Academic Rating Index: Learning Analytics for Empowering Supervisors and Advancing Student Success

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Abstract: Postgraduate supervision is a complex, relational process in which student–supervisor engagement strongly influences students' experiences and completion. Yet universities often lack systematic ways to capture and translate supervision experiences into actionable insights. The Academic Rating Index (ARI) was originally published as a tool for recording students' perceptions of supervisors using the 7C framework. This article extends ARI from a rating instrument into a Learning Analytics (LA) platform that converts supervisory feedback into evidence-informed guidance. Current institutional approaches rely on annual surveys that offer limited direction, and learning analytics research has largely overlooked postgraduate researchers. Using Design Science Research, the study redevelops ARI, so students assess supervisors via an adapted Tripod 7Cs framework across two design cycles. Cycle 1 identified key limitations—unfair supervisor comparisons, inability to generate scores with few evaluations, and links between reviews and student identities—leading to 20 requirements. Cycle 2 rebuilt the system with a 51-item instrument, withheld scores when fewer than five responses were available, separated responses from identifying data, added automated integrity checks, and implemented a privacy-first learner data foundation validated through automated testing. Of the 20 requirements, 9 are fully met, 6 partially met, 4 are planned, and 1 remains unmet. Future work will validate the instrument, finalise the learner-data foundation, and pilot an extended Technology Acceptance Model to assess acceptance. Impacts on supervision and student outcomes still require empirical evaluation. The paper also reports how the requirements were traced to their design responses and verification evidence, and how the evaluation will proceed under the Framework for Evaluation in Design Science (FEDS), moving from artificial, formative checks of privacy safeguards to a naturalistic pilot. The intended contribution is to advance learning analytics in postgraduate education by extending ARI from measurement towards continuous analysis and evidence-based intervention; benefits for supervisors, institutions and student success are intended outcomes that remain to be demonstrated.

Keywords: Educational Technology; Higher Education; Learning Analytics; Postgraduate Education; Student Success; Supervisor Empowerment

1. Introduction

The Academic Rating Index (ARI) has evolved from a supervisor-evaluation tool into a Learning Analytics (LA) platform. It initially let students rate supervisors, join a forum, and aggregate verified student–supervisor ratings to complement citation indexes and support quality assurance (Mokole, 2021). In South Africa, postgraduate studies show low knowledge production in mathematics, science, statistics, and engineering, rising interest in social studies, and persistently high dropout rates. To improve research quality, the Department of Higher Education introduced the Research Outputs Policy (ROP) in 2015, replacing the 2003 policy (DHET, 2023).

To help address these challenges, University of South Africa students developed ARI as a 4IR-aligned digital supervision model grounded in a tested framework (Mokole, 2021). This paper extends that work by addressing issues found during testing at several universities: limited knowledge depth and forecasting, weak intelligent digital persona development, and poor supervisor search by expertise and availability.

This study aims to mature ARI into a learning analytics platform that combines supervision feedback with student engagement and progress data, so that risks can be detected early and supervisors can intervene. The study is structured around three research questions, each aligned with a design cycle.

1. What limits a rating-only instrument's ability to generate actionable insight for postgraduate supervision? (Cycle 1)
2. What requirements are needed to evolve it into a learning analytics platform for postgraduate supervision? (Cycle 1 evaluation, Cycle 2 objectives)
3. How can the platform collect and process learner data while protecting identity and ensuring informed consent? (Cycle 2)

A separate, out-of-scope question is supervisor and student adoption, to be examined in a planned pilot. This study contributes: (1) a redesigned supervision rating system with an anonymity threshold, identity separation, and automated integrity checks; (2) 20 requirements for transitioning from ratings to learning analytics, each

linked to a specific limitation of the original instrument; and (3) principles for responsible learner data collection, including purpose-specific pre-collection consent, pseudonymous storage, anonymity enforced at the data layer (not just the UI), and a separate authorization gate for real-world data collection independent of software completion.

2. Literature and Theoretical Framing

Postgraduate supervision is vital to research quality and timely completion. Institutions must uphold supervision standards, and supervisors must support students academically and personally. However, supervision is often poorly monitored, opaque, and weak in accountability (Espinosa and Beaudoin, 2022). Learning analytics (LA)—the collection, analysis, and reporting of learner and contextual data to improve outcomes—can reveal student progress (Manly et al., 2026) but is rarely used in postgraduate supervision because LA typically targets undergraduates. As postgraduate study involves distinct trajectories, supervision practices, and research goals, it requires tailored data and analysis.

