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The Dimensions of Abundance in AI-Generated Feedback

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Abstract

Feedback is an integral part of the learning process. However, delivering feedback effectively remains challenging, particularly within massified higher education systems that are characterised by large cohorts and increasingly diverse student populations. The emergence of generative artificial intelligence (GenAI) enables new ways of embedding feedback into educational offerings, some of which may be highly beneficial. In this paper, we introduce Abundant Feedback as a conceptual lens for examining the new capabilities that may be enabled by GenAI. We present a four-dimensional framework identifying the dimensions of GenAI feedback as abundance of Volume, of Availability, of Relevance and of Character. Through a systematic literature search, we describe how these dimensions manifest in recent empirical studies, and identify two educational domains, Computer Programming and Foreign Languages, as early adopters of AI-generated feedback. Beyond merely digitising existing scarce feedback processes, we discuss the emergence of new learner-driven feedback practices that are enabled by abundance, that both stimulate and demand student feedback literacy. Our multi-dimension abundance framework provides a lens, as well as the vocabulary and conceptual tools, to guide the implementation of GenAI feedback in ways that help realise the potential of artificial intelligence to enhance student learning.

Keywords: generative AI; AI feedback; abundant feedback; feedback scalability; personalised learning; feedback literacy; student agency

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1. Introduction

Feedback plays a pivotal role in education. It is widely recognised as one of the most powerful tools to enhance student learning, helping learners to understand their strengths and identify areas for development (Wisniewski et al., 2020). In both theory and practice, we have a reasonably robust understanding of what constitutes high-quality feedback, and there is a substantial body of research in the past decade that has explored the characteristics of high-quality feedback and proposed strategies for its further enhancement. These include characteristics such as being timely (Hattie & Timperley, 2007), specific and targeted (Sadler, 1989), aligned with learning goals (Sadler, 2010), actionable and improvement-focused (D. J. Nicol & Macfarlane-Dick, 2006), dialogic and interactive (Carless, 2006),

credible and trustworthy (Carless & Boud, 2018), as well as contextually aligned and constructively balanced (Haughney et al., 2020; Henderson et al., 2019). Further work has examined students' feedback literacy and agency; that is, the capacity to assess the feedback information that they receive, make informed judgements about its usefulness, manage the emotional responses it may evoke, and take constructive action in response (Carless & Boud, 2018; Nieminen et al., 2022).

While our knowledge of what makes feedback effective has grown, the ability to deliver such feedback, particularly at scale, remains elusive. The massification of higher education, driven in large part by digital delivery models, has enabled institutions to reach wider and more diverse student populations than ever before (Hornsby & Osman, 2014; Mulryan-Kyne, 2010). This scale has not been matched by an equivalent transformation in feedback provision. Data from national higher education student surveys such as Australia's Student Experience Survey (SES and the United States' National Survey of Student Engagement (NSSE), consistently show that students report lower satisfaction with feedback compared to other aspects of teaching and learning, highlighting the difficulty of scaling this component of teaching and learning (National Survey of Student Engagement, 2023; Social Research Centre, 2023).

In this context, we introduce the concept of abundant feedback as a conceptual lens for examining the new capabilities that may be enabled by generative artificial intelligence (GenAI). Traditional feedback practices in tertiary education are scarce, most commonly involving a single round of feedback given on assessment pieces by a single staff member, which is returned to students in the weeks following submission. GenAI technologies potentially offer new affordances, which can shift how academics and students deliver and engage with feedback, particularly at scale. GenAI could potentially facilitate formative feedback loops that were previously unthinkable due to their impracticality. We propose that abundance and scarcity should be considered threshold concepts in the design of feedback regimes; i.e., once understood, they allow one to see the topic in a new light.

Through a systematic literature search, we examined existing implementations of GenAI-enabled feedback within an unbiased sample of existing studies. We characterised the alignment of these studies with four proposed dimensions of abundance: volume, availability, relevance and character. We also show that initial work has begun to move GenAI-generated feedback beyond just digitalisation of existing practices and towards an era of agency. By labelling feedback abundance and its dimensions, we provide a language to predict the pedagogical transformations that may be enabled by GenAI. This distinction is critical for the field to move beyond short-term, efficiency-driven implementations, toward long-term, values-aligned innovation and system change.

2. Identifying the Four Dimensions of Abundance

This study aimed to create a foundational understanding of the dimensions of abundance that are demonstrated in the literature, and how they contribute/relate/intersect with existing frameworks or models on feedback practices, notably effective feedback, feedback at scale and feedback engagement. Effective feedback has long been understood as information that enables students to understand the gap between their current performance and desired standards, and to identify the actions required to close that gap (Sadler, 1989). This framing emphasises that feedback is more than just an evaluative comment on student work; it is information that makes quality judgements visible, supports improvement by clarifying expectations, and provides direction for subsequent revision and learning (Hattie & Timperley, 2007).

Feedback is effective when students receive information which helps them not only to understand their current level of performance, but also how they can improve that

performance next time and strengthen their self-regulatory capacity. Wisniewski et al.'s meta-analysis of empirical research on the effects of feedback on student learning (435 studies, 994 effect size, >61,000 learners) shows that high-information feedback, which includes task or process information, and additional information related to self-regulation, has a very large average effect on student learning, compared to reinforcement or punishment and corrective feedback (Wisniewski et al., 2020). Cai et al. likewise report in another meta-analysis (61 studies, 182 effect sizes) that explanatory feedback is the strongest feedback type in technology-rich learning environments (Cai et al., 2023).

The availability of timely, readily accessible feedback, that is, feedback that students can access and use at the point of need, is another important contributor to the educational impact of feedback. 'Point of need' should not be conflated with immediacy; rather, it highlights the pedagogical appropriateness of timing, whereby feedback is provided when it is most likely to be interpreted, acted upon, and taken up by the learner. A meta-analysis (40 studies, 70 effect) by van der Kleij et al. found immediate feedback may be more beneficial for lower-order learning (such as verifying correctness or correcting procedural errors), whereas depending on the context, delayed feedback may be better for supporting higher-order outcomes, including conceptual understanding, strategy development, and reflection (Van Der Kleij et al., 2015). Generally speaking, the educational context influences how the timing of the feedback impacts upon learning outcomes.

Several practice-oriented studies of effective feedback have further proposed mechanisms centred on student engagement with feedback (Broadbent et al., 2018; Hussain et al., 2019). Carless et al. (2011) recommends that feedback practices be designed to foster ongoing learning by engaging students in dialogue about standards and quality, strengthening their capacity to monitor and evaluate their own learning, and developing lifelong learning skills such as goal setting and planning. It further emphasises that assessment tasks should be designed to sustain engagement over time and to enable feedback from multiple sources to be generated, processed, and applied across successive stages of work (Carless et al., 2011). Boud and Molloy's paper on sustainable feedback recommends: reframing feedback as a learner-driven, dialogic process co-constructed with educators; expanding feedback beyond a single teacher source to include multiple contributors; embedding peer involvement as an integral component of feedback practice; and designing feedback as a sequenced, curriculum-level process that develops students' capabilities over time rather than as isolated episodes (Boud & Molloy, 2013).

The requirements for effective feedback and student engagement with feedback are well established in the scholarly literature. What remains largely absent is a means of delivering effective feedback, consistently and equitably, across large and diverse cohorts. This challenge is exacerbated by the massification of higher education, most visibly reflected in intensified internationalisation and constrained staffing (Hornsby & Osman, 2014; Mulryan-Kyne, 2010). Under these conditions, feedback risks becoming increasingly standardised, one-way, one-off, and delayed, undermining the needs for relevance and timeliness (D. Nicol, 2010).

Providing effective feedback at scale becomes even more challenging as student cohorts diversify through high levels of international enrolment and expanded participation among low-equity groups. This heterogeneity of the student body entails greater variation in prior educational experiences, familiarity with academic conventions, language and cultural proficiency, and expectations regarding teacher–student relationships and feedback practices. Pazio Rossiter and Bale (2023), in their review of recent work on feedback literacy, conclude that effective feedback is shaped not only by the information it contains but also by cultural and linguistic factors, and that dissatisfaction may be exacerbated in highly internationalised institutions when these factors are not explicitly addressed

in feedback practices (Pazio Rossiter & Bale, 2023). There is also emerging report that students' confidence, sense of belonging, and willingness to seek clarification vary, and their engagement with feedback may depend on prior experiences of assessment, cultural communication norms, or previous educational disadvantage. As a result, studies suggest focusing on tone, framing, and scaffolding to ensure feedback is accessible, trusted, and equitable (Heron et al., 2023; Rovagnati et al., 2022; Zhou et al., 2023).

GenAI has the potential to address the abovementioned gaps in feedback practices by enabling scalable feedback that is both informationally rich and relational. GenAI can already produce responses to inputs, in a manner that is on-demand, covering any topic, and in a wide range of formats and styles. While there are still significant issues, particularly around accuracy of information and ethical concerns regarding bias and the human–AI relationship, it is important to consider what these systems could potentially be used for in the future. To fully realise their potential, it is necessary to articulate and label the specific ways GenAI can enhance the accessibility and quality of feedback. This allows implementation to be designed, implemented, and evaluated with pedagogical, operational, and equitable coherence. In this work, we identify four dimensions of abundance that comprise an initial framework for consideration. These proposed dimensions are the abundance of volume, of availability, of relevance and of character (see Table 1).

