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Review

A systematic review of the role of learning analytics in enhancing feedback practices in higher education

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ABSTRACT

Learning analytics (LA) offers new opportunities to enrich feedback practices in higher education, but little is understood about the ways different LA can enhance feedback practices for educators and students. This systematic literature review maps the current state of implementation of LA to improve feedback practices in technology-mediated learning environments in higher education. We used strict inclusion criteria to select relevant studies that have investigated the role of LA on feedback practices. To identify common features of LA for feedback studies, we coded relevant publications using an analytical framework that identifies four key dimensions of LA systems: what (types of data), how (analytic methods), why (objectives), and how educators and students are served by LA (stakeholders). Based on findings, we propose a conceptual framework that can guide the implementation of LA for feedback systems and also suggest future empirical research in this area.

1. Introduction

Feedback has long been acknowledged as a powerful tool for learning (Chickering & Gamson, 1987; Hattie & Timperley, 2007; Wisniewski et al., 2020). Feedback not only plays a crucial role in student knowledge and skill acquisition (Shute, 2008), but is also an important factor influencing student motivation (Amiryousefi & Geld, 2021; Erhel & Jamet, 2013). Effective feedback represents one of the key features of quality teaching (Ramsden, 2003). Studies have shown that high-quality feedback contributes to authentic learning by promoting student metacognitive skills, and by providing clear indicators of performance and areas for further improvement (e.g. Callender et al., 2016; Molin et al., 2020). Overwhelmingly, feedback studies have demonstrated that when feedback is delivered appropriately, it can significantly improve both learning processes and outcomes (Hattie & Timperley, 2007; Henderson et al., 2019; Shute, 2008).

Recently, rapid technology development and widespread access to the Internet have significantly increased enrollments in online learning (Castro & Tumibay, 2021); at the same time, access to higher education has increased globally, increasing class sizes year after year. Delivering rapid, effective and personalized feedback to large cohorts of students is difficult in any setting (McDonald et al.,

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2017). Where learners are engaged in online learning environments, however, or making regular use of learning technologies, learning analytics (LA) offer the potential for provision of personalized, real-time, and relevant feedback at scale (Er et al., 2021; Pardo et al., 2019; Ryan et al., 2019; Lim et al., 2021).

Drawing on data from learning technologies, LA can provide students with timely and insightful feedback that can alert them to their learning progress and how they can improve their learning and self-regulation (Noroozi et al., 2019; Roll & Winne, 2015). Since the emergence of the field of LA in 2011, several studies have explored the potential for LA to improve feedback practices (Misiejuk et al., 2021; Pardo, 2018; Sedrakyan et al., 2020). However, only few review studies have focused on providing an overview of the role of LA in feedback. For example, the recent study by Cavalcanti et al. (2021) provide insights into the role of automated feedback in students' performance and instructors' workload. However, the interconnection role of different dimensions of LA systems for guiding LA use in feedback activities within higher education contexts is not discussed in this recent review study. According to the literature, there is no clear understanding of how LA tools can support feedback practices and how LA's use for feedback purposes in higher education can be guided. Therefore, this review aims to map existing relevant literature on LA and feedback in higher education contexts, give an overview of the current state, identify research and theory that connects LA to feedback, determine the role of LA on feedback, and point to areas needing further research. As such, it points the way for more in-depth empirical research on the best approaches to using LA to enhance feedback practices in higher education.

1.1. Learning analytics

The interdisciplinary field of LA has borrowed concepts and ideas from diverse disciplines, including computer science, learning science, statistics, data mining, psychology, and pedagogy (Chatti et al., 2012). The First International Conference on Learning Analytics and Knowledge (LAK) in 2011 defined LA as "*the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs*" (Siemens & Long, 2011, p. 34). LA seeks to translate learning data into knowledge (Wong et al., 2019) that can give students insight into their own learning, and enable educators to make appropriate and evidence-based interventions for the improvement of teaching and learning (Wise, 2014). Early work focused heavily on development of predictive algorithms to identify students at risk, to improve retention, and to predict student success (see for example Arnold & Pistilli, 2012; Dietz-Uhler & Hurn, 2013). Later, several scholars argued that such technologically determinist dependence on technology-derived analytics to predict learner success was insufficient (Banihashem & Macfadyen, 2021; Siemens, 2013; Knight et al., 2014), and that meaningful investigation of learning demands integration of pedagogical perspectives (Gašević et al., 2015; Stewart, 2017; Wong et al., 2019). As a result, more recent LA studies have given greater weight to pedagogical models when designing pedagogical interventions using LA (see for example Hernández-Leo et al., 2019; Wise & Jung, 2019; Banihashem et al., 2022). Consequently, feedback as a core pedagogical practice has therefore gained more attention (e.g. Er et al., 2021; Misiejuk et al., 2021).

1.2. Feedback

Feedback is one of the most powerful educational tools in improving learning and increasing achievement (Hattie & Timperley, 2007; Latifi et al., 2021), however, its impact can be either positive or negative depending on its quality and timeliness (Carless & Boud, 2018; Patchan et al., 2016; Kerman et al., 2022). The research on feedback in educational contexts has a long history, however, in a generally accepted way, feedback is seen as a cognitive and constructive information that is provided to a learner, and also the process that the learner makes sense of the received information to improve his/her learning and fill the gap between his/her current level of performance and the desired level (Boud & Dawson, 2021; Carless & Boud, 2018; Sadler, 1989; Shute, 2008). Based on this definition, the notion of feedback in educational contexts not only focuses on the outcome of the feedback but also sees feedback as a learning process (Carless & Boud, 2018; Noroozi et al., 2016) in which both teachers and students are actively involved. The traditional perspective on feedback only has seen educators as the feedback provider to inform students about their strengths and weaknesses in their learning and how to improve it (Carless & Winstone, 2020; Zacharias, 2007), while in recent years feedback from students has shown great potential to assist quality teaching and learning in higher education, especially in large size classes where teachers are not fully capable to provide one by one feedback to students (Taghizadeh et al., 2022). Therefore, in this study, feedback in educational contexts including higher education contexts is seen as an instructional and learning activity that can be performed by both teachers and students for the purpose of improving learning. In such feedback, students in their role as the feedback receiver are also actively engaged in the process to think about the received feedback and to make use of the feedback to bridge the gap between the current status of their learning and the desired goal.

1.3. Learning analytics and feedback

Feedback influences learning (Hattie & Timperley, 2007; Shute, 2008; Wisniewski et al., 2020), however, its effectiveness depends on its quality (how it is conceived and applied by students) and its timeliness (Carless et al., 2011; Er et al., 2021). Several studies have offered indications that LA can support provision of meaningful and timely feedback to students (e.g. Lim et al., 2020; Zheng et al., 2021). Van der Schaaf et al. (2017) reported that LA enhanced the quality and efficiency of feedback in professional education. Sedrakyan et al. (2020) and Lim et al.'s (2021) found that the use of LA-based feedback supported self-regulated learning, while Broos et al. (2017) reported that LA dashboards provided actionable feedback for improving learning skills. In addition, some evidence exists to suggest that LA can support student engagement (e.g. Er et al., 2021; Iraj et al., 2020; Yilmaz & Yilmaz, 2021, pp. 1–12), student interpretation of feedback (e.g. Lim et al., 2020; Misiejuk et al., 2021), provision of actionable feedback (e.g. Broos et al., 2017; Gutiérrez et al., 2020; Lim, Gentili, et al., 2021); or delivery of timely and personalized feedback at scale (e.g. Pardo et al., 2019; Zheng et al., 2021). A further interesting area of work involves the use of feedback analytics to support student academic writing (Gibson et al., 2017; Knight et al., 2020).

In summary, existing literature reveals that LA can offer significant practical support for feedback practices (e.g. Er et al., 2021; Lim, Gasevic, et al., 2021; Misiejuk et al., 2021), and it has been suggested that LA should therefore be an essential component of feedback design in data-rich environments (Er et al., 2021; Pardo, 2018). To date, however, no conceptual frameworks have been offered to guide such role of LA for the design of feedback practices. To address this gap in the literature, this study was initiated with the goal of mapping the current state of knowledge in this area and to develop an evidence-based conceptual framework that could guide the design and practice of future LA-based feedback practices.