Current approaches to evaluating postgraduate supervision fall into three groups: (1) national experience surveys (e.g., the UK Postgraduate Research Experience Survey) that provide aggregated, often annual, findings with limited value for individual supervisors (Neves, 2026); (2) specialised instruments (e.g., the Questionnaire on Supervisor–Doctoral Student Interaction) that offer rich detail but are mainly research tools rather than routine formative feedback (Mainhard et al., 2009); and (3) learning analytics, which remains focused on taught courses with a limited evidence base in postgraduate research contexts (Dennehy et al., 2023). Postgraduate research students present a methodological and data gap because key learning occurs in supervision meetings, iterative writing and revision, and milestone progression—activities not well captured by learning management systems. ARI aims to address this by combining routine, confidential feedback on supervision with structured indicators of progression through the postgraduate research pathway, but it has not yet been validated for supervision, and no learner-level data have been collected. Although the Tripod 7Cs framework (Tripod Education, 2014) was developed for classroom instruction, it has been adapted for postgraduate supervision based on documented effectiveness (Mokole, 2021). Lee (2008) identifies five supervision modes—functional, enculturation, critical thinking, emancipation, and relationship development—and the seven "Cs" align with at least one mode (Table 1), suggesting the framework captures key supervisory roles. The 51 items were therefore reworded to refer to the supervisor. As relevance may vary by candidature stage, the adaptation remains provisional until empirically validated.

Table 1: Justification of the 7Cs Framework and Development of a Mapping Table

7Cs Dimension	Lee (2008) Approach	Supervision Example
Care	Relationship development	Consideration of the student's wellbeing and personal circumstances
Confer	Emancipation, relationship development	Appreciating the student's input and guidance in shaping the research
Captivate	Enculturation	Explaining why the research and the field are important
Clarify	Functional, critical thinking	Clear explanations and useful feedback on draft iterations
Consolidate	Critical thinking	Supporting the student in linking evidence to their argument
Challenge	Critical thinking	Promoting rigour, excellence, and perseverance
Classroom management	Functional	Planning sessions, key milestones, and the research project

The updated instrument will be validated in three phases: (1) content validity assessed by a panel of experienced supervisors, (2) internal consistency (Cronbach's alpha) and confirmatory factor analysis using pilot data, and (3) an examination of whether the items operate equivalently for honours, master's and doctoral students. Mokole (2021) notes that the initial version was piloted at the University of Limpopo, Stellenbosch University, the University of KwaZulu-Natal, the Cape Peninsula University of Technology, and the University of South Africa. Drawing on identified gaps and Davis's (1989) Technology Acceptance Model (TAM), the study assumes that users develop beliefs regarding perceived usefulness and perceived ease of use (Ma and Liu, 2011). Table 2 maps the TAM constructs to example items for supervisors and students; actual use will be captured from system logs.

Table 2: A Summary of the mapping using the Technology Acceptance Model

Construct	What it Measures	Supervisors	Students
Perceived usefulness	Belief that the ARI will improve supervision or the experience of it	The ARI would help me see where my supervision needs attention	The ARI would help me get better supervision
Perceived ease of use	The belief that the ARI requires little effort; also increases perceived usefulness.	The ARI dashboard would be easy to read	Submitting ratings would take little effort
Intention to use	Plan to use the ARI; used as a proxy for actual use during development	I intend to check my ARI results for each cycle	I intend to complete the ratings for each cycle.
Attitude toward use	Overall positive/negative view of the use of the ARI	Using the ARI in my supervision is a good idea	Rating my supervision through the ARI is a good idea
Actual use	Degree of ARI use in practice; available only after launch via system logs	Logins and dashboard views per cycle	Ratings completed per cycle

3. Design Science Research Methodology

This study uses Design Science Research (DSR), a problem-solving methodology that develops and evaluates innovative IT artifacts such as models, methods, and systems (Akoka et al., 2023) . DSR has been defined as the creation of a purposeful artefact to address a generalised problem type and the evaluation of its usefulness (Teperi et al., 2020) . Peffers et al. (2007) highlight the value of DSR in the design of complex IS artefacts (e.g., learning analytics platforms, frameworks, architectures and decision-support systems) due to its structured, replicable design and evaluation cycles, making it well suited to system architectures, prototypes and algorithms. The study develops a learning analytics platform to improve postgraduate supervision by efficiently collecting and integrating data to help supervisors monitor student progress. Following Peffers et al. (2007), Cycle 1 covered problem identification, definition of objectives and the technical evaluation of the original tool, which produced the requirements in Table 3. Cycle 2 covers the design and development of the beta platform; demonstration and naturalistic evaluation follow in the pilot.

