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The two-way mirror of learning analytics: Reflections of student engagement in learning management system data

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Abstract: As universities increasingly use Learning Management Systems (LMS) to facilitate online learning, digital activity traces have become proxies for student engagement. In the Canvas LMS used in this study, monitoring is largely unidirectional: student actions are recorded, but their interpretation remains opaque to students. This study applies the metaphor of a “two-way mirror,” where analytics make engagement visible to educators while obscuring its meaning from students. Using Redmond et al.’s online engagement framework, which encompasses behavioural, cognitive, social, and collaborative dimensions, LMS data from 690 first-year Bachelor of Education and Postgraduate Certificate in Education students enrolled in a Computer-Integrated Education module at a South African university were analysed. Indicators included page views, timely submissions, forum participation, and final grades. Descriptive statistics explored cohort-based engagement differences, while Mann–Whitney U tests and Spearman’s rank correlations assessed associations between engagement and grades. Internal consistency of LMS-derived metrics was high (Cronbach’s α = 0.79), and exploratory factor analysis revealed a one-factor structure explaining 49.3% of the variance. Results showed moderate positive correlations between engagement and grades, along with cohort differences. The initial low Cronbach’s α before standardisation underscored the significance of methodological precision in creating composite indicators. Engagement measures risk distortion and inequity without scale alignment, potentially supporting punitive or reductive analytics. The results highlight the potential and limitations of LMS data, reinforcing the need for participatory, contextually sensitive learning analytics that prioritise formative uses and address support needs over predictive or classificatory applications, particularly in digitally unequal contexts.

Keywords: Higher education, learning analytics, learning management systems, student engagement, two-way mirror.

1. Introduction

Online learning has become central to higher education globally, driven by technological advances and demands for accessibility, flexibility, and inclusion (Veluvali & Surisetti, 2022). In alignment with SDG 4.3, which promotes equitable access to quality tertiary education, institutions have expanded their digital infrastructure (Johar et al., 2023), with learning management systems (LMS) emerging as key tools for instructional delivery and student engagement. LMS facilitate synchronous and asynchronous interaction, supports content dissemination and assessment, and integrates learning analytics (LA) (Simelane-Mnisi, 2023), offering opportunities to investigate how students engage with online environments.

In South Africa, the transition to hybrid and online learning has created both opportunities and constraints: digitalisation has expanded access through resources such as massive open online courses (MOOCs), smart devices, and LMS; however, many institutions still face inadequate infrastructure, limited internet access, overcrowded classrooms, and shortages of digitally skilled educators (Mhlongo et al., 2023). These disparities became more pronounced during the COVID-19 lockdowns, which accelerated the adoption of online learning but also exposed the persistent digital divide, as students from rural and under-resourced areas struggled with poor connectivity, lack of devices, and unsuitable study spaces (Jakoet-Salie & Ramalobe, 2023). Simultaneously, digital technologies proved essential for sustaining instruction, facilitating remote participation, and generating rich engagement data, underscoring the necessity to address socioeconomic and infrastructural inequalities while leveraging digital tools for equitable participation.

Broadly defined as the time, attention, and effort students invest in their learning, student engagement has often been correlated as a strong predictor of academic success (Bowden et al., 2021; Kahu & Nelson, 2018), with high engagement linked to improved outcomes and retention, particularly in online contexts where isolation and attrition represent significant challenges (Caspari-Sadeghi, 2022). Redmond et al.'s (2018) Online Engagement Framework identifies behavioural, cognitive, social, collaborative, and emotional dimensions, which can be mapped to indicators within LMS: frequency of logins or resource views (behavioural), time on problem-solving tasks (cognitive), forum posts or peer feedback (social/collaborative), and participation patterns or discussion sentiment (emotional) (Bergdahl et al., 2024). However, these dimensions are often examined in isolation, thereby limiting comprehension of how they interact to shape learning (Johar et al., 2023).

Alongside these conceptual developments, the use of Learning Analytics (LA) has expanded, with platforms such as Moodle and Canvas generating digital traces—logins, clicks, discussion posts, and submissions—that offer insights into student activity. These data streams can help identify at-risk students, support adaptive instruction, and promote equity (Mougiakou et al., 2023). However, in many institutions, particularly in the Global South, this potential remains underutilised. Learning Management System (LMS) data are often collected for administrative purposes such as attendance and grading, rather than to inform pedagogy or provide personalised feedback (Veluvali & Surisetti, 2022). Moreover, students are frequently excluded from the analytics process: their activities are monitored, yet they rarely see how their data is interpreted or applied, creating a "two-way mirror" effect, in which educators observe engagement but students possess little visibility (Selwyn, 2019). This asymmetry raises critical questions regarding transparency, agency, and the ethical use of data (Tsai et al., 2020).

Two key tensions emerge from this dynamic: first, the tension between the micro-level behavioural data captured by LMS and broader theoretical constructs of engagement; and second, the tension between institutional control of analytics and students' limited access or agency. These tensions are particularly salient in contexts such as South Africa, where infrastructural disparities and diverse learner backgrounds shape engagement patterns (Naidoo & Naranjee, 2024). Without alignment between LA practices and engagement frameworks, such systems risk reinforcing rather than reducing educational inequalities (Broughan & Prinsloo, 2020). Addressing this challenge requires clarity on how engagement is measured through LMS data and how these measures can be used to benefit rather than surveil students (Farley & Burbules, 2022; Simelane-Mnisi, 2023).

In response to these concerns, this study examines how LMS data capture multidimensional student engagement in a computer-integrated education (CIE) module at a South African university. Guided by the framework established by Redmond et al. (2018), it analyses how LMS interactions render behavioural, cognitive, social, collaborative, and emotional dimensions visible—or obscure them—and evaluates the reliability and validity of these indicators while considering the implications of the "two-way mirror" for transparency, agency, and equity. To explore how student context shapes engagement, the study compares two cohorts: first-year students, for whom the module is a component of their Bachelor of Education (BEd) degree, and Postgraduate Certificate in Education (PGCE) students transitioning into the teaching profession. This comparison provides insight into how differing academic backgrounds influence engagement patterns, illustrating how LA practices can promote equitable and pedagogically meaningful outcomes.

1.1 Problem statement

Since the COVID-19-driven expansion of online and hybrid learning, LMS platforms have become integral to South African higher education (Mhlongo et al., 2023). However, institutional practices often reduce engagement to narrow behavioural metrics, neglecting its multidimensional nature as outlined by Redmond et al. (2018). Although LMS-generated data are rich, persistent digital inequality can distort the representation of students from under-resourced contexts (Simelane-Mnisi, 2023). Moreover, limited transparency and lack of student agency in learning analytics risk inequitable or misleading interpretations (Broughan & Prinsloo, 2020), highlighting the need to critically examine the use of LMS data in the post-pandemic landscape.

