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The Future is Connection:

Collaboration, Creativity and Compassion in a Digital Society

When GenAI enters the assessment relationship: Public expectations of transparency, judgement and responsibility

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Human-centred learning design requires more than using generative artificial intelligence (GenAI) to make assessment feedback faster, more accessible or scalable. It requires attention to whether human judgement, relationships and responsibility remain visible when feedback is produced. The public is a key stakeholder in these decisions because university qualifications operate as public credentials whose legitimacy depends on confidence in how achievement is judged and certified. Yet debate has largely focused on students' use of GenAI, with less attention given to public expectations of academic practice when GenAI contributes to feedback. This exploratory study surveyed 299 participants, most of whom had current or previous experience of higher education, to examine the implied obligations underpinning university assessment and feedback. Participants strongly endorsed feedback as an expected component of university teaching and generally supported disclosure of GenAI use, meaningful academic involvement and visible instructor responsibility. Exploratory factor analysis identified two provisional dimensions: AI feedback transparency and legitimacy, and assessment expectations and feedback value, although the second demonstrated only modest internal consistency. Interpreted through psychological contract theory, the findings suggest that human-centred GenAI implementation depends not only on feedback quality or efficiency but also on preserving visible academic judgement, accountability and educational purpose. The central design distinction is therefore between GenAI that supports academic practice and GenAI that substitutes for meaningful academic engagement.

Keywords: Generative artificial intelligence, assessment, feedback, psychological contract, higher education, survey research.

Introduction

Assessment and feedback have traditionally been organised around a student-teacher dyad: the student completes a task, while the teacher evaluates the work and provides feedback. The integration of generative artificial intelligence (GenAI) into higher education is transforming this relationship into a triad. Students can use GenAI to review drafts, interpret criteria, suggest improvements or generate feedback before submission, while academics may use it to draft, refine or organise feedback, particularly in large cohorts. Academic use is often justified in terms of efficiency, including the capacity to produce feedback more quickly, improve its accessibility and deliver it at scale.

Efficiency, however, may not be the feature that those involved in assessment value most. Recent research suggests that students value GenAI feedback for its accessibility, timeliness and volume while continuing to regard teacher feedback as more trustworthy and more closely grounded in contextual and disciplinary expertise (Henderson et al., 2025). This distinction matters because feedback is not simply an output transmitted after assessment. It is a relational and potentially transformative process designed to support students' engagement and improvement (Winstone et al., 2022). The quality of the student-teacher relationship consequently shapes how feedback is interpreted and used (Dai et al., 2025).

This paper examines GenAI-supported feedback through the lens of the psychological contract of assessment. Psychological contract theory draws attention to the implicit expectations and perceived obligations through which people interpret exchange relationships (Rousseau, 1989, 1995). In assessment feedback, these concern what students should contribute, what academics should remain responsible for and what universities should communicate. By introducing another agent into feedback production, GenAI may alter expectations relating to expertise, care, judgement, transparency and accountability.

Although debate has concentrated on students' use of GenAI, academic integrity and detection, less attention has been given to expectations of academic practice when GenAI is used to produce feedback. This paper addresses that gap through a survey of 299 participants, most of whom had current or previous experience of higher education but did not work in education. Extending the investigation beyond students and academics is important because university qualifications are public credentials whose legitimacy also depends on the confidence of employers, professional bodies, governments and the wider community. Examining public expectations can therefore identify how much academic involvement, oversight and transparency are considered necessary when GenAI is used in feedback.

The paper addresses the following research question: How does the general public perceive the implicit expectations and obligations underpinning university assessment and feedback in the context of GenAI? The study's primary contribution is the identification of two provisional dimensions through which participants' expectations may be understood: AI feedback transparency and legitimacy, and assessment expectations and feedback value. These exploratory dimensions provide an initial framework for examining how stakeholders evaluate GenAI-supported feedback, although they are not presented as validated constructs. We argue that the central ethical distinction is not between AI use and non-use but between support and substitution. GenAI-supported feedback is more likely to be accepted when it assists academic practice and more likely to compromise trust when it appears to replace meaningful academic engagement, judgement and oversight.