3.1 Procedures

3.1.1 Code Review

The initial application (v3) was reviewed through its source code, database seeding scripts, and UI code, focusing on the rating tool, index computation, identity and moderation management, and user-group interfaces. The computation was independently rebuilt and tested with designed examples to confirm expected behaviour (e.g., a supervisor with one evaluation always scores zero). The beta platform was reviewed similarly, with additional review of the project plan, requirements document, and test outputs.

3.1.2 Requirements

Each gap in the original tool was documented with evidence and rewritten as a requirement for the next design. Six further requirements were derived by comparing the tool with Clow's (2012) learning analytics cycle, which indicated the tool captured data and produced metrics but did not support intervention. Requirements affecting student privacy and the validity of the score were prioritised, followed by feedback and action, and then new data sources.

3.1.3 Implementation Verification

A requirement was verified only when implemented in the beta code and confirmed by a passing automated test or recorded manual check. Features found in code without confirmation were marked implemented but not verified. Throughout this paper, implemented means present in the beta code and confirmed by a test or recorded check, planned means scheduled in the project roadmap, and proposed means recommended by the authors but not yet scheduled.

3.1.4 AI Output Validation

A generative AI assistant (Claude, Anthropic) was used to summarise the codebases; its outputs were treated as leads. For each flagged issue, the author identified the relevant file and code, verified behaviour by reading or running it, and recomputed any stated values. Unverifiable issues were excluded.

4. Cycle 1: the Current ARI Requirement and Design

ARI is a working, end-to-end system. Once a student rates a supervisor on 43 categorised questions and an administrator moderates the review, the rating engine aggregates every review into a single, whole-number ARI score, complete with a category-by-category breakdown. Students and supervisors access ARI through a Flutter mobile app or web client, while administrators manage everything in a dedicated Angular portal. The architecture is simple and unified: three client applications, one API—with the rating engine and sentiment analysis running directly inside the API illustrated in Figure 1.

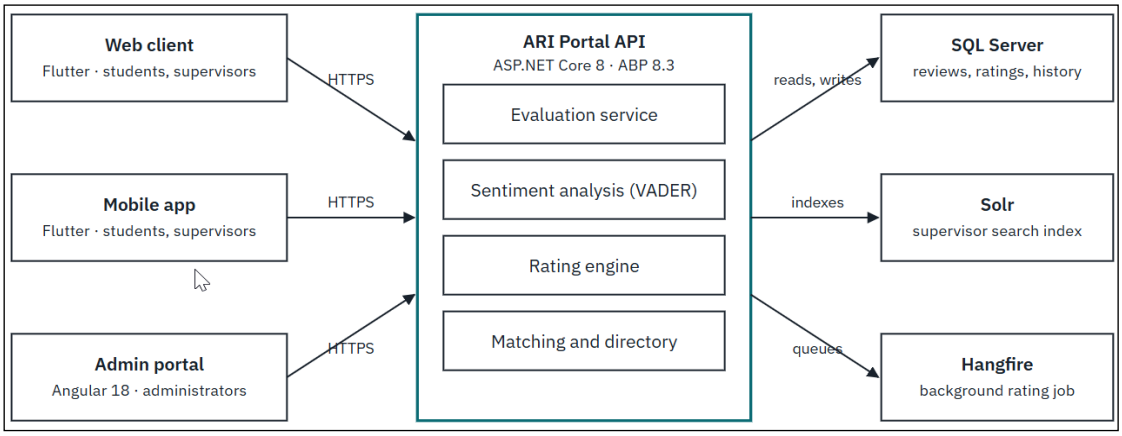

Figure 1: The current system architecture and design

The rating instrument has three levels. It includes 17 indicators in seven categories, and those indicators comprise 43 questions. Each question is scored on a 1–5 scale. In the database, this grouping is labelled the "7cs Framework" because it matches the effective teaching model of Tripod 7Cs (Tripod Education, 2014) . Each submission stores the 43 responses and a sentiment score for each comment.

