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The Future is Connection:

Collaboration, Creativity and Compassion in a Digital Society

Exploring AI-mediated justice and fairness in collaborative learning

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Generative artificial intelligence (GenAI) is increasingly entering educational practice, yet its implications for justice and fairness in group work remain underexplored. This exploratory qualitative study examines 28 anonymous written responses collected from a Blended Intensive Programme (BIP) on AI pedagogy and well-being involving higher-education students from five European universities. Participants responded to an open-ended question about how AI affects justice or fairness in education and group work. Using inductive thematic analysis and multi-label coding, the study identified recurring concerns around access, learning support, group-work support, contribution visibility, bias, agency, transparency and assessment. The findings should be read as a pilot mapping of fairness-related perceptions within this specific educational context rather than as representative evidence. We synthesise these perceptions into six preliminary dimensions of AI-mediated collaborative justice: access, contribution, assessment, epistemic and linguistic, agency, and transparency justice. The framework provides a starting point for future research and for the design of fairer AI-supported collaborative learning.

Keywords: artificial intelligence, justice, fairness, group work, collaborative learning, higher education, AI-mediated justice

Introduction

Generative artificial intelligence (GenAI, later referred to as AI) is increasingly becoming part of students' everyday study practices. Much of the educational debate has focused on academic integrity, feedback, personalised support and responsible use (Kasneci et al., 2023). However, AI also raises a more specific problem for collaborative learning: How does it change the fairness of group work? Group work already involves familiar justice concerns, such as uneven contribution, social loafing, unequal recognition, conflict over effort and difficulty assessing individual learning. AI may introduce new conditions under which these concerns become more difficult to recognise or address, while also offering new forms of support for brainstorming, language, organisation and access to learning resources.

Justice and fairness within higher education group work have a long line of debate. Previous research has highlighted persistent tensions around social loafing, free riding, uneven workload, peer assessment, individual accountability, recognition of contribution and trust in group-based assessment (Davies, 2009; Hall & Buzwell, 2013; Karau & Williams, 1993). Much of this literature examines fairness problems arising from human participation, motivation, group processes and assessment practices. GenAI adds a new socio-technical layer by introducing a source of ideas, text, explanations and organisation into collaborative work, potentially changing how effort, authorship and contribution are produced and recognised (Lindsay, 2026). The specific justice implications of this shift for educational group work remain underexplored.

This paper takes a small exploratory dataset as a starting point for conceptualising AI-mediated justice in educational group work. The research question was: How do higher-education students with recent exposure to AI pedagogy and collaborative learning perceive the effects of AI on justice and fairness in education and group work? The study is intended as a pilot mapping of perceptions rather than a representative account of educational stakeholders. Its practical contribution is to identify fairness issues that lecturers, curriculum designers, teacher educators and policy makers may need to consider when designing online and face-to-face group activities, including permitted AI use, contribution visibility, individual accountability, equitable access and assessment.

Background: Justice, fairness and AI-mediated collaboration

Fairness in education can be understood through multiple justice dimensions. Distributive justice concerns the fairness of outcomes, rewards and benefits; procedural justice concerns the fairness of processes and rules; and interactional justice concerns the fairness of interpersonal treatment and communication (Adams, 1965; Colquitt, 2001). These distinctions are relevant to group work because students' perceptions of fairness depend not only on the final grade, but also on whether contributions are visible, rules are transparent, responsibilities are shared, and assessment procedures are trusted.

Collaborative learning research also emphasises positive interdependence, individual accountability and promotive interaction as conditions for productive cooperation (Johnson & Johnson, 2009).

GenAI complicates these conditions. Subscription-based tools raise questions of equal access, while differences in familiarity and prompting ability may further shape who benefits from AI support. In group work, AI can support ideation, explanation and coordination, but it may also obscure authorship, automate parts of contribution, privilege students with better access or prompting skills, and make authentic effort harder to judge. The term AI-mediated collaborative justice is used here to describe how AI may reshape the distribution of support, visibility, agency and responsibility in group learning.