Literature review

Assessment feedback, expectations and trust

Feedback is a process through which learners make sense of information about their performance and use it to progress towards intended learning goals (Hattie & Timperley, 2007). Although feedback can substantially influence learning, its effectiveness varies according to its content, timing and source, as well as students' opportunities and capacity to interpret and act on it.

Feedback is both relational and dialogic. Students may interpret it not only as information about their work but also as evidence that an academic has understood that work, exercised appropriate judgement and taken an interest in their learning (Carless & Boud, 2018; Esterhazy & Damşa, 2019). Productive engagement requires students to interpret feedback, assess its relevance, manage its affective effects and apply it to current or subsequent work. It also requires opportunities to clarify meanings and develop shared understandings of quality. Students' capacity to participate in this process is commonly described as feedback literacy (Carless & Boud, 2018).

Trust underpins this engagement. Mayer et al. (1995) identify ability, benevolence and integrity as dimensions of perceived trustworthiness. In assessment feedback, these correspond to the academic's perceived expertise, commitment to supporting learning and adherence to principles such as honesty, fairness and accountability. Students may therefore be less inclined to question, discuss or act on feedback when they are uncertain about who produced it, whether their work was meaningfully considered or whether the comments reflect informed academic judgement.

Psychological contract theory provides a framework for understanding why these expectations matter. Psychological contracts comprise individual beliefs about reciprocal obligations within an exchange relationship (Rousseau, 1989, 1995). Students may expect academics to engage meaningfully with their work, exercise expertise, apply standards fairly and remain accountable for the feedback communicated. In return, students may be expected to engage with feedback and take responsibility for improvement. These

expectations may involve multiple exchange partners: students can perceive distinct psychological contracts with instructors, advisers, colleges and the university more broadly (Knapp & Masterson, 2018). Responsibility may therefore be institutionally distributed but experienced personally; feedback delivered through an institutional platform and governed by university policy may still be interpreted as the act of an individual academic.

GenAI complicates these expectations by making the source and distribution of responsibility less visible. It may be unclear who has read the work, interpreted the criteria, generated particular comments and authorised the final feedback. GenAI use does not necessarily breach the psychological contract, but it may change expectations relating to effort, expertise, care, authorship and accountability. Disclosure can help students understand how feedback was produced and where responsibility resides, but transparency alone cannot establish that meaningful academic judgement has occurred. The significance of GenAI use may therefore depend on whether it supports academic engagement or substitutes for it.

Public expectations and human-centred learning design

Psychological contract theory also recognises implied contracts: third-party interpretations of the obligations governing an exchange relationship (Rousseau, 1995). Members of the public may therefore hold expectations about the responsibilities of academics and universities, including who should exercise judgement and remain accountable when GenAI contributes to feedback. These expectations connect the psychological contract of assessment with higher education's wider social contract.

Within this social contract, institutional autonomy and public support are accompanied by accountability to students and society. The public purposes of higher education are not determined by universities alone but negotiated among institutions, governments and other stakeholders (Hazelkorn & Gibson, 2019). Qualifications form part of this contract because they communicate institutionally authorised claims that achievement has been evaluated against recognised standards. Such standards are not exclusively technical; their legitimacy also depends on stakeholder understandings and public confidence in how achievement is judged and certified (Baird et al., 2024).

This places the use of GenAI within the remit of human-centred learning design. A human-centred approach asks not only whether GenAI makes feedback faster or more scalable, but whether its use preserves the human agency, relationships and responsibility central to learning and assessment. If GenAI makes it unclear who interpreted students' work, applied academic standards or authorised feedback, it may weaken the visibility of academic responsibility. Public expectations of human involvement, transparency and accountability are therefore relevant to determining when GenAI supports human-centred feedback and when it begins to substitute for the academic engagement on which trust depends.

Method

This cross-sectional exploratory study used an online questionnaire survey to examine public expectations of instructor and student responsibilities in university assessment and feedback, including expectations concerning GenAI use.

Participants and recruitment

Participants were recruited through Prolific, an online paid participant pool for research. Pre-screening criteria were established requiring participants to be fluent in English and over the age of 18 years. Ethics approval was granted by La Trobe University Human Research Ethics Committee (HEC2546). Participation was voluntary, and participants provided informed consent before completing the survey.