The score works like an h-index for supervision. For each evaluation, the proportion of the 43 items rated 4 or 5 is discounted to the lower bound of its 95% Wilson score interval. The ARI is the highest rank r at which the r-th largest lower bound is at least r divided by the number of evaluations, so a supervisor scores highly only with many strongly favourable evaluations.

Table 3 lists the gaps identified in the code and in use, read against Clow's (2012) learning analytics cycle of capture, report, predict, act and refine. The original tool captured data and produced a metric but stopped before any intervention: a supervisor saw a score without guidance, and no one was prompted to act on poor results.

Table 3: Gaps from current tool (Author, AI-Assisted Identification)

Function	Need, Rationale, and Platform Requirements
Measurement	**R1.** A single evaluation always yields 0; with a lower bound of 0.918 (<1). Provide an interpretable small-n result or display "not enough data" below the stated minimum **R2.** The score increases with the student count (h-index style). Make results comparable across supervision loads **R3.** The category intervals use a fixed constant n=43. Compute intervals from the actual number of responses **R4.** Favourable is inconsistent (score uses 4–5; percentages use supervisor percentiles). Use one fixed, published definition everywhere **R5.** All questions are equally weighted. Either justify equal weights or derive weights via an expert panel
Instrument	**R6.** The questions are classroom-teaching orientated (lessons, quizzes, exit slips). Rewrite for postgraduate supervision and validate

Function	Need, Rationale, and Platform Requirements
Data quality	**R7.** Flagged reviews still count; rating ignores validation flags. Include only validated reviews in the calculations. **R8.** Students can create unverified supervisor profiles on submission. Verify supervisor identity/link before counting reviews
Trust/ethics	**R9.** Reviews are confidential, not anonymous. Administrators can see student names and emails. Keep identity separate from responses and clearly state who can see what. **R10.** Score purpose is unclear and not used in the system; implement a written policy limiting it to development and excluding it from performance appraisals.
Feedback/action	**R11.** Supervisors see scores without guidance. Map weak areas to suggested actions/resources **R12.** No notification when new reviews arrive. Notify users when the results are ready **R13.** History is stored but not shown. Display dated/versioned trends over time on the dashboard
Operations	**R14.** The rating run is unprotected and unscheduled (anonymous endpoint; scheduling off). Run on a fixed schedule with access control
Needs a ratings tool never addressed	**R15.** Supervision process details: key milestones, meeting frequency, and feedback turnaround. **R16.** Track each supervisor–supervisee relationship over time. **R17.** Early alerts to flag students at risk of falling behind or dropping out, linking the platform to completion rates and throughput. **R18.** Separate views for students, supervisors, departments, and institutions. **R19.** Benchmarks appear only when the minimum group size is met. **R20.** Student self-reflection alongside ratings.

The next section describes how the redesigned platform responds to these requirements.

5. Cycle 2: the Learning Analytics Platform in Progress

In this section, this study describes the redesigned ARI in the beta codebase, then sets out what must be added before it meets the standard definition of a learning analytics platform. The beta platform is past the rating tool and short of the full definition. It has a complete supervision-feedback system, a simple predictive layer, and the consent and identity machinery for the learner's data. The learner data itself, and the analytics and interventions that use them, are the work of milestones v8.0 to v11.0. In Figure 2, solid boxes exist in the code; dashed boxes are v8.0 phases still to be built inside the Learning module, and the two external systems they will read from.

