Computers & Education 237 (2025) 105360

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

Analytics of Learner-Centered Feedback: A Large-Scale Case Study in Higher Education

Ahmad Ari Aldino [a], Yi-Shan Tsai [a], Siddarth Gupte [a], Michael Henderson [b], Debarshi Nath [c], Dragan Gašević [a], Guanliang Chen [a,*]

[a] Centre for Learning Analytics at Monash, Faculty of Information Technology, Monash University, Clayton, Victoria, Australia
[b] Faculty of Education, Monash University, Melbourne, Australia
[c] IIT-Bombay Monash Research Academy, Mumbai, Maharashtra, India

ARTICLE INFO

Keywords:
Learner-centered feedback
Learning analytics
Higher education
Learning management systems
Digital learning environment

ABSTRACT

Feedback plays a crucial role in guiding students towards achieving their learning goals. The conceptualization of feedback has shifted from *teacher-centered* to *learner-centered* approaches, underscoring the evolving role of educators and students in educational settings. Despite the growing emphasis on learner-centered feedback frameworks, there remains a gap in understanding how these frameworks are implemented in actual teaching practices. This case study addresses this gap by examining the alignment of current feedback practices with learner-centered feedback principles in the Computer Science School at an Australian higher education. We gathered feedback data from the Master of Data Science and Bachelor of Computer Science program that were communicated through the Learning Management System. The dataset included feedback from 4959 students, provided by approximately 200 instructors across 95 courses. To ensure a representative sample, 10% of feedback entries from each course were analyzed, resulting in 16,408 feedback sentences. The findings reveal a pronounced emphasis on the sensemaking dimension, particularly in evaluating students' strengths and weaknesses to help them understand their performance. Feedback patterns varied by student performance, with high achievers receiving affirmations, medium achievers receiving actionable suggestions, and low achievers receiving comprehensive evaluations. Feedback in the Master's program prioritized future impact by offering actionable guidance for advanced tasks, while the Bachelor's program emphasized fostering agency through active student engagement and participation.

1. Introduction

Feedback plays a pivotal role in enhancing students' learning experiences in higher education (Satish, Reddy, Dubey, Verma, & Singh, 2023). Through feedback, students gain insights into their performance, understand areas of improvement, and receive guidance on how to better approach their studies (Hsia, Hwang, & Hwang, 2023). Feedback not only serves as a reflection of past performance but also as a roadmap guiding students towards academic success (Chung, Chen, & Olson, 2021). However, the landscape of higher education presents several challenges in sharing constructive and effective feedback (Henderson, Ryan, & Phillips, 2019; Meiras, 2021). As class sizes grow and student diversity increases, the capacity of teaching staff to provide feedback that caters to the unique needs of each student becomes strained (Maringe & Sing, 2014). Moreover, there is an underlying challenge

* Correspondence to: Centre for Learning Analytics at Monash, Faculty of Information Technology, Monash University, Clayton, VIC 3168, Australia.
E-mail address: guanliang.chen@monash.edu (G. Chen).

https://doi.org/10.1016/j.compedu.2025.105360
Received 30 September 2024; Received in revised form 27 March 2025; Accepted 8 May 2025
Available online 26 May 2025
0360-1315/

where educators might not always possess the requisite knowledge or training to discern what constitutes quality feedback (Heritage, 2007; To, Tan, & Lim, 2023).

Recent shifts in the conceptualization of feedback have seen a transition from a traditional focus on feedback as mere information sharing, towards a more holistic view that positions feedback as an interactive process in which learners play an active role instead of being merely passive recipients of information (Winstone, Boud, Dawson, & Heron, 2022). In earlier literature, the essence of effective feedback was often encapsulated in its informational value and timely sharing (Hattie & Timperley, 2007), whereas contemporary perspectives advocate for a nuanced approach, emphasizing learners' role in actively seeking and making meanings of feedback (Winstone et al., 2022). To facilitate such an interactive feedback process, it is crucial to ensure that feedback is learner-centered; this approach takes into account the needs of learners and actively encourages their productive engagement with feedback. To support this approach, various theoretical frameworks have been proposed, providing structured methodologies and insights for educators to implement learner-centered feedback effectively (Kneebone et al., 2008; Ryan, Henderson, Ryan, & Kennedy, 2021a, 2021b; To, 2022; To et al., 2023; Vivekananda-Schmidt, MacKillop, Crossley, & Wade, 2013). Educators equipped with this knowledge can better tailor strategies that resonate with learners' needs, fostering deeper engagement in the feedback process (Narciss et al., 2014). However, the extent to which these principles are implemented in current feedback practices in higher education remains relatively under-explored (To, 2022; To et al., 2023). This limited exploration raises questions regarding the alignment between existing feedback practice and learner-centered feedback principles that are deemed crucial for an effective feedback process (Shahzad, Ström, & Mozelius, 2023). According to Ryan et al. (2021b), learner-centered feedback has three dimensions, collectively comprising eight components. The three key dimensions are future impact, sensemaking, and agency. future impact involves actionable feedback that guides students' future learning. sensemaking helps students understand their strengths and weaknesses. agency promotes active student engagement and acknowledges their accomplishments. These dimensions and components constitute the core elements of learner-centered feedback. Table 1 provides a comprehensive summary of these dimensions along with their components and definitions, illustrating how feedback is categorized and analyzed in this study.

Considering the inherent diversity in student populations in higher education, feedback needs might vary across different student performance groups (Guo, Lau, & Wei, 2019; Salehian Kia, Pardo, Dawson, & O'Brien, 2022). For example, while high-achieving students might lean towards feedback that pushes their learning capabilities, those low achievers might be more receptive to foundational and supportive feedback, bolstering their academic self-belief and comprehension (McCoach & Siegle, 2001). However, research indicates a noticeable misalignment in the feedback provided based on student performance, especially in its tone and content (Dai, Tsai, Fan, Gašević, & Chen, 2022). While feedback should meet the needs of individual students, existing studies Dai et al. (2022) show that educators may inadvertently favor certain student groups, potentially limiting the academic progress of others.

To address these issues, the current study aimed to contribute to the ongoing efforts to improve feedback practices in higher education. Our study was guided by the following two Research Questions:

- **RQ1** To what extent does the current feedback practice align with learner-centered feedback and vary across different student performance groups?
- **RQ2** How do the components of learner-centered feedback relate to each other and vary across different student performance groups?

We addressed the research questions by examining feedback data communicated through the Learning Management System (LMS) from one Master's and one Bachelor's program at an Australian university. To answer RQ1, we employed a manual labeling process, categorizing feedback based on the key components specified in a well-established learner-centered feedback framework (Ryan et al., 2021b). We chose this framework because it was developed using a rigorous methodology, and it offers a robust approach to identifying learner-centric feedback, focusing on three dimensions: future impact on learning, sensemaking, and agency. We investigated the presence of eight core components that make up the three dimensions above (Ryan et al., 2021b) in the current feedback practices and compare them across different student performance groups. Although Ryan et al. (2021b) proposed the three dimensions as distinct aspects, it is worth exploring the interactive dynamics among these dimensions to deepen our understanding of their potential connections and how the connections may vary by the nature of students and their academic performance. To answer RQ2, we utilized Ordered Network Analysis (ONA) to analyze the connections between codes representing the eight components of learner-centered feedback. This method specifically allows us to identify directed relationships by considering the sequence of occurrences, thereby clarifying whether certain feedback components tend to lead to other components, and whether or not there is a difference in the patterns among different performance groups of students. This approach aimed at gaining a holistic understanding of how learner-centered feedback practices are adopted in higher education and subsequently providing suggestions for improving quality feedback provision.

2. Background

The varied aspects of feedback covered in the following sections give a broad overview of its role in education. We delve into the principles of learner-centered feedback, its impact on students of varying performance levels, and the co-occurrence of different feedback components. Additionally, we examine the role of feedback in different feedback sharing modalities and the influence of technological advancements in automated feedback analysis and provision. Each of these facets offers a different view of feedback. When combined, they offer a comprehensive understanding that can guide educators to enhance their feedback practices to support student learning process.

Table 1
Dimensions, definitions, and components of the learner-centered feedback framework (Ryan et al., 2021b).

Dimension	Label (Component)	Definition
agency	A_Active_Role	Motivate the student to participate actively by engaging in conversations with the teacher or tutor about their work, exploring additional studying opportunities, or seeking assistance from alternative resources apart from the teacher. *(e.g. "You might find it helpful to explore other examples online or talk to a peer about your draft.")*
agency	A_Affirm_Encourage	Acknowledge the student's accomplishment in their completed performance and offer words of encouragement for their future work. *(e.g. "Well done on getting this submitted. Keep up the good work for the next task!")*
agency	A_Strengthen_Relationship	Provide information that will bolster the connection between the teacher and the student. *(e.g. "It has been a pleasure seeing your progress throughout the semester.")*
future impact	FI_Future_Improvement	Offer actionable information to assist the student in enhancing specific areas of similar tasks they might encounter in the future. *(e.g. "Try to ensure each section is clearly structured with headings and supporting evidence in future reports.")*
future impact	FI_Learning_Outcomes	Offer actionable information to aid the student in attaining the desired learning outcomes for the subject. *(e.g. "For the next task, make sure your analysis directly addresses the units key objectives.")*
future impact	FI_Skill_Development	Offer actionable information to support the student in developing learning skills, processes, or strategies that can be beneficial throughout and beyond their academic journey. *(e.g. "Consider revising your draft with a grammar tool to catch minor writing issues before submission.")*
sensemaking	S_Strengths_Weaknesses	Identify the strong points and areas that need improvement in specific aspects of the student's task, including grammar, content, structure, and more. *(e.g. "Your analysis is clear, but the referencing format needs attention.")*
sensemaking	S_Performance_Summary	Provide an overview of the student's accomplishments and areas for improvement in relation to the learning objectives and assessment standards. *(e.g. "This assignment shows a good grasp of the topic, though more critical discussion was expected at this level.")*

2.1. Learner-centered feedback

Feedback in educational systems, as outlined by researchers Hattie and Timperley (2007) and Nicol and Macfarlane-Dick (2006), was primarily designed to bridge the gap between students' current achievements and intended goals. These traditional approaches emphasized clear performance benchmarks, self-evaluation, and a linear flow of information from educators to students. However, recognizing the limitations of such a unidirectional approach, contemporary research, as seen in the Mark 2 feedback model (Boud & Molloy, 2013), dialogic feedback (Yang & Carless, 2013), feedback literacy framework (Carless & Boud, 2018), and the Typology of Feedback Impact (Henderson et al., 2019), has shifted towards more learner-centric feedback models. The Mark 2 feedback model positions feedback as a participatory process where both teachers and learners share responsibility, focusing on learner independence through skills like evaluative judgment and feedback agency (Boud & Molloy, 2013). The Dialogical Triangle model highlights the importance of interaction in feedback, emphasizing cognitive, social-affective, and structural dimensions (Yang & Carless, 2013). Carless and Boud (2018) proposed the Feedback Literacy framework, defining it as learners' ability to appreciate, evaluate, manage affective responses, and act on feedback to enhance performance and learning strategies. Additionally, the Typology of Feedback Impact outlines how feedback influences learners' cognitive and metacognitive processing, affective responses, identity formation, and relational dynamics with teachers, emphasizing both positive and negative impacts (Henderson et al., 2019). Despite this shift, there remains a need to understand how these learner-centered feedback theories are implemented in actual teaching practices. Our study examines the alignment of current feedback practices with these theories, providing insights into their practical application within technology-mediated contexts.

