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# The self-regulatory paradox of learning analytics: student expectations and the conditions for fair algorithmic assessment in higher education

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Learning Analytics (LA) are increasingly positioned as tools to foster self-regulated learning (SRL) in higher education. As assessment-related data are progressively processed, interpreted, and acted upon through algorithmic systems, the fairness, transparency, and perceived legitimacy of these systems depend not only on their technical design but on whether students recognise themselves as agents within them. Yet students' own expectations regarding the institutional use of LA remain underexplored, particularly in face-to-face university contexts. This study investigates the service and feature expectations of 1,020 undergraduate students at a large Spanish research university, using the Student Expectations of Learning Analytics Questionnaire (SELAQ). Descriptive analyses and between-group comparisons were applied to seven items rated on a five-point Likert scale. Findings reveal a consistent asymmetry: students most strongly expect professors to act on analytics when academic risk is detected, and show comparatively lower expectations for LA to support their own decision-making. This pattern—expecting LA to function as a teacher-mediated intervention tool rather than a learner-directed resource—constitutes what we term a *self-regulatory paradox*: students endorse the outcomes of self-regulated learning while simultaneously delegating its data-informed enactment to their instructors. A direct within-student comparison confirmed that instructor- and institution-oriented expectations exceeded student-oriented ones (paired-samples test, medium effect). Gender-based differences were statistically significant for all seven items but small in size and, after Bonferroni correction, robust for five of them (Cohen's  $d = 0.18$ – $0.29$ ), female students consistently reporting higher expectations. These findings have direct implications for the design of LA dashboards, data literacy training, and institutional strategies aimed at repositioning students as active, data-informed agents of their own learning. More broadly, the paradox specifies an empirical precondition for fair and transparent algorithmic assessment: systems cannot be considered legitimate by virtue of being technically accessible to learners if those learners do not recognise themselves as entitled to interpret and act upon their own assessment data. We argue that perceived fairness and transparency in automated and AI-assisted assessment are contingent on building, rather than presupposing, students' data-informed agency.

### KEYWORDS

algorithmic transparency, data literacy, fairness, higher education, learning analytics dashboards, self-regulated learning, student agency, student expectations

# 1 Introduction

Self-regulated learning (SRL) has been widely recognised as a foundational competency for university students, not only for academic achievement but for lifelong engagement with knowledge in professional and civic life (European Commission, 2018; Gargallo et al., 2020; Ruíz, 2020). The capacity to learn how to learn—to plan, monitor, evaluate, and adjust one's own learning strategies—is increasingly understood as a prerequisite for navigating knowledge-intensive environments rather than a by-product of formal instruction. Yet this capacity does not emerge spontaneously. It requires structured pedagogical conditions and, crucially, access to meaningful, actionable information about one's own learning process (Boud, 2000; Nicol and Macfarlane-Dick, 2006; Panadero et al., 2017).

Feedback occupies a central role in this picture. Contemporary scholarship has substantially transformed how feedback is conceived: no longer a unidirectional transmission of judgement from teacher to student, but a dynamic, iterative process in which students actively interpret, internalise, and act upon evaluative information from multiple sources (Carless and Boud, 2018; Henderson et al., 2019). This reframing has given rise to the concept of feedback literacy—defined as students' capacity to understand, engage with, and productively use feedback to guide future work (Carless, 2020). Developing feedback literacy is not incidental: it requires deliberate exposure to feedback from diverse sources, including peers, self-assessment, and, increasingly, data-generated insights about learning behaviour (Tai et al., 2018).

Learning Analytics (LA) represent one of the most significant, and as yet underexploited, potential sources of this kind of data-informed feedback. LA encompasses the measurement, collection, analysis, and presentation of data about students and their learning contexts, typically conveyed through visual dashboards, with the aim of understanding and optimising the conditions of learning (Siemens and Gasevic, 2012). Learning Analytics Dashboards (LADs), when well designed, can operate across multiple levels of analytical depth: describing what has happened, diagnosing why, predicting probable outcomes, and prescribing actionable directions (Knight and Buckingham Shum, 2017; Matcha et al., 2020). In principle, this positions LA as a powerful support for SRL—providing students with the kind of meaningful, timely, and personalised information that might otherwise be inaccessible (Heikkinen et al., 2023; Lodge et al., 2018).

The pedagogical logic underlying LA-for-SRL, however, rests on a critical assumption: that students are willing and able to engage with analytic data as active agents of their own improvement. This assumption, while theoretically plausible, may be empirically fragile. Research in related areas—including AI-assisted learning—has found that when students receive regular, detailed, and personalised algorithmic feedback, they tend to rely on it rather than internalise the evaluative capacities it is meant to build (Darvishi et al., 2024). Extending this

finding to the LA context raises a troubling possibility: that data-rich interventions, when offered without adequate pedagogical scaffolding, may deepen interpretive dependency rather than foster autonomous self-direction. Meaningful engagement with LA data also requires a degree of data literacy—the ability to locate, interpret, evaluate, and use digital information—that is not uniformly present among undergraduates (Vuorikari et al., 2022). Without these conditions, dashboards risk remaining unused or misread, or worse, reinforcing the delegation of evaluative authority to those perceived as more technically capable (Jivet et al., 2018; Winne, 2017).