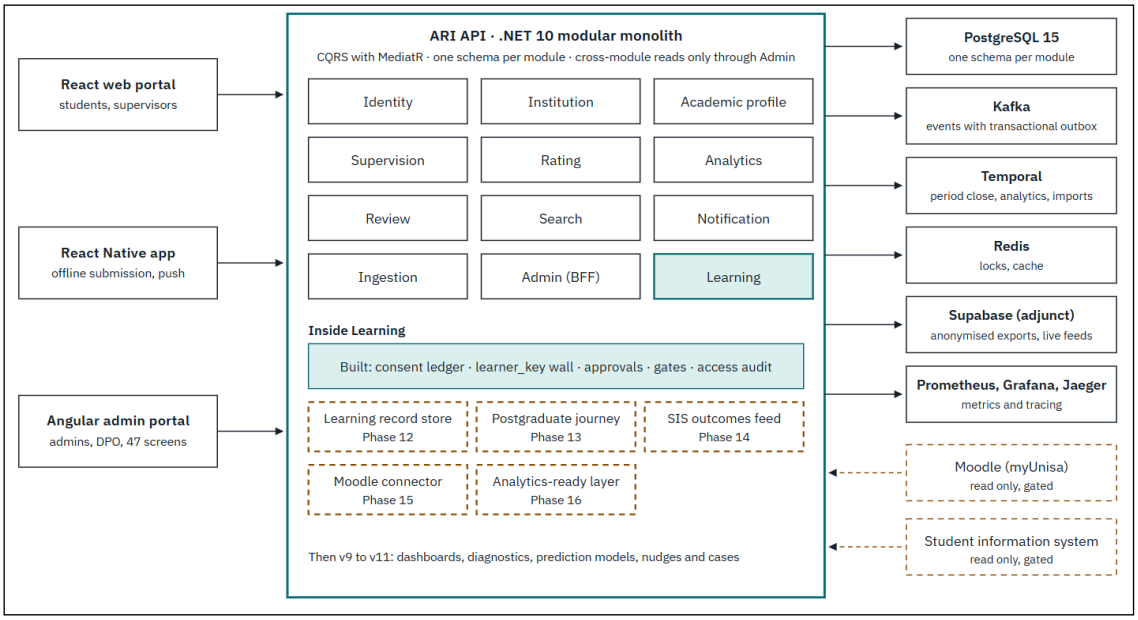

Figure 2: Learning analytics platform architecture

Siemens and Long (2011) define Learning Analytics as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimising learning and the

environments in which it occurs." This interpretation is echoed in the project's planning documentation, currently in version 8.0 and still in the development phase. Because most of the previous ARI data focused on supervisors, the platform aims to become a genuine LA system by storing learner data and using it to inform changes—only then does it meet the definition's criteria. Seven milestones were completed between May and September 2026; v8.0 is in progress, and v9.0 to v11.0 are specified but not yet scheduled.

Manly et al. (2026) distinguish four levels of analytics, which set the study's boundaries. Descriptive analytics are implemented for supervision ratings, diagnostic and predictive analytics are partly in place, and prescriptive analytics are planned for v11.0.

- **Descriptive analytics** (i.e., "what occurred") are implemented for supervision ratings: 7Cs scores with trend sparklines and rank-change indicators, and department, faculty and institution reports with PDF/CSV export. Dashboards on learner engagement, milestone attainment, throughput and time-to-degree are planned for v9.0.
- **Diagnostic analytics** (i.e., "why it occurred") are partly implemented through response-integrity checks for anomalous ratings. Supervisor-level links between supervision measures and learner outcomes, anomaly flags, comment themes and self–student perception gaps are planned for v9.0.
- **Predictive analytics** (i.e., "what is likely to occur") are partially implemented: a next-period supervisor score predictor (univariable linear regression) and non-participation flags. Planned for v10.0: non-completion risk models, time-to-completion forecasts, milestone-slip warnings, and model governance.
- **Prescriptive analytics** (i.e., "what should be done") are not yet implemented; alerts are currently limited to administrative users. Planned for v11.0: rule-based nudges, owned intervention case assignment/tracking, and randomized holdouts to assess effects and causal impact.

The beta platform is a rebuild, not an update. It keeps the 7Cs framework and the idea of rating supervision and replaces almost everything else. Table 4 compares the two versions; each beta entry was checked against the code, except where the table marks a feature as still to be built.

Table 4: Current application compared with the learning analytics platform

Aspect	Current Application	Learning Analytics Platform
Instrument	43 classroom-worded questions	51 supervision-worded items ("My supervisor…"), dimensions shown by student level
Who can rate	Any student, for any supervisor, creating profiles as needed	Only students with an administrator-assigned supervision relationship, once per supervisor per rating period
Identity	Each review tied to the student record	Responses stored without a student ID; identity kept in a separate table and never joined in scoring
Score	h-index style count of strong evaluations	Mean of all item scores per supervisor per period, shown only when at least 5 students have responded (configurable)
Integrity	Manual malicious flag, ignored by the score	Automatic detectors for straight-lining, duplicate answer patterns and improbable distributions, with a review queue and period quarantine
Processing	Manual call to a rating endpoint	Durable Temporal workflows for period close, analytics, imports, and privacy requests
Analytics	Score and category bounds	Dimension scores, trends, rank change, reports, predictions, non-participation flags, live dashboards
Privacy	None specified	POPIA retention on every identity-bearing record, subject access and erasure, consent ledger, access audit
Learner data	None	Consent and identity wall built; learning record store, journey, SIS and Moodle sources to build