Given the differing academic demands and developmental stages of Bachelor's and Master's students, understanding how feedback strategies vary across these levels is essential to tailoring learner-centered practices that meet the unique needs of each group. For instance, Bachelor's students typically require feedback that emphasizes foundational skills, fosters self-efficacy, and promotes engagement (Carless & Boud, 2018), whereas Master's students benefit from feedback focused on advanced applications, critical analysis, and research-oriented tasks (Lin et al., 2023). It remains unknown, however, to what extent educators' feedback practices align with such previous research findings and how they vary in different educational settings. This study empirically investigates whether such differences in feedback align with the core dimensions and components of learner-centered feedback, as defined by Ryan et al. (2021b).

In light of recent shifts towards a learner-centered feedback paradigm in feedback theories, Ryan et al. (2021b) recognized a potential disconnect between theories and actual pedagogical practices. Noting that many existing practices are still rooted in 'old paradigm' conceptualizations of feedback, they developed a set of learner-centered feedback components through a rapid systematic review and empirical validation with teachers and students at two Australian universities. These components are designed to help teachers create feedback that supports learners in understanding and using feedback to improve future work and learning strategies. Ryan et al. (2021b) identified three key dimensions that contribute to effective learner-centered feedback: future impact, sensemaking, and agency, which are further divided into eight components. Table 1 outlines these components in detail, providing definitions and examples that guide the analysis in this study.

The first dimension, future impact, emphasizes the need for feedback to provide insights and recommendations that can guide students' future learning. By focusing on the future impact, feedback becomes actionable and it empowers students to make meaningful changes to their work. The second dimension, sensemaking, recognizes the significance of helping students understand their strengths and weaknesses and guides them in developing a deeper comprehension of their learning progress. sensemaking empowers students to reflect on their work and connect the feedback to their learning goals. The third dimension, agency, underscores the importance of student involvement and active participation in the feedback process. This component encourages students to become proactive learners, fostering a sense of responsibility and autonomy. Building upon their work, our study evaluates the alignment of the current feedback practices in two popular programs, one Master's and one Bachelor's, at a large faculty of a research-intensive university with the three key dimensions and the core components in each dimension (RQ1). In light of the observation in Ryan et al. (2021b) that sensemaking can effectively lead to future impact, our study further investigates the sequential connections among learner-centered feedback components to explore the existence and nature of these and other potential connections within the framework (RQ2).

2.2. Feedback in different feedback sharing modalities

As digital learning environments become an integral part of education, understanding how feedback can be effectively designed and shared in these contexts is crucial (Raubenheimer, Jeffries, & Yacef, 2021). Leveraging technology-mediated platforms, such as LMS, can streamline feedback sharing, fostering more effective engagement between educators and students (Sabri et al., 2024). Raubenheimer et al. (2021) proposed a feedback classification framework tailored for digital learning environments based on two key dimensions: problem vs solution-oriented feedback and instance vs theory-oriented feedback. Problem-oriented feedback identifies issues without offering solutions, encouraging students to engage in critical thinking. Conversely, solution-oriented feedback provides actionable steps to address specific challenges. Instance-oriented feedback targets specific errors for immediate correction, while theory-oriented feedback emphasizes broader concepts to foster deeper, long-term understanding. The study highlighted that combining instance-oriented feedback with solution-oriented guidance was particularly effective in helping students progress in programming tasks.

Challenges in providing personalized, constructive, and timely feedback in computer science education, particularly through LMS, has been widely recognized (Falcao, Arêdes, Wagner, Uchoa, Luisi, & Mello, 2022). Workload and time constraints present significant barriers for instructors, making it difficult to share actionable, specific, and constructive feedback with clear directions for improvement. Falcao et al. (2022) explored these challenges through interviews with Brazilian instructors and students, identifying the high value students place on feedback that balances acknowledgment of strengths with constructive criticism, fosters dialogue with instructors, and supports their overall learning process. To address these issues, the study introduced "Tutoria", a platform designed to enhance feedback efficiency within LMS environments. Similarly, natural language processing (NLP) and learning analytics have been leveraged to assist instructors in assessing open-response submissions, helping to reduce workload while maintaining feedback quality (Mello et al., 2022). The importance of inclusive feedback formats in digital learning environments has been emphasized, as they enable learners to compare their performance with peers, track progress towards course goals, and identify milestones achieved by others (Sedrakyan, van den Berg, Veldkamp, & van Hillegersberg, 2023).

Additionally, research suggests that students engage with text-based feedback (e.g., shared via an LMS) and face-to-face feedback (including feedback shared based on real-time, synchronous interactions such as teleconferencing) differently due to the absence of real-time dialogue, non-verbal cues, and immediate clarifications that are naturally embedded in face-to-face interactions (Eberle & Hobrecht, 2021; Jensen, Bearman, & Boud, 2021). While text-based feedback enables structured, asynchronous communication, allowing students to revisit feedback multiple times and engage at their own pace, face-to-face feedback fosters immediate, dialogic exchanges that enhance sensemaking and real-time adjustments (Carless & Winstone, 2023; Henderson et al., 2019). Furthermore, studies indicate that students perceive text-based feedback in online environments as less personalized and engaging than oral feedback, which can influence motivation and receptivity (McCarthy, 2015). This is supported by Sedrakyan, Borsci, Abdi, van den Berg, Veldkamp, and van Hillegersberg (2023), who found that students strongly preferred digital feedback channels such as conferencing tools (e.g., Zoom) due to their ability to facilitate engagement. Their findings emphasize that interactive feedback mechanisms, particularly real-time conferencing, are more effective in addressing the limitations of asynchronous text-based feedback by promoting engagement, clarity, and responsiveness.

Research highlights the importance of multimodal feedback formats (text, audio, video) in online environments. Sedrakyan, Borsci, et al. (2023) found that students favored real-time feedback features and multimodal formats enabled by digital tools, as these enhanced engagement and provided a more interactive alternative to static text-based feedback, partially compensating for the lack of real-time interaction in face-to-face exchanges. Their study indicates that synchronous conferencing, and structured peer feedback workflows are particularly effective in fostering a more interactive and engaging digital feedback environment. Studies suggest that synchronous feedback, by enabling real-time clarification and negotiation, often emphasizes interactive, dialogic aspects of feedback (Ajjawi & Boud, 2017). This may affect the frequency of use of learner-centered feedback components like agency and sensemaking in face-to-face or multimodal feedback environments, as these settings allow for spontaneous dialogue, immediate clarification, and dynamic adjustment of feedback based on student reactions (Ajjawi & Boud, 2017). However, text-based comments remain the predominant form of feedback provided to students in higher education settings (Ryan, Henderson, & Phillips, 2019). Thus, this study focuses on investigating the presence of different learner-centered feedback components and their co-occurrence in text-based feedback shared through an LMS.

2.3. Technological advancements in automated feedback analysis and provision

Technological advancements have revolutionized feedback mechanisms by enabling real-time, personalized, and efficient processes (Cavalcanti et al., 2021; Song, Shin, & Shin, 2024). Automated feedback systems, powered by artificial intelligence (AI) and machine learning (ML) have become essential tools for enhancing learning experiences (Munir, Vogel, & Jacobsson, 2022). For instance, real-time feedback ensures immediate knowledge acquisition and skill development, helping learners address gaps without delays (Deeva, Bogdanova, Serral, Snoeck, & De Weerdt, 2021). Intelligent Tutoring Systems utilizing techniques such as Natural Language Processing adapt feedback to align with students' aptitudes, particularly in computational disciplines like programming and algorithms (Jamaludin & Romli, 2023). In e-learning environments, advancements in emotion recognition have allowed platforms to capture and analyze students' emotions through image processing, offering feedback that enhances engagement and comprehension (Grabusts, Teilans, Kapenieks, et al., 2023). Similarly, unit testing frameworks in computational science education have emerged as critical tools, assessing student submissions and providing iterative feedback for continuous improvement (Fangohr et al., 2020).

Educational chatbots have emerged as a transformative tool in education, demonstrating the potential to improve learning performance, satisfaction, and engagement (Kuhail, Alturki, Alramlawi, & Alhejori, 2023). However, their effectiveness hinges on the extent to which they align with pedagogical principles and cater to the unique needs of learners. For chatbots to contribute meaningfully to educational outcomes, Sedrakyan, Borsci, van den Berg, van Hillegersberg, and Veldkamp (2024) emphasize the importance of designing them as interactive feedback dialogues that trigger regulatory mechanisms central to learning processes. Such feedback should not only address immediate questions but also guide learners towards achieving specific learning goals through adaptive and context-aware communication. By tailoring content depth and complexity based on the learner's performance and orientation, these chatbots can complement broader efforts to enhance personalized feedback in education, bridging gaps identified in traditional approaches. While these feedback systems, including Intelligent Tutoring Systems and chatbots, demonstrate immense potential, their primary focus has been on automated feedback generation and real-time analysis rather than evaluating the structure of feedback (Deeva et al., 2021; Fangohr et al., 2020; Grabusts et al., 2023; Jamaludin & Romli, 2023). In contrast, this study examines the extent to which current feedback practices align with learner-centered feedback principles, a key factor in determining whether technology-mediated feedback effectively supports Future Impact, Sensemaking, and Agency—core dimensions of learner-centered feedback (Ryan et al., 2021b). Understanding this alignment is essential to ensuring that feedback goes beyond information sharing to foster student engagement, metacognitive reflection, and self-regulated learning. Furthermore, this study considers variations across student performance groups and educational levels, employing Ordered Network Analysis (ONA) to analyze feedback sequences and uncover structural patterns. Examining these patterns is critical for both theoretical and practical reasons. Theoretically, it provides insights into how feedback components interconnect within technology-mediated learning environments, contributing to a more nuanced understanding of effective feedback practices.