Table 1. Four dimensions of abundance that capture the informational and relational value, as well as the accessibility and content, of AI-generated feedback. These are arranged such that dimensions that have similarities or minor overlapping features share a column or row.

	Informational Value	**Relational Value**
Accessibility of Feedback	**VOLUME (V)** Scalability of feedback provision across large and diverse student bodies.	**AVAILABILITY (A)** Timing and modes through which student can access and engage with feedback.
Content of Feedback	**RELEVANCE (R)** Topic focus of information contained within feedback that supports learning.	**CHARACTER (C)** Modality, tone and style of the feedback.

We performed a PRISMA search of the literature to: (a) determine whether these dimensions provided an adequate description of existing work in an unbiased sample of the literature; (b) explore the various implementations of different dimensions in the tertiary education feedback literature; and (c) characterise the extent to which each has been investigated. We hypothesised that we would find evidence of GenAI feedback that exhibited one or more dimensions of abundance. Our specific research questions are:

- **RQ1**: How have the dimensions of abundant feedback been implemented across GenAI-enabled feedback in different disciplinary contexts?
- **RQ2**: Do the proposed dimensions of abundant feedback provide an adequate framework for describing the informational and relational value, as well as the accessibility and quality of GenAI feedback?
- **RQ3**: What affordances of GenAI feedback are reported that might shape the design, implementation, and educational impact of future feedback practices?

3. Methods

To perform the audit of an unbiased sample of the current literature, a systematic scoping review was conducted using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) framework (Page et al., 2021). Whilst the PRISMA framework

allows for a structured approach, it may omit relevant papers due the development of the search string and selected databases which is a commonly cited limitation of the method (Lagisz et al., 2025). To adhere to the PRISMA 2020 checklist, the review established clear inclusion and exclusion criteria for the current literature.

3.1. Inclusion and Exclusion Criteria

The development of these criteria was informed by the research aims and previous author experiences with PRISMA-based systematic literature reviews. The following criteria were used in selecting the studies:

1. The research needed to report empirical findings related to the use of GenAI for feedback on student work, i.e., not a literature review nor a hypothetical or simulated example.
2. The research needed to include original contributions where feedback was a central part of the study and the use of GenAI tools were a focus, not tangential or incidental.
3. The study needed to give feedback to the student, rather than simply directly edit the students' work without any discussion of the changes that were made.
4. The study needed to be related to a tertiary education setting.
5. Publications needed to be in the English language.
6. Publications needed to be indexed via either SCOPUS or IEEE.
7. Publications needed to be either conference papers or research articles.
8. Publications must have been published from 2023 onward.

Due to the recent uprise of GenAI since 2022 and the lag between conducting research and publishing journal articles, both journal papers and conference papers (that have a more immediate publication cycle) were assessed to identify the articles for review. Scopus represents a large online repository of peer-reviewed literature (Borrego et al., 2015; Mazzurco et al., 2021). IEEE Xplore represents another large database that contains many conferences in the fields of technology and computing. The reduced time range of this study was due to the current era of GenAI technology only reaching public consciousness in late 2022 (Teubner et al., 2023). We recognise that this may exclude a number of works that implemented systems using earlier generations of natural language processing software, which may have also exhibited dimensions of abundance.

Quality was not used as an inclusion/exclusion term. Our research question concerns the presence or absence in the literature of the concepts of abundance. It does not require any further potentially subjective judgements about quality beyond the existing implied criterion of having already satisfied peer review. The papers contained in our review are all from 2023 or later; as such, there has been insufficient time for traditional objective measures of paper quality (e.g., citations) to emerge.

3.2. Databases and Search Terms

The database search was undertaken in May 2025. The search string that was used can be seen below:

TITLE-ABS-KEY ("feedback") AND TITLE-ABS-KEY ("automat*" OR "mark*" OR "grad*" OR "peer") AND TITLE-ABS-KEY (genAI OR chatgpt OR "Generative AI" OR "generative artificial intelligence") AND TITLE-ABS-KEY (educat* OR "stud*" OR "teach*") AND DOCTYPE (ar) AND DOCTYPE (cp) AND PUBYEAR > 2022 AND LANGUAGE (english).

The search string was developed to ensure it would capture relevant articles for both feedback mechanisms, GenAI and higher education. The search strategy combined the term 'feedback' with variations of 'Generative AI', including 'ChatGPT' (4.0), to account for differences in terminology across studies and stakeholder groups. At the point in time when

the search was performed, 'ChatGPT' was commonly used as a genericised term covering all GenAI systems. Utilising the keyword of feedback with GenAI proved challenging with many of the captured articles concerning health implications or control systems theory. As such, the word 'feedback' was captured with the words 'mark* 'or 'grad*' to ensure that more traditional AI and control systems engineering papers were not captured. The words 'peer' and 'automat*' were used with feedback to further provide a smaller scope to the output. To limit the volume of papers that did not meet the inclusion criteria based on title, the search term 'artificial intelligence' was removed from the variations in GenAI. This reduced the number of falsely included papers that did not focus on GenAI. All these terms were required to be found in either the title, abstract or keywords.

The study was not intended to be comprehensive, and the use of a systematic literature search was mainly intended to ensure that the review was unbiased by the authors preconceptions. The search string may not contain all variations in some of the key search words, or these may have only been present in the body of the article. However, it was consensus within the research team that if a study was not found using the current terms, it would be unlikely to meet the inclusion criteria. Furthermore, as our aim was to categorise the different broad forms of abundance seen in the existing literature, the absence of any single paper was considered not to be a significant problem.

3.3. Screening Protocol

The screening protocol had several steps to ensure the correct articles were assessed in the final review. The first step is to review the title for suitability. Each of the titles were reviewed by two researchers and where there was disagreement it was discussed with the research team until a consensus was determined.

The next stage of screening was through an evaluation of the articles abstract. Three criteria were used to assess the articles that met the inclusion criteria. For a paper to move on to the next step of screening it must (1) be focused on feedback, (2) include the use of GenAI and (3) be an empirical study in higher education. Again, two reviewers read the abstracts for consensus. When a disagreement occurred, it was discussed between the reviewers.

3.4. Synthesis Methods

The final stage of screening was a full article evaluation. At this point, only a single reviewer evaluated the full papers due to the large volume that met the criteria for a full paper read (n = 182). The papers were categorised firstly based on the proposed dimensions of abundance (defined in Section 2), and secondly on the major affordances that were enabled using GenAI feedback. This categorisation was carried out independently by the first reviewer of the full paper and then discussed openly with the authorship team, and the designated categories were discussed and updated among the reviewing team at multiple stages during the process. Disagreements regarding classification, particularly in cases where feedback practices spanned multiple mechanisms, were resolved through discussion and reference to the stated pedagogical aims within each study. Where articles demonstrated hybrid or ambiguous features, notes were recorded for further discussion, though each study was ultimately assigned a primary category for synthesis. Once the articles had been included into the final synthesis, they were categorised by discipline, affordances discussed, and dimensions of abundance that were visible.

3.5. Use of AI in This Paper

Artificial Intelligence was not used in the collection or analysis of data in this paper. Figure 3 was created by manually modifying output from an AI-based image generation tool.

4. Results and Discussion

4.1. PRISMA Results

A total of 533 articles were included in the initial title screening from the search return from Scopus and IEEE Xplore. There was a total of 182 articles that passed both the title and the abstract screening. Finally, 83 papers were included in the full article assessment, and 99 did not meet the eligibility criteria. As such, 83 articles were included in the final analysis. Figure 1 details the PRISMA inclusion and exclusion process.