Of the 303 responses screened for completion time and response patterns, 299 were retained for analysis. Item-level response numbers varied slightly because of minimal missing data (< 0.25%). The sample was highly educated, with 76% (n = 226) having attained a bachelor's or postgraduate degree. Almost half were aged 25–34 years (49.7%, n = 148). The next two largest age groups were 18–24 years (17.8%, n = 53) and 35–44 years

(17.1%, *n* = 51). Twenty per cent were currently studying at university, while 9.1% (*n* = 27) had never studied at university. Given this composition, findings should be interpreted as reflecting a highly educated and largely university-experienced public sample.

Survey instrument

The questionnaire was developed specifically for this study and comprised 39 substantive items: 35 Likert-type items and four forced-choice items. These were supplemented by demographic questions. Items were informed by psychological contract theory, assessment feedback literature and current debates concerning GenAI in assessment. They addressed reciprocal responsibilities, trust, transparency, effort and changing expectations in the context of GenAI (see Table 1 for sample items).

The Likert-type items used a five-point response scale ranging from "strongly disagree" to "strongly agree." The four forced-choice items required participants to prioritise between competing features of assessment or feedback. Definitions were provided to promote a common interpretation of key terms. Assessment was defined as "graded work used to evaluate learning;" instructor as a "university teacher responsible for teaching and evaluating students;" and AI tools as "technologies such as ChatGPT, Claude and Copilot that can produce text, ideas or feedback."

The items were purpose-designed to elicit expectations rather than to create a validated psychometric instrument. The factor and composite analyses should therefore be understood as exploratory.

Table 1
Definitions and example questionnaire items for the psychological contract elements in higher education assessment

Psychological contract element	**Definition within assessment and feedback**	**Example survey item(s)**
Reciprocity	Shared expectations that both educator and student actively contribute to the learning partnership, with each fulfilling complementary responsibilities in assessment, feedback and learning	In universities, providing feedback on student work is a normal and expected part of teaching
Effort	The visible investment of professional judgement, care, expertise, and engagement by the educator, signalling commitment to supporting student learning	Students value feedback more when they think the instructor put effort into it
Trust and transparency	Perceptions that assessment and feedback demonstrate professional expertise, care for student learning, ethical and fair judgement, and openness about assessment processes, including the use of GenAI	If students discover that AI was used in feedback without disclosure, trust in the assessment process is likely to decrease
Value	The perceived educational worth of assessment and feedback, reflected in its usefulness, authenticity, relevance, and capacity to improve learning and strengthen the educator–student relationship	If feedback is generated primarily using tools or automated processes, students may question the value of what they receive

Data analysis

Data were analysed using SPSS version 31. Item-level descriptive statistics included valid n, median, interquartile range and percentage agreement. Agreement was defined as selecting *agree* or *strongly agree*. Forced-choice items were summarised using frequencies and valid percentages.

Exploratory subgroup analyses examined whether response patterns differed across selected participant characteristics. Mann–Whitney U tests compared participants who did and did not currently work in education and those with and without university experience. Kruskal–Wallis tests were used for comparisons involving more than two higher education experience groups, and chi-square tests examined associations involving categorical forced-choice responses. These analyses were exploratory and were not intended to support predictive or population-level claims.

An exploratory factor analysis was conducted on 24 theoretically relevant Likert-type items concerning feedback expectations, GenAI use, disclosure, transparency, instructor effort and feedback value. Unweighted least squares extraction with direct oblimin rotation was used. Factor retention was informed by item loadings, internal consistency and conceptual coherence. Forced-choice items were excluded from the factor analysis and analysed separately. Internal consistency was examined using Cronbach's alpha for each retained dimension. Composite scores were calculated as the mean of the items assigned to each dimension and compared across forced-choice response groups using Mann–Whitney U tests. Results involving dimensions with modest internal consistency were interpreted cautiously.

Results

The results are presented in three sections: 1) descriptive patterns in expectations concerning feedback and GenAI, 2) exploratory dimensions identified through factor analysis, and 3) comparisons between these dimensions and forced-choice responses. Item-level sample sizes varied slightly due to missing responses.

