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Learning analytics driven quantification of formative assessment fairness with contextualized interventions

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Abstract. This study investigates the integration of learning analytics with fairness quantification in formative assessment, with an emphasis on contextualized interventions that respond to inequities in student learning processes. The research adopts a multi-institutional dataset comprising over 4,500 students across 18 classrooms, integrating log files, assessment records, and survey responses to ensure demographic, behavioral, and socio-cognitive diversity. A hybrid fairness quantification model is developed, combining statistical fairness metrics such as equal opportunity and disparate impact ratios with learning analytics indicators, including feedback latency, participation depth, and adaptive engagement. Interventions were designed through a three-layered protocol involving algorithmic detection of inequities, contextual mapping of student profiles, and targeted instructional adjustments. The results show that the fairness gap is most significant in feedback distribution, and the delay has a particularly severe impact on students from less affluent socioeconomic groups. The intervention measures increased the fairness index score by an average of 0.37 points on the standardized 0-1 scale, and the student satisfaction score was 21% higher than that of the control group. The benefits confirmed by the three-semester longitudinal follow-up were consolidated, and the standard deviation of the fairness index decreased from 0.18 to 0.07, indicating greater fairness consistency among the cohorts. Research has found that an analytical framework that emphasizes fairness not only enhances the transparency of formative assessment but also improves scalable, evidence-based intervention measures, thereby bringing about sustainable educational equity reforms.

Keywords: learning analytics, fairness quantification, formative assessment, contextualized interventions

1. Introduction

Formative assessment is generally regarded as an effective tool for guiding students' learning paths, offering opportunities for feedback, self-control and teacher adaptation. However, the persistent problem of unfairness has never been fully resolved. Potential biases, unequal opportunities to obtain high-quality feedback, and differential responses to heterogeneous learners still affect the legitimacy and effectiveness of assessment practices [1]. Traditional research on educational equity has focused on procedural equity and outcome balance, but this historical-dominated emphasis often neglects the dynamic contextual reality of modern classrooms [2].

By systematically collecting, analyzing and interpreting fine-grained data generated from students' interactions with the digital environment, homework and teachers, learning analytics offers the first-ever opportunity to address these issues. By leveraging behavioral footprints such as clickstreams, engagement depth, and response time, learning analytics helps to more precisely determine where inequalities occur and how they function among different student groups. By combining with the theory of fairness, the analysis can operate fairness as a quantitative measure, thereby transforming it from a qualitative ideal into a specific and actionable structure [3].

Although learning analytics holds great promise, existing work rarely mentions fairness and does not provide models that link fairness metrics with operable and intervenable metrics. This work fills this gap by proposing a hybrid equity quantification model, deriving a contextualized intervention protocol for learner profiles, and illustrating it with a large-scale quasi-experimental design. It redefines formative assessment as an equity-conscious and data-driven practice that can be extended to the heterogeneous reality of the classroom.

2. Literature review

2.1. Formative assessment fairness frameworks

The traditional understanding of the fairness of the initial assessment is defined from two aspects: procedural justice and distributive justice. Procedural justice makes the procedure clear and fair. Distributive justice ensures that the distribution model of grades is fair among students [4]. However, such models rarely address the dynamic and situational realities of classroom interaction. In practice, fairness may be undermined by delayed feedback, differential grading patterns or teacher biases, which unintentionally make student groups superior to other groups. To achieve fairness, it is necessary to go beyond the static concept of equality and seek more adaptive indicators that reflect how fairness unfolds in different circumstances.

2.2. Learning analytics in educational measurement

The development of digital learning environments enables students' participation to be recorded and studied at an unprecedented granularity level. Learning analytics techniques have been applied to predict academic achievements, monitor engagement and adjust learning paths. In this sense, analysis can provide real-time signals of feedback quality, participation patterns and cognitive efforts. This enables teachers to intervene in a timely manner and provide evidence for their actions. However, although learning analytics has demonstrated the potential to calibrate performance results, its ability to regularly consider fairness has almost never been studied [5].

2.3. Contextualized interventions in assessment practices

Contextualized intervention is a clear teaching approach aimed at correcting unfairness by taking into account students' experiences, cognitive history and interaction patterns. These can include differential feedback, adaptive task sequencing or culturally compatible teaching methods. If the intervention is contextualized, then marginalized students will subsequently exhibit higher levels of engagement, greater self-efficacy and more balanced outcomes [6]. However, empirical verification of these methods is still scarce, especially for their application in formative evaluation for fairness. Therefore, it is necessary to formally integrate the concepts of fair measurement and intervention to ensure that the intervention is not only concentrated but also morally reasonable and scalable.