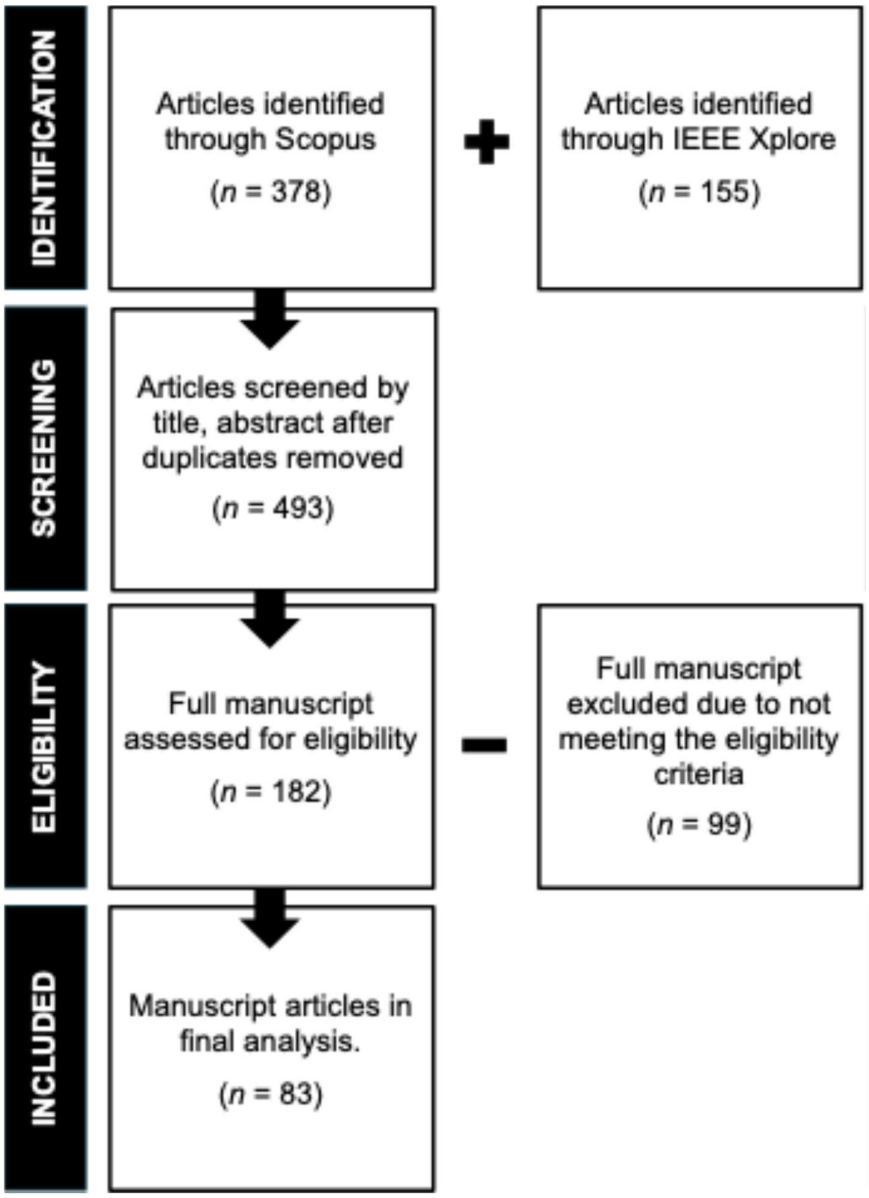

Figure 1. PRISMA inclusion and exclusion diagram.

4.2. Presentation of Included Studies

There was a total of 83 studies that were included in the final analysis of the literature. These 83 articles are presented in Table 2, with the following features identified for each article:

- The authors and year of publication.
- The dimensions of abundance that were observed in the article, where the letters V, A, R and C represent volume, availability, relevance and character, respectively.

- The key affordances of the work described in the article, such as efficiency or personalisation.
- The discipline area in which the students were learning.
- The context of the work.
- A short summary of the findings of the article, particularly in relation to feedback.

Table 2. Articles included in the final analysis.

Paper #	Authors, Year	Dimensions of Abundance	Affordances	Discipline	Context	Findings
1	(Akiba & Garte, 2024)	-A--	Efficiency	Medical and Healthcare	Using AI to support iterative improvement in writing tasks	AI integration supports student autonomy and engagement
2	(Alanazi et al., 2025)	VAR-	Agency	Foreign Language	Students completed a writing task, following which they could interact with an AI system to get feedback	Students who received AI feedback performed better on a follow up task compared to those who did not
3	(Alers et al., 2024)	----	Efficiency, Personalisation	Information Technology	Automatically marking and providing feedback on exams	Strong correlation between AI marks and human marks. Massive reduction in the time required to complete the marking and provide feedback
4	(Ali et al., 2025)	VAR-	Personalisation	Medical and Healthcare	AI tools used to provide personalised study materials	No differences between the experimental and control groups with regard to marks and exam anxiety
5	(Bacon & Maneerutt, 2024)	VAR-	Agency	Foreign Language	AI feedback was integrated with peer discussion	Observations were made on how different demographics interacted with AI feedback
6	(Bai & Wei, 2024)	V---	Efficiency	Foreign Language	AI was used to provide alternative rewritings of student essays	Students' choices on whether to incorporate changes depended on their ability to interpret the rationale for it
7	(Bassner et al., 2024)	--RC		Programming	Embedding AI-generated feedback into a learning management system	AI-generated feedback was more readable and consistent than human instructors
8	(Becerra et al., 2024)	V-RC	Personalisation	Not Specified	Personalised guidance tool integrated into a MOOC platform	Tool developed—tested different prompts and systems
9	(Bernal, 2024)	----	Personalisation	Programming	Automatic generation of MCQs	Technical implementation is feasible

Table 2. *Cont.*

Paper #	Authors, Year	Dimensions of Abundance	Affordances	Discipline	Context	Findings
10	(Brainnita Oktarina et al., 2024)	-A-C		Foreign Language	Experimental/control group study of using AI chatbots to improve student learning	Experimental group showed significant increases in grades and in feedback literacy
11	(Bucol & Sangka-wong, 2025)	----	Efficiency, Richer experiences	Foreign Language	Student essays were marked by human staff and by AI, using a defined rubric	AI marks were comparable to human
12	(Chan et al., 2024)	----		Foreign Language	Students were asked to write an essay, and then later revise it, having received either AI feedback or no feedback	Students who used AI feedback reported greater motivation and engagement on average, and improved more strongly when the revised essays were graded, compared to those who revised their essays with no feedback
13	(E. Chen et al., 2023)	----		Programming	A custom AI code feedback system was created	Comparisons were made between the feedback given by different AI language models
14	(Z. Chen et al., 2024)	----		Foreign Language	Students provided peer feedback on essays	Paper presented different ways in which students integrated AI into their process
15	(A. Chen et al., 2025)	---C		Foreign Language	Comparing AI-provided feedback to human-provided feedback	Students engaged with AI-generated feedback in a non-linear way, but are less reflective as they do so
16	(Coenen & Pfenninger, 2025)	V---	Efficiency	Professional Communica-tion	Staff used generative AI to create personalised feedback to student reflections	Feedback could be completed much more quickly
17	(Cortez & Schmelzen-bach, 2024)	V--C	Agency	Programming	Students used AI to explore their marked answer to an exam question	Students had varying qualitative responses to the task.
18	(Cronje, 2023)	----	Efficiency	Information Technology	Students were given prompts to make AI act as a coach in their career planning	Teaching students to interpret the response of AI systems was critical
19	(Dai et al., 2023)	--R-		Information Technology	AI was used to create feedback on project proposals	Feedback from AI was more readable and generally more positive than that of human markers

Table 2. *Cont.*

Paper #	Authors, Year	Dimensions of Abundance	Affordances	Discipline	Context	Findings
20	(Dai et al., 2024)	--RC	Richer experiences	Information Technology	Students completed a project proposal. Feedback was then generated by human markers and two different AI systems	A GPT-4 based model was able to provide feedback that was more readable and better aligned to a framework for good feedback practice vs. human or GPT-3.5 feedback
21	(Diyab et al., 2025)	V-R-	Efficiency, Richer experiences	Information Technology	Development and testing of a system to provide feedback	The system was able to provide feedback to a range of question types, and also identify general areas of weakness across multiple questions
22	(Du et al., 2025)	V--C	Agency	Foreign Language	Students completing an argumentative writing task are given either an AI peer or AI expert to work with	Differences were found in the way that students worked with AI of different character
23	(ElEbyary & Shabara, 2024)	--R-		Foreign Language	Feedback provided by AI was compared to that from human staff	AI provided more indirect feedback and more metalinguistic feedback than human markers
24	(Escalante et al., 2023)	----	Efficiency	Foreign Language	EFL students received regular feedback on their writing via either an AI or human tutor	AI and human feedback were seen as having different advantages
25	(Fiore & Mongiello, 2025)	---C		Information Technology	Using AI to engage in dialogue with students on sample assignments	The learning experience was more interactive and engaging. The approach improved the quality of peer feedback amongst the students
26	(Frankford et al., 2024)	VA-C	Agency	Programming	Students submitted code to a system for feedback, response in either English or German	Qualitative investigation of student usage showed most found it easy to use, but feedback was often generic
27	(Gozali et al., 2024)	VA--	Agency, Richer experiences	Foreign Language	Students were encouraged to use various AWE tools to gain feedback on their writing, followed by qualitative interview	Students discussed various aspects of their usage that were related to the development of feedback literacy skills
28	(Grandel et al., 2024)	----	Efficiency	Programming	AI feedback on coding assessments was compared to a tutor. A system was then implemented that used an AI pre-check before human grading	AI was found to provide mostly similar feedback to a human tutor

Table 2. *Cont.*

Paper #	Authors, Year	Dimensions of Abundance	Affordances	Discipline	Context	Findings
29	(K. Guo & Wang, 2024)	--R-	Efficiency	Foreign Language	Comparing AI-generated feedback to human-generated feedback	AI tools generate more feedback, and with a more even balance across different feedback foci
30	(K. Guo et al., 2024)	VAR-		Foreign Language	Students drafted peer feedback on essays, on which an AI system gave feedback	Students who received AI feedback improved both their ability to give feedback and their own writing, compared to a group that did not receive AI feedback
31	(K. Guo, 2024)	VA--		Not Specified	A platform was developed to assist students to give peer feedback on other's writing	The capabilities of the platform were presented
32	(X. Guo, 2025)	-A-C	Efficiency	Foreign Language	Students received either teacher or AI-written feedback on their German essays	Interviewed students reported that AI feedback was useful, but they had concerns about its accuracy. They implemented teacher feedback at a higher rate
33	(Gutiérrez-Ferré et al., 2024)	----		Programming	AI submissions were incorporated into an online discussion platform	The AI gave feedback differently to students, and in discussions where an AI was involved, students also gave feedback differently
34	(Holderried et al., 2024)	----	Efficiency	Medical and Healthcare	AI-simulated patient to train medical students to take medical histories, with AI then also providing feedback to students	Could give feedback after a session with few flaws
35	(Huo et al., 2024)	VAR-	Efficiency	Programming	An LLM is trained to respond to student queries on an online forum	System can answer some simpler enquiries well. Intended as a supplement to human feedback
36	(Hutson et al., 2024)	--R-	Efficiency, Richer experiences	Video Game Design	A case study is described of AI producing feedback on a student's work	AI feedback is potentially adaptable to complex assessment tasks and can potentially save time
37	(Ivanović, 2023)	--R-	Efficiency	Not Specified	AI was used to grade essays and compared to human markers	AI grading could potentially save significant time

