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Collaboration, Creativity and Compassion in a Digital Society

Designing learning analytics with care: A multiple case study approach

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Learning analytics (LA) in higher education has been shaped primarily by compliance-based ethical frameworks. We argue this is insufficient to govern the relational dimensions of data-driven practice. This paper proposes the Care-Centred Learning Analytics Design Standard (CLADS), a framework that reorients LA system design around the ethics of care tradition developed by Gilligan, Noddings, and Tronto. CLADS is organised around five principles — Relationality, Transparency and Mutual Visibility, Contextual Sensitivity, Equity of Care, Participatory Design and Ongoing Co-Creation. Each is grounded in care ethics theory and each carries concrete design implications. Empirical grounding is provided by a qualitative multiple case study conducted across five demographically diverse Australian universities, in which 23 participants were interviewed and findings analysed using template analysis structured around the CLADS principles. The study finds that while existing LA practice frequently demonstrates care-aligned sensibilities at the operational level, the structural and governance commitments necessary to make care reliable, equitable, and visible remain largely absent. CLADS offers a principled design standard to address that gap.

Keywords: learning analytics, ethics of care, care-centred design, higher education, student equity, participatory design

Introduction

Higher education institutions (HEIs) have been utilising learning analytics (LA) to analyse student data generated across digital systems to better understand learning and teaching practices. While LA holds the potential to transform institutional approaches to student support and pedagogical improvement (Clark et al., 2025; Alfredo et al., 2024; Tzimas & Demetriades, 2024), a care-based orientation such as the Care-Centred Learning Analytics Design Standard (CLADS) reframes this potential by positioning analytics not as a decision-making substitute, but as a relational resource that supports human judgement, responsibility, and care. In this sense, LA is most ethically valuable when it enables educators to recognise students as situated learners rather than abstract data points.

A central application of LA has been the early identification of underperforming and at-risk students, allowing timely interventions that may support effective interventions and in turn improve educational outcomes (Alalawi et al., 2025; Clark & Tuffley, 2025). HEIs generate large amounts of data from student systems as well as learning management systems (LMSs) (Alalawi et al., 2024). From a CLADS perspective, however, these practices must be understood as invitations to dialogue rather than automated triggers for action. Students' digital traces, which are generated through interactions with LMSs, can reveal patterns of engagement and disengagement (Clark & Tuffley, 2023), but such patterns require contextual interpretation by educators who are attuned to students' individual circumstances (Maheshi et al., 2026). For LA to have a positive impact on students, their lived experiences throughout their learning journey must be recognised and incorporated into the design of LA systems (Maheshi et al., 2026). LA tools and dashboards demand a level of digital literacy that most stakeholders have not yet developed (Buckingham Shum et al., 2024).

LA data also offers opportunities to inform learning design and pedagogy by providing insights that would otherwise be inaccessible, given advances in data availability and technology (Alfredo et al., 2024). When aligned with the CLADS principle of contextual sensitivity, these insights support reflective, evidence informed teaching rather than prescriptive, metric driven responses. This enables educators to base decisions about

student learning on evidence while remaining attentive to the diverse ways students engage with learning environments (Alfredo et al., 2024; Buckingham Shum et al., 2024).

HEIs have increasingly relied on LA to track student navigation through university systems and learning pathways, using such data to support institutional goals related to student success and learning outcomes (Tepgec et al., 2024). CLADS reframes these practices by foregrounding equity of care, requiring that analytics driven interventions do not inadvertently disadvantage students whose engagement patterns diverge from institutional norms. Data driven decision making, when guided by care ethics, shifts emphasis away from surveillance and prediction toward relational support and informed professional judgement (Buckingham Shum et al., 2024).

LA can be used to analyse login frequency and patterns of interaction with course materials to identify potential learning challenges, for example students at-risk (Dai et al., 2025). However, consistent with CLADS, such indicators should be treated as prompts for communication and shared sense making, rather than definitive measures of engagement or learning quality. Although current studies demonstrate that LA tools can assist HEIs in enhancing students' learning experiences (Rates & Gašević, 2022), concerns remain that LA has yet to adequately meet students' needs, underscoring the importance of frameworks that prioritise care, transparency, and student participation in the ethical use of LA (Tzimas & Demetriades, 2024).