2. Conceptualizing the review

For this study, we adopted a reference model for LA (see Fig. 1) suggested by Chatti et al. (2012). According to this model, LA consists of four dimensions including (1) *what* (what types of data does the system capture and analyze), (2) *how* (how does the system perform analytics), (3) *why* (for what reasons does the system gather and analyze data), and (4) *who* (who is served by the analytics) (Chatti et al., 2012). The proposed dimensions in this model are in line with the findings of related studies (see Greller & Drachsler, 2012).

Because LA is data-driven, it is critical to identify the types of data it uses; here, we are inspired to pinpoint which types of data LA can use for supporting feedback. Various analytics methods (techniques) can be applied at different levels, depending on data type and LA goals (Chatti et al., 2012); which analytic methods at which level are most relevant for feedback practices? For example, there is no overview at which levels social network analysis methods can be used. Are social network analysis methods only used at the descriptive level for describing the connections between the nodes and the flow among the nodes, or are they used at the predictive level for predicting the value of a variable based on the value of another variable (Turkington et al., 2018)? This needs to be clarified. The goals of LA may also vary – and may include monitoring, reflection, prediction, intervention, feedback, personalization, adaptation, or recommendation (Chatti et al., 2012; Greller & Drachsler, 2012); it is important, then to understand the objectives of LA methods employed for feedback purposes. Finally, LA can serve different stakeholders - students, educators, tutors, mentors, institutions, researchers, and/or system designers (Chatti et al., 2012), and no LA system can serve all stakeholders. It might be clear that for feedback practices in higher education, educators and students tend to be the key stakeholders, however, little is known about how educators and students have benefitted from LA applications in higher education? This needs to be further examined. Therefore, Chatti et al.'s four dimensions model can guide our review of LA for feedback practices in higher education. This systematic review, therefore, aimed to address the following research questions:

1. For what reasons is LA used in feedback studies in higher education?
2. What types of data does LA use to support feedback in higher education?
3. What methods does LA use to support feedback in higher education?
4. How does LA support feedback stakeholders in higher education?

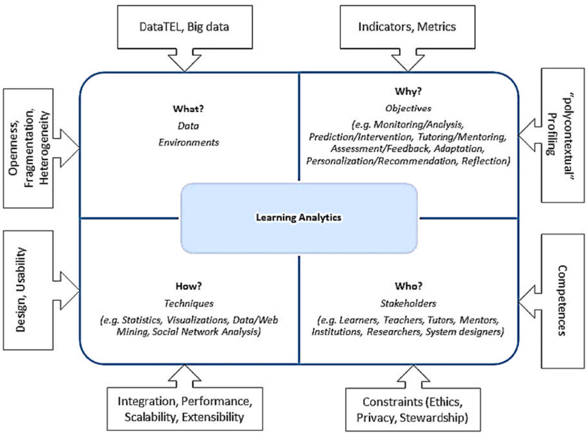

Fig. 1. LA reference model (Chatti et al., 2012, p. 322).

3. Method

This study adopted the PRISMA methodology for the systematic review (Moher et al., 2009) to undertake a transparent process of search strategy development, definition of inclusion criteria, and identification of relevant publications. Then, Theelen et al.'s (2019) critical appraisal strategy was applied to review the quality of publications. Next, a coding scheme was developed based on the suggested theoretical framework and used to analyze these publications.

3.1. Search strategy

Our systematic search strategy made use of the most relevant terms and synonyms that overlap the focus concepts of this study, identified based on prior systematic reviews of LA (Blumenstein, 2020; Ifenthaler & Yau, 2020; Mangaroska & Giannakos, 2018; Matcha et al., 2019) and feedback (Eggen et al., 2011; Najafabadi et al. 2016; Winstone et al., 2017). The selected terms were as follows: ("learning analytics" OR analytic* OR "data mining") AND (feedback OR feedforward OR "formative assessment"). Based on their reputation for covering the body of the literature in the field of LA and feedback studies, we identified Web of Science, Scopus, ERIC, and IEEE as the most relevant databases for search queries. In addition, we included the compiled Proceedings of the International Conference on Learning Analytics and Knowledge (LAK) because of the notable peer-reviewed publications by the LA community.

3.2. Criteria for inclusion

Three primary inclusion and exclusion criteria were applied in the first phase of literature screening. We included only studies published in the English language (because most of the publications in this area of research are written in English). We only included publications from 2011 to 2022, since LA as a new field of study emerged in 2011. Finally, to ensure the originality, validity, and quality of selected publications, we included only peer-reviewed articles published in scholarly journals.

In the second phase of screening, we selected only empirical studies (conceptual studies were therefore excluded). We also focused exclusively on studies undertaken in higher education settings. Because higher education settings require different learning approaches than other educational settings such as K-12 education contexts. Higher education students are supposed to be independent and self-regulated learners, and with respect to age, prior knowledge, learning experiences, and domain knowledge of higher education students, their learning strategies and expectations are different than K-12 education (UC San Diego, 2021). As a consequence, the use of LA in K-12 education contexts tends to focus on guiding teachers and supporting them to enhance students' learning (Kovanovic et al., 2021), because K-12 students are not expected to be highly independent and self-regulated learners to make use of LA insights (Jossberger et al., 2010). On the other hand, in higher education contexts, LA tends to focus on supporting students by guiding them to become self-regulated and self-directed learners (Viberg et al., 2020). Given attention to these differences, there is a need to separate review studies for higher education and K-12 education students. It would be interesting to compare the outcomes of these review studies in separate contexts at a later stage to examine similarities and differences.

Finally, we only included publications that reported findings, implications, or evidence that could address at least one of the research questions. That is to say that the included publications must either entail information regarding the LA data and methods used in higher education contexts to support feedback practices (what and how) or clearly explain the objectives of LA regarding supporting feedback practices in higher education contexts (why).

3.3. Identification of relevant publications

In the first phase of screening in selected databases, we identified a total of 1318 papers (Web of Science (n = 807), Scopus (n = 200), ERIC (n = 101), IEEE (n = 166), and LAK Conference contributions (n = 53)). After an initial screening, 308 were removed as duplications; a further 25 found to not be peer-reviewed articles, leaving a pool of 994 publications. These were screened using our second phase inclusion criteria, by reading titles and abstracts. 711 papers did not meet the second phase criteria, leaving 283 for full-text screening. A further 237 papers were excluded in this round mostly due to non-empirical nature and non-higher education context of the reviewed studies that leaving a final pool of only 46 studies for quality appraisal.

3.4. Quality appraisal

We used criteria for quality appraisal suggested by Theelen et al. (2019) (Table 1). This criteria were built on the study of Savin-Baden and Major (2007) for critical evaluation of qualitative studies and NICE (2012) checklist for critical appraisal of quantitative studies. The quality appraisal criteria for the quality of the methodology scored from no mention (0) to extensive mention (3) and we intended to exclude studies whose average score was less than 2 points (good mention). All 46 studies in fact met the minimum score for the quality of methodology and were therefore included in the final analysis. The stages of our screening and selection process are illustrated in Fig. 2.

Table 1
Quality appraisal criteria.