Table 2. *Cont.*

Paper #	Authors, Year	Dimensions of Abundance	Affordances	Discipline	Context	Findings
38	(Jiang, 2025)	---C	Efficiency	Culture and Writing	Control/Experiment in using AI to provide feedback to students in a writing class	Hybrid feedback (AI and teachers) provides the best results vs. teacher-only or AI-only feedback
39	(Jaashan & Alashabi, 2025)	--R-		Foreign Language	Improving spelling of English foreign language students	Students receiving LLM-generated feedback outperformed students in the control group
40	(Kimmel et al., 2024)	VA--		Programming	Students submitted code to solve an exercise to an automated analysis tool. AI was used to provide further interpretation of the error messages	Student survey results showed mixed popularity and usefulness of the intervention
41	(Koltovskaia et al., 2024)	VAR-		Foreign Language	Six STEM graduate students using AI to revise their research proposals	Students were engaged and critically judged the feedback they received
42	(Kupershtein et al., 2023)	---C	Richer experiences	Programming	A tool was developed that could read sentiment in feedback and pick matching emojis to automatically insert	Surveyed students reported that they believe that emojis were appropriate to include in feedback
43	(Kurt & Kurt, 2024)	VAR-	Agency	Foreign Language	English teaching/education students writing essays in English, participated in interviews on their experience	AI feedback has various affordances and constraints, and could be a useful complement to teacher and peer feedback
44	(Lee et al., 2024)	----		Teacher Education	AI tool developed for analysis of video footage to provide feedback to teachers	The tool supported reflection by the teachers
45	(Letteri & Vittorini, 2024)	---C		Mathematics and Statistics	Supplementing static feedback using dynamic LLM-generated feedback	Improved feedback quality
46	(L. Li & Kim, 2024)	-ARC		Foreign Language	Students engaging with automated feedback tools to meet self-selected goals	Tools were well received by students, with gains in confidence and learner autonomy
47	(T. Li et al., 2025)	-A--	Agency	Teacher Education	STEM teaching students were mentored by experienced teachers, AI mentors, or a combination	The three approaches to providing mentoring feedback had different advantages

Table 2. *Cont.*

Paper #	Authors, Year	Dimensions of Abundance	Affordances	Discipline	Context	Findings
48	(J. Lin et al., 2025)	----		Teacher Education	AI was used to give feedback to trainee teachers on their feedback style	The system classified the feedback and was able to suggest alternatives, which in some cases were improvements on human suggestions
49	(S. Lin & Crosthwaite, 2024)	----		Foreign Language	Using AI to provide automated written corrective feedback	Strong evidence that chatbots provide different feedback than humans
50	(Lohr et al., 2025)	---C		Programming	Explored the characteristics of LLM-generated feedback	GPT-4 can automatically generate appropriate outputs for a range of different desired types of feedback
51	(Luo et al., 2024)	V---		Foreign Language	Using AI-generated content tools to improve masters research proposals	AI tools were helpful, but students still relied on human instructors
52	(Machado et al., 2025)	-A--	Richer experiences	Engineering	Remote lab activity with a neural network used to analyse student activity and generate feedback	The system was able to provide new forms of feedback
53	(Mahapatra, 2024)	VAR-		Foreign Language	Students completing writing tasks following training on AI	AI feedback was well received by students and students who used it showed greater improvement in marks
54	(Mehnen & Pohn, 2024)	----	Efficiency, Personalisation	Programming	Using AI to automate the creation of teaching materials	Improved student engagement and learning outcomes
55	(Mi et al., 2025)	VAR-		Foreign Language	AI bot used to provide feedback on student essays	The bot was useful to students, although students did not take full advantage of its features and expressed reservations about using it
56	(Morales-Chan et al., 2024)	----	Personalisation	Teacher Education	Embedding AI feedback into a MOOC	Students found the feedback timely and valuable
57	(Nofal et al., 2025)	-A--	Efficiency	Not Specified	A virtual reality interview simulation platform was trialled, which gave students feedback on their interview	The system was found to give consistent scores, but may have shown slight biases to various groups of interviewees

Table 2. *Cont.*

Paper #	Authors, Year	Dimensions of Abundance	Affordances	Discipline	Context	Findings
58	(Odesola et al., 2024)	--RC	Efficiency	Medical and Healthcare	A custom AI system was trained to convert keyword observations of physiotherapy student practical assessments into prose feedback	The model was able to provide structured, human-like text with a desired more positive tone than human assessors
59	(Parker et al., 2023)	-AR-	Agency	Medical and Healthcare	AI-based automated writing evaluation (AWE) provided feedback on macro-level writing features	The AI-based AWE supported multiple submission cycles and promoted learner autonomy without increasing instructional burden
60	(Phan et al., 2024)	VARC	Richer experiences	Foreign Language	AI was used to provide automatic assessments of spoken language	The AI system was able to provide corrective feedback on language content, rather than only pronunciation
61	(Pozdniakov et al., 2024)	----		Information Technology	Developing a "Feedback Copilot" to overcome the challenges of text-based interfaces	The Feedback Copilot produced better quality feedback
62	(Rigaud Téllez et al., 2024)	---C		Mathematics and Statistics	A framework was used to instruct an AI system on how to give feedback to students solving mathematical problems	The system could provide feedback, but it had various deficits compared to human feedback
63	(Roest et al., 2024)	V-RC		Programming	Using LLMs to provide next step hints for programming exercises	Initial pilot showed that students found the hints mostly useful
64	(Sajadi et al., 2023)	----	Personalisation	Engineering	Peer feedback in project-based learning subjects	AI can generate high-quality syntheses of peer feedback from students without revealing specific teammates as the source
65	(Sebastian et al., 2024)	----		Medical and Healthcare	Written assignments from anatomy students	AI scores were mostly correlated with human marker scores
66	(Smerdon, 2024)	VAR-	Agency	Economics	Students were allowed to use AI tools to complete a writing task, and were then surveyed on their usage. Usage was compared with student demographic data	Student usage patterns were diverse, with a common one being to use it as a personalised tutor

Table 2. *Cont.*

Paper #	Authors, Year	Dimensions of Abundance	Affordances	Discipline	Context	Findings
67	(Sreedhar et al., 2025)	----	Efficiency	Medical and Healthcare	AI was used to give feedback on essays and compared to human graders	AI could potentially save time, but there were variations in the feedback given
68	(Tam, 2025)	----		Foreign Language	Using AI to provide feedback on assignment writing	Engaging proactively with AI-generated feedback promoted independent learning and self-regulation
69	(Taylor & Marino, 2024)	---C	Efficiency	Foreign Language	Students creating a chatbot tailored to their preferred learning styles	The chatbots had difficulty providing some types of feedback, but the process of building them was a valuable learning experience
70	(Teng & Huang, 2025)	---C		Foreign Language	Randomised control trial of using AI to provide feedback to students	Students in the group using AI displayed higher levels of engagement
71	(Troussas et al., 2024)	VAR-	Agency	Programming	Students could request AI feedback on their work or theory concepts through an online system	Students were satisfied with the system, completed tasks more quickly and with fewer errors
72	(Tsai et al., 2024)	V---	Personalisation	Foreign Language	Using AI to revise essays written in class	Average test scores improved, although many students actually performed worse. Students in general found the tool useful
73	(Velicea et al., 2025)	-A--	Personalisation	Programming	Using AI to generate customised questions for exams	First group of student users are happy with the user experience
74	(Venter et al., 2025)	VA--		Accounting	Examined whether AI feedback on written answers could display various principles of effective feedback	A prompt was developed that generated feedback that aligned well with the principles in the framework
75	(Villagrán et al., 2024)	VAR-		Medical and Healthcare	Physiotherapy instructors create feedback based on video of students performing procedures	AI was used to analyse the manually created feedback and provide suggestions for improvement. Most commonly, the original feedback lacked suggested plans for students to improve

Table 2. *Cont.*

Paper #	Authors, Year	Dimensions of Abundance	Affordances	Discipline	Context	Findings
76	(Vinutha et al., 2025)	VAR-	Personalisation	Not Specified	An LMS system was developed that incorporated various AI-enabled features	Modules included a mock interview platform and content-based questions, where students received feedback after completing tasks
77	(Wan & Chen, 2024)	----	Efficiency	Physics	Students answered conceptual physics questions, and were given feedback produced by both human markers and an AI system	Students could not discern AI feedback from human feedback. Most AI feedback was judged to be broadly useful by instructors
78	(Yan & Zhang, 2024)	---C		Foreign Language	Using AI to provide feedback on writing exercises	Automated feedback was well received, but its effectiveness is dependent upon the learner's language proficiency
79	(Yan, 2025)	VAR-	Agency	Foreign Language	Three students followed in detail on the way they prompted an AI system to give them feedback	Differences in student usage of AI systems were observed
80	(Ye, 2025)	VAR-	Efficiency	Foreign Language	Within a larger IT system, AI was used to provide feedback on students' spoken English	Students were engaged and showed greater improvement vs. a control group
81	(Yu et al., 2025)	V---	Efficiency	Teacher Education	Pilot study of improving peer feedback on video recordings of teaching practice	Hybrid intelligence feedback leads to deeper reflections and an improved focus on pedagogical indicators
82	(Zhang et al., 2024)	--RC		Programming	Investigating student perceptions of AI-generated feedback	Incorporating student code improves the quality of feedback. Students expressed different preferences for feedback tone
83	(Zou et al., 2025)	--R-	Efficiency	Foreign Language	Using AI-generated feedback to iteratively improve essay writing	Students found human-generated feedback better for language-related feedback but AI better for organisation

4.3. The Affordances of Automated Feedback

Not every study had clear affordances discussed. Where an alternative model of feedback was not clearly specified, no affordance was recorded. A small number of studies had discussed multiple affordances. If we consider these affordances through the

lens of "Exploitation vs. Exploration" (March, 1991) we saw a larger number of studies focussed on exploiting the new technology to improve current processes (staff efficiency and personalisation), as opposed to exploring new opportunities (richer experiences and student agency).