Hence, the following questions guided the study:

- What patterns of multidimensional engagement emerge from LMS-generated data in an online course?
- What associations exist among temporal LMS-based engagement metrics and students' academic performance?
- To what extent do these LMS-based engagement patterns reliably and validly represent the construct of multidimensional engagement?

2. Literature Review

This literature review explores student engagement as a multidimensional construct and investigates the influence of learning management systems and learning analytics on its behavioural, cognitive, emotional, and social dimensions. It illuminates both the opportunities and risks associated with digital tools, particularly in contexts characterised by inequality, and situates engagement within frameworks that are culturally responsive and pedagogically grounded.

2.1 Student engagement as a multidimensional meta-construct

In higher education, student engagement is valued not only for its links to academic success and retention but also for encapsulating the interplay of motivation, affect, cognition, and context that underpins meaningful learning (Kahu & Nelson, 2018). Early definitions emphasised observable behaviours, effort, time on task, and participation; however, these provide only a partial view (Bowden et al., 2021; Caspari-Sadeghi, 2022). A major conceptual shift occurred with Fredricks et al.'s (2004) tripartite model, which distinguishes between behavioural (attendance, participation, task completion), cognitive (mental effort, learning strategies, persistence), and emotional (interest, boredom, anxiety, enjoyment) dimensions.

Subsequent expansions, such as Reschly and Christenson's (2022) inclusion of social engagement, positioned student engagement as both a process and an outcome embedded in academic, institutional, and sociocultural contexts. This reframing recognises engagement as a meta-construct that integrates collaboration, academic integration, student experience, and partnership (Bowden et al., 2021), emerging through ongoing interactions between students, educators, and broader systems (Kahu & Nelson, 2018). Valence, or affective tone, further shapes its impact: positive emotions (pride, curiosity, satisfaction) promote immersion and problem-solving, whereas negative emotions (frustration, fear, boredom) erode motivation (Bowden et al., 2021). Engagement thus acts as the "glue" binding behavioural participation, cognitive investment, and emotional involvement within a complex learning ecosystem.

2.2 LMS and learning analytics as facilitators and limiters of engagement

Building on this multidimensional view, it is critical to examine how motivation, emotion, cognition, and context intersect in online environments. While not unique to digital spaces, these factors are often amplified by self-paced structures that can heighten isolation, cognitive overload, and reduced social interaction (Caspari-Sadeghi, 2022). Karaoglan Yilmaz and Yilmaz (2022) argue that research on online engagement must move beyond behavioural proxies to consider self-regulation, intrinsic motivation, and emotional–social dynamics. For students in under-resourced contexts, such challenges can lead to surface learning or disengagement (Farley & Burbules, 2022). LMSs mediate engagement by providing the infrastructural core for online and blended learning, delivering content, structuring assessment, enabling communication, and logging student behaviours (Simelane-Mnisi, 2023). Although their analytics often privilege behavioural metrics—such as submissions, clicks, and attendance (Veluvali & Surisetti, 2022)—pedagogically designed LMS environments can scaffold deeper engagement, promoting collaboration, reflection, and a sense of belonging (Johar et al., 2023).

Features such as discussion forums, group workspaces, and peer feedback tools enable affective and social interactions that move beyond click counts and submission rates (Caspari-Sadeghi, 2022). Yet much empirical work remains technocentric, relying on behavioural system logs to measure engagement and overlooking the cognitive, emotional, and cultural dimensions that shape the student experience (Henrie et al., 2018; Bergdahl et al., 2024).

To counter this reductionism, Redmond et al. (2018) propose a five-dimensional Online Engagement Framework—behavioural, cognitive, social, collaborative, and emotional—that builds on Fredricks et al. (2004) and expands engagement beyond transactional activity. Within LMS environments, social engagement fosters community and peer interaction, while collaborative engagement supports the co-construction of knowledge through group projects and shared inquiry, underscoring that engagement is relational, contextual, and shaped by platform design (Johar et al., 2023).

However, digital engagement is not simply a matter of personal agency. Structural and historical conditions—particularly in South Africa—fundamentally shape students' ability to engage. Legacies of colonialism, racial inequality, poverty, language barriers, and infrastructural limitations create enduring divides (Mhlongo et al., 2023). These are not peripheral issues; they lie at the heart of students' interactions with online learning environments. Ignoring them risks re-inscribing exclusion through seemingly neutral platform analytics (Selwyn, 2019).

LA, often embedded within LMS, offers tools to observe and interpret student engagement through digital trace data (Veluvali & Surisetti, 2022). However, the epistemic value of this data lies not in its collection but in its interpretation. Without critical and contextual framing, LA can become a surveillance tool, flattening the complexity of learning into depersonalised dashboards and reinforcing systemic inequities (Tsai et al., 2020). Conversely, when embedded within culturally sensitive and pedagogically grounded frameworks, LA can illuminate how students engage, resist, and adapt in complex learning systems (Viberg et al., 2023).

2.3 (Re)imagining LMS-supported engagement through a LA lens

Beyond content hosting and assessment, LMSs are dynamic, data-rich environments capable of offering nuanced insights into how students engage, tracking patterns such as login frequency, forum activity, time-on-task, and resource access (Veluvali & Surisetti, 2022; Johar et al., 2023). These behavioural traces form the basis of learning analytics. Nevertheless, despite this analytical potential, in South African higher education institutions, LMS data are often underutilised and limited to administrative tracking rather than pedagogical innovation (Simelane-Mnisi, 2023).

LA, broadly defined, involves collecting, analysing, and interpreting student data to inform evidence-based decision-making in education (Mougiakou et al., 2023). When integrated meaningfully, analytics can support early-warning systems, personalised feedback, and equitable intervention strategies—especially if data sources include temporal, affective, and behavioural dimensions (Saint et al., 2022). Analytic techniques range from machine learning and social network analysis to qualitative modelling. However, the field remains dominated by reductive approaches prioritising frequency over meaning, which erodes a holistic understanding of engagement (Johar et al., 2023).

Crucially, LA is not value-neutral. Cultural scripts, institutional logics, and epistemological assumptions shape how analytics are designed, interpreted, and acted upon (Viberg et al., 2023). When analytic tools ignore these dimensions, they risk creating epistemic dissonance, where students' lived experiences clash with the expectations encoded in learning platforms (Broughan & Prinsloo, 2020). In such cases, learning analytics reinforce dominant models of knowing while marginalising diverse epistemologies and engagement strategies. The asymmetrical power dynamics of current analytics practices further amplify these risks. Students are routinely tracked but are seldom invited into the interpretive process. This "two-way mirror" phenomenon undermines essential components such as transparency, agency, and reflective practice (Tsai et al., 2020). Ethical concerns surrounding surveillance, consent, and the instrumental use of student data are increasingly urgent (Selwyn, 2019).