Criteria	No mention (0)	Some mention (1)	Good mention (2)	Extensive mention (3)
Criteria for qualitative studies				
Study methodologically is clear	1	1	14	2
Study theoretically substantiated	2	1	12	3
Ethical process transparent	2	2	10	4
Researcher(s) relation to participants are clear	0	3	11	4
Researchers(s) relation to the data are clear	0	2	11	5
Researcher(s) take a critical stance towards own research	1	1	10	6
Congruence between methodology and methods used for data collection, analysis, and interpretation	0	2	13	3
Participant involvement in data interpretation	1	2	9	6
Limitations voiced	1	2	12	3
Criteria for quantitative studies				
Is the source population or source area well-described?	1	3	27	4
Were interventions and comparisons well-described?	0	4	25	6
Were outcome measures reliable?	0	5	23	8
Were outcomes relevant?	0	2	24	9
Were the analytical methods appropriate?	1	4	25	5
Are the study results internally valid (i.e., unbiased)?	1	6	22	6
Are the findings generalizable to the source population?	3	4	20	8

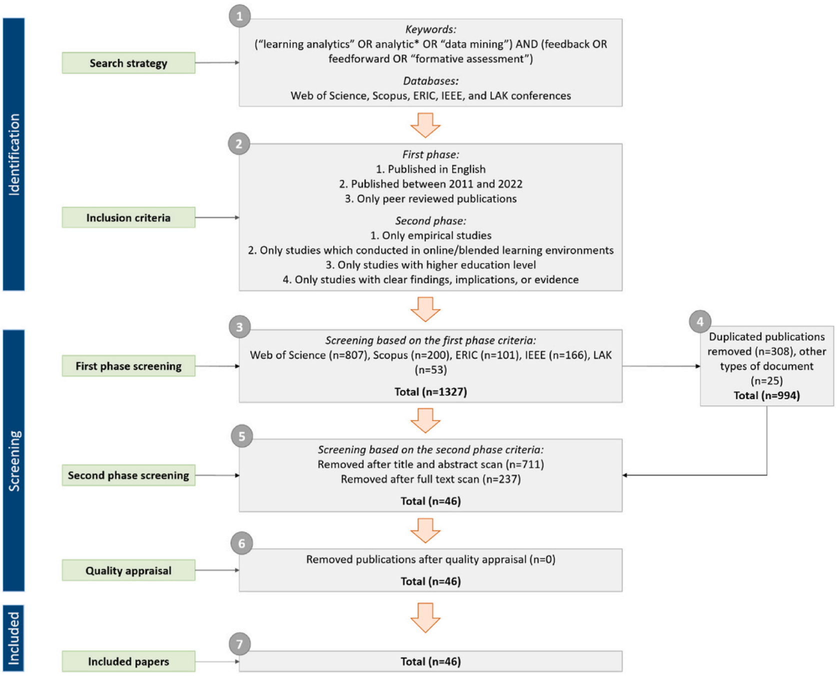

Fig. 2. Flowchart of the selection process.

3.5. *Included publications*

Our final pool of 46 selected publications for final analysis is detailed in Table 2.

As shown in Table 2, most of the included papers have been published since 2019 (N = 37, 80%). They also have been published in a wide variety of scholarly journals, ranging from writing research to information technology. However, some outlets generated more relevant papers: 6 papers (13%) were drawn from LAK Conference Proceedings, and the Journal of Computer Assisted Learning (N = 4, 9%), Computers in Human Behavior (N = 4, 9%), and Assessment & Evaluation in Higher Education (N = 3, 7%) had each published at least two relevant papers. A considerable number of papers reported on studies conducted in Australia of the OnTask platform (N = 10, 22%). Studies from The Netherlands (N = 5, 11%), Turkey (N = 5, 11%), and The UK (N = 3, 8%) were the next most common. Most of the studies reported were quantitative (N = 28, 61%), alongside 11 qualitative studies (24%), and 7 mixed methods studies (15%). Study context varied - from medicine to statistics – but studies of courses in the field of computer science were found most common (N = 11, 24%).

Table 2
Characteristics of included publications.

Authors and year	Journal/Conference	Country of study	Type of study	Field of study	Platform
Afzaal et al. (2021)	Frontiers in Artificial Intelligence	Sweden	Quantitative	Programming	LMS
Arnold and Pistilli (2012)	LAK Conference	USA	Quantitative	N/A	Blackboard
Azcona et al. (2019)	User Modeling and User-Adapted Interaction	Ireland	Quantitative	Computer Science	LMS
Baneres et al. (2019)	IEEE Transactions on Learning Technologies	Spain	Quantitative	Computer Science	LMS
Broos et al. (2020)	Assessment & Evaluation in Higher Education	Belgium	Quantitative	N/A	LASSI – REX
Chaudy and Connolly (2019)	Entertainment Computing	UK	Quantitative	N/A	EngAGe
Choi and Cho (2020)	Sustainability	Korea	Mixed method	Statistics	SCE
Conijn et al. (2020)	Journal of Computer Assisted Language Learning	Netherland	Qualitative	N/A	N/A
Cornide-Reyes et al. (2020)	Sensors	Chile	Mixed method	Programming	NAIRA - Zoom
Dalla Valle et al. (2018)	Research in Learning Technology	UK	Qualitative	N/A	N/A
Gibson et al. (2017)	LAK Conference	Australia	Qualitative	N/A	AWA
Hunt et al. (2021)	Education Sciences	Netherlands	Qualitative	N/A	EPASS
Iandoli et al. (2014)	International Journal of Human-Computer Studies	N/A	Quantitative	Engineering	CCSAV
Iraj et al. (2021)	Journal of Learning Analytics	Australia	Quantitative	Bioscience & Marketing	LMS
Iraj et al. (2020)	LAK Conference	Australia	Quantitative	Science	OnTask - LMS
Karaoglan Yilmaz (2022)	Journal of Computing in Higher Education	Turkey	Quantitative	Computing	Moodle
Knight et al. (2020)	Journal of Writing Research	Australia	Qualitative	Pharmacy, Law, Business	AcaWriter - AWAT
Kohnke et al. (2022)	SAGE Open	Hong Kong	Quantitative	English for Academic Purposes	LMS
Lee and Lim (2016)	Information Technology in Industry	Malaysia	Qualitative	N/A	N/A
Lewis et al. (2021)	Student Success	Australia	Quantitative	Psychology, Communication and Media	OnTask - LMS
Lim et al. (2020)	Australasian Journal of Educational Technology	Australia	Qualitative	N/A	OnTask - LMS
Lim, Gentili, et al. (2021)	Learning and Instruction	Australia	Quantitative	Biological science	OnTask - LMS
Lim, Gasevic, et al. (2021)	LAK Conference	Australia	Mixed method	Biology and Computer Engineering	OnTask - LMS
Lim, Dawson, et al. (2021)	Assessment & Evaluation in Higher Education	Australia	Qualitative	N/A	OnTask - LMS
Lu and Cutumisu (2022)	International journal of educational technology in higher education	Canada	Quantitative	Educational Assessment	Moodle
Matcha et al. (2019)	LAK Conference	Australia	Quantitative	Computer Science	N/A
Misiejuk et al. (2021)	Computers in Human Behavior	Norway	Mixed method	N/A	PeerGrade
Pardo et al. (2019)	British Journal of Educational Technology	Australia	Quantitative	Computer System	LMS
Perikos et al. (2017)	International Journal of Artificial Intelligence in Education	Greece	Mixed method	N/A	NLtoFOL
Sedrakyan et al. (2016)	Computers in Human Behavior	Belgium	Mixed method	Architecture and Management	Management Information Systeem (MIS)
Shibani et al. (2020)	The Internet and Higher Education	Australia	Qualitative	N/A	AcaWriter
Smith (2020)	Journal of Applied Research in Higher Education	UK	Qualitative	Medicine	LMS
Sun et al. (2019)	Educational Psychology	Taiwan	Quantitative	Science, Social Sciences, and Management	LMS
Tempelaar et al. (2015)	Computers in Human Behavior	Netherlands	Quantitative	N/A	BlackBoard - MyMathLab
Tempelaar et al. (2018)	Computers in Human Behavior	Netherlands	Quantitative	Mathematic and Statistics	LMS -MyMathLab
Tempelaar et al. (2021)	Frontiers in Education	Netherlands	Quantitative	Mathematic and Statistics	SOWISO - MyStatLab
Tsai et al. (2021)	LAK Conference	Brazil	Quantitative	Computer Science	OnTask - LMS
Ustun et al. (2022)	Journal of Research on Technology in Education	Turkey	Quantitative	Computer Science	Moodle
Wang and Han (2021)	Journal of Computer Assisted Learning	China	Quantitative	Computer Science	iTutor