4.3.1. Staff Efficiency

A clear theme that emerged from the analysis was that of efficiency. A total of 24 papers described instances where the final outcome of the feedback process was similar, but for example taking less time/effort. Typically, academics are using GenAI to help themselves generate feedback more efficiently. GenAI was described as a tool that "could greatly lessen teachers' burden and workload in providing feedback on student writing" (K. Guo & Wang, 2024), and that it "can significantly enhance productivity by automating routine tasks and delivering rapid responses" (Alanazi et al., 2025). One paper went so far as to quantify the efficiency gains as being "anywhere between 10 and 30 min per essay" (Ivanović, 2023). Kurt and Kurt (2024) also noted student comments that their system also saved student time. For the most part, this cluster was devoted entirely to achieving the same feedback outcomes, but with a reduced burden upon the academics, rather than exploring the additional possibilities that the affordances of GenAI could provide. From these studies, 38% did not describe any of the dimensions of abundance, and 46% only described one dimension.

4.3.2. Personalisation

A total of 10 studies were identified as showing personalisation as an affordance. From these, five did not show any dimensions of abundance, two showed one dimension and three studies showed three dimensions. The use of GenAI to personalise feedback was a common theme in a number of papers (Alers et al., 2024; Bernal, 2024; Holderried et al., 2024; J. Lin et al., 2025; Sajadi et al., 2023), but it went largely underexplored in those papers. While the idea that the feedback could be personalised was clear, what that actually meant in practice was often not articulated. It was not uncommon for personalisation to be presented in the introduction of a paper as an advantage of GenAI, and then remain unaddressed throughout the actual paper itself.

There was, however, one explicit example that addressed lack of personalisation as an emergent theme in students' responses to GenAI feedback, with students noting that "It didn't feel personal" and also that they "didn't know if Prof [name] agrees with the feedback" (Akiba & Garte, 2024). This suggests that students see personalised feedback as more than just being tailored to them (vs. generic), and that there is a human element to the nature of the feedback itself.

4.3.3. Enriched Feedback Experiences

There were eight studies that were considered to have created richer feedback experiences. For example, unlike papers which studied staff efficiency as an outcome in and of itself, other papers presented the efficiency gains as an opportunity to adjust the feedback process. There were instances in which the authors noted that the time saved by using these tools could be reallocated (Bucol & Sangkawong, 2025; Grandel et al., 2024), such that "The reduction in grading time allows for an increase in time spent with students" (Diyab et al., 2025).

Alternatively, GenAI was to improve the depth of feedback that was given on a verbal speaking task (Phan et al., 2024; Ye, 2025). This was also considered to be an enrichment of the feedback experience for students.

4.3.4. Student Agency

The group of studies that we believe is the most likely to significantly affect the practice of student feedback in the longer term were studies that gave students the ability to influence the feedback process. In most cases, these studies reflected the earliest stage of creative ideation and the immediate qualitative exploration in response to the release of ChatGPT and subsequent platforms.

Our review showed that, of the 12 studies which afforded student agency, all were identified as discussing either volume or availability abundance and 11 involved multiple dimensions of abundance. Seven studies referred to three dimensions, most commonly volume, availability and relevance dimensions; this combination generally corresponded to a common model and was for students to be given a brief introduction to an AI chatbot and how to interact with it, after which they were asked to use it in whatever way they wished to complete one or more tasks. The intervention was then evaluated qualitatively via surveys or interviews with students and/or staff (Koltovskaia et al., 2024; Mahapatra, 2024; Smerdon, 2024), via analysis of demographic data (Smerdon, 2024), or via analysis of the students' prompting history (Yan, 2025).

4.4. Mix of Disciplines

Between them, the 83 papers addressed a wide range of discipline areas, indicating that adoption of GenAI feedback is not constrained to only a narrow set of learning areas. Most prominent were Foreign Language Teaching (32 articles), followed by Programming (16 articles). The next most common specific discipline was Teacher Education (five studies). Even broad combination discipline areas such as Medical and Healthcare (eight studies spread across psychology, anatomy, physiotherapy, medicine, pharmacy and nursing) and Information Technology (distinct from programming; seven studies spread across computer science, software engineering and data science) were represented in far less depth. Other disciplines included Engineering, Mathematics and Statistics, Physics, Accounting, Economics and Video Game Design. Five studies did not specify any discipline.

The two largest clusters, Foreign Language Teaching and Programming, were more advanced in their adoption of automated feedback technology, which manifested in how they were using GenAI to support students.

4.4.1. Cluster 1: Language Teaching

Language Teaching was the most commonly identified field of study (32 studies), notably English as Foreign Language (EFL) teaching (30/32). This is a field where feedback to students is already very structured, with teachers having clearly identified dimensions on which to provide feedback to students on their work. Notably, automated writing evaluation (AWE) systems have been used for some time in EFL teaching to provide automated feedback. A convergent body of work indicates that GenAI can provide timely and scalable feedback, and that it can function as an editing aid, a tutoring resource, and a catalyst for feedback literacy when thoughtfully integrated into instruction (Chan et al., 2024; Gozali et al., 2024; Mi et al., 2025; Teng & Huang, 2025). The same body of work showed GenAI presents advantages relative to human markers in traditional feedback dimensions, notably timeliness, breadth of feedback, and surface-level correction like spelling, but displayed limitations in other dimensions, especially deep content-level judgement, nuanced rhetorical feedback, and affective attunement. Several papers suggest that GenAI should be used as a supplement to human markers to ensure better coverage but did not make the jump to suggest that GenAI feedback could in fact be abundant (Teng & Huang, 2025). Others highlight the need for design considerations (e.g., frameworks integration, course design, and prompts) and cautions regarding AI literacy, risks to writing

proficiency, and the limitations of GenAI in capturing affective and nuanced facets of writing (Gozali et al., 2024; L. Li & Kim, 2024; Mi et al., 2025; Yan, 2025).

4.4.2. Cluster 2: Programming

Introductory Programming courses, commonly known in the education literature as "CS1", are foundational courses typically offered in the first year of computer science, engineering, science, information technology, or related disciplines. Their primary aim is to introduce students to the core principles of computer programming, including algorithmic thinking, problem-solving, and the syntax and semantics of at least one programming language. Students learn how to write, debug, and test code, and often complete exercises or small projects involving control structures (e.g., loops, conditionals), data types, functions, and basic data structures. These courses are critical because they lay the groundwork for more advanced study in computing and help students develop computational thinking, a transferable skill across STEM disciplines. However, they are also widely recognised as challenging to support, due in part to large class sizes, students' characteristics, teaching methods, and the nature of programming which create significant pedagogical and logistical constraints (Alammary, 2019).

The use of automation in Introductory Programming courses is well established, with both automated testing and the use of test outcomes as feedback long recognised as standard practices in software engineering and programming education (Keuning et al., 2019; Messer et al., 2024). What now emerges is the ability to provide automated feedback with greater pedagogical alignment and improved instructional design quality in real-time (Kimmel et al., 2024; Roest et al., 2024; Velicea et al., 2025). Lohr et al. mapped AI-generated feedback to a predefined feedback taxonomy for Introductory Programming tasks; this framing shifts the focus away from correctness checks, to differentiated, type-specific feedback that meets the needs of novice programmers (Keuning et al., 2019; Lohr et al., 2025).

Several authors point to limitations of GenAI-generated feedback for complex scenarios and 'edge cases', reinforcing the need for explicit attention to task-type specificity, as well as design-level (prompts, rubrics) and implementation-level (human-in-the-loop) mitigations (e.g., Lohr et al., 2025). Also notable are studies which explored students' perceptions and uptake of AI-generated feedback. Kimmel et al. found students wanted more specific feedback on their work and were open to AI input but are concerned about vague or inaccurate responses wasting their time (Kimmel et al., 2024).