LA must be reimagined as a socio-technical assemblage, a system shaped as much by histories and power relations as by algorithms and dashboards, to move beyond these limitations (Viberg et al., 2023). In structurally unequal contexts, culturally responsive and pedagogically grounded analytics are not optional but imperative (Broughan & Prinsloo, 2020). This requires a shift from deficit framings towards participatory, reflexive models that centre student agency and context.

2.4 Theoretical grounding

This study contributes to the reimagining of engagement by investigating how LMS-generated data can be used to profile multidimensional engagement in a computer-integrated education module at a South African university. Anchored in Redmond et al.'s (2018) Online Engagement Framework, the study explores how behavioural, cognitive, social, collaborative, and emotional engagement become visible—or remain obscured—through platform data. By interrogating the "two-way mirror," it critiques how current analytics practices risk reducing learning to static, culture-neutral proxies. Instead, it advocates for a reflexive approach to LA, one capable of revealing not just who is disengaged, but why, by attending to the institutional, cultural, and historical realities that shape student engagement. This study responds to calls for ethically grounded, pedagogically informed, and culturally sensitive LA practices that support equitable and sustained student engagement in higher education (Broughan & Prinsloo, 2020; Viberg et al., 2023).

3. Methodology

This study was conducted within a year-long blended Curriculum and Instructional Education (CIE) module at a large, research-intensive South African university. Offered as part of the initial teacher education programme, the module addressed the increasing integration of digital technologies in classroom settings. Baseline diagnostic tasks and institutional evaluations indicated that, despite access to digital tools, many prospective educators struggled to incorporate them into lesson plans, align them with curriculum outcomes, or utilise them to enhance learner engagement. The module aimed to develop reflective, digitally fluent educators through technical training and pedagogical intervention. Digital pedagogy served as both a method and content, grounded in the principle that teacher preparation should model the environments that educators are expected to create. Praxis-based tasks—such as digital storytelling, multimedia lesson design, collaborative inquiry, and peer reviews—required students to adapt digital resources for authentic classroom contexts, fostering an ecology in which instructional design and engagement mutually reinforced one another.

A quantitatively driven design, incorporating theoretical and interpretive frameworks, explored how student engagement was enacted, experienced, and made visible through Learning Management System (LMS) data. Engagement was understood as multidimensional and socioculturally situated, shaped by student activity, institutional design, infrastructure, and epistemic orientations. The study included all students enrolled in the CIE module: 659 first-year Bachelor of Education (BEd) students and 31 Postgraduate Certificate in Education (PGCE) students. Data were anonymised, aggregated, and restricted to students who provided informed consent. The study adhered to institutional ethical protocols, permitting the use of such data for approved research purposes with safeguards in place. Despite varying educational backgrounds, both groups engaged with the same digital infrastructure and pedagogical design, enabling a focus on how students' positionalities and prior experiences mediated engagement rather than attributing differences to curriculum or digital exposure.

Data collection and analysis were conducted within the ethical and pedagogical parameters of the CIE module. Canvas, the LMS, functioned both as a teaching tool and a data source, providing discussion boards, assessments, media-rich resources, and submission portals, while its New Analytics feature unobtrusively captured engagement data. In Phase 1, digital trace data—including pseudonymised User IDs, page views, participations (forum posts, quiz attempts, submissions), on-time submission rates, and final grades—were mapped to Redmond et al.'s (2018) Online Engagement Framework: course performance for cognitive engagement, submission timing and page views for behavioural engagement, and participatory activity for social/collaborative engagement. Emotional engagement was excluded due to the limitations of log data (Caspari-Sadeghi, 2022), reflecting broader concerns regarding the epistemic narrowing of engagement in analytics (Johar et al., 2023). Phase 2 applied temporal analysis to weekly engagement patterns to identify key learning moments, such as assessments and collaboration (see Figure 1), recognising engagement as dynamic and shaped by pedagogical rhythms, digital affordances, and student agency (Saint et al., 2022; Tsai et al., 2020), and as a culturally and materially mediated activity trace of presence in the learning environment.

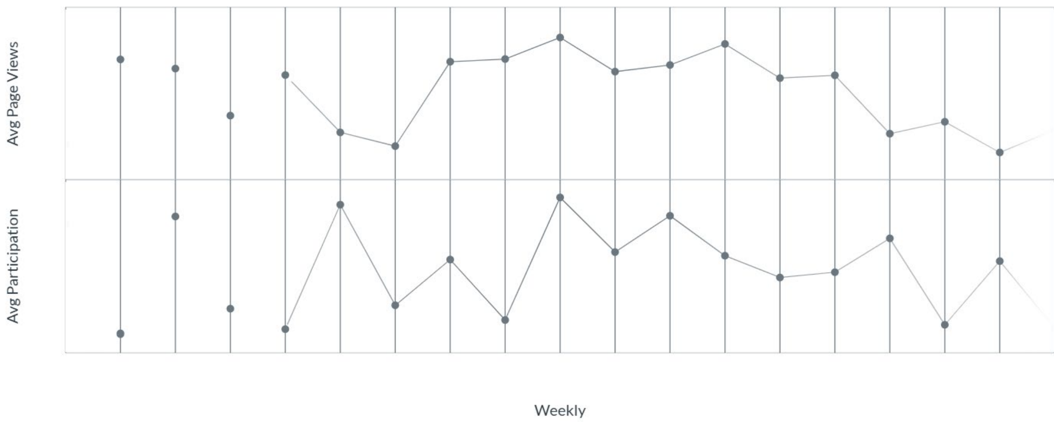

***Figure 1**: Patterns of student engagement represented by weekly average page views and participation*

To complement descriptive insights, the analysis in SPSS began with descriptive statistics to examine engagement across cohorts and how pedagogical aims were enacted in relation to research question 1. Due to the non-normal distribution of some variables (e.g., pageviews), nonparametric methods were employed. Spearman's rank-order correlation was used to assess relationships between metrics, while the Mann-Whitney U test compared cohorts for research question 2.

3.1 Reliability and validity

The reliability of engagement constructs—designed to reflect the module's pedagogical outcomes—was assessed using Cronbach's alpha for internal consistency in research question 2. Principal Axis Factoring was employed to explore convergent validity and the latent structure of engagement. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity confirmed the data's suitability for factor analysis, indicating adequate shared variance.