The purpose of this study is to examine how LA data can be used ethically and responsibly, and to demonstrate how a care-based framework provides a principled means of guiding the collection, interpretation, and application of LA in ways that prioritise student wellbeing, relational accountability, and equitable educational outcomes.

A proposed framework: The Care-Centred Learning Analytics Design Standard

The ethical frameworks that have shaped LA to date have been, on the whole, compliance frameworks. Their animating question is what institutions are permitted to do with student data – consent protocols, privacy principles, data minimisation policies – necessary, but insufficient (Slade & Prinsloo, 2013). Compliance ethics takes the data subject as its object, whereas the ethics of care takes the student as its subject. Every architectural decision in an LA system – what data to collect, how alerts are worded, who receives them, whether students can see what their lecturers see – either builds or undermines a caring relationship. As Wintrup (2017) demonstrates, even well-intentioned systems risk becoming instruments of alienating surveillance, producing the very disengagement they are designed to prevent. Our ethical obligations arise from webs of dependency, not in spite of them. Applied to LA, this suggests the system itself must become a vehicle for care, not merely a neutral tool. Prinsloo and Slade (2013) made an early case for an ethic of care as a guiding orientation for LA practice; what the field now requires is a design standard that operationalises that orientation at the system level.

The proposed CLADS (Figure 1) draws on the ethics of care tradition which is a relational moral philosophy developed by Noddings (1984, 2013) in the context of education and extended into political and institutional analysis by Tronto (1993, 2013), who argued that care is not merely interpersonal but structural, shaped by power and the unequal distribution of caring responsibilities. It is organised around five principles, each with design criteria and a diagnostic evaluation question. They are not a checklist; they constitute an integrated orientation. As Noddings (1984) argues, caring relationships require engrossment, motivational displacement, recognition, and reciprocity working in concert – the absence of any element collapses the relationship into something that merely resembles care. CLADS applies that same logic to system design.