4.4.3. Contextual Similarities of the Two Most Common Disciplines

In both these contexts, learning is based around practicing the syntax and structure of a new language and is commonly enacted and assessed via repeated small practical exercises, where students produce text in the language of instruction. In hindsight, it is unsurprising that GenAI platforms based on large language models (LLMs), i.e., statistical models of what "correct" writing looks like, would find ready application in these units. The most common format of GenAI, where short texts are submitted to a chatbot, is also easily adaptable to giving feedback on these types of exercises. Both of these contexts commonly involve large class sizes, where we expect to see the greatest benefits in the efficiency of providing feedback. Each has paradigms with clear structures and expectations of the kinds of feedback they intend to provide to their students, as well as existing models of automated feedback which reduce the gap between current practice and abundance. These may again reduce the perceived difficulty in applying GenAI feedback in these units, which meshes with this review primarily covering the early days following the general release of ChatGPT and similar platforms. This analysis also highlights areas where GenAI

feedback may be less beneficial or more problematic to apply, i.e., the converse of these common factors.

5. The Dimensions of Abundance

Almost all of the sixteen possible combinations of the dimensions of abundance were represented in our 83-article dataset. Of the 83, 22 of the articles showed none of the dimensions of abundance, 27 showed exactly one dimension, and 34 articles showed multiple dimensions of abundance. A total of 31 articles showed volume, 30 showed availability, 32 showed relevance and 23 showed character. The 83 articles can be found with their included categories of analysis in Figure 2.

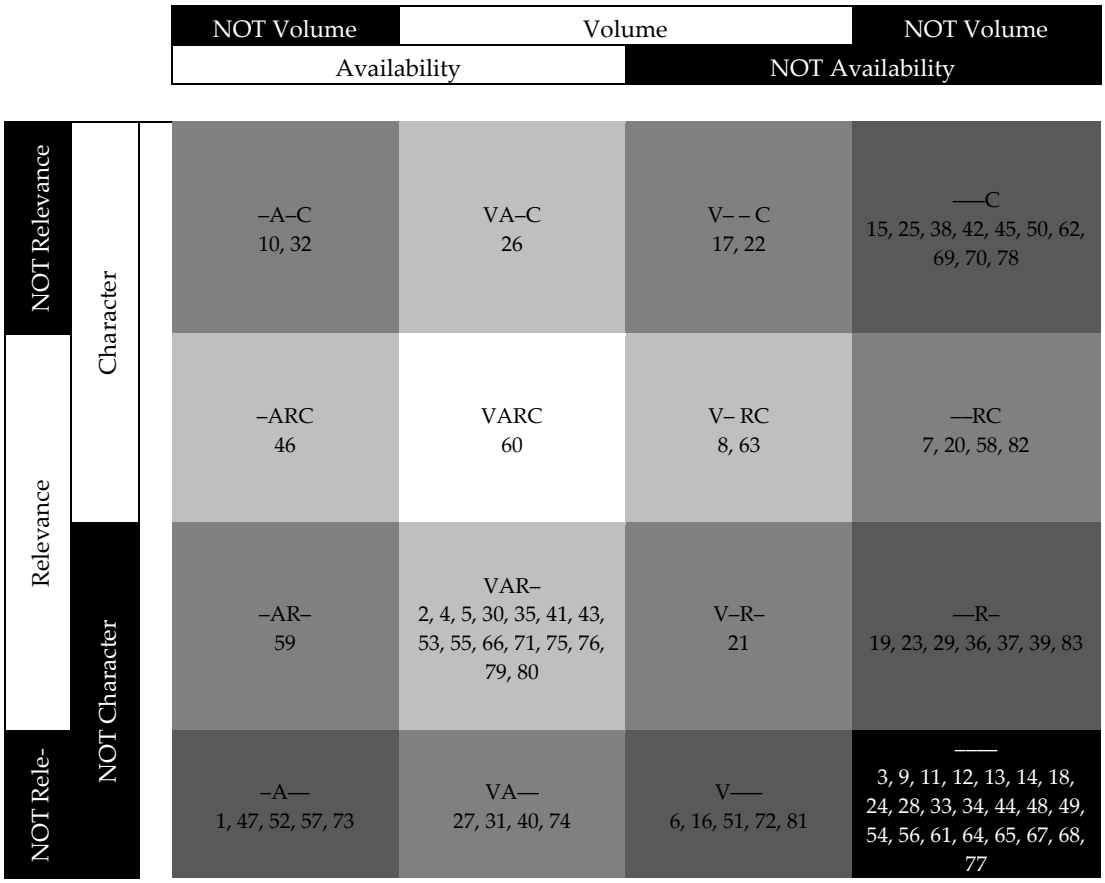

Figure 2. Studies included in final analysis, with paper numbers from Table 2.

It is important to note that the dimensions were not necessarily orthogonal—a particular use case may in fact draw upon multiple dimensions, which were not always clearly distinct. For instance, the ability to have multiple personas provide feedback is inherently character abundance, but offering multiple personas may in turn lead to an increase in volume as students engage with them all.

5.1. Volume Abundance

Perhaps the most easily understood dimension of abundance is that of volume—the ability of GenAI to produce as much feedback as the students want, without the resource constraints of requiring an academic to generate it, particularly in large classes: "GenAI can automatically score student assignments, answer their questions, and provide instant feedback to address the lack of interaction and feedback that arises due to the large number of students, especially in massive open online courses (MOOC)" (Aksoy & KurSun, 2024). This leads to an environment where "Students could ask for feedback on their whole code as many

times as they wanted" (Frankford et al., 2024). The abundance manifests at different levels of complexity in the feedback, ranging from quite complex through to GenAI being presented as a way for students to ask for as many hints as they wish (Roest et al., 2024).

There was also an example of the feedback including the dynamic generation of new learning activities, such as AI-generated quizzes, flashcards and interview questions (Vinutha et al., 2025). This allowed not just for repeated attempts at the same activities, but the guided evolution of the learning experience for the student. This represented a feedback-based use of the generation of tasks concept that was otherwise excluded from the literature review.

The potential of volume abundance was clear in these articles, although it was not always made clear to what extent students actually take advantage of this abundance. One article explored the extent to which students take advantage of this abundance (Yan, 2025), exploring the extent and ways in which students engaged with feedback in an environment where it is abundant. In another article it was made clear that students could continue their conversations with the chatbots, however there was no mention of how many students did, nor to what extent (Venter et al., 2025).

The dataset also included an article that demonstrated a clear awareness of the potential for volume abundance, but explicitly chose not to make use of it: "Notably, we only used the first output from ChatGPT in response to each prompt, although ChatGPT had a 'try again' function and could generate multiple different outputs in response to the same prompt" (K. Guo & Wang, 2024).

5.2. Availability Abundance

Abundance of availability manifests in a number of different ways. Multiple articles refer to the fact that GenAI is instant, and is accessible without the delays involved in traditional human-generated approaches; e.g., "Learners also appreciated the instant and unlimited access to quantifiable feedback, as they used this to indicate their progress as frequently as needed" (L. Li & Kim, 2024).

The concept of universal availability also ties to the students' workflow, with one article conceptualising the availability as students being able to ask for feedback at any stage of the coding process (Frankford et al., 2024). A further article identified how use of GenAI meant that "students could promptly implement changes and refine their work during the writing process" (Alanazi et al., 2025). Another article noted that GenAI could be used to address the constraint that "In-service teachers' limited availability due to school commitments often compromised interaction time and quality" (T. Li et al., 2025). These conceptualisations tie more closely to ideas of student learning, rather than simply to flexibility of time of access.

While the majority focus of the literature was upon having feedback available at different times, there were also a number of articles whose focus was having feedback available through different channels. One article noted the value of having feedback provided to students on their experiments without an instructor being present, which is a traditional constraint of laboratory classes in engineering (Machado et al., 2025). Some articles explicitly identified that GenAI tools are inherently online, which in turn makes them ubiquitous and able to be accessed "anytime, anywhere, without any restrictions" (Kurt & Kurt, 2024), providing students with "detailed, fast and accessible feedback" (Akiba & Garte, 2024). The benefits of abundant availability were also shown to go beyond just the ability to reschedule the feedback to the students' timetable, with positive emotional impacts of availability noted in one study (Akiba & Garte, 2024).

One subdimension of availability abundance that emerged from the analysis was the accessibility of feedback, often from a disability perspective: "Accessibility is a key

focus of [the platform]. The platform includes dedicated support for visually impaired students, featuring text-to-speech and speech-to-text functionality" (Velicea et al., 2025). In this way, GenAI provides access that would previously have been difficult or impossible to implement at scale: "Additionally, a strong commitment to accessibility and inclusivity meant that the platform was developed to be compliant with accessibility standards, thereby catering to a wide audience, including those with disabilities" (Bernal, 2024).

5.3. Relevance Abundance

Our third identified dimension of abundance was that of "relevance". We used this term to denote the ability of GenAI to provide feedback that focusses on different aspects of the student work.

Difference in focus can be an emergent property of GenAI. One study observed that ChatGPT inherently leaned towards providing feedback on particular aspects that differed from human markers: "Conversely, ChatGPT tended to provide more metalinguistic feedback, often rewriting correct sentences and offering guidance that was perceived as less direct" (ElEbyary & Shabara, 2024). While in this instance, this is an emergent property of the tools, it is also possible to deliberately prompt the GenAI to focus on different kinds of feedback, which leads to the relevance dimension of abundance.