3.2 Ethical considerations

The study adhered to institutional ethical protocols, received clearance from the University of the Witwatersrand's Human Research Ethics Committee, and included only anonymised, aggregated LMS data from students who provided informed consent. Guided by Slade and Prinsloo's (2013) ethical framework, students were treated as co-interpreters of their engagement data, resisting behaviourist reductions of learners to mere metrics (Broughan & Prinsloo, 2020; Viberg et al., 2023). Engagement was framed within pedagogical and sociocultural contexts (Silvola et al., 2021) and aligned with the "two-way mirror" metaphor, recognising that while systems like Canvas capture behavioural data, students often remain unaware of its scope (Selwyn, 2019). Three ethical domains shaped the study: the constructed nature of data and its interpretation; informed consent and transparency; and governance and storage implications for student identity and futures. These principles challenged top-down, instrumental approaches to learning analytics, prioritising agency, transparency, and reflexivity in the selection and interpretation of engagement measures (Tsai et al., 2020).

4. Presentation of Results

This section presents the findings in relation to the study's research questions. Descriptive statistics addressed research question 1 concerning patterns of multidimensional engagement in LMS data. Spearman's rank-order correlations examined research question 2, focusing on the associations between temporal engagement metrics and academic performance. Due to the non-normal distribution of certain variables (e.g., page views), non-parametric methods were applied, and cohort differences were tested using Mann-Whitney U procedures. For research question 3, reliability and factor analysis assessed the extent to which LMS indicators reflect the broader construct of multidimensional engagement.

4.1 Patterns of multidimensional engagement from LMS data

This subsection reports on the patterns of behavioural, cognitive, collaborative, and social engagement captured through LMS logs, highlighting similarities and differences among cohorts.

4.1.1 Cognitive engagement

Comparative performance data in Figure 2 revealed that PGCE students (Group 2) achieved slightly higher overall scores (Mean = 78.14%, Median = 80.94%) than undergraduates (Group 1: Mean = 75.46%, Median = 79.76%). Trimmed means supported this pattern, suggesting the difference was not due to outliers. Score variability was greater in Group 1, which spanned the full range (0–100%) and had higher variance (330.90) compared to Group 2's narrower range (41.49–97.52, variance = 180.16), indicating inconsistency among undergraduates.

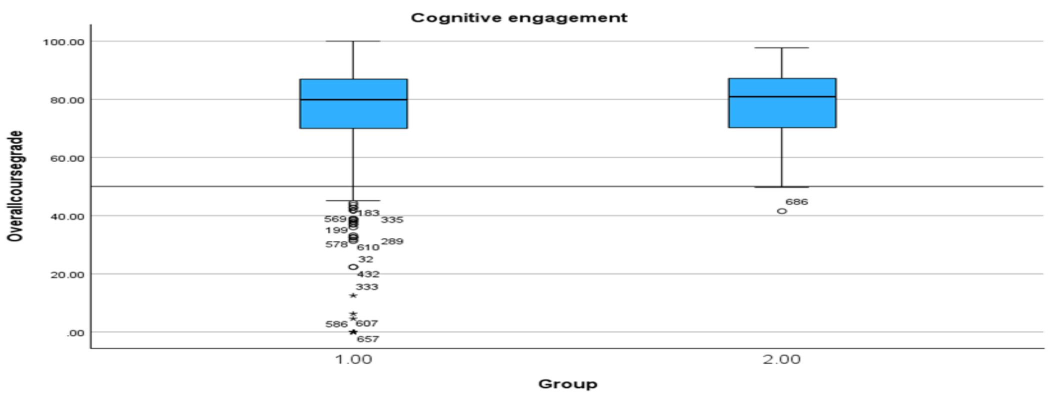

Figure 2: *Distribution of overall course grades by instructional group*

These contrasts were also evident in the distributional patterns shown. Group 1's distribution was highly leptokurtic (kurtosis = 5.910) and negatively skewed (skewness = -2.161), indicating a cluster of high scores and a tail of low-performing outliers. Group 2's scores were more symmetrically distributed (skewness = -0.906, kurtosis = 0.747), suggesting a consistent cognitive performance. However, a Mann-Whitney U test (= 9732.00, = 0.656) in Table 1 found no statistically significant difference between the two groups, implying that while their engagement patterns differed in shape and spread, central tendencies remained comparable.

4.1.2 Behavioural engagement

Visualised in Figure 3, temporal submission patterns showed a higher rate of on-time assignment completion among PGCE students (Group 2: Mean = 84.71%, Median = 90.00%) compared to undergraduates (Group 1: Mean = 79.36%, Median = 84.60%). This difference was statistically significant (U = 6933.50, p = 0.002), indicating greater behavioural consistency and alignment with deadlines in Group 2.