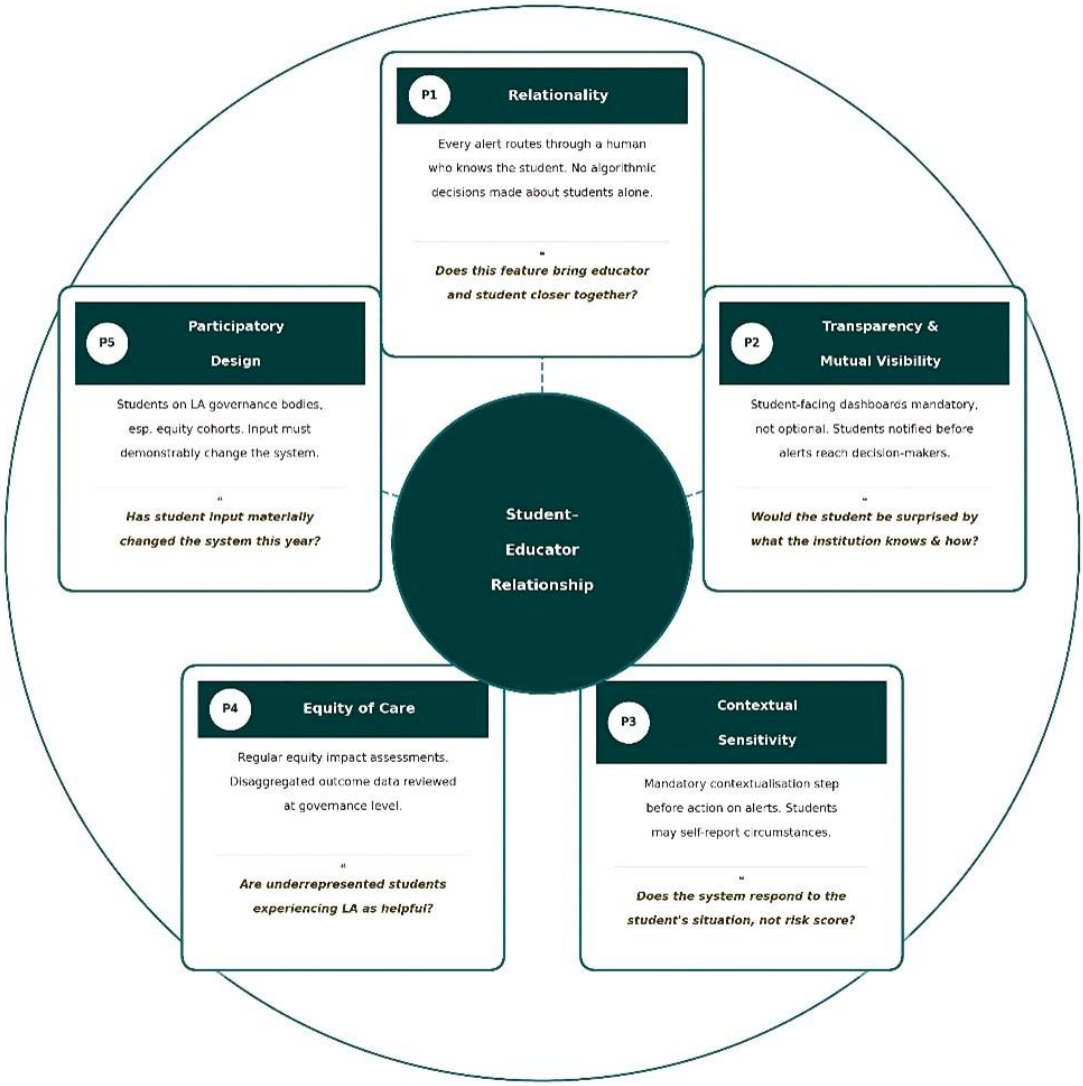


Figure 1. The Care-Centred Learning Analytics Design Standard (CLADS) framework, illustrating the shift from data-driven to relational-driven oversight.

Principle 1: Relationality

An LA system exists to support and strengthen human caring relationships, not to substitute for them. As established by Noddings' (1984) concept of engrossment (that is the authentic, open attention of the one-caring to the particular situation of the cared-for) cannot be reproduced algorithmically. A risk score does not attend to a student; it pattern-matches them against a population distribution. Every automated alert must therefore be routed through a human who has a meaningful prior relationship with the student, and no consequential decision about enrolment, progression, or support should be made by the system alone (Alfredo et al., 2024; Dollinger et al., 2019).

Evaluative question: Does this feature bring the educator and student into closer contact, or interpose bureaucratic distance between them?

Principle 2: Transparency and mutual visibility

Noddings' (1984) concept of recognition requires that the cared-for genuinely experience being cared for, rather than merely be the object of benevolent intervention. In the LA context, students must have access to substantially the same view of their data that their institution has, in a form they can interpret and act upon.

The principle goes beyond informed consent, which is a compliance concept, to require student-facing dashboards as a standard feature of every implementation. Despite Slade and Prinsloo's (2013) early identification of transparency as a core ethical requirement, institutions rarely account for student perspectives during design phases (Korir et al., 2022; Tsai et al., 2020). Under CLADS, students would receive proactive notification before any alert is shared with decision-makers, and have a genuine mechanism to annotate, contest, or contextualise their data.

Evaluative question: Would the student be surprised by what their institution knows about them and how it is being used?

Principle 3: Contextual sensitivity

A statistical signal is not an understood situation. Noddings' (1984) concept of motivational displacement which is the one-caring's capacity to set aside their own frame of reference and receive the reality of the cared-for calls for the system to prompt for contextual information before acting on data patterns. A student whose LMS login frequency drops may be grieving, adjusting to life in a foreign country, caring for a family member, managing a mental health crisis, or working additional shifts. Yet none of these human concerns is visible to an algorithm.

CLADS requires that intervention workflows include a mandatory contextualisation step, and that students have a supported mechanism to self-report qualifying circumstances. This would be to operationalise Slade and Prinsloo's (2013) argument that student identity is a transient, context-bound construct at the system-design level.

Evaluative question: Does the system enable educators to respond to the student's unique situation, or only to their population-level risk profile?