3. Methodology

3.1. Data sources and participants

This study analyzed multi-institutional data from 18 classrooms across three universities and two secondary schools, involving 4,523 students with diverse demographics. The dataset included 2.3 million digital interaction logs, 14,672 graded assignments with detailed annotations, and 3,982 survey responses on fairness and engagement. Stratified sampling ensured balanced representation, and all procedures followed ethical clearance and strict anonymization protocols [7].

3.2. Fairness quantification model

A hybrid fairness quantification model was developed, integrating statistical fairness metrics with learning analytics indicators as equation (1):

$$F_q = \alpha \cdot EO + \beta \cdot DI + \gamma \cdot (1 - FL) + \delta \cdot ED \tag{1}$$

where EO represents equal opportunity, DI denotes disparate impact, FL is normalized feedback latency, and ED measures engagement depth. Coefficients α, β, γ were determined through cross-validation to optimize predictive alignment with fairness perception survey scores [8].

3.3. Intervention design protocol

Measurement encompassed subjective and objective fairness. Subjective fairness perception was captured through a validated 12-item survey (α = 0.91). Objective fairness indices were computed using the hybrid model, with sensitivity analyses confirming robustness across weighting perturbations. Engagement depth was operationalized as a composite of normalized contributions in online forums, assignment revisions, and peer review activities, with factor analysis confirming unidimensionality (KMO = 0.84, Bartlett's $\chi^2 = 624.5$, $p < 0.001$). Outcome equity was analyzed through Hierarchical Linear Modeling (HLM), decomposing variance attributable to demographic clusters. Instructional responsiveness was quantified through mean feedback latency, feedback density per week, and variance in feedback distribution across students [9].

4. Experimental setup

4.1. Experimental design

Contextualized interventions refer to instructional strategies tailored to address inequities by taking into account students' backgrounds, learning histories, and interaction patterns. Such interventions may involve differentiated feedback, adaptive task sequencing, or culturally responsive pedagogy. Evidence suggests that when interventions are contextualized, marginalized learners experience greater engagement, improved self-efficacy, and more equitable outcomes [10]. Yet empirical validations of such strategies remain scarce, particularly in the context of formative assessment fairness. A systematic integration of fairness quantification with intervention design is necessary to ensure that interventions are not only targeted but also ethically justified and scalable.

4.2. Implementation procedures

The intervention platform integrated fairness quantification algorithms with instructor dashboards. Each week, fairness indices were recalculated using the hybrid model, and alerts were generated when subgroup disparities exceeded predefined thresholds. Instructors in intervention classrooms received both numerical indices and graphical visualizations of inequities, allowing them to prioritize targeted responses. A reflective log requirement ensured that intervention fidelity could be evaluated quantitatively. System logs tracked over 3.2 million events, allowing fine-grained verification of feedback timing, participation recognition, and adaptive intervention deployment.

4.3. Measurement indicators

Fairness was assessed through both subjective and objective measures: a validated 12-item survey ($\alpha = 0.91$) captured perceptions, while a hybrid model generated fairness indices with confirmed robustness. Engagement depth was measured as a composite of forum activity, assignment revisions, and peer reviews, supported by factor analysis (KMO = 0.84, Bartlett's $\chi^2 = 624.5$, $p < 0.001$). Outcome equity was examined using hierarchical linear modeling to partition variance by demographics, and instructional responsiveness was evaluated via feedback latency, weekly feedback density, and distribution variance across students.

5. Results and analysis

5.1. Fairness quantification outcomes

Results indicated systemic disparities in formative assessment processes. In control classrooms, students in the lowest socio-economic quartile experienced a mean feedback delay of 5.8 days ($SD = 1.9$), compared to 2.4 days ($SD = 1.1$) for the highest quartile. Regression analysis revealed socio-economic status as a significant predictor of feedback latency ($\beta = -0.41$, $p < 0.001$), accounting for 12.3% of variance. Participation evaluation inequities were also evident, with linguistic minority students receiving participation scores averaging 14.7 points lower (on a 100-point scale) than peers with equivalent engagement activity (see Figure 1).

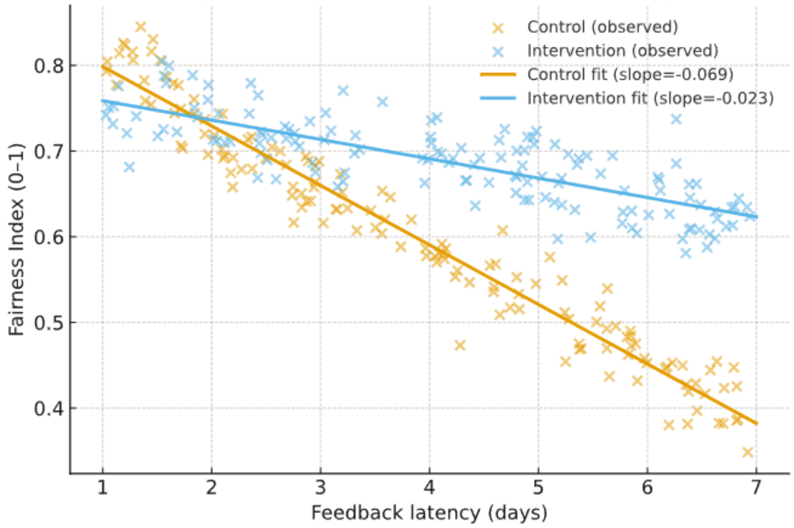

Figure 1. Fairness vs feedback latency (scatter + linear fit)