This tension becomes particularly salient in face-to-face university contexts, where LA is less established than in fully online or MOOC environments, students have fewer prior experiences with data-driven learning tools, and institutional data collection is more limited in scope. Despite the growing body of research on LA adoption (Hilliger et al., 2020; Whitelock-Wainwright et al., 2019; Wollny et al., 2023), relatively little is known about what students in these contexts actually expect LA to do—for them, or on their behalf. The few existing studies addressing student expectations directly—notably Whitelock-Wainwright et al. (2019) in the UK, and Wollny et al. (2023) across multiple European countries—have not fully examined the locus of expected action: whether students expect to be the primary agents of LA use, or whether they expect these functions to be mediated by institutional and teaching staff. This distinction is theoretically significant. If students systematically expect LA to function as a tool in their teachers' hands rather than their own, the prevailing paradigm of student-centred LA design requires recalibration.

This recalibration is not only a matter of pedagogical design; it bears directly on the fairness, transparency, and validity of the algorithmic systems through which assessment-relevant data are increasingly mediated. As higher education moves towards automated and AI-assisted forms of assessment and feedback, the legitimacy of these systems is commonly framed in terms of their technical properties—accuracy, explainability, the mitigation of bias—and of the institutional safeguards that govern them (EU AI Act, 2024; OECD, 2019; UNESCO, 2021). Yet a system can be technically transparent and procedurally fair while remaining, in practice, opaque or alien to the very learners it is meant to serve. Perceived fairness and transparency depend on whether students regard themselves as legitimate interpreters of their own assessment data, rather than as passive subjects of measurement carried out and acted upon by others. If students systematically delegate that interpretive authority, then making algorithmic assessment accessible to them does not, in itself, make it fair or transparent from their standpoint. Understanding students' expectations about who should act on learning data is therefore a precondition, not a peripheral concern, for the responsible deployment of automated assessment in higher education.

This study addresses that gap. Drawing on data from 1,020 undergraduate students at a large Spanish research university, we examine students' expectations of institutional LA services using the Service and Feature Expectations dimension of the SELAQ (Whitelock-Wainwright et al., 2019). Specifically, we address the following research questions:

## Abbreviations

LA, learning analytics; SRL, self-regulated learning; SELAQ, student expectations of learning analytics questionnaire; LAD, learning analytics dashboard; LMS, learning management system.

RQ1: What are undergraduate students' expectations regarding institutional learning analytics services, and which service dimensions are perceived as most and least relevant for supporting their learning?

RQ2: Do students' expectations of learning analytics services differ significantly by gender or age group?

RQ3: What do these expectations imply for the fairness, transparency, and perceived legitimacy of automated and AI-assisted assessment systems in higher education?

We expect to find an asymmetry between expectations of instructor-mediated and student-directed uses of LA—what we call a self-regulatory paradox. If it holds, the paradox matters beyond dashboard design, since it bears on whether learners can experience algorithmic assessment as fair and transparent at all, a question we return to in the discussion.

## 2 Theoretical background

### 2.1 Sustainable feedback, self-regulation, and feedback literacy

The growing emphasis on SRL in higher education has repositioned feedback as a developmental resource rather than a terminal evaluation. In this framework, feedback is most powerful not when it corrects past performance, but when it builds students' long-term capacity to evaluate and improve their own work independently—what Carless et al. (2011) describe as sustainable feedback. Sustainable feedback practices explicitly aim to develop the metacognitive and evaluative competencies that underpin self-regulation: the ability to set learning goals, monitor progress, assess the quality of one's own output, and adjust strategies accordingly (Nicol and Macfarlane-Dick, 2006; Panadero et al., 2017).

Critically, this reorientation requires something of students that is not often explicitly taught: feedback literacy. Carless and Boud (2018) define this as the capacity to appreciate feedback, make evaluative judgements about the quality of work, and productively manage affect when engaging with critical information. Feedback literacy is not passive; it requires students to adopt an active epistemic stance—to seek information, interrogate it, and translate it into action. It is also cumulative: students who are systematically exposed to diverse feedback sources, including peer assessment, self-assessment, and rubric-based criteria, develop stronger evaluative judgement over time (Tai et al., 2018). The relevance of this construct to LA is direct: for learning analytics to function as a source of SRL-supporting feedback, students must bring to them a form of data-informed feedback literacy.

### 2.2 Learning analytics as data-informed feedback for self-regulated learning

LA dashboards can, in principle, provide exactly the kind of multi-layered, personalised information that supports SRL (Matcha et al., 2020). At the descriptive level, they narrate patterns of engagement and performance; at the diagnostic level, they contextualise these patterns; at the predictive level, they signal risk or opportunity; and at the prescriptive level, they suggest actionable responses (Knight and Buckingham Shum, 2017). This progression parallels the stages of effective self-regulation: awareness, interpretation, goal-setting, and strategy adjustment.