2.4. Feedback and student performance

Feedback plays a pivotal role in shaping students' learning trajectories. Its primary function is to inform learners about their progress and to help them identify where they are and help them move towards the desired goals (Nicol & Macfarlane-Dick, 2006). As highlighted by Hattie and Timperley (2007), feedback often serves as a reflection of a student's current performance against the teacher's anticipations of their future achievements. These anticipations can be influenced by the student's past performance. Thompson, Warren, and Carter (2004) noted that students who consistently demonstrate academic excellence (high achievers) often receive affirmative feedback. However, it is crucial to recognize that affirmative feedback, characterized by positive acknowledgment of efforts and achievements, is pivotal for all students, irrespective of their performance levels, as it can significantly bolster motivation, self-efficacy, and engagement—essential elements for sustained academic growth (Aseery, 2023). Thus, tailoring feedback strategies to effectively meet the diverse needs and recognize the varied impacts on students across performance levels becomes essential for enriching the learning experiences of every student.

Building on this understanding of different student performance groups and their relationship with feedback, Lin et al. (2023) offers valuable insights. Their research analyzed feedback content using a comprehensive learner-centered feedback framework (Ryan et al., 2021b), examining differences in feedback characteristics among students who showed performance improvements and those who did not, after receiving feedback on consecutive assignments in a postgraduate course. While Lin et al. (2023) did not study the direct impact of feedback on performance, their findings reveal significant differences in feedback content between these groups, which suggests potential areas for enhancing feedback practices based on observed patterns. Understanding these intricacies of feedback becomes imperative for educators aiming to optimize their feedback practices for students across the performance spectrum. Compared to Lin et al. (2023) study, our research further explores the practical application of feedback principles, applying ONA to investigate the sequential connections among learner-centered feedback components communicated through LMS.

2.5. Co-occurrence of effective feedback components

While learner-centered feedback components have their distinct influence on student learning, understanding their connections provides a more intricate perspective of the feedback landscape. Nicol and Macfarlane-Dick (2006) detailed seven good feedback practices: (1) clarifying what good performance is, (2) facilitating the development of self-assessment, (3) sharing high-quality information to students about their learning, (4) encouraging teacher and peer dialogue around learning, (5) encouraging positive motivational beliefs and self-esteem, (6) providing opportunities to close the gap between current and desired performance, and (7) using feedback to improve teaching. While examining these practices individually can offer insights into specific aspects of feedback, the student experience is often shaped by a combination of these factors. Cavalcanti, de Mello, Rolim, André, Freitas, and Gaševic (2019) acknowledged this complex dynamic and delved into the co-occurrence of feedback practices in a Brazilian higher education setting. Their analysis revealed a significant pattern where feedback practices related to clarifying "what good performance is" and "how to close the gap" often occur together, suggesting a holistic approach in feedback sharing that addresses both understanding expectations and pathways for improvement. Recognizing the co-occurrence of different good feedback principles can yield a comprehensive, multi-faceted viewpoint (Cavalcanti et al., 2019). Building on this idea, our study focuses on the sequential connections between the eight components of learner-centered feedback to understand how these components interact in current feedback practices, especially those communicated through LMS.

3. Methodology

3.1. Data preparation

3.1.1. Data acquisition

To comprehensively address our research questions, we utilized feedback data communicated through the LMS from the Computer Science School at an Australian university. Feedback collected through LMS can be used by educators to reflect on and improve their teaching practices, ultimately enhancing student learning outcomes (Novák, 2023). This dataset included feedback from the two largest programs within the school: the Master of Data Science and the Bachelor of Computer Science, collected during Semester 1 and Semester 2 of 2022. Instructors responsible for providing feedback were expected to participate in training sessions focused on assessment and feedback practices provided by the university at which these instructors are employed, though not mandatory. Our study did not involve any intervention; rather, it was an exploratory investigation into existing feedback practices. Feedback was provided based on each instructor's expertise and pedagogical approaches, without adhering to a standardized template. The research goal of our study was not to compare educators' feedback practices in individual courses. Instead, the aim was to investigate the alignment between educators' feedback practices in authentic settings and the well-investigated learner-centered feedback theories, while analyzing the differences between two very large data samples (Bachelor vs. Master programs). This diversity highlights the natural dynamics of real-world educational settings and aligns with our aim to investigate the extent to which learner-centered feedback is practised in authentic contexts. The data encompassed a total of 95 courses across all study years, involving 4959 students and approximately 200 instructors. The selected programs represented the largest student populations within each degree level, with 2187 students in the Master's program and 2772 in the Bachelor's program. Due to confidentiality, all the data that we obtained was anonymized (all personal information removed). To ensure a representative sample, we employed a proportional stratified random sampling (Särndal, 1968) strategy, selecting 10% of the feedback from each course within both programs. This sampling rate (Särndal, 1968) was chosen to balance the need for a comprehensive representation of feedback practices with the practicalities of data analysis. A higher sampling rate could have burdened the analysis process without notably increasing representativeness, whereas a lower rate risked overlooking subtle variations in feedback practices. Consequently, the 10% sampling rate yielded 885 feedback entries from the Master's program, containing a total of 6527 feedback sentences, and 1391 entries from the Bachelor's program with 9881 sentences.

3.1.2. Data labeling

To effectively analyze feedback practices, we used the learner-centered feedback framework proposed by Ryan et al. (2021b). This framework comprises three dimensions, namely future impact (FI), sensemaking (S), and agency (A), which further break down into eight distinct components. We manually labeled the feedback dataset according to these 8 learner-centered feedback components. Given the multifaceted nature of feedback, we decided on sentence-level labeling. If feedback consisting of multiple sentences was not context-dependent (for example, one sentence might compliment the student's coding efficiency, 'Your code is very efficient,' followed by an unrelated feedback, 'Remember to submit your project by the deadline'), each sentence was labeled individually using a single component. However, for feedback that was context-dependent (where there is a connection between two sentences, such as 'Your function implementation lacks error handling. Adding try-catch blocks will make your code more robust'), we employed multi-labeling, i.e., both sentences would be labeled together with one code. While we do not limit the coding to be only one code per labeling, there is no case where one sentence or multiple context-dependent sentences are labeled with multiple codes. In other words, each unit selected for coding corresponds to only one particular component of the learner-centered feedback framework. To facilitate the labeling process, we employed the YEDDA Annotator, a Python-based tool developed by Yang, Zhang, Li, and Li (2017). The choice of the YEDDA Annotator was influenced by its user-friendly interface and its capacity to manage annotation tasks at various levels. The detailed breakdown and definitions of these components are provided in Table 1.

Ensuring the reliability of our data labeling process was paramount. Thus, two trained independent human coders, a Ph.D. student and a Master's student from the Faculty of Information Technology with expertise in learner-centered feedback research, labeled 2% of the data, totaling 309 feedback sentences. The process was iterated three times, ensuring that the coders reached consensus on the labeling. When disagreements emerged, the coders reviewed feedback that was labeled differently, discussed their disagreement, and collaboratively relabeled the feedback. The first labeling round resulted in a Cohen's κ of 0.50, with most disagreements arising from confusion between "future impact" and "agency" related feedback. The second round yielded a κ of 0.70, with some disagreements echoing those from the first round. By the third round, a substantial agreement with a Cohen's κ of 0.84 was achieved. With this level of agreement in place, the dataset was divided, and each coder proceeded to label 50% of the remaining data.

Table 2
Student distribution across performance groups.

Program	Performance group	Number of students
Bachelor	High Achiever	1046
	Medium Achiever	242
	Low Achiever	103
	Total	**1391**
Master	High Achiever	573
	Medium Achiever	281
	Low Achiever	31
	Total	**885**

Table 3
Feedback component counts across student performance groups and study programs (High = High achievers, Medium = Medium achievers, Low = Low achievers).

Component	Master			Bachelor		
	High	Medium	Low	High	Medium	Low
A_Active_Role	71	92	15	904	333	105
A_Affirm_Encourage	560	93	11	1275	142	31
A_Strengthen_Relationship	70	42	3	244	64	15
FI_Future_Improvement	923	937	89	939	323	88
FI_Learning_Outcomes	38	54	8	34	14	8
FI_Skill_Development	29	73	4	59	26	5
S_Performance_Summary	317	149	26	566	198	120
S_Strengths_Weaknesses	1674	1038	79	2656	1034	342
Non Learner-centered feedback	88	40	4	281	67	8
Total Count (Performance Group)	3770	2518	239	6958	2201	722
Total Count (Program)		**6527**			**9881**	

3.2. Data analysis

3.2.1. Descriptive and inferential statistics

To address RQ1, we calculated the prevalence of learner-centered feedback components from the labeled feedback data. We visualized the prevalence of each components using a bar plot with the `Matplotlib` library in Python. This prevalence was further visualized in stacked bar plot showing the prevalence of learner-centered feedback components in relation to student performance groups to discern the differences in the feedback provided to students with varying levels of performance. Although we categorized students into different performance groups, our goal was not to compare their academic performance. Instead, our goal was to examine feedback practices across different performance groups to better understand how educators tailor their feedback and how these patterns can inform more inclusive and equitable feedback strategies in the future. Since the dataset includes a total of 429 assignments from 95 different courses in a faculty, the score weighting and the scoring rubrics varied. To ensure consistency in our analysis, we normalized all scores to a 100-point scale. The classification of student performance groups was based solely on the final provided scores, without considering specific grading criteria for each assignment type, as the dataset comprises a mix of coding-based assignments, written reports, data analysis tasks, and other project-based assessments. We intentionally included a diverse range of assignments and courses to enhance the validity and generalizability of our findings. Based on the grading guidelines of the university from which this data was collected, the students with assignment scores above 80 marks were categorized as receiving a High Distinction (HD) grade, those with scores between 70 and 79 marks receive a Distinction (D) grade, those with scores between 60 and 69 marks receive a Credit (C) grade, those with scores between 50 and 59 marks receive a Pass (P) grade, and those with scores between 0 and 49 receive a Fail (F) grade. To facilitate analysis, we recategorized the student performance groups as follows: High Achievers correspond to HD and D grades, Medium Achievers correspond to C and P grades, and Low Achievers correspond to F grade. This categorization is supported by educational research (Farooq & Regnier, 2011; Jibeen & Khan, 2016; Kam & Umar, 2023), which highlights the importance of grouping students by performance levels to better tailor feedback to their learning needs and promote targeted improvements. After the data labeling process, the feedback in the Master's program comprised 6527 entries, split among High (3770), Medium (2518), and Low (239) Achievers. In the Bachelor's program, out of 9,881 entries, High Achievers accounted for 6958, Medium for 2201, and Low for 722. The distribution of students across performance groups is detailed in Table 2, while Table 3 presents the feedback component counts across student performance groups and study programs.