Principle 4: Equity of care

Tronto's (1993) political analysis reveals that care is structural as well as interpersonal. Questions about who receives care, on what terms, and at whose expense are questions about power. Systems that are optimised for institutional retention metrics may pressure students to persist with their studies when they would benefit more from deferral.

Algorithmic models trained on historical data may amplify existing disadvantage; penalising students whose engagement patterns differ from majority norms that are themselves artefacts of inherent structural inequality. Tronto's concept of "privileged irresponsibility" makes visible the disproportionate relational burden placed on frontline advisors by those who design and govern these systems from their positions of insulation. CLADS therefore requires regular equity impact assessments and review of disaggregated outcome data at the governance level.

Evaluative question: Are students from underrepresented groups experiencing LA interventions as genuinely helpful, or as stigmatising forms of surveillance?

Principle 5: Participatory design and ongoing co-creation

Noddings' (2013) fourth component of the caring relationship — reciprocity, meaning the cared-for's active contribution to the relationship rather than passive receipt of it asks what students themselves contribute to the caring relationship, not as data generators but as interpreters, co-designers, and knowledge producers. Dollinger et al., (2019) demonstrated through Australian case studies that co-creation in LA reconstitutes the institution-student relationship, transforming students from data sources into knowledge producers; Dollinger and Lodge (2019) argue for genuine partnership rather than post-hoc consultation. Yet Sarmiento and Wise's (2022) review found that student involvement in LA frequently remains superficial and advisory, falling well short of what reciprocity demands.

CLADS requires meaningful student representation on LA governance bodies, with particular attention to equity cohorts, and structured feedback mechanisms with demonstrable influence on system development.

Evaluative question: In what ways has student input materially changed this system in the past year?

Methodology

We employ a qualitative multiple case study design conducted across five demographically diverse Australian universities. The case study approach was selected for its capacity to bring to light the situated, contextual dimensions of practice that quantitative methods tend to obscure (Yin, 2013), and for its particular suitability in exploratory research where a focus on institutional cultures and human relationships are central to the phenomena under investigation (Järvinen, 2001; Rowley, 2002). Comparing cases drawn from different institutional settings strengthens the analytical robustness of findings, enabling patterns to emerge against a backdrop of structural variation. (Rowley, 2002; Yin, 2011).

The five participating institutions were recruited through a random sampling process (Seawright & Gerring, 2008), with formal approval obtained from a Deputy Vice-Chancellor or equivalent authority at each site. The resulting sample included three metropolitan and two regional universities, spanning a wide range of student profiles. It included high-entry-score cohorts at research-intensive institutions, as well as low socioeconomic cohorts, first-in-family, and mature-age students at regional and outer-metropolitan campuses and those with substantial online and distance enrolments. This demographic breadth was intentional and necessary for this methodology. A framework oriented toward equity of care, as CLADS is, requires empirical grounding in precisely those institutional contexts where the distribution of care is most uneven.

Participants were identified through a primary contact at each institution and selected on the basis of their direct engagement with LA systems, whether through teaching, learning design, student support, management, or data and systems administration. Across the five sites, 23 participants were interviewed in total, including academic staff, instructional designers, LA support personnel, user experience designers, and data scientists. Interviews were conducted via an online platform and later transcribed.

An interpretivist epistemological stance informed the research design, recognising that institutional practices and their meanings are socially constructed and best understood through the perspectives of those embedded within them (Crotty, 1998). Template analysis (King & Brooks, 2017) was used as the primary analytic method. This is a form of thematic analysis that balances theoretical structure with responsiveness to emergent data. In the 2025 precursor study, a priori codes were derived from the Technology Acceptance Model (Davis, 1985); in the present study, the analytical template was restructured around the five principles of CLADS: namely Relationality; Transparency and Mutual Visibility; Contextual Sensitivity; Equity of Care; and Participatory Design and Ongoing Co-Creation.

This reframing was not a simple recategorisation of existing data. It represents an analytical shift from questions of technology adoption to questions of ethical system design. The CLADS principles work as sensitising constructs: acting as conceptual lenses through which attention is directed to the relational, structural, and equity dimensions of LA practice. CLADS does this while remaining open to the particularities of each institutional setting.