However, the pedagogical effectiveness of LADs depends heavily on design decisions that are often made without sufficient input from students. A recent systematic review of student-facing LADs identified a discernible trend towards pedagogically informed, student-focused designs—yet concluded that this design trajectory alone does not guarantee meaningful student engagement (Paulsen and Lindsay, 2024). Jivet et al. (2018) argued persuasively for co-design approaches that incorporate student voices into dashboard development; the present study extends this rationale by examining whether students conceptualise LA as a tool for their own use or, rather, as a resource whose outputs they expect others to act upon.

A complementary concern relates to effectiveness. A systematic review of 38 empirical studies found no consistent evidence that LADs have delivered on their promise of improving student achievement, participation, motivation, or attitude (Kaliisa et al., 2024). This finding suggests that the problem extends beyond student readiness to encompass the broader conditions under which analytic information is offered, contextualised, and integrated into pedagogical practice.

### 2.3 Student agency, data literacy, and the platformisation of education

The broader context in which LA operates is shaped by the growing platformisation of education (Parcerisa et al., 2022)—the mediation of teaching and learning by digital platforms that collect, process, and present data according to algorithmic logic. This raises questions about agency: who selects what data is collected, who decides how it is displayed, and who controls the interpretive frameworks applied to it? In environments increasingly mediated by AI-driven analytics, these questions carry particular urgency (UNESCO, 2022).

Darvishi et al.'s (2024) investigation into AI-assisted peer review found that students who received regular automated feedback tended to rely on algorithmic assistance rather than develop independent evaluative capacity—even when they had been explicitly prepared to work autonomously. This finding points to a broader risk: systems designed to support agency may, without careful calibration, inadvertently reinforce dependency. For students to exercise genuine agency within data-rich learning environments, they need the competencies outlined in the DigComp 2.2 framework (Vuorikari et al., 2022)—particularly the ability to critically evaluate digital information and use it to inform decisions. Similarly, the DigCompEdu framework (Redecker and Punie, 2017) calls on educators to

develop students' data information literacy as an explicit pedagogical objective, not merely as an incidental outcome. It is against this backdrop that we examine what students actually expect LA to do—and for whom.

These concerns are increasingly codified in international policy frameworks for trustworthy artificial intelligence, which are directly relevant as LA evolves into AI-mediated forms of assessment and feedback. The OECD principles on AI (OECD, 2019) and UNESCO's recommendation on the ethics of AI (UNESCO, 2021) foreground transparency, accountability, and human agency as conditions for the legitimate use of automated systems, while the European Union's AI Act (2024) classifies AI systems used to evaluate learning outcomes in education as high-risk, imposing requirements of transparency, human oversight, and the protection of those subject to algorithmic decisions. A recurring assumption in these frameworks is that fairness and transparency can be secured through the technical and procedural properties of the system and through institutional safeguards. What such frameworks address less directly is the standpoint of the learner: whether students perceive themselves as entitled to access, interpret, and act upon the data generated about them, or whether they regard algorithmic assessment as something done to them by more competent others. This distinction matters because perceived fairness and transparency are not reducible to a system's technical attributes; they are also a function of the user's position within it. A system whose subjects do not see themselves as legitimate interpreters of their own data may satisfy formal transparency requirements while failing to be transparent in any experientially meaningful sense. Students' expectations about who should act on learning data therefore offer an empirical window onto a dimension of fairness and transparency that technical and policy framings tend to leave implicit.

## 3 Materials and methods

### 3.1 Study design and context

This study adopts a non-experimental, descriptive cross-sectional design and follows a quantitative approach. It forms part of a broader research project [blinded for review], conducted during the 2022–2023 academic year. The study received clearance from the institutional bioethics committee, and all participants provided informed consent prior to participation. Data were collected at a large face-to-face research university in Spain [institution blinded for review]. This context is significant: unlike fully online environments or MOOCs, face-to-face universities generate more limited digital data traces, and their students are less routinely exposed to analytics-based feedback, making student expectations in this setting particularly informative for institutions considering the transition towards data-informed pedagogies.

### 3.2 Instrument

We administered the Service and Feature Expectations dimension of the Student Expectations of Learning Analytics Questionnaire (SELAQ; Whitelock-Wainwright et al., 2019). This dimension

comprises seven items capturing students' expectations of what LA services institutions should provide. The items were translated into Spanish by the research team for administration through the institution's official survey platform. This was a working translation prepared for the study; a formal cross-cultural adaptation procedure (independent back-translation, expert panel review, and cognitive pretesting) was not carried out, a point we return to in the Limitations. Items were rated using a five-point Likert scale (1 = *strongly disagree*; 5 = *strongly agree*), adapted from the original seven-point scale for consistency with the institution's standard survey platform. The seven items addressed expectations related to: (1) teaching staff intervention when failure risk is detected; (2) LA-enabled promotion of academic and professional skill development; (3) staff competency in integrating LA into feedback; (4) comprehensive learning profiling per module; (5) institutional progress communication; (6) progress comparison against course objectives; and (7) student decision-making informed by LA data. As this adaptation alters the response scale, direct score-level comparisons with studies using the original seven-point SELAQ (e.g., Wollny et al., 2023) are not appropriate; directional and rank-order findings, however, remain fully interpretable.