Next, the study will create a Learning Record Store (LRS) for each user. An LRS is a digital record of learning experiences that supports tracking across activities (Labba et al., 2020). The first learning-data milestone is complete: postgraduate students can grant or withdraw consent for four purposes, recorded in an append-only ledger. Records will be stored under a random pseudonym and protected by automated architecture testing. Before activating any data source, the data-sharing agreement, ethics approval, and data-protection sign-off must be recorded. Later phases will add an xAPI-based LRS, a model of the postgraduate journey (milestones, supervision meetings, feedback turnaround), student information system results, and Moodle activities. Figure

3 outlines the proposed ingestion flow, including approval gates and student opt-in. Against the numbered requirements in Table 3, requirements 1, 2, 4, 8, 9, 12, 13, 14 and 18 are met; 3, 5, 6, 7, 17 and 19 are partly met; 11, 15, 16 and 20 are planned; and 10 is not met.

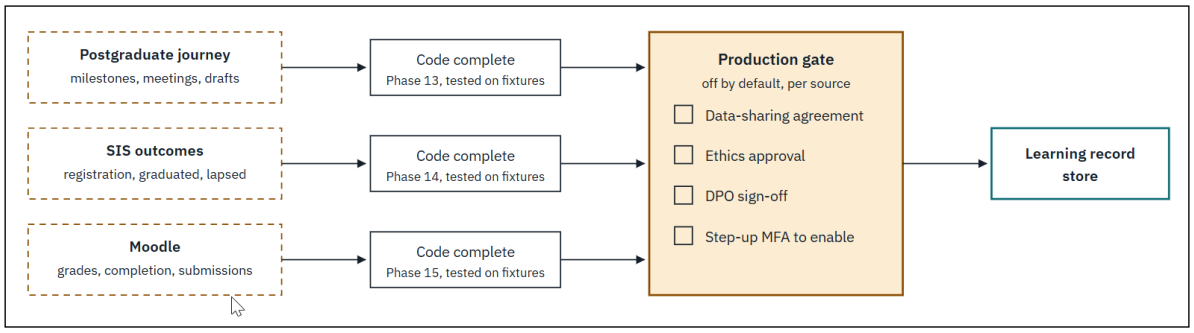

Figure 3: Data ingestion workflow to create a learning record

6. Evaluation and Discussion

The evaluation is structured according to the FEDS framework (Venable et al., 2016) and proceeds through six post-milestone stages: (1) a tool review to identify strengths, limitations, and technical prerequisites (Completed); (2) beta testing of privacy-related functionality, including consent management, deletion, and access controls (Partly completed); (3) psychometric validation of the 51-item rating instrument (Planned); (4) usability testing with students and supervisors (Planned); (5) a single-faculty/department pilot employing surveys, interviews, and usage logs to assess user acceptance and actual use (Planned); and (6) learning-analytics analyses to determine whether dashboards improve supervisory practice and learning outcomes (Planned, contingent on dashboard implementation). Given that the platform processes sensitive data pertaining to students and supervisors, the evaluation is intentionally sequenced to commence with artificial, formative episodes that verify design assumptions and privacy safeguards without engaging real users, followed by naturalistic, summative episodes once requisite checks and approvals have been completed. Within the FEDS paradigm, this staged approach—prioritizing technical risk reduction and subsequent demonstration of effectiveness—is particularly appropriate for evaluations involving high risk and/or substantial cost when conducted with real users.

The initial technical audit reviewed index validity, student-data protections, and output actionability, and found several issues: individual assessments could not score above zero; aggregate scores rose with the number of assessments, advantaging supervisors with larger cohorts; malicious submissions still affected scoring; and reviews were linked to individual student identities. Later automated testing confirmed privacy controls in the learning data foundation before collecting learner data: the learning code could not access survey responses (validated by an intentional-breach test); identifying tables had retention dates and were deleted nightly; consent changes were stored append-only; and data sources stayed inactive until three independent approvals were recorded. All tests passed, and the security review found no residual risks above the agreed threshold.