To test for statistical significance in feedback component differences between the Bachelor's and Master's programs, we conducted a Z-test for proportions (Zou, Fielding, Silverman, & Tempany, 2003). The Z-test compares the observed proportions of feedback components across the two programs to determine whether the differences are statistically significant, given the sample sizes. For each component, the Z-statistic quantifies the number of standard deviations the observed difference in proportions is away from the null hypothesis (i.e., no difference between the programs). A positive Z-statistic indicates that the feedback component is more

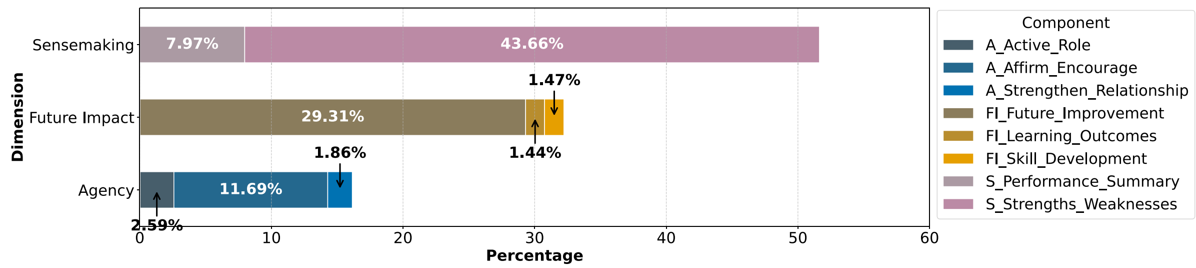

Fig. 1. The Prevalence of Learner-Centered Feedback in the Master's Program. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

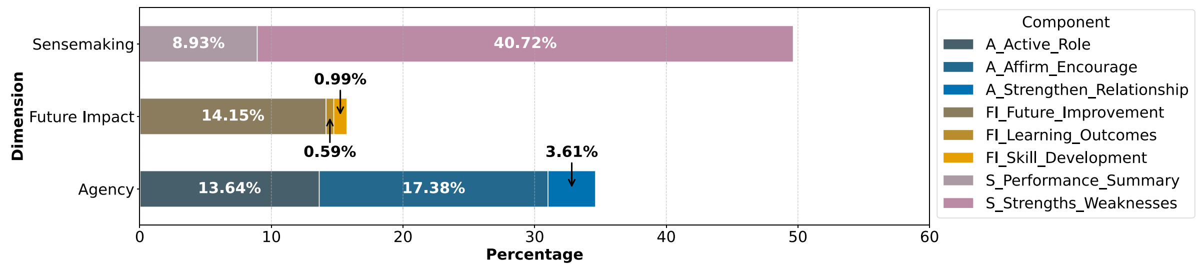

Fig. 2. The Prevalence of Learner-Centered Feedback in the Bachelor's Program. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

prevalent in the Bachelor's program, while a negative Z-statistic indicates greater prevalence in the Master's program. A *p*-value is derived from the Z-statistic to assess the likelihood that the observed differences occurred by chance. A small *p*-value (typically $p < 0.05$) indicates strong evidence against the null hypothesis, suggesting that the difference is statistically significant.

3.2.2. Ordered Network Analysis

To address RQ2, we utilized ONA, employing the `ONA` package within the R programming. This approach is informed by the methodologies outlined in Shaffer, Collier, and Ruis (2016) and further developed in recent studies by Fan et al. (2023) and Tan, Ruis, Marquart, Cai, Knowles, and Shaffer (2022). ONA is an extension of Epistemic Network Analysis (ENA) which adeptly captures and quantifies directed connections among coded data, emphasizing the sequence and directionality of these interactions. A key feature distinguishing ONA from ENA is its construction of an asymmetric adjacency matrix, which accounts for the sequential nature of connections, wherein the connections from code A to code B may differ in number from those from B to A. The analysis facilitates the generation of low-dimensional representations for each network via dimension reduction techniques like singular value decomposition. This reduction enables effective statistical comparisons across different groups of networks. In our study, each unique feedback sentence and student performance groups (low, medium, and high) was treated as a unit of analysis, unique feedback sentence as stanzas or conversations, and eight learner-centered feedback components as codes. For quantitative comparison of these networks across the various student performance groups, we used t-tests (Kim, 2015) supplemented by Cohen's *d* (Cohen, 2013) to determine the effect size.

4. Results

4.1. Results on RQ1

To address RQ1, we generated stacked bar plots to showcase the three primary dimensions of learner-centered feedback: sensemaking (purple), future impact (orange), and agency (blue). Each segment in these plots further delineates to reveal corresponding components, as depicted in Figs. 1 and 2 for the Master's and Bachelor's programs, respectively. Both programs highlight a significant emphasis on the sensemaking dimension, particularly in "evaluating the strengths and weaknesses of specific aspects of student tasks" (S_Strengths_Weaknesses, 43.66% in the Master's program and 40.72% in the Bachelor's program). This shared focus highlights a fundamental pedagogical strategy used for feedback regardless of degree levels.

Differences between the programs are marked in their approaches to the other two feedback dimensions. The Master's program places a significant emphasis on future impact dimension, which includes offering detailed guidance on how to enhance future performances (FI_Future_Improvement, 30.43%). In contrast, the Bachelor's program more strongly supports student agency, focusing on nurturing student agency through encouragement and active participation in their learning processes (A_Affirm_Encourage, 17.38%; A_Active_Role, 13.64%).

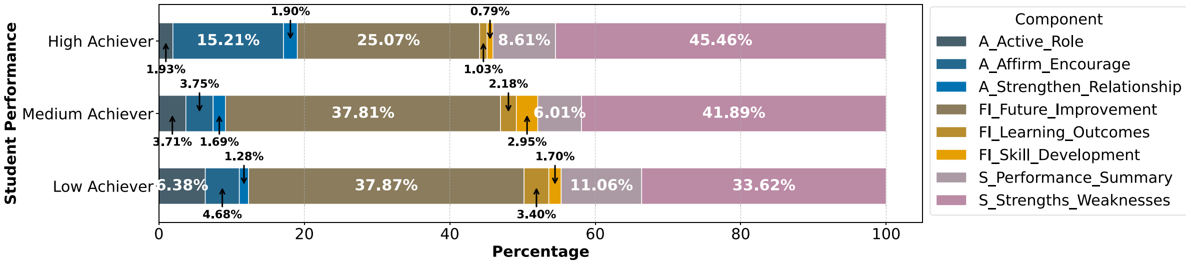

Fig. 3. The Prevalence of Learner-Centered Feedback in Relation to Student Performance in the Master's Program. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

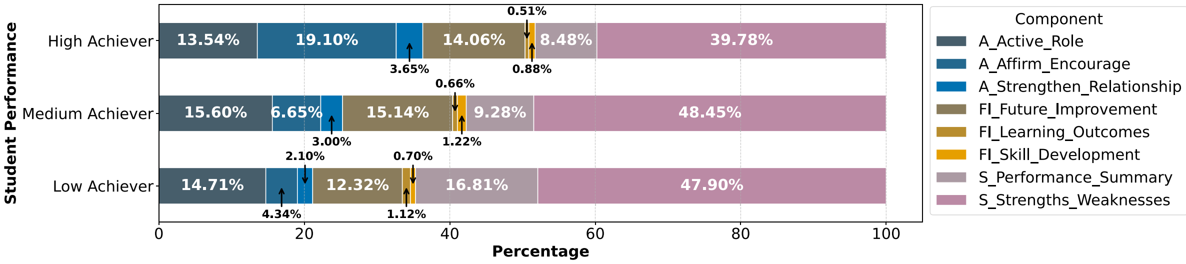

Fig. 4. The Prevalence of Learner-Centered Feedback in Relation to Student Performance in the Bachelor's Program. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Statistical significance of feedback component comparisons across student performance groups and study programs (High = Comparison of high achievers in master's and bachelor's programs, Medium = Comparison of medium achievers in master's and bachelor's programs, Low = Comparison of low achievers in master's and bachelor's programs).

Component	Z-Statistic			P-Value		
	High	Medium	Low	High	Medium	Low
A_Active_Role	19.11	3.35	13.74	<0.001	<0.001	<0.001
A_Affirm_Encourage	4.56	−0.20	4.35	<0.001	0.84	<0.001
A_Strengthen_Relationship	4.84	0.81	2.87	<0.001	0.42	0.00
FI_Future_Improvement	−14.35	−8.66	−17.46	<0.001	<0.001	<0.001
FI_Learning_Outcomes	−3.15	−2.35	−4.34	0.00	0.02	<0.001
FI_Skill_Development	0.43	−1.36	−4.11	0.67	0.17	<0.001
S_Performance_Summary	−0.49	2.14	4.04	0.62	0.03	<0.001
S_Strengths_Weaknesses	−6.28	3.87	3.97	<0.001	<0.001	<0.001

Diving deeper into the prevalence of learner-centered feedback, we examined the nuances of feedback components across different student performance levels. Figs. 3 and 4 illustrate these distributions for the Master's and Bachelor's programs, respectively. For clarity, each student performance group is represented as 100%, facilitating a more discernible comparison of feedback components within each group. In the dataset, the Master's program consists of 65.05% High Achievers, 28.98% Medium Achievers, and 5.97% Low Achievers, while the Bachelor's program comprises 70.10% High Achievers, 22.40% Medium Achievers, and 7.50% Low Achievers. High achievers often receive "motivational affirmations of accomplishments" (A_Affirm_Encourage, 15.21% in the Master's and 19.10% in the Bachelor's), which motivate continued excellence. Medium achievers in the Master's program receive a significant amount of feedback aimed at 'improving future task performance' (FI_Future_Improvement, 37.81%), compared to a notably lesser but focused proportion in the Bachelor's program (FI_Future_Improvement, 15.14%). In contrast, feedback for low achievers frequently includes "comprehensive overviews of performance" (S_Performance_Summary, 11.06% in the Master's and 16.81% in the Bachelor's), with a specific focus in the Bachelor's program on "encouraging active engagement in educational processes" (A_Active_Role, notably higher for low performers).