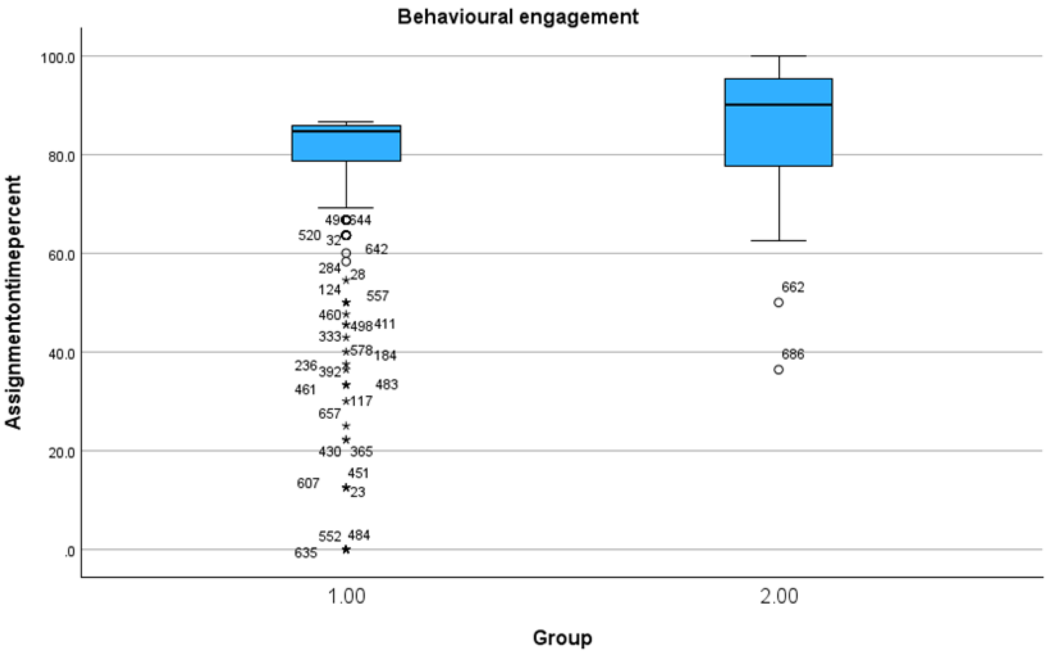

Figure 3: *Distribution of assignment on-time percent by instructional group*

The distributional patterns supported these findings. Group 1's data exhibited extreme negative skew (-4.019) and high kurtosis (17.811), indicating that most students submitted on time, but a few lagged significantly. Group 2's engagement curve was smoother (skewness = -1.422, kurtosis = 1.980), showing an even distribution of timely submissions. In contrast, LMS page view activity (Figure 4) painted a more complex picture. Group 1 had a higher mean number of page views (1549.30) but also exhibited broader variability (range = 0–5883, Standard Errors [SE] = 29.567). Group 2 showed slightly lower mean engagement (1423.13) with considerable dispersion (SE = 131.862, range = 275–3170). Despite these differences, the Mann-Whitney U test (U = 9011.50, p = 0.267) found no significant variation in overall platform use, suggesting both groups engaged with the LMS to similar extents, albeit with distinct patterns of interaction.

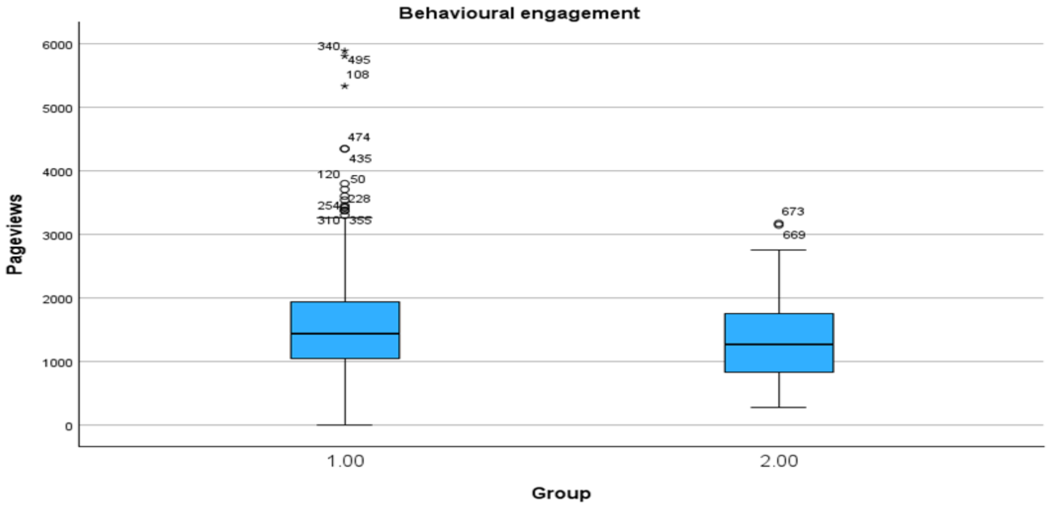

Figure 4: *Distribution of page views by instructional group*

4.1.3 Collaborative and social engagement

Patterns of peer engagement pointed to stronger social learning participation among undergraduates (Group 1: Mean = 59.67, Median = 58.00) than PGCE students (Group 2: Mean = 52.10, Median = 48.00). As shown in Figure 5, Group 1's scores were symmetrically distributed (skewness = 0.486, kurtosis = 0.748), with most students demonstrating moderate to high engagement. In contrast, Group 2 exhibited a sharply right-skewed distribution (skewness = 1.398, kurtosis = 3.067), indicating minimal participation for the majority, with a few highly engaged outliers. Trimmed means (Group 1 = 57.97, Group 2 = 49.90) further confirmed that a small number of active contributors inflated Group 2's mean.

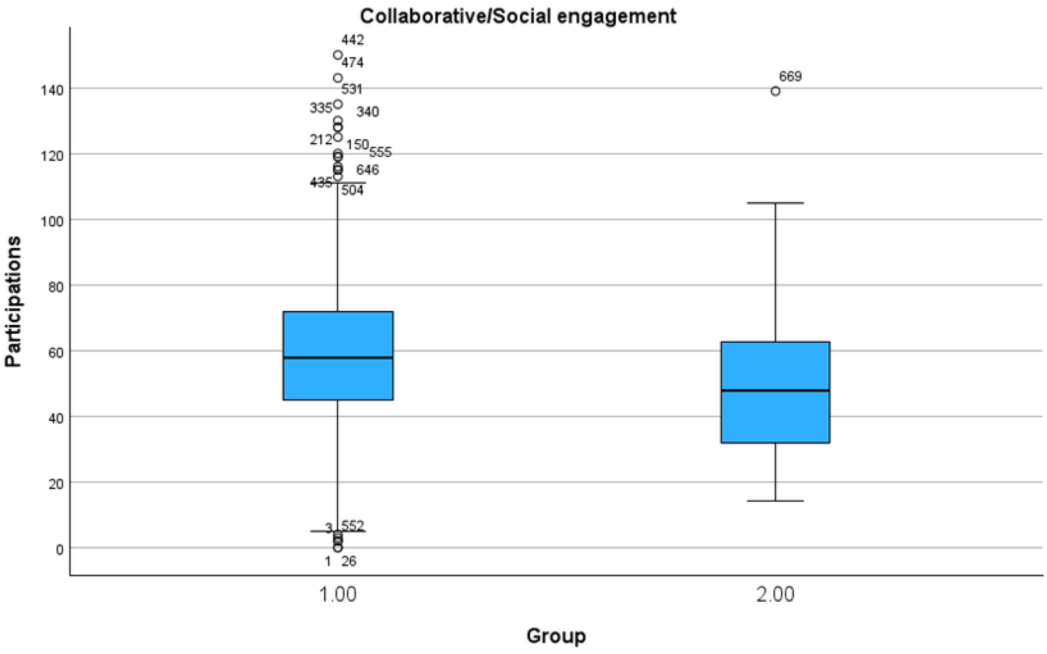

Figure 5: *Distribution of participations by instructional group*

The inferential analysis provided additional support for these descriptive patterns. According to a Mann-Whitney U test presented in Table 1, there was a statistically significant difference in the participation scores of the two groups (U = 7794.000, p = 0.026). This indicates that the observed disparities in social and collaborative engagement were unlikely to have arisen by chance, as first-year students outperformed their PGCE counterparts in terms of participation in discussion forums and peer-driven interactions.