Fairness in group work has long been complicated by social loafing, defined as the decrease of individual effort when responsibility is shared across a group (Karau & Williams, 1993). Contribution visibility is already an issue in learning, but with AI-supported group work, this problem may become harder to identify because AI can obscure who contributed what, how much effort was invested, and whether a final output reflects students' own thinking. AI-supported assessment also raises a related concern: recent evidence suggests that AI and human raters may show substantially different levels of agreement when evaluating complex university coursework (Zacharis & Papadakis, 2025).

Epistemic and linguistic justice provide an additional lens for these concerns. Fricker (2007) conceptualises epistemic injustice as unfair disadvantage in knowledge-related practices and recognition. In AI-supported collaboration, this lens draws attention to whose language, knowledge and ways of expressing ideas are more readily recognised, supported or taken up within group work, particularly where AI systems provide uneven language support.

Method

The study used an exploratory qualitative design. The Blended Intensive Programme (BIP) cohort comprised higher-education students from five European universities: University of Latvia, Riga, Latvia (two bachelor's, two master's, one PhD); Lucian Blaga University of Sibiu, Romania (nine master's); University of Valencia, Spain (five bachelor's); Ludovika University of Public Service, Budapest, Hungary (two bachelor's, two master's); and University of Jyväskylä, Finland (seven master's, two PhD). The analytic dataset consisted of 28 anonymous written responses. Participation was voluntary.

Data were collected anonymously at the start of a BIP lecture delivered by the first author, keeping research participation strictly separate from course assessment. In accordance with University of Jyväskylä research ethics guidelines, participants received advance research information and provided voluntary informed consent. No sensitive personal data were requested, and anonymized responses were stored securely on university servers.

The analysis used inductive thematic analysis as the overarching analytic approach (Braun & Clarke, 2006), with Saldaña (2021) informing the coding procedures. Initial coding was conducted by the first author, after which all authors collaboratively refined category boundaries until reaching full consensus. Because many responses contained more than one idea, multi-label coding was applied: one response could be assigned to several themes. Descriptive frequency counts were calculated to organise the results.

Findings

Table 1 summarises the nine coded categories. The analytic status of the categories is differentiated because they do not all function in the same way: seven are recurring empirical themes; "conditional fairness" is treated as a cross-cutting interpretive condition; and "fairer or more objective evaluation" is retained as a minority perception expressed by two respondents. Because responses could receive more than one code, the counts are not mutually exclusive and should be read as descriptive indicators of salience within this dataset.

Table 1
Themes in educational professionals' responses

Analytic status	Category	Count	Interpretation
Empirical theme	Access and unequal familiarity	7 (25.0%)	AI may widen gaps linked to tool access, paid versions, language and prior familiarity.
Empirical theme	Learning support and personalisation	7 (25.0%)	AI can support brainstorming, information access, task organisation and personalised learning.
Cross-cutting condition	Conditional fairness	7 (25.0%)	Fairness may depend on prompts, design quality, teacher guidance and responsible implementation.
Empirical theme	Group work support	6 (21.4%)	AI may help groups coordinate, understand one another and manage participation.

Analytic status	Category	Count	Interpretation
Empirical theme	Academic integrity and contribution visibility	6 (21.4%)	AI can hide unequal effort and make individual contribution harder to assess.
Empirical theme	Bias and discrimination	6 (21.4%)	Participants noted algorithmic, prompt and language bias.
Empirical theme	Overreliance and loss of agency	5 (17.9%)	AI may reduce thinking, creativity, personal voice and student independence.
Empirical theme	Transparency and disclosure	3 (10.7%)	Students should explain how they used AI and under what rules.
Minority perception	Fairer or more objective evaluation	2 (7.1%)	A minority viewed AI as reducing face-value judgement or human bias.

The themes were grounded in participants' open-ended responses. Table 2 provides example quotations illustrating the main categories identified in the analysis.