(continued on next page)

Table 2 (*continued*)

Authors and year	Journal/Conference	Country of study	Type of study	Field of study	Platform
Yilmaz (2020)	Journal of Computer Assisted Learning	Turkey	Qualitative	Computing	Moodle
Yilmaz and Yilmaz (2020)	Innovations in Education and Teaching International	Turkey	Quantitative	Computing	Moodle
Yilmaz and Yilmaz (2021)	Technology, Knowledge and Learning	Turkey	Quantitative	Computing	Moodle
Yousef and Khatiry (2021)	Interactive Learning Environments	Egypt	Quantitative	Computer Science	Open CourseLab
Yu et al. (2018)	Journal of Computer Assisted Learning	Taiwan	Mixed method	Computer Science	LMS
Zheng, Zhong, and Niu (2021)	Assessment & Evaluation in Higher Education	China	Quantitative	N/A	Collaborative learning platform
Zheng, Niu, and Zhong (2021)	British Journal of Educational Technology	China	Quantitative	N/A	Collaborative learning platform

3.6. *Analytic strategy*

A coding scheme (Table 3) was developed based on the theoretical framework (Fig. 1) to thematically analyze included publications (Schreier, 2014; Wilson-Lopez et al., 2020), consisting of four categories, in line with the research questions foci on types of data (what), methods (how), objectives (why), and stakeholders (who). All 46 papers were entered into ATLAS.ti 9 (Friese, 2019) environment and were analyzed and coded based on the coding scheme. To examine the inter-rater reliability between the two coders, two papers were randomly selected and coded. The Kappa results showed 91 percent agreement between the two coders ($\kappa = 0.84$, $p < .001$), which confirms the high consistency and reliability of the coding.

Table 3
Coding scheme to analyze included publications.

Category	Code	Label	Definition
Types of data (what)	Type of data	A1	Refers to any kind of data such as academic data, performance data, interaction data, etc. that are collected by LA tools to support feedback practices in higher education
Methods (how)	Information visualization	B1	Refers to the information visualization methods such as concept mapping, graph drawing, heatmap, etc. that are used to analyze LA data to support feedback practices in higher education
	Data mining	B2	Refers to the data mining methods such as clustering, classification, decision tree, regression, etc. that are used to analyze LA data to support feedback practices in higher education
	Social network analysis	B3	Refers to the social network analysis methods such as epistemic network analysis that are used to analyze LA data to support feedback practices in higher education
	Other	B5	Refers to other methods such as text mining, content analysis, etc. that are used to analyze LA data to support feedback practices in higher education
Objectives (why)	Monitoring	C1	Refers to the monitoring goal of LA such as tracking students' learning performance during the learning processes to support feedback practices in higher education
	Prediction	C2	Refers to the prediction goal of LA such as predicting students' learning behavior to support feedback practices in higher education
	Assessment	C3	Refers to the assessment goal of LA such as providing an evidence-based assessment of students' learning performance to support feedback practices in higher education
	Adaptation	C4	Refers to the adaptation goal of LA such as providing an adaptive and flexible learning environment to support feedback practices in higher education
	Personalization	C5	Refers to the personalization goal of LA such as providing individualized feedback to support feedback practices in higher education
	Recommendation	C5	Refers to the recommendation goal of LA such as recommending what to do next to support feedback practices in higher education
	Reflection	C8	Refers to the reflection goal of LA such as assisting students with self-observation of their learning processes to support feedback practices in higher education
	Other	C9	Refers to any other goal of LA that can help to support feedback practices in higher education
Stakeholders (who)	Students	D1	Refers to the students as the stakeholder of LA application for feedback practices in higher education
	Educators	D2	Refers to the educators as the stakeholder of LA application for feedback practices in higher education

4. Results

4.1. RQ1: for what reasons is LA used in feedback studies in higher education?

The objectives we found for the use of LA in feedback studies have gone beyond sole improvements of feedback practices in higher education and it has included additional pedagogical objectives. We categorized the objectives of LA in feedback offered in our selected papers as objectives for enhancing feedback practices in higher education (Table 4) and pedagogical objectives that were achieved through LA-supported feedback practices in higher education (Table 5).

Table 4
LA objectives for enhancing feedback practices in higher education.

Objectives	N of studies	Pct.	References
Reflection	20	43%	Azcona et al. (2019), Choi and Cho (2020), Cornide-Reyes et al. (2020), Gibson et al. (2017), Hunt et al. (2021), Iandoli et al. (2014), Iraj et al. (2020), Karaoglan Yilmaz (2022), Lee and Lim (2016), Lim et al. (2020), Lim, Gasevic, et al. (2021), Sedrakyan et al. (2016), Shibani et al. (2020), Smith (2020), Tempelaar et al. (2015), Tsai et al. (2021), Wang and Han (2021), Yilmaz (2020), Yousef and Khatiry (2021), Yu et al. (2018)
Personalization	13	28%	Azcona et al. (2019), Conijn et al. (2020), Hunt et al. (2021), Iraj et al. (2020), Iraj et al. (2021), Lewis et al. (2021), Lim, Gentili, et al. (2021), Lim, Gasevic, et al. (2021), Lim, Dawson, et al. (2021), Pardo et al. (2019), Tempelaar et al. (2021), Ustun et al. (2022), Zheng, Zhong, and Niu (2021)
Prediction	11	24%	Arnold and Pistilli (2012), Azcona et al. (2019), Baneres et al. (2019), Broos et al. (2020), Conijn et al. (2020), Knight et al. (2020), Sedrakyan et al. (2016), Smith (2020), Tempelaar et al. (2018), Tempelaar et al. (2021), Yu et al. (2018)
Assessment	11	24%	Chaudy and Connolly (2019), Choi and Cho (2020), Dalla Valle et al. (2018), Kohnke et al. (2022), Lim et al. (2020), Lim, Gasevic, et al. (2021), Misiejuk et al. (2021), Shibani et al. (2020), Smith (2020), Tempelaar et al. (2015), Tempelaar et al. (2018)
Adaptation	10	22%	Chaudy and Connolly (2019), Gibson et al. (2017), Iandoli et al. (2014), Iraj et al. (2020), Lewis et al. (2021), Lim et al. (2020), Lim, Gentili, et al. (2021), Lim, Gasevic, et al. (2021), Lim, Dawson, et al. (2021), Pardo et al. (2019)
Recommendation	10	22%	Afzaal et al. (2021), Azcona et al. (2019), Gibson et al. (2017), Karaoglan Yilmaz (2022), Kohnke et al. (2022), Lewis et al. (2021), Perikos et al. (2017), Sedrakyan et al. (2016), Tempelaar et al. (2018), Ustun et al. (2022)
Monitoring	6	13%	Choi and Cho (2020), Conijn et al. (2020), Cornide-Reyes et al. (2020), Iandoli et al. (2014), Smith (2020), Yousef and Khatiry (2021)

Table 5
Pedagogical objectives achieved through LA-supported feedback practices.