The statistical test, detailed in Table 4, reveal several key findings. Notably, some feedback components exhibited statistically significant differences across all student performance groups. For instance, 'active participation' (A_Active_Role) was consistently more prevalent in the Bachelor's program (High Achievers: $Z = 19.11$, $p < 0.001$; Medium Achievers: $Z = 3.35$, $p < 0.001$; Low Achievers: $Z = 13.74$, $p < 0.001$), emphasizing the program's focus on fostering student agency by encouraging active engagement and self-directed learning. Similarly, the 'future improvement' component (FI_Future_Improvement) was significantly more common in the Master's program across all groups (High Achievers: $Z = -14.35$, $p < 0.001$; Medium Achievers: $Z = -8.66$, $p < 0.001$; Low Achievers: $Z = -17.46$, $p < 0.001$), reflecting the Master's program's emphasis on guiding students with actionable and forward-looking feedback. Additionally, 'strengths and weaknesses' (S_Strengths_Weaknesses) showed a consistent pattern of being more

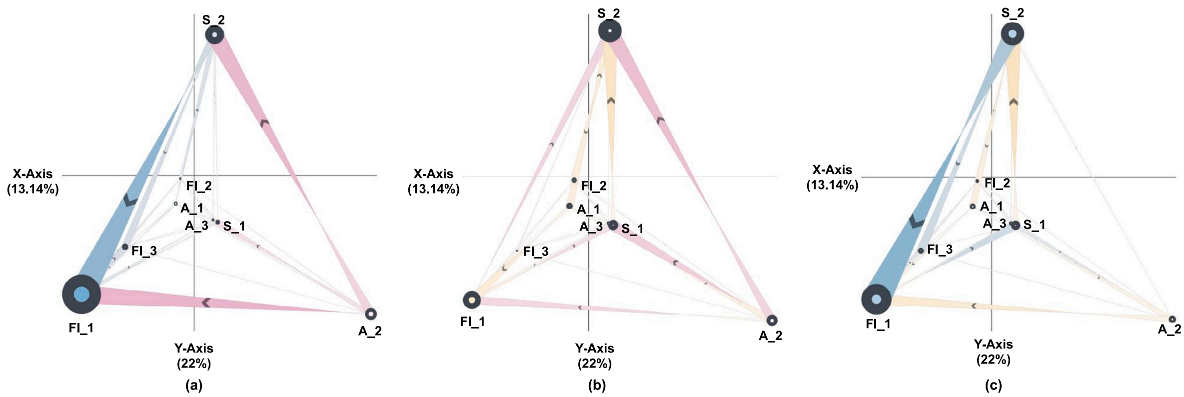

Fig. 5. The Sequential Connection of Learner-Centered Feedback in the **Master** Program. (a) difference between High Achiever (blue) and Medium Achiever (purple), (b) difference between Medium Achiever (purple) and Low Achiever (orange), and (c) difference between High Achiever (blue) and Low Achiever (orange). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

prevalent in the Bachelor's program for all performance groups (High Achievers: $Z = -6.28$, p< 0.001; Medium Achievers: $Z = 3.87$, p< 0.001; Low Achievers: $Z = 3.97$, p< 0.001), highlighting that instructors tended to employ more feedback that helps students understand specific areas of strength and improvement. However, some components showed significant differences only in specific performance groups. For example, 'affirmations and encouragement' (A_Affirm_Encourage) was significantly more prevalent in the Bachelor's program for High Achievers ($Z = 4.56$, p< 0.001) and Medium Achievers ($Z = -0.20$, p< 0.84) but showed no significant difference for Low Achievers ($Z = 4.35$, p< 0.001). This indicates that while affirmation is a common strategy to sustain motivation among high and medium achievers, it might not be as frequently employed for low achievers, who might require more foundational and supportive feedback. For other feedback components, significant differences were observed in only one student performance group. For instance, 'learning outcomes' (FI_Learning_Outcomes) was significantly different for Low Achievers ($Z = -4.34$, p< 0.001), while no significant differences were found for High ($Z = -3.15, p = 0.00$) or Medium Achievers ($Z = -2.35, p = 0.02$). Similarly, 'skill development' (FI_Skill_Development) showed significant differences only for Low Achievers ($Z = -4.11$, p< 0.001), and 'performance summary' (S_Performance_Summary) was significantly different only for Low Achievers ($Z = 4.04$, p< 0.001).

4.2. Results on RQ2

In the Master's program, the ONA analysis, as seen in Fig. 5, highlighted distinct patterns in the flow of feedback among various student performance groups. Overall, high achievers were primarily moving from A_Affirm_Encourage (A_2) to FI_Future_Improvement (FI_1) or to S_Strengths_Weaknesses (S_2). This sequence indicates that feedback for these students often begins with affirming their achievements, then provides them with actionable steps for further improvement or evaluates specific aspects of their performance. In contrast, medium achievers primarily demonstrated feedback pathway from identifying their strengths and weaknesses S_Strengths_Weaknesses (S_2) to providing them with suggestions for future task improvements (FI_Future_Improvement (FI_1). This pattern suggests a more task-oriented feedback approach, where medium achievers are first made aware of their performance aspects and then guided towards specific areas for improvement. For low achievers, the feedback sequence notably shifted from providing an overall summary of their performance S_Performance_Summary (S_1) to highlighting their strengths and weaknesses S_Strengths_Weaknesses (S_2). This indicates an approach that begins with a broad perspective of their performance, narrows down to specific areas of strength and weakness.

In the Bachelor's program, as illustrated in Fig. 6, the ONA results presented a different feedback landscape. High achievers in this program typically received feedback that started with positive reinforcement A_Affirm_Encourage (A_2), then progressed to an evaluation of their task performance S_Strengths_Weaknesses (S_2). This indicates a balance in feedback that both acknowledges their success and critically assesses their work. Additionally, a significant feedback flow was noted from encouraging active participation A_Active_Role (A_1) to providing affirmation A_Affirm_Encourage (A_2). Medium achievers in the Bachelor's program were more likely to experience a transition from evaluating their task performance S_Strengths_Weaknesses (S_2) to offering a comprehensive summary of their performance S_Performance_Summary (S_1), or to providing actionable suggestions for improvement FI_Future_Improvement (FI_1). This feedback pattern suggests a structured approach that first provides a detailed assessment of their task and then offers an overall summary or guides them on how to improve in future tasks. For low achievers, the feedback primarily focused on moving from performance evaluation S_Strengths_Weaknesses (S_2) to providing a detailed summary S_Performance_Summary (S_1), indicating a focus on helping them understand their overall performance in relation to specific task elements.

Statistical analysis underscored significant differences in feedback patterns across student performance groups in both programs (Tables 5 and 6). In the Master's program, high versus medium achievers showed a substantial difference on the X-axis (t-score: 9.36, p-value: <0.01, effect size: 0.70), indicating varied feedback sequences. High versus low achievers exhibited a moderate difference on the X-axis (t-score: 1.87, p-value: 0.07, effect size: 0.34). The medium versus low achiever comparison showed a marginal difference

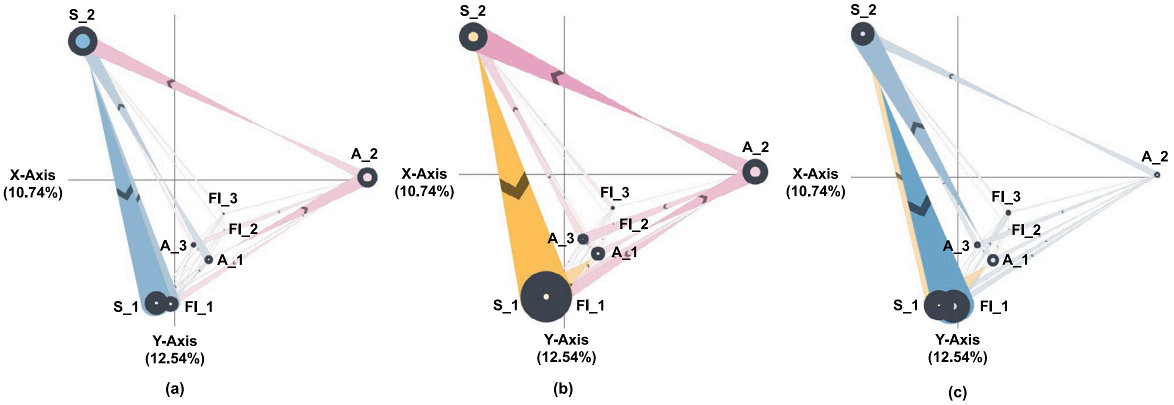

Fig. 6. The Sequential Connection of Learner-Centered Feedback in the **Bachelor** Program. (a) difference between High Achiever (blue) and Medium Achiever (purple), (b) difference between Medium Achiever (purple) and Low Achiever (orange), and (c) difference between High Achiever (blue) and Low Achiever (orange). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 5
Statistical difference of learner-centered feedback components among different student performance groups in Master program using t-test and Cohen's d. Significant values are indicated with bold.

Groups	Dim	t-score	p-value	Mean (X)	Mean (Y)	Lower limit	Upper limit	Effect size
High vs Medium	X-Axis	9.36	**<0.01**	0.06	−0.12	0.14	0.22	0.70
	Y-Axis	0.00	1.00	0.00	0.00	−0.05	0.05	0.00
High vs Low	X-Axis	1.87	0.07	0.06	−0.03	−0.01	0.18	0.34
	Y-Axis	0.12	0.90	0.00	−0.01	−0.12	0.14	0.02
Medium vs Low	X-Axis	−2.00	**0.05**	−0.12	−0.03	−0.19	0.00	0.35
	Y-Axis	0.12	0.91	0.00	−0.01	−0.12	0.14	0.02

Table 6
Statistical difference of learner-centered feedback components among different student performance groups in Bachelor program using t-test and Cohen's d. Significant values are indicated with bold.

