholders may understand the value of innovation but face systemic and contextual constraints that inhibit adoption. This gap manifests in three dimensions:

1. **Cognitive Recognition:** Lecturers understand LA's potential benefits.
2. **Practical Constraints:** Systemic barriers prevent translating understanding into action.
3. **Aspirational Tension:** Desire for innovation exists alongside realistic assessment of limitations.

5.3 Contextual Adaptation of Learning Analytics Theory

Findings suggest that LA adoption models from resource-rich contexts require significant adaptation in developing country settings. Implementation must consider constraints such as limited infrastructure, capacity deficits, and competing institutional priorities. LA should therefore be conceptualised as a socio-technical system, integrating technological, human, and organizational dimensions to achieve context-sensitive adoption.

5.4 Trust as a Critical Success Factor

Trust emerged as a mediating factor in LA acceptance, extending traditional technology adoption models. Lecturers' engagement and willingness to act on analytics insights depend on confidence in system reliability, data quality, and institutional support. In developing contexts, where prior experiences with unreliable systems may foster scepticism, trust is both a technical and social prerequisite for adoption (Rana et al., 2024).

5.5 Theoretical Implications

1. **Extending Innovation Adoption Theory:** The study highlights that systemic constraints can override individual adoption motivations, suggesting the need for "constrained innovation" models in developing contexts (Cardol et al., 2025).
2. **Reconciling Learning Analytics Success Metrics:** Awareness, understanding, and readiness may be as important as full implementation in resource-limited settings.
3. **Human-Centered Analytics Frameworks:** Incorporating ethics, trust, and stakeholder perspectives is essential for effective socio-technical LA adoption.

6. Conclusion

This study provides empirical evidence of both the universal appeal of LA benefits and the context-specific nature of implementation challenges in South African higher education. Key contributions include:

- Identification of a recognition-implementation gap, highlighting how contextual constraints can override individual motivation to adopt LA.
- Demonstration of trust as a critical mediator, reinforcing the importance of reliable systems and transparent data practices.
- Extension of innovation adoption theory to account for resource constraints and institutional realities in developing country contexts.

Practical, Policy, and Institutional Recommendations:

- **Awareness and Capacity Building:** Systematic professional development to enhance understanding and competency in LA.
- **Ethics and Data Governance:** Clear frameworks for privacy, consent, and responsible data use.
- **Incremental Implementation:** Phased deployment strategies to build confidence and trust.
- **Institutional Support:** Investment in reliable technical infrastructure, stakeholder engagement, and change management strategies.
- **National Coordination:** Policy frameworks, funding mechanisms, and inter-institutional collaboration to support sustainable LA adoption.

This study has several limitations. The sample was limited to four universities, which may not fully represent the diversity of higher education institutions in South Africa. Additionally, the number of respondents was relatively small, and the study relied on self-reported data, which may be subject to bias. These factors limit the generalizability of the findings.

Future studies could address these limitations by conducting longitudinal research to examine changes in learning analytics adoption over time, employing larger quantitative studies to validate the findings, and undertaking cross-country comparisons to explore contextual differences in implementation challenges and strategies. Such research would deepen understanding of how learning analytics can be effectively adopted in diverse educational contexts.

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