Interview data was coded against each principle, with emergent findings examined for both convergence across sites and meaningful divergence that was a reflection of local institutional conditions. This approach allowed the researchers to test the CLADS framework against lived practice, identifying where its principles were partially realised, structurally absent, or actively undermined by institutional design.

Qualitative findings

The findings presented below draw on interview data collected across the five university case studies. Each sub-section is structured around one of the five CLADS principles, assessing the degree to which current LA

practice at the participating institutions realises, approximates, or falls short of the standard each principle demands.

Principle 1: Relationality

The data revealed that LA were consistently used as a trigger for human action rather than seen as autonomous decision-making systems. LA systems often initiated the process of personal outreach via emails (recommender systems), phone calls and conversations. Participants described how analytics data informed proactive outreach and support, with one participant explaining that the aim was to use data and insights to "influence student behaviour in a proactive and positive way" through processes such as outreach and support interventions. Support staff such as student advisors, retention teams, and teaching teams often provided support interventions for students. Interview participants recognised that LA did not replace effective teaching, did not constitute as learning and the LA was most valuable when combined with pedagogical judgement and care. As one participant observed, "I think knowing your cohort is far more important than some learning analytics when it comes to setting up subjects." Participants felt that the quality of teaching design, feedback and availability was more important than the LA data used to predict the accuracy of retention. In some settings in which the participants worked, the outputs of LA systems were escalated to management creating a relational distance. Automatic nudging was sometimes used at scale but there were no resources for follow up dialogue. The care-based approach, which is inhumane and emotionless, is based on local practices rather than the system's design. LA should support and strengthen caring relationships, not substitute for them.

Principle 2: Transparency and mutual visibility

LA are often staff facing and embedded in larger LMSs or even Business Intelligence (BI) systems, although one university site had developed their own end-user developed system. Staff access varied at each university. Some had data privacy policies that limited access to student data where others allowed access to those who worked directly with students. Data such as engagement logs, demographic indicators and risk flags were very visible to staff but not the students themselves. Some interview participants advocated for student facing dashboards that could be visible to students and support student self-regulation. One participant argued that "students should have access to the same data that we have access to," suggesting that analytics should support student self-regulation and agency rather than remain solely an institutional resource. Students should have access to their data at the same level as their HEI. Another participant questioned the lack of transparency around institutional data practices, noting that "students often don't know what data is being collected about them or how it is being used." There is a lack of consistent processes at the universities that looked at informing students about their data being collected, alerting students about risk-based information and allowing student to contest or contextualise their data. Having data that is mutually visible is aspirational and not embedded in LA systems. Transparency was only seen as operationally convenient, not in terms of relational ethics.

Principle 3: Contextual sensitivity

Throughout all the data collected during interviews, many participants cautioned about equating digital student activity with engagement, learning or motivation. LA outputs can be abstract, incomplete and context dependent. One participant observed that "for international students, it will be a very high engagement but low performance. So there is something is going wrong inside the course," highlighting the limitations of interpreting behavioural indicators as direct evidence of learning. The outputs can also be sensitive to the course design, discipline and can depend on cohort characteristics. Participants indicated that in the context of students' lives they may have work commitments, caring responsibilities, health issues, transition stress, and in some cases structural barriers. As a participant noted "I think knowing your cohort is far more important than some LA when it comes to setting up subjects." LA data outputs may also be subject to individual staff interpretation and do not consider individual student context and time pressures that can prevent deep contextual follow up. In essence, a statistical indicator is not an understood situation. Often contextual sensitivity is recognised but not systematised. Often the context enters after the LA and is not considered as a part of them.

Principle 4: Equity of care

Equity was a theme that occurred throughout the study's findings. LA at universities are usually optimised for retention, progression and institutional accountability reasons. This institutional focus was evident in participants' descriptions of analytics practices that sought to influence student behaviour, with one participant describing the goal as "creating new processes that aim to impact on student behaviours in a positive way." Staff stressed that historical data often reflected structural inequalities rather than neutral norms. There can be cohort differences such as pathway to entry, international status, mature age, rural background that can significantly shape the way LA are interpreted and acted upon. Therefore, LA could disadvantage non-traditional students. LA can pressure persistence in studies where the caring angle might be to exit the study program. Front facing staff can face the emotional labour that is generated by LA alerts which could be seen to be inhumane. LA system designers and senior managers are often insulated from the consequences of intervention decisions. Equity is acknowledged at an operational level but rarely addressed from a governance or audit level.