Objectives	N of studies	Pct.	References
Academic performance	17	37%	Arnold and Pistilli (2012), Azcona et al. (2019), Broos et al. (2020), Knight et al. (2020), Iraj et al. (2021), Karaoglan Yilmaz (2022), Kohnke et al. (2022), Lewis et al. (2021), Lim, Gentili, et al. (2021), Lim, Gasevic, et al. (2021), Lu et al. (2022), Matcha et al. (2019), Pardo et al. (2019), Perikos et al. (2017), Ustun et al. (2022), Wang and Han (2021), Zheng, Niu, and Zhong (2021)
Engagement and community of inquiry	11	24%	Iraj et al. (2020), Iraj et al. (2021), Kohnke et al. (2022), Lim et al. (2020), Lim, Dawson, et al. (2021), Lu et al. (2022), Smith (2020), Sun et al. (2019), Tempelaar et al. (2021), Yilmaz (2020), Yilmaz and Yilmaz (2021)
Self-regulation	8	17%	Afzaal et al. (2021), Karaoglan Yilmaz (2022), Lim et al. (2020), Lim, Gentili, et al. (2021), Lim, Gasevic, et al. (2021), Tsai et al. (2021), Ustun et al. (2022), Yu et al. (2018)
Motivation and emotion	8	17%	Lewis et al. (2021), Lim et al. (2020), Lim, Dawson, et al. (2021), Misiejuk et al. (2021), Smith (2020), Tempelaar et al. (2021), Yilmaz (2020), Zheng, Zhong, and Niu (2021)
Time management	3	6%	Iraj et al. (2020), Lim, Gasevic, et al. (2021), Shibani et al. (2020)
Perception of feedback	2	4%	Lim et al. (2020), Misiejuk et al. (2021)
Cognitive load	2	4%	Sun et al. (2019), Zheng, Zhong, and Niu (2021)
Reduce procrastination	1	2%	Lim et al. (2020)
Satisfaction	1	2%	Pardo et al. (2019)
Self-efficacy	1	2%	Tsai et al. (2021)
Reflective thinking skills	1	2%	Yilmaz (2020)
Transactional distance	1	2%	Yilmaz and Yilmaz (2020)

4.1.1. LA objectives for enhancing feedback practices in higher education

Reflection: Timely actionable feedback that prompts learner reflection is understood to be critical for the learning process, by allowing learners to critically evaluate their progress and make necessary changes (Greller & Drachsler, 2012). In our pool of papers, 'LA for reflection' described an array of different metrics used, including information about the student learning process (Azcona et al., 2019; Choi & Cho, 2020; Lee & Kim, 2008), level of participation (Cornide-Reyes et al., 2020), timeliness of formative feedback (Hunt et al., 2021; Tsai et al., 2021; Yu et al., 2018), actionable feedback (Gibson et al., 2017; Iraj et al., 2020), and self-reflection (Lim, Gasevic, et al., 2021).

Personalization: The capacity for LA to provide individualized feedback to large numbers of students is a core focus of many LA feedback studies (Iraj et al., 2020; Lim, Gentili, et al., 2021; Pardo et al., 2019). Personalized feedback aims to provide feedback to a specific student based on their learning performance, rather than on personal characteristics (Koenka & Anderman, 2019). Our pool of studies report the use of LA to offer personalized feedback of various kinds: Azcona et al. (2019) report the use of LA to send personalized notifications to students based on their learning progression and whether they are at risk of failure; Conijn et al. (2020) describe the use of LA-driven personalized feedback to improve student writing. In other studies, LA allowed the delivery of personalized feedback at scale, to each student in a large class (Lewis et al., 2021; Lim, Gentili, et al., 2021; Pardo et al., 2019).

Prediction: The development of accurate models that predict learning outcomes based on student activity or behavior is an area of LA research that contributes to feedback for earlier intervention or adaptation (Greller & Drachsler, 2012). In this review, we found that predictive feedback is developed to support student retention, early warning, and detect students at risk of failure (e.g. Arnold & Pistilli, 2012; Azcona et al., 2019; Broos et al., 2020). Predictive feedback can be considered as automated feedback for automatic decision-making for learning paths (Conijn et al., 2020; Knight et al., 2020) which could save time for educators for more personal interventions (Greller & Drachsler, 2012).

Assessment: Much LA research has as a goal the development of meaningful metrics that allow assessment of efficiency and effectiveness of the learning process (Chatti et al., 2012; Chaudy & Connolly, 2019). In a number of reviewed studies, LA was used to offer formative assessment to students (e.g. Chaudy & Connolly, 2019; Choi & Cho, 2020; Tempelaar et al., 2018). In others, LA was used to support self-assessment (e.g. Lim et al., 2020; Lim, Gasevic, et al., 2021; Shibani et al., 2020), or peer assessment (Misiejuk et al., 2021; Smith, 2020).

Adaptation: LA helps students with adaptive learning based on the self-observation and self-control process (Lim, Gasevic, et al., 2021), contextual feedback (Gibson et al., 2017), and self-reactions (Lim et al., 2020). LA-based feedback assists students with modifying their learning based on their individual needs (Chatti et al., 2012). Analysis of the selected publications indicated that student adaptation can be fostered by the contextualization of feedback (Iandoli et al., 2014), providing personalized feedback (Iraj et al., 2020; Lim et al., 2020), and given attention to metacognition skills such as self-regulation (Lim, Gasevic, et al., 2021).

Recommendation: LA-based feedback can provide students with a recommendation on what to do next (Chatti et al., 2012). Analytics-based recommender systems foster student self-directed learning through explicit recommendations based on student activities and preferences (Chatti et al., 2012). In a few of the studies we reviewed, LA is used as a recommender system to guide learners and the learning process (Sedrakyan et al., 2016), and suggest useful course material (Azcona et al., 2019).

Monitoring: Monitoring refers to tracking student learning activities, and identifying challenges that students are facing, in order to better support them with timely interventions and decision-making (Chatti et al., 2012; Cornide-Reyes et al., 2020). In some studies reviewed here, LA is used for monitoring learning activities and processes to provide formative feedback to facilitate and improve student learning (Choi & Cho, 2020; Cornide-Reyes et al., 2020; Smith, 2020).

4.1.2. Pedagogical objectives achieved through LA-supported feedback practices

As summarized in Table 5, our review revealed a range of other pedagogical objectives that LA-supported feedback has brought to higher education. In a considerable number of reviewed studies (e.g., Karaoglan Yilmaz, 2022; Kohnke et al., 2022) we found that when feedback practices are enhanced by LA insights, students' academic performance has also been improved. This could be due to different reasons. For example, in Karaoglan Yilmaz (2022), it was found that LA-guided feedback provides evidence-based recommendations on how to improve academic achievements. Or, Arnold and Pistilli (2012) found that LA provides predictive feedback which entails information on how students are expected to perform in the future and can prevent dropout of students who are at risk of academic failure.

LA-supported feedback can also help with improving students' self-regulation skills (e.g., Afzaal et al., 2021; Lim, Gasevic, et al., 2021). The quality of students' self-regulation performance highly depends on their cognitive and metacognitive awareness of their own learning processes (Karaoglan Yilmaz, 2022). If students can be well-informed about how they are doing, they are more expected to be self-regulated learners (Roll & Winne, 2015). LA-supported feedback entails real-time reflections on students' performance during their learning processes and that personalized and reflective feedback can help students to be more aware of their own learning processes in order to regulate their learning (Lim, Gasevic, et al., 2021).

We found that LA-based feedback can also impact students' motivation (e.g., Smith, 2020) and engagement (e.g., Iraj et al., 2020). This could be due to fact that students may perceive LA-supported feedback as a personalized, actionable, and real-time feedback that they can benefit from it and this results in their high motivation to be engaged with LA-based feedback (Lim et al., 2020, 2021c; Zheng, Zhong, & Niu, 2021). In addition, since LA-based feedback relies on each student's learning data, it makes it easier for teachers to target students who need support. A good example is the insights provided by SNA in terms of students' interaction with each other (Choi et al., 2020). These insights help teachers to have an overview of students' interactions with each other and to identify which student is less engaged to support him/her.

LA-based feedback has shown the potential to save time for educators (Iraj et al., 2020; Shibani et al., 2020). In general, educators put a lot of time and effort to give one-by-one feedback to students in a traditional way (Iraj et al., 2020). However, using LA-based feedback has made it easier for educators to monitor their students' learning progress and to provide personalized and real-time feedback (Shibani et al., 2020). In addition, LA can be used to understand students' perceptions of feedback (Misiejuk et al., 2021). Insights provided by LA methods particularly Epistemic Network Analysis (ENA) can help educators to understand how students perceive feedback (Lim et al., 2020; Misiejuk et al., 2021). Based on these insights, educators, as well as students, can modify their feedback activities.