### 3.3 Participants and data collection

Invitations were distributed by email to students across multiple courses and faculties with institutional support. Participation was voluntary. A total of 1,068 students initiated the survey; after excluding 48 cases that did not complete the questionnaire or did not provide informed consent, 1,020 valid responses were retained. Because the survey required completion of all items before submission, the retained cases contained no missing data on the seven SELAQ items; only self-reported age showed minor non-response (13 cases gave a non-numeric entry and were excluded from the age analysis). The sample comprised female respondents (70%;  $n = 714$ ), male respondents (28%;  $n = 286$ ), non-binary respondents (1%;  $n = 12$ ), and respondents who selected another or undisclosed category (1%;  $n = 8$ ). Age distribution was as follows: 17–18 years (39%), 19–20 years (31%), 21–22 years (19%), and 23 years or older (9%). Respondents spanned all major faculties of the university and were grouped into four broad knowledge areas: Social Sciences (34%), Health Sciences (29%), Humanities and Arts (28%), and Sciences (9%). As participation was voluntary and self-selected, the sample over-represents women and the health and social sciences relative to the overall student body, and is best understood as a large convenience sample rather than a probability sample; this is considered further in the Limitations. All data were stored on secure institutional systems and treated as confidential in accordance with responsible research practices.

### 3.4 Data analysis

Four analytical procedures were applied. First, descriptive statistics (means and standard deviations) were computed for each of the seven SELAQ items. Second, an independent-samples *t*-test was conducted to compare mean scores by gender. Given the minimal representation of non-binary respondents ( $n = 12$ ) and of those

selecting another or undisclosed category ( $n = 8$ ), insufficient for reliable group-level inference, these groups were excluded from inferential gender comparisons; analyses contrasted female and male respondents exclusively ( $n = 1,000$ ). Effect sizes were calculated using Cohen's  $d$ , following conventional benchmarks (Cohen, 1988): small ( $d \geq 0.20$ ), medium ( $d \geq 0.50$ ), large ( $d \geq 0.80$ ). Third, Chi-square tests of independence examined whether the frequency distribution of responses differed across four age categories (17–18, 19–20, 21–22,  $\geq 23$  years); we used a contingency-table approach here, rather than a comparison of means, because age was recorded in ordered bands rather than as a continuous variable. To account for multiple simultaneous comparisons (seven tests), a Bonferroni-corrected significance threshold of  $\alpha = .007$  was applied. Fourth, to test the central proposition directly rather than infer it from the ordering of item means, we compared, within respondents, the mean of the instructor- and institution-oriented items (Items 1–3) against the mean of the student-oriented items (Items 6–7) using a paired-samples  $t$ -test, with the Wilcoxon signed-rank test as a non-parametric check and Cohen's  $d_z$  as the effect size for paired data. Items 4 and 5, which concern the receipt of information rather than the locus of action, were not assigned to either pole. All analyses were conducted using SPSS, version 27.

## 4 Results

### 4.1 Student expectations of learning analytics services: descriptive findings

Table 1 presents the means and standard deviations for each of the seven SELAQ items. Across all items, responses clustered in

TABLE 1 Mean scores and standard deviations for the seven SELAQ service and feature expectations items ( $N = 1,020$ ).

| Item | SELAQ item (original English wording)                                                                                 | M    | SD   |
|------|-----------------------------------------------------------------------------------------------------------------------|------|------|
| 1    | The teaching staff will have an obligation to act if the analytics show that I am at-risk of failing                  | 3.87 | 1.07 |
| 2    | The feedback from the learning analytics service will be used to promote academic and professional skill development  | 3.86 | 1.03 |
| 3    | The teaching staff will be competent in incorporating analytics into the feedback and support they provide to me      | 3.83 | 1.03 |
| 4    | The learning analytics service will present me with a complete profile of my learning across every module             | 3.60 | 1.06 |
| 5    | The university will regularly update me about my learning progress based on the analysis of my educational data       | 3.51 | 1.11 |
| 6    | The learning analytics service will show how my learning progress compares to my learning goals/the course objectives | 3.49 | 1.08 |
| 7    | The learning analytics service will be used to promote student decision making                                        | 3.47 | 1.06 |

Items are presented in their original English wording (Whitelock-Wainwright et al., 2019); the instrument was administered in a Spanish working translation prepared by the research team (see Methods and Limitations).

the moderate-to-high range ( $M = 3.47$ – $3.87$ ), indicating general endorsement of LA services while revealing a meaningful gradient in the intensity of expectations.