Groups	Dim	t-score	p-value	Mean (X)	Mean (Y)	Lower limit	Upper limit	Effect size
High vs Medium	X-Axis	11.13	**<0.01**	0.05	−0.14	0.15	0.21	0.70
	Y-Axis	0.00	1.00	0.01	0.01	−0.05	0.05	0.00
High vs Low	X-Axis	9.32	**<0.01**	0.05	−0.16	0.17	0.25	0.79
	Y-Axis	0.70	0.49	0.01	−0.02	−0.04	0.09	0.09
Medium vs Low	X-Axis	1.09	0.28	−0.14	−0.16	−0.02	0.08	0.13
	Y-Axis	0.60	0.55	0.01	−0.02	−0.06	0.10	0.07

(t-score: −2.00, p-value: 0.05, effect size: 0.35). In the Bachelor's program, differences between high and medium achievers were significant on the X-axis (t-score: 11.13, p-value: <0.01, effect size: 0.70). High versus low achievers differed significantly on both axes (X-axis t-score: 9.32, p-value: <0.01, effect size: 0.79; Y-axis t-score: 0.70, p-value: 0.49, effect size: 0.09), with medium versus low achievers showing smaller effect sizes (X-axis effect size: 0.13; Y-axis effect size: 0.07).

The contrasting ONA results between the Master's and Bachelor's programs reflect different feedback emphases across student education levels. In the Master's program, there is a clear trend towards integrating affirmation with actionable feedback, suggesting a comprehensive feedback strategy that balances encouragement with growth-oriented advice. The Bachelor's program, however, exhibits a more varied approach with a notable focus on engaging students with their learning progress.

5. Discussions and implications

The findings from the study conducted in one Master's and one Bachelor's program within a large faculty at an Australian university, using feedback data communicated through the LMS, highlight several key implications for feedback practices in higher education.

First, text-based feedback provided through LMS in Both the Master's and Bachelor's programs emphasize the sensemaking dimension, particularly in evaluating the strengths and weaknesses of specific aspects of student tasks (S_Strengths_Weaknesses). This aligns with Nicol and Macfarlane-Dick (2006), who argue that feedback should help students identify their strengths and areas for improvement to foster self-regulation and learning strategies. The Master's program places a significant emphasis on the future impact dimension, offering actionable guidance to improve future performances (FI_Future_Improvement). This aligns with findings from Lin et al. (2023), which highlight that postgraduate students benefit from feedback that guides them in applying complex concepts practically. In contrast, the Bachelor's program strongly emphasizes student agency, encouraging active participation in learning processes (A_Affirm_Encourage, A_Active_Role), reflecting Carless and Boud (2018)'s recommendations for supporting foundational academic skills and self-efficacy.

Second, the analysis of text-based feedback shared through LMS reveals notable distinctions in feedback practices across different student performance groups. In both programs, high achievers frequently received affirmations of accomplishments (A_Affirm_Encourage), which sustain motivation but could be supplemented with more future-oriented guidance (FI_Future_Improvement) to push these students towards mastering advanced skills. Medium achievers, particularly in the Master's program, benefited from actionable feedback focused on improving future performance, yet this approach was less prominent in the Bachelor's program. For medium achievers, feedback that balances constructive criticism with motivational encouragement can better support their transition to higher performance levels (Brooks, Carroll, Gillies, & Hattie, 2019). Low achievers, while receiving feedback summarizing performance (S_Performance_Summary) and encouraging engagement (A_Active_Role), may require more detailed, actionable feedback to address specific gaps (Rodriguez Gil, Hughes, Scheffel, & Balliester Reis, 2023). As also highlighted by Raubenheimer et al. (2021), balancing acknowledgment of strengths with constructive criticism is essential for effectively supporting students' learning progression across performance levels.

While our study examines differences in teachers' feedback practices across different student performance groups from the perspective of learner-centered feedback, it is essential to consider how feedback strategies can be designed to support diverse learning needs effectively. Although we observe differences in teachers' feedback practices, we cannot yet determine whether teachers intentionally use different learner-centered feedback practices for different performance groups of students, or whether they lack sufficient knowledge of learner-centered feedback to provide better quality feedback. More importantly, we do not know yet how such differences affect students' perceived usefulness of the provided feedback and the subsequent impact on their learning. All these issues call for further research, which can be built on the findings delivered in this study.

Third, computational analysis of text-based feedback using ONA provides valuable insights into how feedback components are interconnected and aligned with pedagogical goals. In the Master's program, feedback sequences frequently transition from evaluative comments (S_Strengths_Weaknesses) to future-oriented suggestions (FI_Future_Improvement), indicating that feedback highlighting students' strengths and weaknesses is often followed by actionable guidance to help them improve specific aspects of similar tasks they may encounter in the future. This aligns with Raubenheimer et al. (2021), who emphasize that the combination of evaluative and actionable feedback is often adopted for fostering student learning. Conversely, in the Bachelor's program, feedback sequences frequently transition from evaluative comments to fostering student agency (A_Active_Role), where feedback that identifies students' strengths and weaknesses is often followed by guidance motivating active participation, such as engaging in discussions with instructors, seeking additional resources, or exploring further learning opportunities. These patterns highlight the differing pedagogical practices: instructors in the Master's program often emphasize preparing students for advanced academic and professional challenges by focusing on practical application and future improvement, whereas instructors in the Bachelor's program stress on developing foundational skills and promoting independence through active student engagement.

Fourth, analyzing technology-mediated feedback in computer science and data science programs reveals how discipline-specific feedback practices align with prior research findings, emphasizing the role of structured digital feedback. Raubenheimer et al. (2021) employed a mixed-method approach to analyze feedback practices and their effectiveness. They highlighted that combining instance-oriented feedback—targeting specific errors for immediate correction—with solution-oriented guidance, providing actionable steps to address challenges, is particularly effective in supporting student progress in programming tasks. In comparison, our study applies computational approaches, such as ONA, to quantitatively reveal feedback sequences transitioning from evaluating strengths and weaknesses (S_Strengths_Weaknesses) to actionable suggestions for future improvement (FI_Future_Improvement), extending the evidence for these practices. Similarly, Falcao et al. (2022), in a study conducted at a Brazilian university's computer science program, identified students' preference for actionable, specific, and constructive feedback. Our study extends these findings by leveraging ONA to analyze learner-centered feedback components, such as FI_Future_Improvement, A_Affirm_Encourage, S_Strengths_Weaknesses, and A_Active_Role, providing additional empirical evidence. While our findings demonstrate current feedback practices in technical disciplines like computer science, further research is needed, as learner-centered feedback practices have not yet been extensively explored in non-technical disciplines.

Fifth, teacher feedback literacy plays critical roles in the effectiveness of feedback practices (Carless & Boud, 2018). While in this study, teachers were expected to attend professional development sessions on assessment and feedback practices, their knowledge of learner-centered feedback principles may vary. This variability could influence the alignment of feedback with the learner-centered feedback principles. Strengthening teacher feedback literacy through targeted training on crafting feedback tailored to student performance levels, educational phases, and using effective sequential patterns of different feedback elements could enhance the quality of effective learner-centered feedback. Similarly, student feedback literacy is essential (Carless & Boud, 2018), given that different feedback were provided to students based on their performance levels or educational phases in this study. For example, high achievers predominantly received affirmations, while low achievers were provided with more comprehensive and evaluative feedback. Helping students recognize the purpose of such feedback, along with guidance on how to act upon and apply it effectively, is crucial to ensuring that feedback not only informs but also empowers them in their learning journey (Henderson et al., 2019).

Sixth, our study focuses on text-based feedback shared through an LMS, as this is the most common form of feedback provided to students in higher education settings (Ryan et al., 2019). The observed occurrence frequency of different learner-centered feedback components or their co-occurrence patterns should be interpreted by keeping in mind the nature of the feedback-sharing technology or methods. It would be interesting to replicate this study using other forms of feedback data to examine whether different technologies influence the presence of learner-centered components. Moreover, future research should explore how to measure the effectiveness of learner-centered feedback—for example, whether using a specific learner-centered feedback component more frequently would enhance the perceived usefulness of text-based feedback, and thus potentially alleviate the teaching workload of educators when facing a large number of students.

Seven, advancements in feedback systems, including intelligent feedback technologies such as automated feedback generation (Chamoun, Schlichktrull, & Vlachos, 2024), personalized feedback systems (Feng, Wang, Miao, Xi, & Xia, 2023), and real-time interaction tools (Bakonyi, Illés, & Szabó, 2022), have enhanced how feedback is shared in digital learning environments. These technologies offer scalable, personalized solutions that increase learner engagement and share actionable insights tailored to individual learners (Deeva et al., 2021; Jamaludin & Romli, 2023). Recent work by Sedrakyan et al. (2024) presents a comprehensive learner-centered framework for feedback technology emphasizing usability, effectiveness, and key considerations such as stakeholder engagement, security, privacy, and trust. Their study highlights how digital feedback systems should facilitate interactive dialogues that empower both educators and learners to collaboratively construct the feedback process.

Our study complements this line of research by showing how empirical data from text-based feedback, stored and shared via an LMS, reveals the prevalence of learner-centered feedback components. Moreover, the use of a computational method—Ordered Network Analysis (ONA)—uncovered the co-occurrence patterns of these components across different student performance groups. The findings indicate that educators tend to provide different combinations of feedback components depending on student performance levels. While we do not yet know how the prevalence and co-occurrence of learner-centered feedback components impact different student performance groups, these findings can inform the development of intelligent feedback systems that integrated ONA to visualize teachers' feedback structures, helping them better understand the sequencing and emphasis of their feedback. This is particularly important because each learner-centered feedback dimension carries its own pedagogical focus (Ryan et al., 2021b)—for example, sensemaking is more likely to lead to future impact when comments include clear evaluative information. Furthermore, Sedrakyan et al. (2024) emphasize that intelligent feedback systems should be designed as feedback dialogues that support students in managing and guiding their own learning. In our study, through ONA, we found that in the Bachelor's program, when teachers provide feedback that highlights students' strengths and weaknesses, it is frequently followed by dialogic feedback—comments that encourage students to take an active role in their learning. Although we do not yet know the effectiveness of this practice, ONA can potentially offer valuable insights into how dialogic feedback co-occurs with other feedback components, revealing structural patterns that can inform the design of more interactive, learner-centered feedback systems.