We also found that LA-based feedback influences students' cognitive load (Sun et al., 2019). Generally, providing feedback causes cognitive load including mental load (the load caused by a certain task) and mental effort (the cognitive effort for solving the task) (Paas & Van Merriënboer, 1994). If LA-based feedback relies only on warning systems, then it can increase the mental load, while putting warning systems with the encouragement of what to do can lead to higher emotional and cognitive engagement (Sun et al., 2019). This suggests that LA-based feedback should include encouragement to enhance the appeal of the learning journey (Sun et al., 2019).

It was revealed that LA-based feedback can reduce students' procrastination (Lim et al., 2020). LA-based feedback can work as a reminder system for students to bring their attention to tasks and the subsequent actions that need to be taken (Lim et al., 2020). In addition, LA-based feedback can increase students' satisfaction with feedback (Pardo et al., 2019). This could be due to the reason that the provision of feedback through LA results in personalized and real-time feedback that aligns well with each student's learning activities and needs (Kim, Jo, & Park, 2016; Pardo et al., 2019). This means that students found LA-based feedback as an important factor to support their success (Pardo et al., 2019).

Analysis of the reviewed papers also has shown that there is a correlation between students' self-efficacy and LA-based feedback. Students with higher self-efficacy more appreciated LA-based feedback and had positive experiences with it (Tsai et al., 2021). This could be due to the reason that students with high self-efficacy are more able to execute behaviors that are necessary to produce a specific performance (Bandura et al., 1999).

Furthermore, LA-based feedback can influence students' reflective thinking skills and transactional distance (Yilmaz, 2020; Yilmaz et al., 2020). The reason why LA-based feedback can improve students' relfective thinking skills is that feedback provided by LA allows students to see how they are doing, what are the weaknesses and strengths in their learning processes and students can use these insights to reflect on their learning processes to see what needs to be improved or modified (Yilmaz, 2020). Furthermore, the reason why LA-based feedback can decrease the transactional distance in online learning environments is the fact that LA-based feedback entails consistent reports of weekly activities and guiding messages build on the reports and this feedback is useful as a metacognitive tool in supporting students in online learning environments and make them aware of their shortcomings (Yilmaz et al., 2021). Such metacognitive support in online learning environments can decrease transactional distance (Yilmaz & Keser, 2017; Zhang, 2003).

4.2. RQ2: what types of data does LA use to support feedback in higher education?

We identified 65 codes from the included publications based on our coding scheme that describing types of data used by LA to support feedback in higher education. Based on the nature and the goal of the identified data, we followed a bottom-up inductive approach to group data into six main groups: including trace data, assessment data, academic history data, demographic data, survey data, and interview data. In the next step, we divided these groups of data into two main category including (a) data used for LA feedback intervention and (b) data used for researching LA feedback intervention (Table 6). These categories are further discussed below.

Table 6
Types of data used by LA to support feedback in higher education.

Category	Types of data		N of codes	Pct.	References
Data used for LA feedback intervention	Trace data	Date and time of the submission, engagement, activities, verbal interactions, speaking time, total posts, responses to the posts, student clicks, learner trace data, interactions, watching videos, learning behavior observations, learning event data, learning style, learning dispositions, learning emotions and motivation, epistemic emotions, goal setting, attendance, in-class participation, feedback data, e-tutorial trace data, log data, tagged data, LMS trace data	23	36%	Afzaal et al. (2021), Azcona et al. (2019), Azcona et al. (2019), Baneres et al. (2019), Choi and Cho (2020), Cornide-Reyes et al. (2020), Gibson et al. (2017), Iraj et al. (2020), Iraj et al. (2021), Kohnke et al. (2022), Lewis et al. (2021), Lim, Gentili, et al. (2021), Lim, Gasevic, et al. (2021), Lu et al. (2022), Pardo et al. (2019), Sedrakyan et al. (2016), Tempelaar et al. (2015), Tempelaar et al. (2018), Tempelaar et al. (2021), Ustun et al. (2022), Yousef and Khatiry (2021), Yu et al. (2018)
	Assessment data	Grades, scores, mid-term quiz marks, assignments, completion of multiple-choice questions, engagement with summative exercises, scores of the mid-term examination, progress data, quiz data, formative assessment data, homework completion, self-evaluation comments,	12	18%	Afzaal et al. (2021), Arnold and Pistilli (2012), Azcona et al. (2019), Baneres et al. (2019), Chaudy and Connolly (2019), Iraj et al. (2020), Iraj et al. (2021), Kohnke et al. (2022), Lewis et al. (2021), Lim, Gentili, et al. (2021), Lim, Gasevic, et al. (2021), Lu et al. (2022), Misiejuk et al. (2021), Pardo et al. (2019), Smith (2020), Tempelaar et al. (2015), Tempelaar et al. (2018), Tempelaar et al. (2021), Yu et al. (2018)
	Demographic data	Age, gender, date of birth, citizenship, domicile, language,	6	9%	Arnold and Pistilli (2012), Azcona et al. (2019), Iraj et al. (2021), Lim, Gentili, et al. (2021), Lim, Gasevic, et al. (2021), Perikos et al. (2017), Tempelaar et al. (2015), Chaudy and Connolly (2019), Conijn et al. (2020),
	Academic history data	Prior to university test scores, high school GPA, SAT exam, date of registration, course registration, program type, program entry score, year of study, prior education, entry test data, SIS system data	11	17%	Afzaal et al. (2021), Azcona et al. (2019), Lee and Lim (2016), Lim, Gentili, et al. (2021), Tempelaar et al. (2015), Tempelaar et al. (2018)
Data used for researching LA feedback intervention	Survey data	Student experiences, questionnaire, cognitive load scale, engagement scale, the community of inquiry scale, reflective thinking scale, transactional distance scale, motivated strategies for learning questionnaire,	8	12%	Broos et al. (2020), Cornide-Reyes et al. (2020), Dalla Valle et al. (2018), Hunt et al. (2021), Iraj et al. (2021), Karaoglan Yilmaz (2022), Lee and Lim (2016), Matcha et al. (2019), Pardo et al. (2019), Perikos et al. (2017), Shibani et al. (2020), Smith (2020), Sun et al. (2019), Tempelaar et al. (2021), Tsai et al. (2021), Ustun et al. (2022), Yousef and Khatiry (2021), Wang and Han (2021), Yilmaz (2020), Yilmaz and Yilmaz (2020), Yilmaz and Yilmaz (2021), Zheng, Zhong, and Niu (2021), Zheng, Niu, and Zhong (2021)
	Interview data	Focus group data, qualitative data, open-ended questions, unstructured texts, semi-structured interviews,	5	8%	Conijn et al. (2020), Hunt et al. (2021), Iraj et al. (2021), Lee and Lim (2016), Lewis et al. (2021), Lim et al. (2020), Lim, Gasevic, et al. (2021), Lim, Dawson, et al. (2021), Shibani et al. (2020), Yilmaz (2020), Zheng, Zhong, and Niu (2021), Zheng, Niu, and Zhong (2021)

4.2.1. Data used for LA feedback intervention

In the reviewed studies, this category of data refers to data types that directly are used by LA to enhance feedback practices in higher education. This category includes trace data, assessment data, demographic data, and academic history data which are further explained below.