The three highest-rated items (Items 1–3,  $M = 3.83$ – $3.87$ ) share a defining characteristic: they position teaching staff—not the student—as the primary actor. Students most strongly expected professors to intervene when failure risk is identified (Item 1), to leverage LA for skill development (Item 2), and to be competent at integrating analytic data into their feedback practices (Item 3). The three lowest-rated items (Items 5–7,  $M = 3.47$ – $3.51$ ), by contrast, are those requiring students themselves to act as agents of data use. The item eliciting the lowest agreement—Item 7, using LA to inform one's own academic decisions ( $M = 3.47$ )—most directly captures student-directed LA engagement.

The ordering is telling. It points to what we read as a *self-regulatory paradox*: in the context of a dashboard designed explicitly to support self-regulation, students most strongly expect LA to be operationalised by others on their behalf. The gap between the highest-rated item (teaching staff intervention,  $M = 3.87$ ) and the lowest-rated item (student-directed decision-making,  $M = 3.47$ ) spans 0.40 of a scale point, and the items in between fall in the same order: the more an item asks students to act on the data themselves, the lower it is rated.

To test this asymmetry directly rather than read it from the rank order, we compared each respondent's mean rating of the instructor- and institution-oriented items (Items 1–3;  $M = 3.86$ ) with their mean rating of the student-oriented items (Items 6–7;  $M = 3.48$ ). The difference was statistically significant in a paired-samples test,  $t(1019) = 14.75$ ,  $p < .001$ , with a medium effect size ( $d_z = 0.46$ ); the non-parametric Wilcoxon signed-rank test confirmed the result ( $p < .001$ ). On average, students rated instructor- and institution-oriented uses of analytics roughly four-tenths of a scale point higher than uses requiring their own data-informed action—a substantially larger and more reliable difference than any of the between-group effects reported below. The paradox is therefore a within-student pattern, not an artefact of how the items happen to rank.

### 4.2 Gender differences in learning analytics expectations

Independent-samples  $t$ -tests comparing female ( $n = 714$ ) and male ( $n = 286$ ) respondents revealed statistically significant differences across all seven SELAQ items (Table 2); five of the seven remained significant after Bonferroni correction ( $\alpha = .007$ ). In every case, female students reported higher expectations than male students. Effect sizes were small throughout, with Cohen's (1988)  $d$  ranging from 0.18 to 0.29.

All seven Cohen's  $d$  values fall below 0.30, indicating small effects. Female students reported higher expectations than male students on every item; the largest differences concerned the expectation that teaching staff act when analytics flag a risk of failure (Item 1), that the university communicate progress proactively (Item 5), and that staff be competent in integrating analytics into feedback (Item 3). The smallest gender gap appeared for student-directed decision-making (Item 7), the item with the lowest overall endorsement. The self-regulatory

TABLE 2 Independent-samples *t*-test results for SELAQ items with statistically significant gender differences (all seven items; female *n* = 714, male *n* = 286, *df* = 998).

| Item                                                                                                                    | <i>t</i> | <i>p</i>          | Cohen's <i>d</i> | Direction     |
|-------------------------------------------------------------------------------------------------------------------------|----------|-------------------|------------------|---------------|
| 1—The teaching staff will have an obligation to act if the analytics show that I am at-risk of failing                  | 4.152    | <.001             | 0.291            | Female > Male |
| 2—The feedback from the learning analytics service will be used to promote academic and professional skill development  | 2.789    | .005              | 0.195            | Female > Male |
| 3—The teaching staff will be competent in incorporating analytics into the feedback and support they provide to me      | 3.823    | <.001             | 0.268            | Female > Male |
| 4—The learning analytics service will present me with a complete profile of my learning across every module             | 3.067    | .002              | 0.215            | Female > Male |
| 5—The university will regularly update me about my learning progress based on the analysis of my educational data       | 3.718    | <.001             | 0.260            | Female > Male |
| 6—The learning analytics service will show how my learning progress compares to my learning goals/the course objectives | 2.517    | .012 <sup>†</sup> | 0.176            | Female > Male |
| 7—The learning analytics service will be used to promote student decision making                                        | 2.657    | .008 <sup>†</sup> | 0.186            | Female > Male |

Items are ordered by mean score (see Table 1). All comparisons are female (*n* = 714) vs. male (*n* = 286), *df* = 998.

<sup>†</sup>significant at the uncorrected threshold (*p* < .05) but not after Bonferroni correction (*α* = .007). Cohen's *d* values below 0.20 indicate negligible-to-small effects and values around 0.20–0.30 small effects (Cohen, 1988).

paradox is therefore present across both gender groups: women express somewhat stronger expectations of the institutional dimensions of LA, but neither group positions itself as the primary agent of LA use.