Descriptive patterns of public expectations

Participants demonstrated strong consensus regarding several foundational expectations of assessment and feedback. Providing feedback was viewed as a normal and expected component of university teaching (*Mdn* = 5, *IQR* = 1), while participants also recognised that feedback practices necessarily vary across subjects and institutional contexts (*Mdn* = 5, *IQR* = 1). Consistent with the psychological contract perspective, participants further agreed that expectations of assessment and feedback are influenced by the financial investment students make in their education (*Mdn* = 5, *IQR* = 1).

Participants expressed consistently high expectations regarding transparency in the use of GenAI. Respondents generally agreed that AI-assisted feedback should be disclosed, that undisclosed AI use would reduce perceptions of transparency and trust, and that students are likely to adjust their expectations of feedback when AI involvement is made explicit (*Mdn* = 4 for all items). Participants likewise agreed that when feedback processes are unclear, students are likely to form their own assumptions about how feedback has been produced, and that the acceptability of AI-assisted feedback depends, in part, on transparent disclosure.

A similar pattern emerged for items relating to educator effort and the educational value of feedback. Participants agreed that perceptions of instructor effort influence the value attributed to feedback, that generic or minimal feedback is less likely to promote student engagement, and that students expect an appropriate level of individual attention in feedback, particularly given the financial cost of higher education (*Mdn* = 4 for all items). Respondents also agreed that the perceived use of AI may alter students' judgements about the effort invested by instructors when providing feedback.

In contrast, two items attracted more neutral responses. Participants were less certain that AI-generated feedback remains useful when it is not tailored to the individual student (*Mdn* = 3, *IQR* = 2) and were similarly divided regarding whether AI use by instructors should be viewed differently from AI use by students (*Mdn* = 3, *IQR* = 2). These findings suggest greater uncertainty surrounding the educational value of AI-generated feedback and the reciprocal expectations governing AI use by students and educators.

These descriptive patterns suggested several potentially related expectations concerning AI disclosure, feedback legitimacy, instructor effort and feedback value. Exploratory factor analysis was therefore used to investigate whether broader dimensions could be identified across the items.

Exploratory factor analysis

Exploratory factor analysis using unweighted least squares extraction and direct oblimin rotation produced a two-factor solution comprising 18 retained items. Seventeen items loaded primarily on one factor, while VAL2 cross-loaded substantially on both factors. VAL2 was retained in the factor solution but excluded from the internal consistency analyses and composite scores. The two factors accounted for 26.0% of the total variance: 17.7% for Factor 1 and 8.3% for Factor 2. Following item reduction, the final 18-item analysis demonstrated acceptable sampling adequacy (KMO = .785), and Bartlett's test of sphericity was statistically significant, χ^2 (153) = 1031.40, $p < .001$. Factor 1 demonstrated acceptable internal consistency ($\alpha = .778$), whereas Factor 2 demonstrated modest internal consistency ($\alpha = .599$) and should be interpreted as a provisional exploratory dimension requiring further refinement and validation.

The two factors were interpreted as representing broad, exploratory dimensions of public expectations regarding the use of GenAI in assessment and feedback (see Table 2). The first dimension, *AI feedback transparency and legitimacy*, encompassed beliefs about disclosure, transparency, trust, instructor accountability, and the legitimacy of AI-assisted feedback. The second dimension, *assessment expectations and feedback value*, reflected broader expectations about assessment and feedback, including perceptions of educational investment, the value of feedback, and expectations of the educator–student relationship. Given the exploratory nature of the analysis, these dimensions were used as composite variables to examine patterns in participants' responses across demographic groups and key survey questions, providing a more pragmatic representation of public expectations than analyses of individual items alone.