Table 2
Example participant quotations by theme

Theme	Example quotation
Learning support and personalisation	"personalised learning, helping generate ideas and organising tasks" (R21)
Group work support	"It can help with brainstorming and can help inspire the group to think out of the box" (R19)
Assessment fairness and contribution visibility	"teachers cannot check who used AI and to which extent" (R4)
Unequal effort	"a student who does everything with AI doesn't put in the same effort as one who does it on their own" (R7)
Access inequality	"There is a significant distinction between paid and free versions" (R25)
Bias and fairness risk	"equaliser and potential source of bias" (R5)
Language inequality	"AI is more fluent in certain languages than other" (R12)
Overreliance and loss of agency	"It stops students to think" (R20)
Transparency and disclosure	"Everyone should mention how they use AI" (R17)

The findings show a strong ambivalence. AI was sometimes described as an equaliser, particularly when it provides cheaper access to materials, personal assistance, brainstorming support or help in organising group activity. At the same time, participants repeatedly noted that these benefits are unevenly distributed. Access to paid tools, familiarity with prompting and language differences were seen as potential sources of unfair advantage.

Concerns about assessment and contribution visibility centred on teachers' difficulty in knowing who used AI and to what extent, while other responses raised concerns about students being evaluated through AI-supported products rather than their own thinking. Participants voiced that, in group work, these concerns may become sharper because AI can make it even harder to distinguish between individual effort, group contribution and machine-generated assistance. A further set of responses concerned agency and creativity, with AI described as potentially reducing independent thinking, personal voice and judgement.

Discussion: Towards AI-mediated collaborative justice

The analysis suggests that participants did not perceive AI as inherently fair or unfair. Rather, their responses point to ways in which AI may change the conditions through which fairness is produced and judged. GenAI adds a new layer to these concerns by introducing a new source of ideas, language, organisation and assessment support into collaborative work.

Participants perceived potential access injustice when students with better tools, paid subscriptions, language support or prompting skills could gain more benefit from the same task. They also described potential contribution injustice when AI supports participation but makes individual effort less visible. Assessment justice is similarly implicated because teachers may find it harder to evaluate competence, originality and individual learning when group products include visible or hidden AI assistance. These concerns extend established questions about individual accountability in cooperative learning (Johnson & Johnson, 2009) and about recognition of effort in assessed group work (Davies, 2009). Recent evidence also suggests that AI-based assessment should not simply be assumed to be interchangeable with human judgement: Zacharis and Papadakis (2025) found substantially weaker agreement between an AI rater and human raters than between the two human raters in university coursework assessment.

Participants also pointed to potential epistemic and linguistic injustice. Concerns about language bias and AI-generated answers

suggest that some students' knowledge, language practices and forms of expression may be better supported or more easily legitimised than others. This connects to algorithmic fairness in education: bias and discrimination can enter systems through

measurement, model learning and action (Kizilcec & Lee, 2020), while large language model bias can emerge across the model life cycle (Lee et al., 2024). Fricker's (2007) account of epistemic injustice provides an additional theoretical lens by drawing attention to unfair disadvantage in knowledge practices and recognition. In AI-supported group work, this raises questions about whose language, knowledge and contributions are most readily recognised as legitimate.

Participants' responses also suggest potential agency-related tensions. Some described AI as a support for brainstorming, organisation and personalised learning, while others worried that it may reduce creativity, personal voice or independent thinking. This reflects Sharples' (2023) view of GenAI in education as a social process of interaction and meaning-making rather than a neutral prompt-response tool. In collaborative learning, AI may therefore act as a socio-technical mediator that shapes how ideas are generated, how responsibility is distributed and how learners understand their role in the group.