### 4.3 Differences by age group

Chi-square tests of independence examined response distributions across the four age categories (*n* = 1,007; 13 respondents who did not report a numeric age were excluded) (Table 3). Expected cell counts met the usual assumption (no expected count below five) for the four items reaching

TABLE 3 Chi-square analyses: SELAQ items × age category (17–18, 19–20, 21–22, ≥23 years).

| SELAQ item                                                   | $\chi^2$ | <i>df</i> | <i>p</i>           |
|--------------------------------------------------------------|----------|-----------|--------------------|
| 1—Teaching staff obligation to act if at-risk                | 18.888   | 12        | .091               |
| 2—LA promotes academic and professional skill development    | 16.353   | 12        | .176               |
| 3—Teaching staff competent to incorporate LA into feedback   | 19.151   | 12        | .085               |
| 4—Complete learning profile per module                       | 26.563   | 12        | .009               |
| 5—University regularly updates on learning progress          | 30.143   | 12        | .003 <sup>†</sup>  |
| 6—Dashboard compares progress with learning goals/objectives | 34.689   | 12        | <.001 <sup>†</sup> |
| 7—LA promotes student decision making                        | 28.833   | 12        | .004 <sup>†</sup>  |

*N* = 1,007 (respondents reporting a numeric age). All tests *df* = 12.

<sup>†</sup>significant after Bonferroni correction (*α* = .007). Item 4 was significant only at the uncorrected threshold (*p* = .009).

significance; for the remaining items, fewer than 20% of cells fell below five, within accepted tolerance. Three items differed significantly by age group after Bonferroni correction (corrected *α* = .007): the expectation that the university communicate progress proactively (Item 5;  $\chi^2$  = 30.14, *p* = .003), that analytics show progress against learning goals (Item 6;  $\chi^2$  = 34.69, *p* < .001), and that analytics promote student decision-making (Item 7;  $\chi^2$  = 28.83, *p* = .004), all with *df* = 12. A fourth item (Item 4, complete learning profile) was significant only at the uncorrected threshold ( $\chi^2$  = 26.56, *p* = .009). In each case, the youngest students (17–18 years) reported the highest expectations, which declined across successive age bands. The pattern is consistent: younger entrants expect more institutional communication, goal-referenced feedback, and decision-support from analytics than their older peers.

## 5 Discussion

### 5.1 The self-regulatory paradox

The central finding of this study is an asymmetry in student expectations. Across the seven items, students endorsed most strongly those uses of LA that assign agency to their instructors, and least strongly those that would require them to act as data-informed agents themselves. The item capturing student-directed use—autonomous decision-making based on performance data—drew the lowest agreement, and the ordering held among both women and men.

We describe this as a *self-regulatory paradox* because it sits uneasily with the pedagogical case for LA in higher education. That case rests on the capacity of analytics to extend feedback literacy and strengthen self-regulation, giving students the information they need to monitor progress and adjust their strategies (Lodge et al., 2018; Matcha et al., 2020). The students surveyed here held broadly favorable views of LA, yet they located its use mainly in their teachers' hands—as a means of institutional monitoring and intervention rather than an instrument of their own self-direction.

This finding resonates with, but extends, the work of Wollny et al. (2023), whose European multi-site study documented broadly positive student expectations of LA without specifically examining the asymmetry between teacher-mediated and student-directed uses as a structural pattern. The present study makes this asymmetry explicit and theorizes it: students' expectations reveal deeper dispositions about who bears responsibility for academic monitoring and intervention, not merely preferences about dashboard design.

These dispositions are understandable in context. Many undergraduates have been educated in systems that position teachers as the primary evaluators and guardians of academic progress, with data about learning belonging to and acted upon by institutions—not something students are expected to interpret and act upon autonomously (Parcerisa et al., 2022). Recent evidence reinforces this concern: Darvishi et al. (2024) found that students who received regular automated feedback in a peer review system showed a tendency to rely on algorithmic outputs rather than develop independent evaluative capacity, suggesting that dependency is not merely a starting condition but can be actively reinforced by poorly calibrated data systems. This risk is further contextualized by Kaliisa et al.'s (2024) systematic review, which found no consistent evidence that LADs have improved student achievement, motivation, or participation—indicating that design ambition and learning impact remain disconnected in current implementations. Winne's (2017) insight applies here: for data to support self-regulation, it must be genuinely meaningful to learners. Students who encounter a dashboard without prior scaffolding in how to read it or act upon it may reasonably delegate its interpretation to those who appear better equipped.

The implication is clear: student-centered LA cannot be achieved by designing dashboards that students *can* use. It requires building the conditions under which students *want* to and *know how* to use them—conditions involving explicit data literacy training, co-design of dashboard features responsive to student-identified goals, and the gradual transfer of interpretive authority to students throughout their university trajectory (Carless and Boud, 2018; Jivet et al., 2018).

## 5.2 Gender differences: differential orientations towards institutional support

Female students reported higher expectations than male students on all seven SELAQ items, with the differences reaching significance throughout and surviving Bonferroni correction for five of them. The effects were uniformly small (Cohen's  $d = 0.18$ – $0.29$ ), so the pattern is best read as a consistent gradient rather than a set of large categorical differences. The gap was widest for expectations that staff act on at-risk analytics (Item 1) and that the university communicate progress proactively (Item 5), and narrowest for student-directed decision-making (Item 7), the least-endorsed item overall.