Finally, based on the Learner-Centered Feedback framework by Ryan et al. (2021b), each dimension has its distinct emphasis, with Future Impact serving as the central focus of feedback, supported by Sensemaking and Agency. Sensemaking provides the necessary detail to help students interpret and apply feedback aimed at fostering future improvements, while Agency adjusts its emphasis based on students' individual needs, offering guidance and encouragement where challenges are perceived or underperformance is evident. Our findings suggest that varying student performance and educational levels may require unique feedback strategies; hence, incorporating these variables into the learner-centered feedback framework dimensions could be worth exploring. This study highlights that while both Master's and Bachelor's programs align with the principles of the learner-centered feedback model through a strong emphasis on Sensemaking, they differentiate in their focus areas—tailoring their feedback approaches to meet the unique educational objectives. Specifically, the emphasis on Agency in the Bachelor's program aligns with the developmental needs of undergraduates, fostering foundational skills and independence, while the focus on Future Impact in the Master's program reflects the necessity for postgraduate students to engage with complex, forward-looking guidance. Similarly, tailored feedback for performance groups—such as affirmations for high achievers, actionable improvements for medium achievers, and foundational guidance for low achievers—demonstrates how feedback can be adjusted to support diverse learner needs effectively. However, we recognize that these findings are derived from an analysis of existing feedback practices in authentic educational settings. While they provide critical insights into the dynamics of learner-centered feedback, the impact of such differentiated feedback on actual student learning outcomes needs to be investigated.

5.1. Limitations and future work

This study, while providing valuable insights into feedback practices in higher education, is subject to several limitations that pave the way for future research.

First, the scope of our dataset, primarily drawn from one Master's and one Bachelor's program with the most students in a single faculty, may limit the generalizability of our findings. Despite the large sample size, the specific context of these programs may not fully capture the diversity and complexity of feedback practices across different disciplines or institutions. The observed feedback patterns, such as the emphasis on actionable guidance in the Master's program and fostering agency in the Bachelor's program, are shaped by the nature of the disciplines and the specific tasks analyzed (Evans, 2013). Moreover, the quality and consistency of feedback may vary due to differences in educators' knowledge and experience in providing effective feedback (Gan, An, & Liu, 2021). Future research should aim to include a more comprehensive range of programs and faculties, potentially across multiple universities, to broaden the understanding and applicability of the results.

Second, the anonymized nature of the feedback data precluded the analysis of feedback in relation to specific student demographic factors, such as cultural background, gender, and prior educational experiences. Understanding how demographic variables influence feedback interactions could lead to more effective strategies tailored to diverse student populations. For instance, exploring potential biases, such as variations in feedback sentimental polarity or quality based on students' first-language backgrounds or any other demographic attributes, could address issues of equity and inclusivity in feedback sharing (Dai et al., 2022). Future research could also investigate how feedback practices might vary across demographic groups and identify strategies for mitigating these biases.

Third, a longitudinal investigation is needed to assess how different combinations of learner-centered feedback components influence student learning outcomes and academic progression over time. Such studies could examine how the feedback sequences observed in this study—such as transitions from evaluating strengths and weaknesses to providing actionable future guidance—impact students' development across academic levels. Additionally, incorporating student performance, educational level, and peer feedback into the Learner-Centered Feedback framework—especially within digital formats—holds the potential to enhance its applicability and effectiveness, though further research is needed to fully explore and validate these possibilities.

Fourth, this study focused only on text-based feedback shared through the LMS; hence, differences between text-based and face-to-face feedback practices in terms of the use of various learner-centered feedback components warrant further exploration. Studies suggest that synchronous feedback, by enabling real-time clarification and emphasizing interactive, dialogic aspects, may affect the frequency of learner-centered feedback components, as these settings allow for spontaneous dialogue and dynamic adjustment of feedback based on student reactions (Ajjawi & Boud, 2017). Future research should examine how the frequency and co-occurrence of learner-centered feedback components vary across digital modalities, including text-based feedback, synchronous conferencing, and multimodal formats (e.g., video and audio-based feedback). Investigating these differences will provide deeper insights into how digital feedback environments influence learner engagement and the effectiveness of feedback sharing, providing in-depth insights to guide teachers' feedback practices effectively.

Fifth, to enhance the scalability and effectiveness of learner-centered feedback, future research should integrate AI systems within LMS platforms to automatically categorize feedback into learner-centered feedback components and provide tailored recommendations to teachers, taking into account different student performance groups and education levels, as highlighted in our study. Additionally, future research should explore how AI-generated feedback compares with human feedback in terms of quality and alignment with learner-centered feedback principles. This comparison can help identify where AI effectively supports the pedagogical process, such as offering consistent and scalable categorization of feedback, and where human expertise remains critical, such as addressing context-specific learning needs or fostering emotional engagement. A collaborative feedback generation process—where AI initially generates feedback and human educators refine it—represents a promising direction because it combines the scalability and consistency of AI with the contextual understanding and pedagogical expertise of educators. For instance, AI can efficiently categorize feedback based on learner-centered components, while educators can enhance this by incorporating context-specific insights that address individual student needs.

6. Conclusion

This study highlights that feedback practices in higher education, as examined in specific Master's and Bachelor's programs, align with the learner-centered feedback model to a certain degree, with a strong emphasis on the sensemaking dimension. Sensemaking, which involves evaluating students' strengths and weaknesses to help them understand their performance, provides a foundation for actionable improvements, bridging the gap between current abilities and future growth. However, significant variations were observed across the other two dimensions—future impact and agency—indicating tailored approaches to feedback at different educational levels. Master's programs prioritize future impact, offering actionable suggestions to guide students in advanced academic and professional tasks. Conversely, Bachelor's programs emphasize fostering agency, encouraging active participation and self-efficacy essential for foundational learning.

Furthermore, this study also reveals that feedback practices vary across student performance levels, necessitating differentiated strategies to address the distinct needs of high, medium, and low achievers. High achievers receive affirmations and forward-looking guidance to sustain motivation and mastery, medium achievers benefit from task-specific improvement strategies, and low achievers are supported with detailed evaluations and foundational guidance to address critical gaps. These findings underscore the need for feedback practices that balance encouragement and actionable insights while catering to the diverse needs of learners across performance groups. However, some educators might not have sufficient knowledge or experience in providing quality feedback. Individual preferences and varying levels of feedback literacy could contribute to the observed patterns (Carless & Winstone, 2023). Equipping both educators and students with the skills to understand, interpret, and act on feedback is essential. Incorporating feedback literacy into professional development programs for instructors and providing targeted training for students can enable both groups to engage more effectively with feedback practices aligned with learner-centered principles.

In this study, feedback data was collected from an LMS, highlighting its role as a central platform for managing and sharing feedback in higher education. AI-powered systems can enhance the role of the LMS by automating the categorization of feedback into learner-centered components, as observed in this study, and providing tailored suggestions to educators. This integration can help address the observed variations in feedback practices and ensure consistency by supporting educators in sharing effective feedback to diverse learner groups. These tools can potentially support institutions in fostering effective feedback practices, ultimately improving teaching strategies and student learning outcomes.

CRediT authorship contribution statement

Ahmad Ari Aldino: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Yi-Shan Tsai:** Writing – review & editing, Supervision, Conceptualization. **Siddarth Gupte:** Data curation. **Michael Henderson:** Writing – review & editing. **Debarshi Nath:** Visualization. **Dragan Gašević:** Writing – review & editing. **Guanliang Chen:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research is funded by the Monash University Educational Innovation Funding (The Pitch), Australia and the Advancing Women's Success Grant, Australia. It is also supported by Balai Pembiayaan Pendidikan Tinggi (BPPT) under the Indonesian Ministry of Education, Culture, Research, and Technology, and Lembaga Pengelola Dana Pendidikan (LPDP) under the Indonesian Ministry of Finance.

Data availability

The data that has been used is confidential.

References

Ajjawi, R., & Boud, D. (2017). Researching feedback dialogue: An interactional analysis approach. *Assessment & Evaluation in Higher Education*, *42*, 252–265.

Aseery, A. (2023). Enhancing learners' motivation and engagement in religious education classes at elementary levels. *British Journal of Religious Education*, 1–16.

Bakonyi, V., Illés, Z., & Szabó, T. (2022). Real-time interaction tools in virtual classroom systems. In *Recent innovations in computing: proceedings of ICRIC 2021: vol. 2*, (pp. 625–636). Springer.

Boud, D., & Molloy, E. (2013). Rethinking models of feedback for learning: the challenge of design. *Assessment & Evaluation in Higher Education*, *38*, 698–712.

Brooks, C., Carroll, A., Gillies, R. M., & Hattie, J. (2019). A matrix of feedback for learning. *Australian Journal of Teacher Education (Online)*, *44*, 14–32.

Carless, D., & Boud, D. (2018). The development of student feedback literacy: enabling uptake of feedback. *Assessment & Evaluation in Higher Education*, *43*, 1315–1325.

Carless, D., & Winstone, N. (2023). Teacher feedback literacy and its interplay with student feedback literacy. *Teaching in Higher Education*, *28*, 150–163.

Cavalcanti, A. P., Barbosa, A., Carvalho, R., Freitas, F., Tsai, Y. S., Gašević, D., et al. (2021). Automatic feedback in online learning environments: A systematic literature review. *Computers and Education: Artificial Intelligence*, *2*, Article 100027.

Cavalcanti, A. P., de Mello, R. F. L., Rolim, V., André, M., Freitas, F., & Gaševic, D. (2019). An analysis of the use of good feedback practices in online learning courses. In *2019 IEEE 19th international conference on advanced learning technologies* (pp. 153–157). IEEE.

Chamoun, E., Schlichtkrull, M., & Vlachos, A. (2024). Automated focused feedback generation for scientific writing assistance. arXiv preprint arXiv:2405.20477.

Chung, H. Q., Chen, V., & Olson, C. B. (2021). The impact of self-assessment, planning and goal setting, and reflection before and after revision on student self-efficacy and writing performance. *Reading and Writing*, *34*, 1885–1913.

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Academic Press.

Dai, W., Tsai, Y. S., Fan, Y., Gašević, D., & Chen, G. (2022). Measuring inconsistency in written feedback: A case study in politeness. In *International conference on artificial intelligence in education* (pp. 560–566). Springer.

Deeva, G., Bogdanova, D., Serral, E., Snoeck, M., & De Weerdt, J. (2021). A review of automated feedback systems for learners: Classification framework, challenges and opportunities. *Computers & Education*, *162*, Article 104094.

Eberle, J., & Hobrecht, J. (2021). The lonely struggle with autonomy: A case study of first-year university students' experiences during emergency online teaching. *Computers in Human Behavior*, *121*, Article 106804.

Evans, C. (2013). Making sense of assessment feedback in higher education. *Review of Educational Research*, *83*, 70–120.

Falcao, T. P., Arêdes, V., Wagner, S. S., Uchoa, J. P. C., Luisi, V., & Mello, R. F. (2022). What did I get wrong? Supporting the feedback process in computer science education. In *Anais do XXX workshop sobre educação em computação* (pp. 239–250). SBC.