Table 1: *Mann-Whitney U test statistics*

	Overall course grade	Assignment on-time	Pageviews	Participations
Mann-Whitney U	9732.000	6933.500	9011.500	7794.000
Wilcoxon W	227202.000	224403.500	9507.500	8290.000
Z	-0.445	-3.081	-1.109	-2.232
Asymp. Sig. (2-tailed)	0.656	0.002	0.267	0.026

4.2 Associations between temporal LMS engagement and academic performance

This subsection examines the extent to which temporal LMS activity relates to academic outcomes, using Spearman's correlations to evaluate the strength and nature of these associations.

4.2.1 Assumption testing for Spearman's correlation

Due to the non-normal distributions of several variables, Spearman's rank-order correlation was used. This nonparametric test met the following assumptions: observations were paired, monotonicity was verified, and all variables were continuous or ordinal. A scatterplot matrix (Figure 6) demonstrated consistent monotonic relationships between variable pairs, with no curved or inverted-U trends.

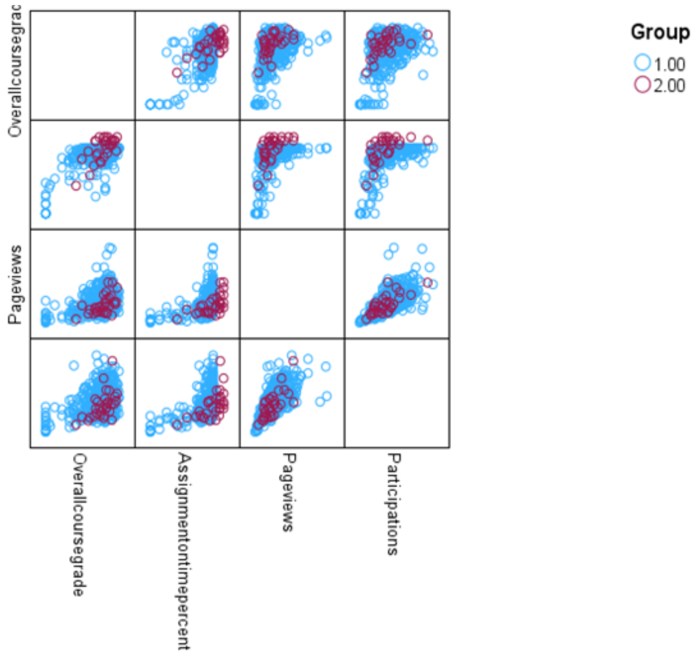

Figure 6: *Scatterplot matrix*

Table 2 presents each comparison's correlation coefficients, significance levels, and confidence intervals.

Table 2: *Confidence intervals of Spearman's correlation coefficients*

	Spearman's correlation coefficients	Significance (2-tailed)	95% Confidence Intervals (2-tailed)	
			Lower	Upper
Overall course grade – Assignment on-time percent	0.421	<0.001	0.355	0.482
Overall course grade – Pageviews	0.288	<0.001	0.216	0.357
Overall course grade – Participation	0.302	<0.001	0.230	0.370
Assignment on time percent – Pageviews	0.458	<0.001	0.395	0.517
Assignment on time percent – Participations	0.459	<0.001	0.397	0.518
Pageviews – Participations	0.711	<0.001	0.670	0.747

There was a moderate and statistically significant positive correlation between students' assignment submission timeliness and their final course grades ($\rho = 0.421$, $p < 0.001$), with a 95% confidence interval (CI) between 0.355 and 0.482. This suggests that students who turned in their assignments on time typically performed better in the module. Among all variables examined, this relationship emerged as one of the strongest predictors of success.

The correlation between pageviews and academic performance was also statistically significant, although weaker in strength ($\rho = 0.288$, $p < 0.001$; CI: 0.216–0.357). While this indicates that students who viewed more pages tended to receive higher grades, the association points to the limited explanatory power of passive content consumption alone.

Active participation, reflected through discussion posts, quiz attempts, and submissions, was positively associated with overall course grade ($\rho = 0.302$, $p < 0.001$; CI: 0.230–0.370). Although the strength of this correlation was similar to that of pageviews, participation reflects a more interactive form of engagement, adding another layer to understanding student success. Further analysis revealed a moderate positive correlation between assignment submission timeliness and pageviews ($\rho = 0.458$, $p < 0.001$; CI: 0.395–0.517). This suggests that students who engaged more frequently with course materials were more likely to submit assignments on time. A comparable relationship was found between assignment on-time percentage and participation ($\rho = 0.459$, $p < 0.001$; CI: 0.397–0.518), indicating that students who met deadlines consistently were also more active in course-related activities.

Lastly, a moderate positive correlation was observed between pageview frequency and participation ($\rho = 0.458$, $p < 0.001$; CI: 0.395–0.517). Students who regularly accessed course content tended to participate actively and meet deadlines, suggesting a socio-behavioural engagement pattern that integrates preparation, interaction, and assessment-oriented behaviours.

4.3 Reliability of LMS indicators as proxies for multidimensional engagement

This subsection assesses the internal consistency and factor structure of LMS-derived metrics, evaluating their reliability and validity as representations of the broader construct of student engagement.

4.3.1 Internal consistency

The internal consistency of the composite engagement construct, comprised of the four LMS-based variables, was evaluated using Cronbach's alpha. The raw Cronbach's alpha was 0.091, indicating poor internal consistency in its unstandardised form and falling far below the traditional acceptable threshold of 0.70. The primary cause of this initial low alpha was the disparity in measurement scales across the variables; for instance, page views varied in the thousands, while the other metrics were limited to a scale of 0 to 100.

To address these discrepancies, the analysis was revised using standardised scores (z-scores) for each variable. The Cronbach's alpha based on standardised items increased to 0.794, surpassing the threshold for acceptable internal consistency. This suggests that the four items collectively measured a coherent engagement construct once scale variations were accounted for. The reliability data are shown in Table 3.

Table 3: *Cronbach's alpha reliability statistics*

Cronbach's alpha	Cronbach's Alpha Based on Standardised Items	Number of items
0.091	0.794	4

4.3.2 Preliminary tests for factor analysis

Before starting factor analysis, two preliminary statistical tests were run to determine whether the data were suitable for factor extraction. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy resulted in a value of 0.662. Bartlett's Test of Sphericity showed statistical significance (χ^2 (6) = 1047.292, $p < 0.001$), showing that the correlation matrix was not an identity matrix and therefore factorable. These results are summarised in Table 4.