7. Measurement, Access and Governance

The beta platform reports a supervisor's mean item score for a rating period and means for each of seven dimensions, enabling comparison across different supervision loads. Because the overall mean is item-based, dimensions with more items carry more weight; equal-weight averaging of the seven dimension means will be considered during validation. Scores are withheld until at least five students respond (institutions may set a higher threshold). This protects privacy but does not ensure reliability: with five raters, the mean can shift materially (e.g., if student means have SD = 0.6, the 95% CI is roughly ±0.5). The pilot will therefore estimate inter-rater reliability (intraclass correlation) to set an evidence-based reporting minimum; results below it will be flagged as provisional.

The pilot will run in one faculty. Postgraduate students with an assigned supervisor, and their supervisors, will be invited via the postgraduate office. Participation is voluntary and does not affect academic standing or performance review. Students will complete the 51-item rating; both groups will complete a survey based on Table 2 constructs, extended with subjective norm, trust, and perceived risk; and a subsample will be interviewed. Analysis will use descriptive statistics, Cronbach's alpha, confirmatory factor analysis, correlations

between acceptance constructs and logged use, and thematic analysis (Braun and Clarke, 2006). No claims are made about effects on supervision quality or student outcomes.

Supervisors see only aggregated scores. Responses are stored without a student identifier; the student link is kept in a separate table not read by scoring. Institutional administrators can view identified individual responses, so data are confidential rather than anonymous. Learner data are pseudonymous: authorised staff can re-identify learners, and all such access is logged. Cohort reporting requires at least five learners per cell; additional cells will be suppressed where values could be derived from totals, and small cohorts will be pooled or withheld. Because 7Cs scores currently feed leaderboards, a policy will be proposed to restrict use to supervisor development and exclude performance appraisal; requirement 10 will be met only once that policy is approved.

8. Conclusion and Future Work

This paper reports two iterative design cycles for the ARI. Cycle 1 produced a functional rating tool and, through technical review, defined 20 requirements for a learning analytics (LA) platform. Cycle 2 rebuilt the system to meet these requirements and introduced a privacy-first architecture to protect postgraduate learner data. The platform's effects on supervision and student progression have not yet been evaluated, so these are presented as intended outcomes. Moving from the tool to the LA platform highlights a privacy–utility trade-off. Requiring at least five responses improves privacy but can exclude small cohorts. Separating identities from responses increases confidentiality, but because administrators can still see who responded, it does not provide full anonymity. The 7Cs supervisor leaderboards also conflict with the project's developmental intent and a policy against ranking supervisors. The study will therefore propose a written policy that excludes 7Cs results from performance appraisal and will review the use of leaderboards before the pilot. Supervisors with fewer than five respondents receive no score, and later cohort reports will suppress or pool groups below five learners. Using Clow's (2012) learning analytics cycle, the platform strengthens data capture and reporting, but the cycle is only complete when insights drive support interventions and their impact is assessed. So far, 9 requirements are fully met, 6 partially met, 4 planned and 1 (a written policy limiting scores to developmental use) not met. Next steps are to complete the learner-data foundation, test rating reliability, and run a live pilot with real student data using an extended technology acceptance model, alongside predictive and prescriptive analytics for full evaluation.

Ethics Declaration

Ethical approval was secured for the ARI study. The study was carried out in accordance with the relevant ethical standards and the terms set out in the approved ethical clearance. Data collection, analysis and reporting were completed with the appropriate attention to participant confidentiality and privacy, as well as the responsible handling of information.

AI Declaration

While preparing this manuscript, the author used Claude (Anthropic), a generative AI assistant, to (i) suggest an outline consistent with the conference call, (ii) compile and integrate descriptions of the two ARI codebases' architecture, scoring logic, and limitations from their source code and planning documents, and (iii) generate preliminary diagrams, interface mock-ups, and draft text. The author independently checked every technical statement by locating it in the source code, confirming the behaviour, and recalculating reported values. A University-approved AI tool (Writefull, 2026) was also used to improve grammar and wording. Any AI-produced content was used only as assistance not as evidence and was critically evaluated before being included. The author accepts full responsibility for the analysis, interpretation of results, and the final version of this study.

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