We are cautious about reading these differences as evidence of greater data literacy or a stronger self-regulatory orientation among women. A more conservative interpretation is that they reflect distinct dispositions towards institutional support and monitoring. On this reading, women's higher expectations for

institutional feedback and skill-development support would point to a preference for proactive, institutionally mediated guidance rather than to a readiness for self-directed engagement with data. We advance this as an interpretive hypothesis to be tested directly rather than as an established explanation, since the present design does not measure the dispositions it invokes. Either way, the pattern complicates discussions of personalization and equity in data-driven environments (Sun et al., 2023): LA services designed around a single image of the ideal self-directed learner risk serving some students better than others.

The age-related differences point in a complementary direction. Expectations that the university communicate progress, that analytics be referenced to learning goals, and that they support student decision-making were highest among the youngest entrants (17–18 years) and declined with age. One reading is developmental: students arriving directly from secondary education may carry expectations of close institutional monitoring formed in more structured settings, which attenuate as they acclimatize to the greater autonomy of university study. If so, the window in which students most expect institutional guidance through analytics is also the period in which the groundwork for later self-direction can most readily be laid—an argument for introducing data-literacy support early rather than assuming it will emerge with seniority. This interpretation is necessarily tentative, given the cross-sectional design, and would need longitudinal data to test directly.

## 5.3 Implications for dashboard design and institutional strategy

The evidence from this study suggests that most undergraduates in face-to-face contexts are not yet positioned to act as autonomous interpreters of their own analytics. Paulsen and Lindsay's (2024) systematic review confirms a positive trend in LAD design towards student-focused, pedagogically informed interfaces—yet the present study shows that design orientation alone is insufficient. Dashboards presenting data without contextual scaffolding, comparative anchoring, or explicit guidance on interpretation risk reinforcing the passivity they aim to overcome. Student co-design must be complemented by co-learning: not merely involving students in decisions about what data to display, but building the interpretive capacity to act on what they see.

The strong endorsement of instructor-mediated LA use need not be treated as a deficit. It is also a pedagogical resource. If early LA implementations demonstrate value through teacher-initiated interventions that students find genuinely useful (Klein et al., 2019), they may generate the experiential foundation from which students gradually develop the confidence to engage with analytics independently. The transition from LA-as-institutional-tool to LA-as-self-regulatory-resource may best be understood as a developmental trajectory requiring sustained institutional investment, pedagogical coordination, and structures that extend beyond the single-course format that currently dominates LA implementation.

Finally, institutions implementing LA in face-to-face contexts must attend to what Parcerisa et al. (2022) describe as the forced

use dynamic: the risk that educational activities are designed for digital platforms not because they are pedagogically optimal, but because they generate data. Collecting data from poorly designed learning processes produces analytics with limited validity and potentially misleading guidance. Pedagogical integrity must be a prerequisite of meaningful analytics, not an afterthought.

## 5.4 Implications for fairness, transparency, and validity in automated assessment

This study measures expectations of learning analytics services, not the properties of any operational grading or feedback system. Its findings nonetheless bear on the fairness, transparency, and validity of algorithmic assessment as that assessment becomes increasingly AI-mediated (RQ3). The frameworks that currently govern such systems—the [EU AI Act \(2024\)](#), the OECD principles (2019), and UNESCO's recommendation (2021)—locate fairness and transparency mainly in the system itself, in its accuracy, explainability, and oversight, and in the institutional safeguards around it. The self-regulatory paradox points to a condition these framings tend to leave implicit. A system may be technically transparent and still be experienced as opaque by a student who does not regard herself as entitled to read and act on her own assessment data. Transparency, on this view, is partly relational: it depends on the position the learner occupies within the system, not on the interface alone. The highest-rated item in our data makes this concrete. That students expect staff, rather than themselves, to act when analytics flag a risk of failure is itself a stance towards an algorithmic assessment function. It can serve equity, by prompting timely support, while also concentrating interpretive authority in the institution and leaving the classifying criteria out of students' view—a cost borne most heavily by those least placed to contest a misclassification. Accessibility does not resolve this. Opening a dashboard to students is necessary but not sufficient for transparency; without data literacy and interpretive scaffolding, access does not become the capacity to question an algorithmic output. The point extends to validity. Beyond whether a system measures what it claims to, its consequential validity ([Messick, 1995](#)) turns on how the outputs are used, and by whom; analytics that learners hand over wholesale cannot support the self-regulatory uses often invoked to justify them, which weakens the case for deploying them as learner-facing tools at all. Student expectations thus belong among the inputs to responsible design of automated assessment, alongside its technical and policy dimensions. Fairness and transparency are not only engineered into systems; they are co-produced by the learners who have to recognize themselves as agents within them.