Table 4: *Kaiser-Meyer-Olkin and Bartlett's Test*

KMO Measure of Sampling Adequacy.		0.662
Bartlett's Test of Sphericity	Approx. Chi-Square	1047.292
	Df	6
	Sig.	<0.001

4.3.3 Communalities

Communality values were calculated using Principal Axis Factoring to assess how much variance in each variable is explained by the extracted factor. As shown in Table 5, all communalities exceeded the proposed threshold of 0.30. With the highest communality (h^2 = 0.551), the assignment on-time percentage showed that the latent component accounts for 55.1% of its variance. Participations came in second with a communality of 0.527, followed by pageviews and overall course grade with communalities of 0.478 and 0.351. These values demonstrate that the shared variance of the four variables is in acceptable ranges.

Table 5: *Communalities*

	Initial	Extraction
Overall course grade	0.484	0.456
Assignment on-time percent	0.520	0.551
Pageviews	0.468	0.438
Participations	0.504	0.527
Extraction Method: Principal Axis Factoring.		

4.3.4 Factor extraction and total variance explained

As seen in Table 6, Principal Axis Factoring identified a single component based on Kaiser's criterion (eigenvalues > 1). Before extraction, the first factor determined 61.87% of the variation, according to the initial eigenvalue of 2.475. Using the Extraction Sums of Squared Loadings to account for shared variation, this declined to 49.28%, meaning that a standard latent dimension accounted for approximately half of the variance across all four variables.

Table 6: *Total variance explained*

Factor	Initial eigenvalues			Extraction of sums of squared loadings		
	Total	**Percentage of variance**	**Cumulative percentage**	**Total**	**Percentage of variance**	**Cumulative percentage**
1	2.475	61.876	61.876	1.971	49.284	49.284
2	0.898	22.444	84.320			
3	0.333	8.329	92.649			
4	0.294	7.351	100.000			
Extraction Method: Principal Axis Factoring.						

A sharp decline in eigenvalues after the first factor, from 2.475 to 0.898, indicates a unidimensional structure, signalling that further factors would yield minimal explanatory gain. This understanding is reflected in the scree plot in Figure 7.

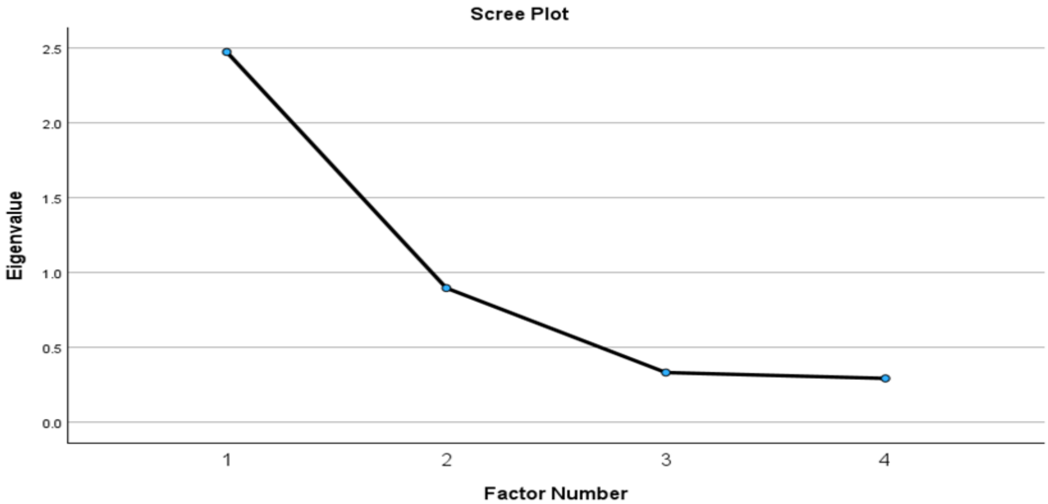

Figure 7: *Scree plot of eigenvalues from Principal Axis Factoring*

Factor loadings represent the strength of the relationship between each variable and the extracted factor. As shown in Table 7, all four LMS-based variables displayed significant loadings, ranging from 0.661 (overall course grade) to 0.742 (assignment on-time percentage).

Table 7*: Factor matrix*

	Factor 1
Overall course grade	0.675
Assignment on-time percent	0.742
Pageviews	0.661
Participations	0.726
Extraction Method: Principal Axis Factoring. 1 factor extracted. 6 iterations required.	

The results presented here demonstrate that each variable has a positive and consistent relationship with the underlying construct of multidimensional engagement, supporting the composite measure's empirical coherence.

5. Discussion of Findings

This study examined how LMS log data can be used to profile multidimensional student engagement in a South African university's CIE module. Framed through Redmond et al.'s (2018) Online Engagement Framework and viewed critically, the findings highlight both the interpretive potential and the epistemic limitations of current learning analytics practices. This is illustrated by the "two-way mirror" that reflects student activity to educators but does not meaningfully reflect it back to students.

5.1 Multidimensional engagement patterns in LMS-generated data

A key finding is the disproportionate visibility and dominance of behavioural engagement in LMS-generated metrics. PGCE students exhibited higher login frequencies, timely submissions, and frequent resource access, echoing studies that link mature student characteristics to platform discipline (Veluvali & Surisetti, 2022). Yet, as critics note (Johar et al., 2023), behavioural metrics, though easy to quantify, offer only partial insights into the intentionality or quality of engagement. This study affirms concerns that LMS analytics often reduce complex learning behaviours to transactional indicators, such as punctuality as a proxy for understanding, or activity for knowledge acquisition (Bowden et al., 2021). Students' recorded behaviours often reflect compliance with schedules rather than intrinsic motivation, shaped by workload pressures, prior digital exposure, and self-regulation habits—factors that are invisible in analytic dashboards (Saint et al., 2022). These blind spots reinforce the need to conceptualise engagement as socio-cultural rather than merely technical (Kahu & Nelson, 2018).

Social and collaborative engagement patterns showed that undergraduates were more active in discussion forums and peer interactions, aligning with literature suggesting that younger or less experienced students rely on peer scaffolding (Bergdahl et al., 2024). However, this may reflect necessity rather than choice, compensating for confusion, solitude, or limited instructor support (Naidoo & Naranjee, 2024). PGCE students, balancing professional and academic roles, may engage less due to time constraints. Such differences reflect institutional histories and socioeconomic realities (Reschly & Christenson, 2022). While LMS logs record participation frequency, they omit relational quality and cultural dynamics.