Trace data: According to the reviewed studies, this is the dominant data type used by LA to support feedback in higher education. Trace data is a type of data that is data derived from computer systems for enhancing student learning. This data refers to any kind of data that is generated by students during the learning process in online learning platforms and it is tracked by LA tools (Hadwin et al., 2007). Trace data can include data about student interactions (Cornide-Reyes et al., 2020), discussion forum posts (Gibson et al., 2017), engagement (Azcona et al., 2019; Sun et al., 2019; Yilmaz & Yilmaz, 2021, pp. 1–12), emotions (Tempelaar et al., 2015), attendance and in-class participation (Yu et al., 2018), or frequency and time of day of video viewing (Pardo et al., 2019). Trace data plays an important role in LA-informed feedback practices because this data is mostly about students' performance during the learning processes and if we admit that LA is about learning (Gašević et al., 2015), and improving the learning process (Siemens & Long, 2011), then, trace data can be seen as the most important data for LA. Likewise, most LA dashboards need trace data for providing learning-related visualizations (Aljohani & Davis, 2013; Greller & Drachsler, 2012). That is to say that, LA dashboards rely heavily on the trace data to inform both educators and students in terms of students' performance during the learning processes and to improve their self-regulation strategies (e.g., Kaliisa & Dolonen, 2022, pp. 1–22; Vigentini et al., 2021). Reviewed publications indicate that without trace data, appropriate interventions by LA might not be possible. Reviewed studies indicate that such data can be used to generate different types of feedback such as reflective feedback (refers to reflections that LA provides for both teachers and students based on their collected data with respect to their teaching and learning processes and outcomes) (Cornide-Reyes et al., 2020; Knight et al., 2020; Sedrakyan et al., 2016), personalized feedback (refers to the predictions that LA provides in terms of students' learning behavior and success based on their academic history, learning processes, and learning outcomes data) (Lewis et al., 2021; Lim et al., 2020; Pardo et al., 2019), and predictive feedback (Arnold & Pistilli, 2012; Azcona et al., 2019; Broos et al., 2020).

Assessment data: This data type includes any kind of 'performance data' developed through assessment: final grades (Arnold & Pistilli, 2012; Baneres et al., 2019; Iraj et al., 2020), mid-term quiz marks (Chaudy & Connolly, 2019; Lim, Gentili, et al., 2021), assignment grades (Misiejuk et al., 2021), engagement grades (Pardo et al., 2019), formative assessment scores (Tempelaar et al., 2018), homework completion marks, and self-evaluation comments (Yu et al., 2018). Assessment data is often used by LA in feedback studies to provide recommendations (Lewis et al., 2021; Tempelaar et al., 2018), assessment (Chaudy & Connolly, 2019; Tempelaar et al., 2018), predictive feedback (Arnold & Pistilli, 2012; Baneres et al., 2019), and personalized feedback (Iraj et al., 2020; Lim, Gentili, et al., 2021). Our review suggests that assessment data mostly serve educators with evidence-based formative and summative assessment (e.g. Choi & Cho, 2020; Tempelaar et al., 2015).

Academic history data: This type of data includes any data related to student academic background, such as high school GPA and SAT scores (Azcona et al., 2019), date of registration and course registration (Lee & Lim, 2016), program type, and program entry score (Lim, Gentili, et al., 2021), year of study (Perikos et al., 2017), prior education (Azcona et al., 2019; Lim, Gentili, et al., 2021), prior academic performance (Azcona et al., 2019; Matcha et al., 2019), entry test data (Tempelaar et al., 2015), and all the data that can be extracted from Student Information System (Tempelaar et al., 2018). Similar to demographic data, this data type has also little to say by itself. That is to say that in LA feedback studies, it is often combined with other types of data to provide reflective (Lim, Gentili, et al., 2021) and predictive feedback (Azcona et al., 2019), and formative assessment (Tempelaar et al., 2018).

Demographic data: This data type is one of the most commonly employed in LA studies (Azcona et al., 2019; Tempelaar et al., 2015). It is usually collected from Student Information Systems (SIS), or may simply be collected by a self-report questionnaire (Tempelaar et al., 2018). It can include items such as student age, gender, date of birth, citizenship, domicile, and language (Arnold & Pistilli, 2012; Chaudy & Connolly, 2019; Conijn et al., 2020). Although demographic data is very common to use in LA, they have little to say solely by themselves and it has been criticized that initial LA tools were too reliant on this type of data for generating early-warning systems (Gašević et al., 2016; Lim, Gentili, et al., 2021). In current most of LA projects, demographic data is used alongside other data types for better interpretations of the data. For example, our review showed that in some studies, demographic data was combined with assessment data such as grades and academic history data to develop predictive feedback on students at risk of failure (Azcona et al., 2019). Or in another study, demographic data was used alongside learning data and assessment data for delivering LA-generated formative assessment (Tempelaar et al., 2015).

4.2.2. Data used for researching LA feedback intervention

In the reviewed studies, this category of data refers to data types that the researchers used for understanding how interventions made by LA-based feedback affect pedagogical aspects of teaching and learning. This category of data includes survey data and interview data that are further explained below.

Survey data: This data type refer to the kind of data that are collected by a survey or a questionnaire. Normally, this data is collected at the end of the learning process where students were asked to fill out, typically a Likert scale, questionnaire. Reviewed publications revealed that LA-based feedback underpinned by survey data can affect student cognitive load (Sun et al., 2019; Zheng et al., 2021), the community of inquiry, reflective thinking skills (Yilmaz, 2020), motivation, and transactional distance (Yilmaz & Yilmaz, 2020), and engagement (Sun et al., 2019; Yilmaz & Yilmaz, 2021, pp. 1–12). What is important to note about the survey data is that this type of data usually contain a high validity, since they have already been validated by other scholars. This implies that LA driven by survey data can be highly relied. Selected studies suggest that survey data-based LA can foster predictive feedback (Broos et al., 2020), recommendation (Perikos et al., 2017), reflective feedback (Smith, 2020; Tsai et al., 2021), and assessment (Dalla Valle et al., 2018). In addition, our review suggests that survey data mostly is used for statistically exploring the relationships among variables. For example, the relationship among personalized feedback, students' academic achievement, and satisfaction (Pardo et al., 2019), or relations among LA-supported feedback, transactional distance perception, and motivation (Yilmaz & Yilmaz, 2020). For this reason, data mining methods are applied mainly on survey data.

Interview data: This type of qualitative data is typically collected either through focus group discussions, unstructured or semi-structured interviews, or written open-ended questionnaires and texts (Hunt et al., 2021; Lee & Lim, 2016; Shibani et al., 2020). It is often supplementary data for other types of data that can be mined from LMS or other online platforms and can offer more in-depth information. In feedback studies, interview data is used by LA for different reasons such as exploring student experiences, preferences, and perceptions of feedback (Conijn et al., 2020; Hunt et al., 2021; Lewis et al., 2021; Misiejuk et al., 2021). Reviewed publications indicate that this kind of data is used for providing personalized, predictive, reflective, adaptive, and recommendation feedback (Conijn et al., 2020; Hunt et al., 2021; Lewis et al., 2021; Lim, Dawson, et al., 2021).

4.3. RQ3: what methods does LA use to support feedback in higher education?

In our pool of 46 published studies, we identified 44 codes representing 'LA methods' (Table 7). These methods are further

Table 7
Methods used by LA to support feedback in higher education.