Fan, Y., Tan, Y., Raković, M., Wang, Y., Cai, Z., Shaffer, D. W., et al. (2023). Dissecting learning tactics in mooc using ordered network analysis. *Journal of Computer Assisted Learning*, *39*, 154–166.

Fangohr, H., O'Brien, N., Hovorka, O., Kluyver, T., Hale, N., Prabhakar, A., et al. (2020). Automatic feedback provision in teaching computational science. In *Computational science–ICCS 2020: 20th international conference, Amsterdam, The Netherlands, June (2020) 3–5, proceedings, part VII 20* (pp. 608–621). Springer.

Farooq, M. S., & Regnier, J. C. (2011). Role of learning styles in the quality of learning at different levels. *Informatica Economica*, *15*.

Feng, J., Wang, K., Miao, Q., Xi, Y., & Xia, Z. (2023). Personalized recommendation with hybrid feedback by refining implicit data. *Expert Systems with Applications*, *232*, Article 120855.

Gan, Z., An, Z., & Liu, F. (2021). Teacher feedback practices, student feedback motivation, and feedback behavior: how are they associated with learning outcomes? *Frontiers in Psychology*, *12*, Article 697045.

Grabusts, P., Teilans, A., Kapenieks, A., et al. (2023). Automation of feedback analysis in asynchronous e-learning. In *ENVIRONMENT. TECHNOLOGIES. RESOURCES. Proceedings of the international scientific and practical conference* (pp. 84–88).

Guo, W., Lau, K. L., & Wei, J. (2019). Teacher feedback and students' self-regulated learning in mathematics: A comparison between a high-achieving and a low-achieving secondary schools. *Studies in Educational Evaluation*, *63*, 48–58.

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research*, *77*, 81–112.

Henderson, M., Ryan, T., & Phillips, M. (2019). The challenges of feedback in higher education. *Assessment & Evaluation in Higher Education*, *44*, 1237–1252.

Heritage, M. (2007). Formative assessment: What do teachers need to know and do? *Phi Delta Kappan*, *89*, 140–145.

Hsia, L. H., Hwang, G. J., & Hwang, J. P. (2023). Ai-facilitated reflective practice in physical education: an auto-assessment and feedback approach. *Interactive Learning Environments*, 1–20.

Jamaludin, N. H., & Romli, R. (2023). Analysis of the effectiveness of feedback provision in intelligent tutoring systems. In *International conference on computing and informatics* (pp. 168–179). Springer.

Jensen, L. X., Bearman, M., & Boud, D. (2021). Understanding feedback in online learning–a critical review and metaphor analysis. *Computers & Education*, *173*, Article 104271.

Jibeen, T., & Khan, M. A. (2016). Development of an academic achievement risk assessment scale for undergraduates: Low, medium and high achievers. *Multidisciplinary Journal of Educational Research*, *6*, 23–50.

Kam, A. H., & Umar, I. N. (2023). Would gamification affect high and low achievers differently? A study on the moderating effects of academic achievement level. *Education and Information Technologies*, *28*, 8075–8095.

Kim, T. K. (2015). T test as a parametric statistic. *Korean Journal of Anesthesiology*, *68*, 540–546.
Kneebone, R., Bello, F., Nestel, D., Mooney, N., Codling, A., Yadollahi, F., et al. (2008). Learner-centred feedback using remote assessment of clinical procedures. *Medical Teacher*, *30*, 795–801.
Kuhail, M. A., Alturki, N., Alramlawi, S., & Alhejori, K. (2023). Interacting with educational chatbots: A systematic review. *Education and Information Technologies*, *28*, 973–1018.
Lin, J., Dai, W., Lim, L. A., Tsai, Y. S., Mello, R. F., Khosravi, H., et al. (2023). Learner-centred analytics of feedback content in higher education. In *LAK23: 13th international learning analytics and knowledge conference* (pp. 100–110).
Maringe, F., & Sing, N. (2014). Teaching large classes in an increasingly internationalising higher education environment: Pedagogical, quality and equity issues. *Higher Education*, *67*, 761–782.
McCarthy, J. (2015). Evaluating written, audio and video feedback in higher education summative assessment tasks. *Issues in Educational Research*, *25*, 153–169.
McCoach, D. B., & Siegle, D. (2001). A comparison of high achievers' and low achievers' attitudes, perceptions, and motivations. *Academic Exchange*, *2*, 71–76.
Meiras, S. E. (2021). The challenges of feedback in higher education. A brief discussion paper based on a review of selected literature. *Journal of Applied Learning and Teaching*, *4*, 138–140.
Mello, R. F., Neto, R., Fiorentino, G., Alves, G., Arêdes, V., Silva, J. V. G. F., et al. (2022). Enhancing instructors' capability to assess open-response using natural language processing and learning analytics. In *European conference on technology enhanced learning* (pp. 102–115). Springer.
Munir, H., Vogel, B., & Jacobsson, A. (2022). Artificial intelligence and machine learning approaches in digital education: A systematic revision. *Information*, *13*, 203.
Narciss, S., Sosnovsky, S., Schnaubert, L., Andrès, E., Eichelmann, A., Goguadze, G., et al. (2014). Exploring feedback and student characteristics relevant for personalizing feedback strategies. *Computers & Education*, *71*, 56–76.
Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education*, *31*, 199–218.
Novák, J. (2023). Evaluation of student feedback as a tool for higher education quality enhancement. *R & E-SOURCE*, 117–127.
Raubenheimer, G., Jeffries, B., & Yacef, K. (2021). Toward empirical analysis of pedagogical feedback in computer programming learning environments. In *Proceedings of the 23rd Australasian computing education conference* (pp. 189–195).
Rodriguez Gil, A., Hughes, P., Scheffel, J., & Balliester Reis, T. (2023). Does feedback improve student performance? are there differences between high, and low achieving students? Evidence from a feedback programme controlling for self-selection effects. Are there differences between high, and low achieving students.
Ryan, T., Henderson, M., & Phillips, M. (2019). Feedback modes matter: Comparing student perceptions of digital and non-digital feedback modes in higher education. *British Journal of Educational Technology*, *50*, 1507–1523.
Ryan, T., Henderson, M., Ryan, K., & Kennedy, G. (2021a). Designing learner-centred text-based feedback: a rapid review and qualitative synthesis. *Assessment & Evaluation in Higher Education*, *46*, 894–912.
Ryan, T., Henderson, M., Ryan, K., & Kennedy, G. (2021b). Identifying the components of effective learner-centred feedback information. *Teaching in Higher Education*, 1–18.
Sabri, S. M., Ismail, I., Annuar, N., Rahman, N. R. A., Abd Hamid, N. Z., & Abd Mutalib, H. (2024). A conceptual analysis of technology integration in classroom instruction towards enhancing student engagement and learning outcomes. *Integration*, *9*, 750–769.
Salehian Kia, F., Pardo, A., Dawson, S., & O'Brien, H. (2022). Exploring the relationship between personalized feedback models, learning design and assessment outcomes. *Assessment & Evaluation in Higher Education*, 1–14.
Särndal, C. E. (1968). The use of a stratification variable in estimation by proportional stratified sampling. *Journal of the American Statistical Association*, *63*, 1310–1320.
Satish, R., Reddy, A. V., Dubey, K. A., Verma, S., & Singh, G. (2023). Assessing the role of student feedback in improving teaching practices. *Journal of Survey in Fisheries Sciences*, *10*, 6071–6082.
Sedrakyan, G., van den Berg, S. M., Veldkamp, B. P., & van Hillegersberg, J. (2023). Analysis of the feedback digitization needs in higher education: experiences from lockdown education in the Netherlands and Germany. *International Journal of Information and Education Technology*, *13*, 778–784.
Sedrakyan, G., Borsci, S., Abdi, A., van den Berg, S. M., Veldkamp, B. P., & van Hillegersberg, J. (2023). Feedback digitalization preferences in online and hybrid classroom: Experiences from lockdown and implications for post-pandemic education. *Journal of Research in Innovative Teaching & Learning*.
Sedrakyan, G., Borsci, S., van den Berg, S. M., van Hillegersberg, J., & Veldkamp, B. P. (2024). Design implications for next generation chatbots with education 5.0. In *International conference on advances in education and information technology* (pp. 1–12). Springer.
Shaffer, D. W., Collier, W., & Ruis, A. R. (2016). A tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. *Journal of Learning Analytics*, *3*, 9–45.
Shahzad, R. K., Ström, E., & Mozelius, P. (2023). Fams: A formative assessment management system for generating individualised feedback. In *European conference on technology enhanced learning* (pp. 642–647). Springer.
Song, C., Shin, S. Y., & Shin, K. S. (2024). Implementing the dynamic feedback-driven learning optimization framework: A machine learning approach to personalize educational pathways. *Applied Sciences*, *14*, 916.
Tan, Y., Ruis, A. R., Marquart, C., Cai, Z., Knowles, M. A., & Shaffer, D. W. (2022). Ordered network analysis. In *International conference on quantitative ethnography* (pp. 101–116). Springer.
Thompson, G. L., Warren, S., & Carter, L. (2004). It's not my fault: Predicting high school teachers who blame parents and students for students' low achievement. *The High School Journal*, *87*, 5–14.
To, J. (2022). Using learner-centred feedback design to promote students' engagement with feedback. *Higher Education Research & Development*, *41*, 1309–1324.
To, J., Tan, K., & Lim, M. (2023). From error-focused to learner-centred feedback practices: Unpacking the development of teacher feedback literacy. *Teaching and Teacher Education*, *131*, Article 104185.
Vivekananda-Schmidt, P., MacKillop, L., Crossley, J., & Wade, W. (2013). Do assessor comments on a multi-source feedback instrument provide learner-centred feedback? *Medical Education*, *47*, 1080–1088.
Winstone, N., Boud, D., Dawson, P., & Heron, M. (2022). From feedback-as-information to feedback-as-process: a linguistic analysis of the feedback literature. *Assessment & Evaluation in Higher Education*, *47*, 213–230.
Yang, M., & Carless, D. (2013). The feedback triangle and the enhancement of dialogic feedback processes. *Teaching in Higher Education*, *18*, 285–297.
Yang, J., Zhang, Y., Li, L., & Li, X. (2017). Yedda: A lightweight collaborative text span annotation tool. arXiv preprint arXiv:1711.03759.
Zou, K. H., Fielding, J. R., Silverman, S. G., & Tempany, C. M. (2003). Hypothesis testing i: proportions. *Radiology*, *226*, 609–613.