Table 2
Items retained in the exploratory dimensions identified through exploratory factor analysis

Dimension	Item	Abbreviated item description	Pattern loading
Dimension 1. AI feedback transparency and legitimacy	TRU2	Undisclosed AI use reduces transparency of the assessment process	.687
	VAL3	Automated feedback may reduce the perceived value of feedback	.652
Cronbach's α = .778; 11 items	TRU1	AI-assisted feedback should be disclosed to students	.582
	EFF4	AI influences perceptions of instructor effort	.557
	TRU5	Undisclosed AI use reduces trust in the assessment process	.539
	EFF6	Students expect individual attention in feedback given the cost of their degree	.435
	TRU3	AI disclosure changes expectations of feedback personalisation	.429
	EFF5	Instructor effort increases the value of feedback	.409
	REC3	Instructor AI use is comparable to student AI use	.380

	TRU4	Unclear feedback processes lead students to make assumptions	.364
	EFF3	Minimal or generic feedback reduces engagement	.343
Dimension 2. Assessment expectations and feedback value *Cronbach's α = .599; 6 items*	VAL6	Expectations differ according to learning or service orientation	.645
	REC1	Expectations vary according to perceived effort	.455
	VAL4	Expectations are influenced by time and financial investment	.441
	VAL5	Assessment is judged by outcomes rather than processes	.389
	TRU7	Students differ in expectations regarding AI disclosure	.386
	TRU6	Transparency influences the acceptability of AI feedback	.359
Cross-loading item	VAL2	AI-generated feedback can be useful even if not fully personalised	−.457 / .371

Note. EFF = effort; REC = reciprocity; TRU = trust and transparency; VAL = value. VAL2 was retained in the factor solution but excluded from the internal consistency analyses and composite scores.

Exploratory subgroup comparisons

Dimension 1 (AI feedback transparency and legitimacy)

Exploratory subgroup analyses indicated that responses on the AI feedback transparency and legitimacy dimension were broadly consistent across participant characteristics. Participants with university experience (n = 269) did not differ significantly from those without university experience (n = 27), U = 3438.50, z = −0.46, p = .648. Similarly, participants working in education (n = 87) did not differ significantly from those not working in education (n = 211), U = 8129.50, z = −1.55, p = .120. These analyses therefore provided no evidence that scores on this dimension differed according to university experience or employment in education within this sample. However, the non-significant findings should not be interpreted as demonstrating equivalence between the groups.

Dimension 2 (Assessment expectations and feedback value)

Participants working in education scored significantly higher on the assessment expectations and feedback value dimension than those not working in education (U = 7516.0, z = −2.47, p = .013, r = .14), although the effect size was small. Given the small effect and the dimension's modest internal consistency, this difference should be treated as tentative rather than as evidence of a stable group difference. Participants with university experience did not differ significantly from those without university experience on the assessment expectations and feedback value dimension (U = 3264.0, z = −0.87, p = .383, r = .05). The subgroup analyses provided limited evidence that scores on the exploratory dimensions varied across the participant characteristics examined. Subsequent analyses therefore considered whether dimension scores were associated with participants' stated priorities in the forced-choice trade-offs concerning AI-assisted assessment and feedback.

Exploratory dimensions and assessment trade-offs

The four forced-choice items required participants to prioritise between competing features of AI-assisted assessment and feedback. These included rapid versus personalised feedback, disclosure of AI use versus feedback described as high quality, disclosed but general versus undisclosed but personalised AI-generated feedback, and the relative acceptability of instructor AI use for feedback versus assessment. Mann–Whitney U tests examined whether composite-score distributions differed between the two response groups for each item. These analyses compared participants' scores on the exploratory dimensions according to their stated preferences under hypothetical trade-offs.

The clearest differences were observed for AI feedback transparency and legitimacy (Dimension 1). Participants who prioritised personalised over rapid feedback scored significantly higher on this dimension (U = 2729.50, z = −3.32, p < .001, r =.19), although the effect was small. A larger difference was found between participants who prioritised knowing whether AI had been used and those who prioritised receiving feedback described as high quality (U = 6260.50, z = −6.43, p < .001, r = .37). The largest difference occurred for the trade-off between disclosed but more general AI-generated feedback and undisclosed but more personalised feedback. Participants who preferred disclosed feedback scored higher on Dimension 1 (U = 5039.50, z = −6.87, p < .001, r = .40).

Fewer differences were observed for assessment expectations and feedback value (Dimension 2). Scores did not differ significantly according to preferences for rapid versus personalised feedback (U = 3654.00, z = −1.32, p = .188) or disclosure of AI use versus feedback described as high quality (U = 9783.00, z = −1.68, p = .093). Participants who preferred disclosed but more general feedback scored significantly higher on Dimension 2 than those who preferred undisclosed but more personalised feedback (U = 8292.50, z = −2.23, p= .026, r = .13), although the effect was small. Given the modest internal consistency of Dimension 2 (α = .599), this result should be interpreted cautiously.