Relevance abundance captures the ability of GenAI to respond to differing feedback needs of students, such a system where the "AI comes up with suitable questions depending with the Job role chosen by the user" (Vinutha et al., 2025), or a tool able to provide an unlimited number of next step hints, but was able to do so across a range of different types of hints, such as hints about how to proceed, hints about mistakes, and hints about task implementation (Roest et al., 2024).

Dai et al. (2024) categorised Gen-AI-generated feedback based on whether it referred to each of four focusses (task, process, self-regulatory and self) and three dimensions (feed up/back/forward), the same components of effective feedback as referred to in (Hattie & Timperley, 2007). One may imagine GenAI systems that focus on each of these aspects individually, that ensure that each of the components are addressed, or that allow students to request feedback on particular components. As noted in this study, several components were commonly neglected by human assessors, purportedly due to time restraints, but were more often addressed by the GenAI systems. In the vast majority of cases, human assessors agreed with the comments made by GenAI on topics where the human assessors did not originally give feedback. This emphasises the potential usefulness of GenAI feedback systems in providing feedback at scale, without restrictions on either the relevance or volume of the feedback.

The desired topic of the GenAI feedback could be adjusted by including or excluding information from the prompt. One study based around an introductory coding class compared student perceptions of GenAI feedback that was created from the numerous outputs and error codes from the students' code. Some prompts also contained the code itself, and it was found that "72.5% (74/102) of the responses preferred the feedback generated with the prompt that contains students' code (feedback 1) over the feedback without students' code (feedback 2). Feedback 1 excels in its specificity, addressing multiple issues within the student's code, rather than proffering vague critiques" (Zhang et al., 2024).

The relevance dimension becomes even more powerful when it is student led, becoming an enabler of student agency, which was a recurring theme during the authors' discussions. This was seen, for example, in a mixed-methods study that introduced ChatGPT as a feedback tool in a science/engineering academic writing course for students with English as their second language. One student noted "The best part about ChatGPT is that you ask for information, and you get it. You can go as specific or detailed as you

wish" (emphasis added). Another noted "We kinda get sucked into curiosity by asking it questions on sentence structure, tense use and other aspects of grammar" (Mahapatra, 2024). Feedback seeking skills are noted as being an important aspect of feedback literacy in the recent literature (Molloy et al., 2020), and here students were empowered by GenAI to seek feedback on different aspects of their work. In another study, students specifically suggested "additional help beyond the assignment scope (16/117) to supplement students' studies" in response to a request for suggestions to improve an AI feedback system where relevance was limited to a single submission (Zhang et al., 2024).

One potential aspect of abundant relevance is the ability of students to receive feedback on work that is not part of the formal assessment regime of their course. This was not observed in this review, likely due to the scope of the search terms, but is expected by the authors to become a common part of university studies. For example, GenAI may allow students to receive feedback on practice exercises, developmental work, external projects or other work where traditionally this feedback is rarely available.

5.4. Character Abundance

We define "abundance of character" to refer to the ability of GenAI to produce approximately the same feedback content, but with differing styles, including human-like characteristics.

Clear examples were studies that took advantage of the multilingual capabilities of GenAI, building systems where, for example, "a [German as a Foreign Language] student can interact with ChatGPT via prompts in their native language (Chinese), German, or English" and where student feedback indicated "its ability to toggle between languages . . . is immensely helpful" (X. Guo, 2025). Another example enabled feedback on software code to be given in either English or German (Frankford et al., 2024). These implementations are in fact a quintessential example of pre-abundant thinking. Chatbots are functionally omni-lingual; provided that they have adequate training sets, they are able to easily move between languages. There is actually no reason to constrain the system to only provide feedback in two or three languages beyond the historical context of the location of the university.

A second important part of the character abundance dimension is the tone of the feedback. Feedback is more than just a process of data transfer; it also depends upon the persona in which the feedback is presented. Rigaud Téllez et al. noted specifically that "ChatGPT can regulate aspects such as tone . . . as part of the prompt generation." (Rigaud Téllez et al., 2024). One paper reported using the capabilities of GenAI to moderate the language used to provide feedback to the students: "Moreover, although Generative AIs usually incorporate built-in filters for offensive language, such as insults, we have established a list of words that we prefer not to be present in the messages. For instance, words like "lazy" and "failure" are considered potentially discouraging to learners and should be excluded" (Becerra et al., 2024). This focus on students' emotional engagement, and the necessity for non-judgemental feedback, was a clear focus of another study (Yan, 2025), in which one of their students responded that "The interactive processes to elicit feedback from ChatGPT, according to Lisa, "works like a black box, in which our shames are hidden, in a positive way" (Lisa, interview#2)." In a third study, students identified preferences for different tones when asked an open-ended question regarding the improvements they would like to see in AI-generated feedback. While opinions on which tone was desirable were varied, multiple students expressed an opinion despite there being no deliberate variation in tone in the feedback they received (Zhang et al., 2024).

Other papers went further, using GenAI to give students a choice of reviewer personalities for their work (Mehnen & Pohn, 2024), or even going so far as to have the GenAI

adopt categorically different personas when providing feedback to students: "CoachTutor presents itself as an ersatz Coach, based on the friendly and approachable, humorous and lighthearted persona that I use in the classroom . . . ReviewerNumber2 had essentially the same prompt, but the persona was "cranky, contrarian"" (Taylor & Marino, 2024). The authors then asked their students to "create their "perfect tutors", according to their learning preferences and needs, prioritising what they valued in writing." A closely related idea was a study that varied the social role of the AI feedback system, telling ". . .ChatGPT to act like (either) a writing expert or peer from the backend at the beginning of the dialogue" and saw differences in the ways students interacted with the feedback (Du et al., 2025).

Other studies used GenAI tools to vary the medium for feedback, such as moving the output from text to speech (Phan et al., 2024), or "[integrating] audio data with a talking head video, creating a more engaging and interactive feedback experience" (J. Lin et al., 2024).

5.5. Not Abundant

About a quarter of our included studies (n = 22) did not show any noticeable abundance (or proto-abundance). In many cases, these studies implemented GenAI as a substitute for human markers—typically in a hypothetical analysis or in parallel with human marking (e.g., Escalante et al., 2023; S. Lin & Crosthwaite, 2024; Sreedhar et al., 2025). There were examples of studies that were identified as non-abundant that nonetheless presented novel feedback implementations. For example, Grandel et al. used GenAI as a pre-check system that could feed into a human marker's workflow (Grandel et al., 2024). This both increased efficiency and kept a "human-in-the-loop" to ensure accountability for the marks and feedback returned. Other studies that were non-abundant, but demonstrated interesting changes to regular practice, included a small group that examined the integration of GenAI into peer feedback. For example, Chen et al. examined different ways in which students used GenAI to produce peer feedback (Z. Chen et al., 2024; Gutiérrez-Ferré et al., 2024). Where AI-generated comments were inserted into peer discussion forums to influence the quality of conversations (Gutiérrez-Ferré et al., 2024; Sajadi et al., 2023), GenAI was used to synthesise and hence de-identify peer feedback comments for students working in project teams (Sajadi et al., 2023). Other studies presented innovations that could easily be extended towards abundance, but did not present this in their work (Cronje, 2023; Holderried et al., 2024).

There was also a cluster of articles (e.g., Alers et al., 2024; Bucol & Sangkawong, 2025) whose objective was to compare the feedback produced by GenAI to that produced by human markers. These articles did offer some useful insights; however, the focus was on the evaluation of the feedback itself as an artefact, and whether it could be used as a direct substitute for human-generated feedback, rather than to explore the new opportunities afforded by GenAI. In this regard, they were inconsistent with the concept of abundance, lying closer to the concept of digitisation.

6. Findings and Implications

6.1. The Dimensions of Abundance Are Beginning to Be Explored

Our survey found that approximately 70% of papers presented innovations that aligned with one or more of the dimensions of abundance. Character abundance was the least commonly observed dimension, and was far more likely to be found as a single dimension compared to other dimensions (43% of instances, more than double other dimensions). A cluster of articles showed the combination of volume, abundance and relevance dimensions; these studies typically involved students being trained to use an AI chatbot system, following which they could ask the chatbot to provide feedback on various aspects of their work at their leisure.

There were no articles that actually presented the concept of abundance itself, by either name or description. Of the studies that were reviewed, most showed variation or choice, but few showed full abundance (release of constraints) within any of our dimensions. There are several possible explanations for this.

Firstly, this may have been due to the recent growth in GenAI systems; the studies we reviewed were often exploratory in nature. Token limits were restrictive in the early GenAI systems that most of these papers used, and educators were still discovering and developing the capabilities of these systems. Over time, as systems are developed further and confidence grows, there may be an expansion from feedback regimes that offer limited choice towards offering true abundance.

Secondly, abundant does not necessarily imply better, particularly when developing feedback systems for student (rather than staff) use. It will be important for teaching staff to consider which feedback dimensions (if any) to make truly abundant in their practice, and which ones to restrict by choice. Abundance simply allows staff to make these decisions, rather than the decisions being forced on them by practicalities. The studies we reviewed generally performed limited evaluation of how abundant GenAI feedback affected how well the students achieved learning outcomes. It is important that this work becomes a focus of research as soon as possible.