Cognitive engagement, inferred from academic performance, showed no significant cohort differences. This may suggest consistent pedagogy but conceal challenges such as surface learning, anxiety, or pressures from high-stakes assessments (Johar et al., 2023). In this sense, LMS data reveal outcomes but not the processes or motivations behind them. Emotional engagement remained largely invisible, consistent with research noting how log-based analytics overlook affective dimensions (Bergdahl et al., 2024). This absence undermines the responsiveness of analytics systems to signs of distress, disengagement, or loss of motivation (Johar et al., 2023). The findings caution against treating engagement indicators as universally valid when they omit or misinterpret critical aspects of the learning experience.

5.2 Associations between LMS-based engagement patterns and academic performance

Building on prior Learning Analytics (LA) research (Karaoglan Yilmaz & Yilmaz, 2022; Silvola et al., 2021), this study explored how multidimensional engagement patterns inferred from LMS log data relate to academic performance. This disaggregated approach, rarely applied in South African higher education, acknowledges how socio-technical and structural disparities shape students' interactions with digital platforms (Naidoo & Naranjee, 2024).

Leveraging Spearman's rank correlation, the strongest correlation was found between page views and participations ($\rho = 0.711$). This suggests that students who frequently accessed course materials were actively involved in learning tasks such as quizzes, discussions, and assignments. This behavioural-cognitive linkage supports previous work (Henrie et al., 2018) on the interplay between content access and task engagement. However, such alignment may also reflect surface-level compliance or habitual LMS use, raising concerns about equating frequent interaction with deep learning (Caspari-Sadeghi, 2022). Moderate, statistically significant correlations were observed between on-time assignment submission and participation (ρ = 0.459) and between on-time submission and page views (ρ = 0.458). These findings align with research linking time management and self-regulation to academic engagement (Veluvali & Surisetti, 2022), suggesting that students with better organisational habits tend to engage more consistently across the LMS.

However, when examining academic performance directly, the correlation between course grades and page views was weaker (ρ = 0.288). This supports the argument that passive content consumption is not a reliable predictor of academic success (Henrie et al., 2018). In contrast, stronger correlations emerged between grades and meaningful engagement (ρ = 0.421), indicating that active involvement in tasks, rather than simple access, better predicts learning outcomes.

Despite these statistically significant patterns, their modest strength highlights key limitations of LMS data, particularly the absence of emotional engagement. Metrics like page views and participation counts fail to capture students' motivation, anxiety, or sense of belonging, nor do they account for informal or off-platform learning (Bergdahl et al., 2024). This reflects broader critiques of the reductionist nature of LA, which risks oversimplifying complex learning behaviours into quantifiable events (Viberg et al., 2023). These findings underscore the need for multi-modal or mixed-method approaches that integrate system data with reflective insights to offer a fuller picture of student engagement.

5.3 LMS-based engagement patterns as proxies for multidimensional engagement

This study also investigated whether LMS-based metrics can serve as reliable and valid proxies for the broader construct of multidimensional student engagement in technology-mediated learning environments. Once scale differences across engagement indicators were standardised, the results revealed a coherent unidimensional structure with acceptable internal consistency (α = 0.794). Factor analysis similarly yielded a unidimensional construct, accounting for 49.28% of the shared variance, with all four items loading positively onto a single latent dimension.

These findings suggest that, when methodologically aligned, LMS-generated variables can collectively approximate specific dimensions of engagement. This supports prior research highlighting the reliability of digital trace data in capturing academic persistence, sustained effort, and engagement over time (Caspari-Sadeghi, 2022). Viewed through the lens of self-regulated learning, such metrics may reflect students' goal-setting, time management, and regulatory behaviours (Saint et al., 2022). Their utility lies in scalability, immediacy, and correspondence with observable participation, such as timely assignment submissions, active content interaction, and resource access.

However, the initially low Cronbach's α before standardisation underscores the need for methodological precision when constructing composite indicators. Without scale alignment, engagement measures risk distortion or inequity (Silvola et al., 2021), potentially reinforcing reductive or punitive uses of analytics. This highlights the importance of using LA as formative, interpretive tools to identify support needs rather than as fixed, predictive classifications.

While the factor structure showed internal coherence, the modest variance explained (49.28%) suggests that LMS metrics capture only part of the engagement picture. In socio-culturally diverse, digitally mediated contexts, engagement also encompasses affective, relational, and identity-based dimensions often invisible in system logs (Veluvali & Surisetti, 2022). These dimensions are better explored through complementary methods such as qualitative, dialogic, and student-informed approaches (Caspari-Sadeghi, 2022; Karaoglan Yilmaz & Yilmaz, 2022).

These insights reaffirm the need for culturally and pedagogically sensitive analytics. Instead of using LMS data to rank or sort students, this study promotes a participatory engagement model grounded in critical reflection, co-construction, and targeted support. This aligns with calls to reframe LA as empowering and equity-oriented, shifting from mechanistic surveillance to discursive, contextually attuned practices (Broughan & Prinsloo, 2020; Selwyn, 2019). Future research should involve students in defining engagement within their lived contexts, thereby strengthening the validity and ethical use of LA systems.

6. Conclusions and Recommendations

This study foregrounds the metaphor of a "two-way mirror" in learning analytics (LA). On one side, system-generated data offers scalable, visible engagement indicators that appeal to institutions for their apparent transparency and predictability. However, what is reflected remains partial. Behind the mirror lies a richer, less visible domain of emotional, cognitive, and socio-cultural engagement that resists easy quantification. The study was constrained in capturing these richer experiential dimensions by relying primarily on log data. In this sense, engagement is both seen and unseen, shaped by what Learning Management System (LMS) systems are designed to detect and what they systematically omit. Findings illustrate this tension. While student activity clustered around measurable actions like page views and submissions, these behaviours may not capture intentions, struggles, or the depth of understanding. LMS data shows what occurs, not why. In contexts of digital inequality and epistemic exclusion, such blind spots have ethical and pedagogical implications. Similar patterns have been observed in other higher education settings, highlighting broader concerns about whose engagement is visible and how it is measured (Viberg et al., 2023). A call to reimagine LA emerges, not as a predictive science, but as an interpretive, context-sensitive practice. Rather than reducing learners to metrics, analytics should prompt reflection on the conditions that shape engagement in the first place. In doing so, they can foster more equitable, inclusive, and pedagogically meaningful participation in digital higher education. Especially in contexts shaped by historical and structural marginalisation, the promise of analytics must lie not in surveillance, but in care, treating students as active participants in learning, not merely as data points.

7. Declarations

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Data Availability: The data is not publicly available due to confidentiality agreements with participants and ethical restrictions imposed by the University of the Witwatersrand's Human Ethics Research Committee. However, de-identified data can be made available from the corresponding author upon reasonable request, subject to approval by the ethics committee.

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