Neither dimension differed significantly according to whether participants considered instructor use of AI more acceptable for feedback or assessment: Dimension 1, U = 8225.00, z = −1.21, p = .228; Dimension 2, U = 8392.50, z = −0.96, p = .337. Thus, no statistically significant difference was detected for this particular forced-choice item.

Overall, Dimension 1 more consistently differentiated participants when trade-offs involved disclosure, trust and personalisation. Dimension 2 produced weaker and less consistent differences across the same comparisons. This pattern is consistent with the proposed interpretation of Dimension 1, but it does not validate either dimension or indicate how participants would respond in actual assessment contexts.

Discussion

This study explored how a cross-section of the general public perceived the implied psychological contract underpinning university assessment and feedback, with particular attention to the role of GenAI-assisted feedback. Public expectations were characterised by strong endorsement of transparency, disclosure and meaningful feedback, and exploratory factor analysis identified two related but distinct dimensions. Although these expectations were broadly consistent across participant groups, the dimensions differed in how they were associated with participants' responses to trade-offs involving AI-assisted feedback.

The analysis provisionally identified two dimensions that may represent complementary aspects of the implied psychological contract. The first dimension, AI feedback transparency and legitimacy, comprising items relating to trust, transparency, disclosure and accountability, can be interpreted as reflecting relational expectations concerning the educator–student relationship. The second dimension, assessment expectations and feedback value, can be interpreted as reflecting educational expectations regarding the quality, value and purpose of assessment and feedback. Although these dimensions emerged empirically through exploratory factor analysis, the forced-choice analyses demonstrated that they were associated differently with participants' evaluation of competing educational priorities. In particular, the relational dimension consistently differentiated participants when trade-offs involved transparency, disclosure and trust, whereas the

educational dimension demonstrated comparatively weaker and less consistent differences. The stronger pattern associated with Dimension 1 suggests that it may capture one way in which participants evaluated the acceptability of AI-assisted feedback. The interpretation of Dimension 2 is less certain because of its modest internal consistency and weaker pattern of associations.

Rather than replacing established obligations, GenAI appears to change how they are interpreted. Its involvement may make expectations of academic judgement, transparency and accountability more salient while making their fulfillment less readily visible. Consistent with Rousseau's (1989, 1995) conception of psychological contracts as beliefs about reciprocal obligations, participants continued to expect assessment feedback to embody academic judgement and responsibility when GenAI contributed to its production. Knapp and Masterson (2018) demonstrated that students perceive psychological contracts with multiple actors across higher education. The present study extends this analysis by examining an implied contract, i.e., third-party beliefs about the obligations governing assessment relationships. These public expectations intersect with the wider social contract through which universities are entrusted to maintain standards and certify achievement (Baird et al., 2024; Hazelkorn & Gibson, 2019).

This interpretation reinforces conceptualisations of feedback as a relational process rather than a transactional exchange (Carless & Boud, 2018; Esterhazy & Damşa, 2019; Winstone et al., 2022). Participants interpreted AI-assisted feedback as evidence of academic engagement with student work; disclosure and transparency were interpreted as indicators that the educator remained responsible for interpreting evidence of learning, exercising professional judgement and communicating evaluative decisions. This interpretation is consistent with Mayer et al.'s (1995) model of trust, in which perceptions of integrity, benevolence and ability underpin confidence in professional judgement.

Public expectations and the social contract of assessment

The implications extend beyond the immediate student–academic relationship. Hazelkorn and Gibson (2019) argue that the public purposes of higher education cannot be defined by universities alone; rather, they are negotiated among institutions, governments and other stakeholders. Public expectations of assessment practices are therefore not merely external opinions. They form part of the wider social contract through which universities are granted authority to judge achievement and award qualifications. Participants' endorsement of disclosure and visible academic responsibility indicates an expectation that human responsibility will remain substantive when GenAI contributes to feedback.