As ever, the teaching staff must carefully consider the students, the context and the desired outcomes, and develop systems that provide appropriate feedback to account for these. Abundance allows new possibilities that were previously impractical, and many of these have potential to improve current situations, but further work is needed to determine which of these possibilities are truly beneficial for students. We hope that our framework will encourage teachers to notice the disappearance of various barriers and implement abundant feedback where it makes sense in their units.

6.2. Empirical Validation of Framework Dimensions

The proposed framework was found to cover all of the current abundances found in our sample of GenAI feedback. It was discussed whether student agency should be considered a dimension. However, we eventually determined that this was better described as an affordance of the other abundance dimensions. We briefly considered whether input type might be a separate extra dimension (Nofal et al., 2025; Ye, 2025), but decided against it; this was essentially just describing different assessment tasks. Otherwise, every other type of variation we observed clearly belonged to one of these categories.

The advent of GenAI is expected to trigger another shift in how feedback is conceptualised, delivered, and experienced. However, good feedback practice will continue to require the teacher to be conscious of how the feedback might be incorporated by the student into their learning process. We believe our four-dimensional abundance framework will be useful to stimulate ideas of how to use the new affordances of AI-generated feedback. It could be used to help generate effective prompts for GenAI feedback systems (for example, by ensuring that the desired relevance and character of the feedback are defined), or to help teachers to consider ways to break away from feedback practices which subconsciously assume that feedback must be scarce (for example, by providing feedback that is unlike that of the teacher themselves).

6.3. Interdependence of Abundant Feedback, Student Agency and Feedback Literacy

Academic understanding of the characteristics of high-quality feedback has evolved over recent decades. While earlier emphasis was placed on aspects such as speed, detail, clarity, structure, and relevance in delivering information to students, the focus has now shifted toward how feedback is interpreted by students and the nature of their interaction

with the feedback provider (Rowe, 2017). Feedback is no longer seen as a one-way transmission of information from lecturer to student, but rather as a dialogic process that may involve multiple channels of communication, reflecting how feedback functions to foster leaners' engagement, self-regulation and agency (D. Nicol, 2010).

Coupled with student agency, feedback literacy is likely to be critical in allowing students to make best use of AI feedback. We propose that there is an interplay between GenAI-enabled abundant feedback, feedback literacy research, student agency, and student driven feedback practices (Figure 3). Recent publications have implied that students will need AI feedback literacy to be able to effectively interact with GenAI feedback (Hawkins et al., 2025; Liu & Deris, 2025).

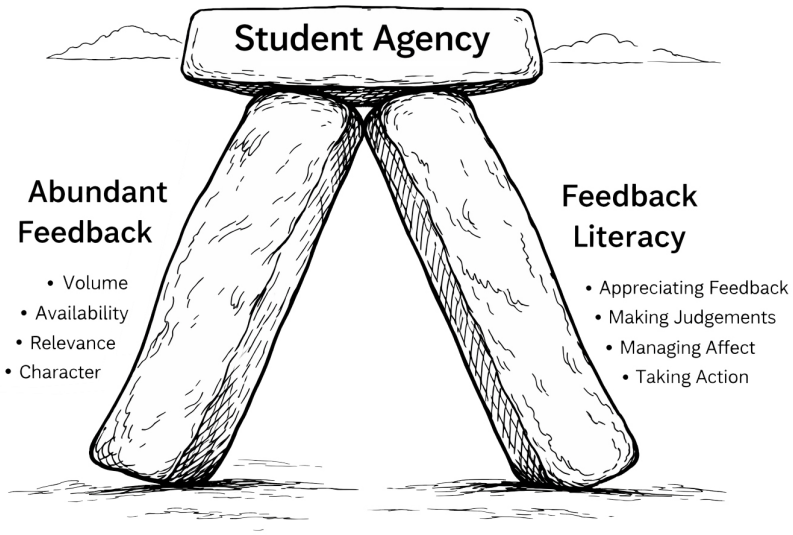

Figure 3. Conceptual illustration of proposed relationships. Abundant feedback and feedback literacy are mutually reinforcing. They also act as the underlying pillars that combine to support student agency in feedback processes.

Symbiotically, the potential abundance of GenAI feedback also increases opportunities for students to practice skills in seeking, interpreting and responding to feedback. Currently, the scarce nature of feedback in many current educational contexts reduces students' exposure to feedback information, and hence their ability to practice comparing the quality and interpreting the meaning of different pieces of feedback information. There is potential for abundant feedback, as enabled by GenAI, to become an important enabler for teaching of feedback literacy, although clear design of the related learning activities and feedback regimes will be critical. Furthermore, abundant feedback potentially enables data-driven investigation of initiatives to improve students' (AI) feedback literacy, at a scale that has until now been impractical.

Caution here is warranted; as discussed earlier, abundant feedback does not imply quality feedback. GenAI is well recognised to hallucinate incorrect answers, and may provide exhaustive feedback that "does not consider the pedagogical implications of overwhelming students" (i.e., excessive volume) (X. Guo, 2025).

Furthermore, creating effective feedback is not a simple matter of supplying truthful and relevant feedback information, but rather of stimulating "processes where the learner makes sense of performance-relevant information to promote their learning" (Henderson et al., 2019). This implies that GenAI could be used to create effective feedback regimes, even in situations where the generated feedback information is only partially reliable, as long as students were adequately prepared and supported through the process.

Related ideas were discussed in several studies from our search. Work from Koltovskaia et al. (2024) saw Persian-speaking graduate students use GenAI to provide feedback on their English language research proposals. The students were able to use their pre-existing feedback literacy skills to separate useful information from that which was incorrect or suggestions that were judged to be inferior to the existing text, rejecting approximately half of suggested changes. Similar low acceptance rates (65%) of GenAI feedback was seen in work by Guo (X. Guo, 2025). Interestingly, studies also discuss students who "trust the teacher blindly" (Kurt & Kurt, 2024), where this "high level of trust in teacher assessments may discourage students from questioning or going beyond the corrections suggested by their instructors" (X. Guo, 2025). It is possible that the widely discussed inaccuracy of GenAI feedback could provide greater impetus for students to engage critically with feedback, an important aspect of feedback literacy (Carless & Boud, 2018).

While the accuracy of AI-generated information will doubtless improve, it will remain important that "novice … students be given some training in reacting to feedback … and engaging in meaningful reflection." (Cronje, 2023). Activities may be designed to stimulate reflection on GenAI-generated feedback, such as sessions where students discuss the AI feedback with peers in order to collaboratively "make meaning" from the feedback information (Bacon & Maneerutt, 2024), or activities where students are asked to reflect on the feedback they accepted/rejected, and explain their reasoning (Bai & Wei, 2024).

Exposure to feedback with abundant characteristics may push students to develop a sense for the types of feedback that is most useful to them in different situations. Zhang et al. (2024) observed students express (unprompted) varying preferences around the tone of feedback that the GenAI system produced. Abundant character allows an instructor to implement these preferences if desired. However, while students may prefer feedback with a particular character/availability/relevance, utilising feedback that is not to their preference and negotiating feedback discussions with their mentors are both important aspects of feedback literacy. With appropriate scaffolding and controls, abundant character could conversely be deployed to explicitly teach students skills in "managing affect", which is a consistent feature of many frameworks that discuss feedback literacy (Carless & Boud, 2018; Dawson et al., 2024; Henderson et al., 2019). Abundance in volume and availability could reduce the separation between feedback instances, allowing comparison to be vivid and regularly reinforced, but could also be used to teach students skills in judging the worth of different forms of feedback. Implementations of student agency with AI feedback typically require prompting, so students are actively seeking feedback and interacting dialogically rather than just receiving information passively (Yan, 2025). This may encourage students to begin to develop skills in seeking and providing feedback information, which have been nominated as important components of feedback literacy (Dawson et al., 2024).

7. Conclusions

GenAI removes many of the current constraints on feedback content and delivery. The literature is beginning to reflect this opportunity. There are areas in the literature where we see new approaches that draw upon the affordances provided by abundant GenAI feedback. These examples are not explicitly conceptualised as being abundant, however when viewed through the lens of abundance, they represent a coherent body of work. Defining abundant feedback provides a conceptual reference point for guiding its coherent and purposeful integration in education. Without such a label, the risk is that abundance will occur in practice but go unrecognised in theory, leaving the field without the language to guide, critique, or build upon it.

Abundance in feedback has no intrinsic value; its value lies in its ability to enable new, valuable pedagogical possibilities. Rather than treating feedback information only as a scarce, rationed resource delivered directly by educators, GenAI allows this information to be considered as an abundant resource, similar to electricity or running water. Abundance is potentially capable of supporting learner feedback literacy, agency and self-regulation, formative assessment cultures, and equity in access to high-quality feedback. Furthermore, it would be capable of doing these in a manner that is as effective in a large class as a small one, due to the tiny marginal cost of running an AI system once it is developed.

The abundance that is enabled by GenAI represents a potential paradigm shift for the future of feedback. As GenAI systems continue to develop, educators will be able to complete the same feedback-related tasks more efficiently, or may be able to improve their current practices by personalising feedback given by automated systems, or freeing up time for high-value interactions with students. They are also able to go further and move their feedback practice beyond scarcity-driven constraints, by empowering students to more effectively seek out and process their own feedback information. Conceptualising abundant feedback along the dimensions of volume, availability, relevance and character provides a framework to assist academics in implementing this abundance in their teaching.

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