The six dimensions in Table 3 represent a second-order conceptual synthesis of the coded responses, rather than six directly observed themes. Building on the findings and established justice perspectives, access justice is linked primarily to distributive justice; contribution and assessment justice combine distributive and procedural concerns; transparency justice is primarily procedural; and epistemic and linguistic justice extend the framework through Fricker's (2007) account of epistemic injustice. Agency justice captures whether learners retain meaningful voice, responsibility and control within collaborative activity. Taken together, these dimensions suggest that responsible AI use in collaborative learning requires more than general academic integrity rules: it requires attention to access, visibility, accountability, recognition, agency and transparent shared responsibility. Table 3 summarises this preliminary synthesis.

Table 3
Preliminary dimensions of AI-mediated collaborative justice

AI-mediated justice dimension	Theoretical grounding	Core question in AI-supported group work	Example from findings
Access justice	Distributive justice	Who has access to useful AI support?	Paid/free access, familiarity, language
Contribution justice	Distributive + procedural justice	Can individual effort still be recognised?	Hidden AI use, unclear contribution
Assessment justice	Procedural + distributive justice	Can learning and effort be fairly evaluated?	AI-supported outputs
Epistemic and linguistic justice	Epistemic justice (Fricker, 2007)	Whose knowledge and language are privileged?	Uneven language support
Agency justice	Agency, voice and responsibility	Does AI support or replace student thinking?	Dependence, reduced creativity, personal voice
Transparency justice	Procedural justice	Is AI use visible and discussable?	Disclosure of AI use

Implications for practice and research

Several implications arise directly from participant concerns about access, contribution visibility, assessment and transparency, while the more specific design proposals below are broader recommendations derived from the authors' synthesis of these concerns with the literature. For practice, teachers should establish AI-use agreements that specify permitted forms of AI assistance, and groups should use disclosure routines in which students briefly explain how AI contributed to their process or final output. Assessment can incorporate process evidence, such as contribution logs, drafts, oral checkpoints or individual reflections, to make individual learning more visible. Teachers should also plan for equitable access by avoiding tasks where paid AI tools, advanced prompting skills or unequal digital access create unfair advantage. Finally, collaborative learning should include critical AI literacy activities in which students discuss bias, overreliance, authorship, language limitations and the difference between support and substitution.

For research, the findings support a focused agenda on AI-mediated collaborative justice. Future studies should observe real student groups using AI, compare transparent and hidden AI-use conditions, and examine how AI affects participation, voice, contribution visibility, trust, accountability and perceived fairness. Larger studies could develop and validate measures of perceived AI fairness in group work, while qualitative studies could investigate how students and teachers negotiate responsibility when AI becomes part of collaborative learning.

Limitations and conclusion

This study explored how higher-education students with recent exposure to AI pedagogy and collaborative learning perceive the potential justice and fairness implications of AI in education and group work. Drawing on 28 anonymous written responses collected in a BIP involving students from five European universities, the analysis used inductive thematic coding and multi-label

categorisation to identify recurring fairness-related concerns. These were synthesised into preliminary dimensions of AI-mediated collaborative justice: access, contribution, assessment, epistemic and linguistic, agency, and transparency justice. The framework is intended as a starting point for future empirical work rather than as a generalisable account of AI's effects on collaborative learning.

This study has several limitations. The analytic dataset is small and exploratory, and the responses were short reflections rather than extended interviews or observations of actual group work. The frequency counts indicate salience within this dataset, not prevalence or strength of belief in a wider population. The authors came to consensus on a coding approach; however, no independent multi-coder reliability procedure was conducted. In addition, the study did not observe actual AI use or compare different AI-use conditions. The findings should therefore be understood as a preliminary perception-based conceptualisation. Future work could involve richer qualitative data, classroom observations, student and teacher interviews, and analysis of actual AI-use traces during collaborative tasks.

Nevertheless, the study highlights a timely problem: AI fairness in education is not only an individual or technical issue, but a collaborative and socio-technical one. If AI is becoming part of group work, then fairness must be redesigned around access, visibility, accountability, agency and transparent shared responsibility. The central challenge is therefore not simply whether students should be allowed to use AI in group work, but how collaborative learning can be designed so that AI use remains visible, accountable, equitable and educationally meaningful.

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