## 5.5 Limitations

Several limitations should inform the interpretation of these findings. First, the study draws on a single institution, and the sample was a large but self-selected convenience sample recruited through a voluntary survey; women and the health and

social sciences are over-represented relative to the wider student body, so the descriptive proportions should not be read as population estimates, and generalization to other contexts cannot be assumed. Second, the seven SELAQ items were administered in a Spanish working translation prepared by the research team rather than through a formal cross-cultural adaptation; independent back-translation, expert review, and cognitive pretesting were not conducted, and this may affect the equivalence of item meaning relative to the original instrument. Third, expectations were collected without direct prior experience of an operational LA dashboard; responses reflect orientations towards an imagined system rather than engagement with an actual one. Fourth, the cross-sectional design precludes examination of how expectations evolve following LA exposure or institutional interventions. Fifth, the response scale was adapted from the original seven-point SELAQ to a five-point format, which may affect psychometric properties and prevents score-level comparisons with other SELAQ-based studies. Sixth, the minimal representation of non-binary respondents ( $n = 12$ ) precluded their inclusion in inferential gender analyses, representing both a methodological constraint and an equity gap. Seventh, differences in SELAQ responses across fields of knowledge were not submitted to rigorous effect size analysis in this study, limiting the interpretability of any field-level variation; this warrants dedicated follow-up investigation. Finally, and most importantly for the framing of this paper, the implications drawn for fairness, transparency, and validity in automated assessment are interpretive extensions of expectation data rather than direct measurements of those constructs. The SELAQ captures expectations of learning analytics services—that is, of learner-facing dashboards and institutional reporting—and not students' perceptions of any operational automated or AI-assisted grading system. These are related but distinct technologies: a dashboard informs a student about their learning, whereas an automated grading system issues an evaluative judgement about it, and students may well regard them differently. The present argument should therefore be read as generating testable propositions about the learner-side conditions of fair and transparent algorithmic assessment, to be examined directly in future research that pairs expectation measures with experience of deployed grading systems.

## 6 Conclusions

This study contributes to the growing literature on student expectations of learning analytics by identifying and theorizing a *self-regulatory paradox*: students who are broadly supportive of LA implementation nonetheless conceptualize it primarily as a teacher-mediated tool, and express comparatively limited expectations regarding its use to inform their own academic decisions. This asymmetry reflects deeper dynamics regarding student agency, data literacy, and the institutional scripts within which students have learned to navigate their academic environments.

Three substantive conclusions follow. First, student-directed LA engagement cannot be assumed or simply designed into a dashboard. It requires deliberate pedagogical investment in data

literacy, interpretive scaffolding, and the progressive transfer of evaluative authority to students—aligned with the sustainable feedback and feedback literacy frameworks that underpin SRL pedagogy (Carless, 2020; Carless and Boud, 2018). Given evidence that even AI-assisted systems may reinforce dependency rather than foster autonomy (Darvishi et al., 2024), the design of LA services must actively create the conditions that make student agency possible, not merely technically available.

Second, LA implementation in face-to-face universities must navigate the paradox strategically. Early phases may reasonably leverage teacher-mediated LA uses to build trust and demonstrate value, while progressively expanding students' roles as data interpreters and active agents. Long-term institutional commitment and pedagogical coordination beyond the single-course format are essential for this developmental progression to occur.

Third, the gender differences observed—small in magnitude but consistent in direction, with female students reporting higher institutional-support expectations across all items—underscore the importance of designing LA services that are responsive to diverse student orientations. A monolithic model of the self-directed data user risks underserving significant portions of the student population.

The self-regulatory paradox documented here is not a reason to abandon the aspiration of student-centered LA. It is an empirical specification of what that aspiration actually requires. Understanding that students tend to delegate data-informed agency to their institutions is the necessary starting point for designing the systems, pedagogies, and institutional policies that can, over time, return that agency to students—building, rather than assuming, the conditions for genuine self-direction in the datafied university. The same condition applies as these systems become increasingly automated and AI-mediated: the fairness and transparency of algorithmic assessment will not be secured by technical design and institutional safeguards alone, but by whether learners come to recognize themselves as legitimate interpreters of, and agents within, the systems that evaluate them.

## Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

## Ethics statement

The studies involving humans were approved by UB bioethical committee approval ref. IRB00003099. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

## Author contributions

LLM: Methodology, Writing – review & editing, Software, Investigation, Writing – original draft, Supervision, Visualization, Resources, Conceptualization, Validation, Formal analysis, Data curation. CLS: Writing – original draft, Visualization, Software, Resources, Conceptualization, Methodology, Writing – review & editing, Investigation, Validation, Supervision.

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## Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Generative AI statement

The author(s) declared that generative AI was used in the creation of this manuscript. The authors verify and take full responsibility for the use of generative AI in the preparation of this manuscript. Generative AI was used to assist with language editing and to improve the clarity, structure, and flow of the text; to support the reframing of the manuscript's argument for the target Research Topic. All AI-assisted outputs were independently verified and validated by the authors, who take full responsibility for the content of the manuscript.

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