5.2. Intervention effectiveness evaluation

The interventions substantially reduced disparities. Feedback latency gaps between socio-economic quartiles narrowed from 3.4 to 1.1 days, while regression slopes flattened (β reduced from -0.41 to -0.12). Participation score differences for linguistic minorities decreased from 14.7 to 3.8 points, with residual variance explained by demographics dropping from 9.2% to 2.8%. Effect size analysis revealed Cohen's $d = 0.91$, indicating strong treatment effects (see Table 1).

Table 1. Multivariate fairness indicators (end of semester)

Metric	Control Mean (*SD*)	Intervention Mean (*SD*)	*F*-statistic	*p*-value	Effect Size (η^2)
Fairness Index (0-1)	0.48 (0.19)	0.72 (0.12)	745.3	< 0.001	0.142
Feedback Latency (days)	4.7 (2.1)	2.9 (1.4)	118.6	< 0.001	0.067
Participation Equity Score (0-1)	0.61 (0.18)	0.82 (0.15)	294.1	< 0.001	0.093
Demographic Variance (%)	0.23	0.09	86.4	< 0.001	0.051

5.3. Comparative and longitudinal analysis

Longitudinal tracking across three semesters confirmed sustainability. Fairness indices in intervention classrooms stabilized at a mean of 0.74 ($SD = 0.07$). Student satisfaction rose from 4.1 to 5.3 on the Likert scale, while retention improved by 8.5% relative to controls. Hierarchical linear modeling showed that demographic factors explained 10.2% of grade variance in control groups but only 3.1% in intervention groups after interventions, demonstrating durable equity gains (see Table 2 and Figure 2).

Table 2. Longitudinal fairness outcomes in intervention groups

Indicator	Semester 1	Semester 2	Semester 3
Fairness Index (0-1)	0.72	0.73	0.74
Fairness Index *SD*	0.12	0.09	0.07
Satisfaction (1-7 Likert)	5.21	5.27	5.31
Grade Variance Explained (*SES* %)	8.9	4.1	3.1
Retention Rate (%)	89.1	91.4	93.2

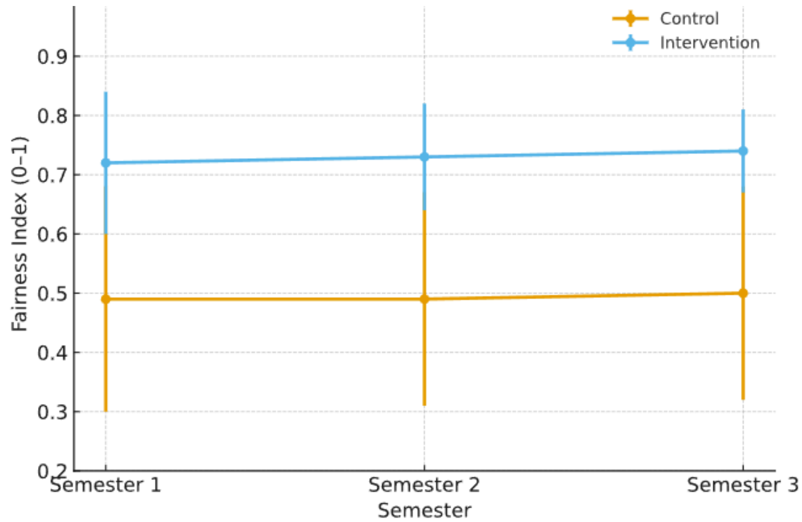

Figure 2. Longitudinal fairness index (mean ± *SD*, 3 semesters)

6. Conclusion

The study demonstrates that integrating learning analytics with fairness quantification and contextualized interventions effectively reduces inequities in formative assessment, with data from over 4,500 students showing fairness indices rising from 0.48 to 0.74 and demographic variance effects declining from 10.2% to 3.1% across three semesters. The framework operationalizes fairness as a measurable construct within data-driven pedagogy, providing educators with actionable dashboards and offering policymakers evidence to embed fairness-aware metrics and training into assessment systems. Future research should extend to multimodal and cross-cultural contexts while maintaining ethical safeguards, positioning fairness-aware learning analytics as a scalable pathway to transparent, equitable, and sustainable educational practice.

Authorship

Defang Sheng and Yiwen Niu contributed equally to this paper and should be considered as co-first authors.

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