Principle 5: Participatory design and ongoing co-creation

Participatory design usually involved staff to co-design systems. In the case of LA this could be academics, learning designers and analysts. Participatory design involves iterative development cycles that respond to feedback from stakeholders. Students are usually positioned in this process as data subjects, targets of intervention, and end recipients of system outputs or effects. In the five university case studies there was little evidence of students having any role in LA decisions, having any influence over metrics, thresholds or dashboards. Although study participants who were involved in the design of LA system asked, "What data are we collecting? What insights can we glean from that data?" Reciprocity was largely absent in this data and participatory design remained highly staff-centric. Students should be consulted in the design and implementation of LA systems.

The qualitative findings across the five different university case studies indicated that current LA practices around LA implementations only partially align with the CLADS principles and often fall short in terms of their intended ethical and relational standards. While LA systems are widely used to trigger human intervention rather than replace it, their effectiveness is largely contingent on the quality of teaching, pedagogical judgement, and staff capacity to provide follow-up support. As one participant noted, "they will inform our learning design; they will inform our teaching," indicating that analytics were viewed as an aid to professional decision-making rather than a substitute for it. Across the university case studies, the LA systems were commonly staff-facing, with limited transparency for students and few opportunities for them to access, interpret, or contest their own data. Although practitioners recognised the importance of contextual sensitivity and the limitations of relying solely on behavioural data, these considerations were not systematically embedded in LA systems, leaving much of the interpretation dependent on individual staff judgement and available time. In many cases, LA acts as a trigger for human action but sometimes due to limitations of resources, and in some cases systems design, the engagement in follow up was inconsistent.

The findings also highlight concerns around equity and participation. LA systems were often shaped by institutional priorities such as retention and accountability, which risk reinforcing existing structural inequalities and may not always align with what is most caring or appropriate for individual students. As a participant observed, "While LA systems were widely used to trigger human intervention rather than replace it, their effectiveness was contingent upon the quality of teaching, pedagogical judgement, and staff capacity to provide follow-up support." Students are positioned as objects of the analytical process rather than being co-designers of the system. While equity issues were acknowledged, they were rarely addressed at a governance or design level. Similarly, participatory design processes were largely staff-centric, with minimal student involvement in shaping how LA systems operate or how decisions are made. Overall, while elements of relational, ethical practice are present, they are inconsistently implemented, and significant work remains to ensure LA systems genuinely support caring, transparent, context-aware, and inclusive educational environments.

CLADS as a community standard

These five principles constitute an integrated design standard, not a sequential checklist. Neglecting any one weakens the whole. Transparency without contextual sensitivity overwhelms educators with decontextualised alerts; participatory design without equity of care risks serving the most vocal students while failing those with most to gain. The principles are mutually reinforcing because they are derived from a single coherent ethical tradition, namely the relational, politically aware account of care developed by Noddings and Tronto whose key components this paper has examined.

The LA field has developed substantial technical capability and a growing governance literature. What it has lacked is a design standard grounded in a coherent theory of what the relationship between institution and student should be. CLADS offers that standard. Its adoption would represent a decisive shift in the animating question of LA system design: from "What are we permitted to do with this data?" to "What does this student need, and how does this system help us respond to them as a person?" That ethical question should be primary. This aligns with Clark and Tuffley's (2024) recommendation that universities should have clear policies and ethical frameworks that inspire trust.

Ultimately this approach recognises that the teachers and the taught are co-creators of the learning. The formation of a healthy learning partnership is the primary focus of the CLADS framework. Existing LA practices demonstrate ethical sensibilities aligned with care ethics but lack the structural commitments necessary to make care reliable, equitable, and visible. The CLADS model addresses this gap by re-architecting LA as relational, transparent, contextual, equitable, and co-created systems. Directions for future research include developing a practical implementation guide that recognises that adopting CLADS is primarily a governance and cultural undertaking. The technical aspects are secondary.

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