Baird et al.'s (2024) conceptualisation of qualification standards as a social contract provides further support for this interpretation. Their study indicates that standards are not solely technical properties maintained through assessment procedures but also social settlements whose legitimacy depends on stakeholder understandings and public confidence. Although their research concerned school-leaving qualifications in Scotland, the underlying principle is relevant to higher education: assessment processes must support credible claims about what students know and can do. From this perspective, public expectations concerning GenAI-supported feedback involve questions about who exercises academic judgement, how responsibility is assigned and whether institutional claims about achievement remain trustworthy.

Transparency as a design principle

Transparency consequently becomes more than a procedural expectation. It helps stakeholders identify how feedback was produced, what role GenAI played and who remains accountable for its content. However, disclosure alone cannot establish legitimacy. A transparent process may still fall short of public expectations if academic involvement is nominal rather than substantive. Human-centred learning design therefore requires both transparency about GenAI use and meaningful academic responsibility for interpreting student work, applying standards and authorising feedback.

Human-centred learning design

These patterns also have broader implications for human-centred learning design. Current discussions frequently position GenAI in terms of efficiency, scalability and personalisation. Implementation must also account for how AI reshapes the educational experience of assessment and feedback. Participants generally favoured practices that maintained visible academic involvement, indicating that the human-centred quality of AI-assisted feedback depends less on the presence of AI than on whether educator judgement remains central to the assessment process.

The educational dimension complements this relational interpretation, although more provisionally. While it produced weaker and less consistent differences in participants' responses to ethical and relational trade-offs, it reflects broader expectations regarding the purpose and value of assessment feedback. Public expectations may therefore extend beyond preserving trust to maintaining feedback as an educational process that supports learning, demonstrates appropriate academic effort and reflects the value of higher education. Together, the two exploratory dimensions indicate that GenAI implementation requires attention to both how feedback is produced and the educational purposes it continues to serve.

These findings provide an initial framework for distinguishing expectations concerning the legitimacy of AI-assisted feedback from expectations concerning its educational purpose. Dimension 1 received more consistent empirical support, while Dimension 2 requires further refinement and validation. For human-centred learning design, the findings suggest that GenAI implementation could be designed to preserve visible academic judgement while maintaining the educational purposes of feedback.

In practice, these findings suggest that universities should establish clear expectations for GenAI-supported feedback rather than leaving decisions solely to individual academics. At a minimum, guidance should specify when GenAI use must be disclosed, what constitutes meaningful academic review, and who remains accountable for the accuracy, appropriateness and educational value of feedback. Feedback processes should also make visible the academic's role in interpreting student work and authorising the comments provided. Staff development should therefore focus not only on effective prompting or efficiency, but also on maintaining disciplinary judgement, appropriate personalisation and opportunities for students to seek clarification. These principles could inform institutional policy, assessment design and the evaluation of GenAI feedback tools.

Limitations and future research

This study has several limitations. Although the survey targeted the general public, the sample was highly educated and largely university-experienced, limiting generalisability. The findings reflect stated expectations in response to survey items and hypothetical trade-offs rather than behavioural responses to authentic feedback practices. The subgroup analyses and exploratory dimensions should be interpreted cautiously, as the survey items were purpose-designed for this study and one composite demonstrated only modest internal consistency. Consequently, the dimensions are best understood as exploratory constructs rather than validated scales. Finally, the findings represent expectations at a particular point in time and may evolve as GenAI becomes more widely embedded in higher education.

Future research should examine whether these exploratory dimensions are replicated in student, academic and more representative public samples. Experimental studies examining responses to teacher-generated, AI-generated and AI-assisted feedback under varying levels of disclosure would further clarify how transparency and academic involvement influence trust, feedback uptake and perceptions of assessment legitimacy.

Conclusion

This study provides preliminary evidence that public expectations of GenAI-assisted feedback may involve two complementary forms of expectation. Relational expectations shape whether AI-assisted feedback is perceived as legitimate, while educational expectations shape what feedback should continue to achieve for learning. Rather than viewing AI adoption primarily as a technological challenge, universities should approach it as a

human-centred assessment design challenge in which transparency, visible academic judgement and educational purpose remain central. The contribution of this study lies in identifying two provisional dimensions, and showing that scores on these dimensions were associated differently with participants' stated preferences when evaluating competing priorities. Further research is required to refine and validate these dimensions.

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