Category	Methods	N of codes	Pct.	References
Information visualization	Dashboard visualizations, influence graph, graph-based methods, knowledge graph, line chart, box and whisker plot, scatter plot, infographics, heat map, bar chart, area graph, time-series graph, concept map, bar chart, radar graph, tree-based methods, pivot chart, word cloud, pie chart, surface chart, histogram plot, flow chart	22	50%	Afzaal et al. (2021), Azcona et al. (2019), Baneres et al. (2019), Broos et al. (2020), Chaudy et al. (2019), Choi et al. (2020), Cornide-Reyes et al. (2020), Dalla Valle et al. (2018), Gibson et al. (2017), Hunt et al. (2021), Karaoglan Yilmaz (2022), Lee et al. (2016), Lewis et al. (2021), Lim et al. (2020), Lim, Gentili, et al. (2021), Lim, Gasevic, et al. (2021), Lim, Dawson, et al. (2021), Matcha et al. (2019), Misiejuk et al. (2021), Perikos et al. (2017), Sedrakyan et al. (2016), Smith (2020), Tempelaar et al. (2015), Tempelaar et al. (2018), Tsai et al. (2021), Ustun et al. (2022), Wang et al. (2021), Yilmaz (2020), Yilmaz et al. (2020), Yilmaz et al. (2021), Yousef et al. (2021), Yu et al. (2018), Zheng, Zhong, and Niu (2021), Zheng, Niu, and Zhong (2021)
Data mining	Predictive modelling, classification, clustering, bayesian network analysis, process mining, behavior modelling, relationship mining, support vector machine, discovery model, neural network, machine learning	11	25%	Afzaal et al. (2021), Azcona et al. (2019), Baneres et al. (2019), Choi and Cho (2020), Iraj et al. (2021), Karaoglan Yilmaz (2022), Kohnke et al. (2022), Lim, Gasevic, et al. (2021), Lu et al. (2022), Matcha et al. (2019), Perikos et al. (2017), Sedrakyan et al. (2016), Tempelaar et al. (2015), Tempelaar et al. (2018), Tempelaar et al. (2021), Tsai et al. (2021), Ustun et al. (2022), Yousef and Khatiry (2021), Yu et al. (2018), Zheng, Zhong, and Niu (2021), Zheng, Niu, and Zhong (2021)
Text analysis	Thematic analysis, writing analytics, text mining, deductive analysis, natural language processing, sentiment analysis, content analysis, natural language processing	8	18%	Conijn et al. (2020), Gibson et al. (2017), Hunt et al. (2021), Knight et al. (2020), Lee and Lim (2016), Lewis et al. (2021), Lim et al. (2020), Lim, Gasevic, et al. (2021), Lim, Dawson, et al. (2021), Misiejuk et al. (2021), Perikos et al. (2017), Shibani et al. (2020), Ustun et al. (2022), Yilmaz (2020), Yu et al. (2018), Zheng, Niu, and Zhong (2021)
Social network analysis	Social network analysis, epistemic network analysis, network diagrams	3	7%	Choi and Cho (2020), Iandoli et al. (2014), Lim et al. (2020), Lim, Dawson, et al. (2021), Misiejuk et al. (2021)

discussed below.

Information visualization: Information visualization alongside data mining methods were the most commonly used LA methods in our selected group of LA feedback studies. This analytics method uses a visual approach to represent and analyze data (Khan & Khan, 2011). We discovered that an information visualization approach was used is used in 34 studies (e.g. Lim et al., 2020; Yu et al., 2018). Baneres et al. (2019) used dashboard visualizations for early warning of students at risk. Lim et al. (2020) adopted a graph-based method for exploring associations between student perceptions of feedback and adaptations of self-regulated learning. Elsewhere, Cornide-Reyes et al. (2020) used "influence graphs" to visualize speech interactions between students. Information visualization methods seem to be commonly used alongside other LA methods to identify students at risk of failure and to understand student perceptions and interactions. In general, most LA reports are intended to be presented visually in a dashboard (e.g. Aljohani & Davis, 2013). This implies that information visualization methods might be the most commonly used LA methods. According to the level of analytics suggested by Maoz (2013; Eriksson et al., 2020), although information visualizations methods are typically used in all four levels of analytics including descriptive, diagnostic, predictive, and prescriptive levels, it is mostly used at the descriptive level to describe what has happened and what is happening.

Data mining: Generally, such methods mainly seek to discover patterns, correlations, and anomalies in large volumes of data (Lee & Siau, 2001). Methods used to support feedback include predictive modelling (Azcona et al., 2019; Tempelaar et al., 2015), classification (Baneres et al., 2019), clustering (Lim, Gasevic, et al., 2021; Tempelaar et al., 2018; Tsai et al., 2021), Bayesian network analysis (Choi & Cho, 2020), natural language processing (Perikos et al., 2017), process mining (Sedrakyan et al., 2016), relationship mining (Tempelaar et al., 2018), support vector machine (Yu et al., 2018), discovery model (Tempelaar et al., 2018), machine learning (Yu et al., 2018), and neural network (Zheng et al., 2021). Of these, predictive modeling (N = 8) and clustering (N = 6) were the most commonly used. According to the level of analytics suggested by Maoz (2013; Eriksson et al., 2020), data mining methods alongside artificial intelligence are usually used at the predictive and prescriptive analytics levels. LA in predictive analytics level tells us "what will happen", while in the prescriptive analytics level, LA recommends actions and interventions for the future (Turkington et al., 2018). In our reviewed publications, an example of this could be the early prediction LA systems and automatic feedback and recommendations that are generated by LA (Azcona et al., 2019; Sedrakyan et al., 2016).

Text analytics: Most of the studies whose method we originally coded as "other methods"(B5) using our coding scheme (Table 3) actually made use of text analysis. Text analytics is defined as a process of drawing meaning from written texts, and typically involves categorizing, summarizing, clustering, and extracting concepts from a text (Fiaidhi, 2014). Text analytic methods were used to support feedback in 16 studies - including thematic analysis (Hunt et al., 2021; Lim et al., 2020), text mining (Lee et al., 2016), deductive analysis (Lim, Gasevic, et al., 2021), sentiment analysis (Misiejuk et al., 2021; Yu et al., 2018), writing analytics (Shibani et al., 2020), and content analysis (Yilmaz, 2020). Text analysis was used to analyze student emotions in self-evaluation comments in one study (Yu et al., 2018); in others, text analysis was employed to mine student perceptions and feelings about peer feedback (Misiejuk et al., 2021; Lim et al., 2021; Lee et al., 2016). Text analytic methods were clearly helpful for exploring in-depth student perceptions, emotions, and feelings during the learning process, by digging into their qualitative data such as comments, posts, chats, etc. According to the level of analytics suggested by Maoz (2013; Eriksson et al., 2020), text analytics is seemed to be more likely used in the descriptive and diagnostic level of analytics. Descriptive analytics normally reports information about what has happened in the learning process (Eriksson et al., 2020). At this level, text analytics methods can be used, for example, for describing students' perceptions and emotions in the discussion forum during the learning process (Yu et al., 2018). At the diagnostic analytics level, LA answers the question "why did it happen" and explores exceptions, anomalies, similarities, and differences in the recorded data (Maoz, 2013). Our review revealed that text analytics methods were used for mining similarities, and differences among students feedback, emotions, and perceptions (Lee & Lim. 2016; Lim et al., 2020; Misiejuk et al., 2021).

Social network analysis (SNA): SNA refers to methods used to study relationships, interactions, and communications between two or more individuals (here, typically, students) (Saqr & Alamro, 2019). We found that SNA was only used in five LA feedback studies (Choi & Cho, 2020; Iandoli et al., 2014; Lim et al., 2020, 2021c; Misiejuk et al., 2021), though with various goals. Choi and Cho (2020) used SNA for formative assessment, while, Iandoli et al. (2014) used it to provide reflective feedback. Elsewhere epistemic network analysis (ENA), another form of network analysis was used to understand student perception of personalized feedback (Lim et al., 2020; Misiejuk et al., 2021), and discover contextual differences that affected the relationship between feedback perception and feedback emotions (Lim, Dawson, et al., 2021). Network analysis methods appear to be helpful in understanding how students perceive feedback and how they reflect on their learning process alongside exploring how students interact with each other. Based on this explanation, it is expected that SNA methods are intended to be used at descriptive and diagnostic levels.

4.4. RQ4: how does LA support feedback stakeholders in higher education?

As our review revealed, unsurprisingly, in all included publications, students were mentioned as the LA-supported feedback stakeholder, followed by educators mentioned in 15 out 46 included studies. These findings imply that LA holds great potential to provide a wide range of support not only for students but also for educators as well. However, the question here is how have students and educators been supported by LA? To answer this question, the authors provided a conceptual figure (Fig. 3), drawn based on the findings of the selected studies, that illustrates the relations among feedback stakeholders, LA objectives, and levels of analytics.

According to this figure, the use of LA for feedback purposes in higher education has brought both enhancements of feedback practices as well as additional pedagogical benefits that have come through LA-based feedback in higher education. For educators, LA-based feedback provides assistance with monitoring students learning activities and progress (e.g. Cornide-Reyes et al., 2020), helps educators with a formative and summative assessment of students (e.g. Chaudy & Connolly, 2019), supports educators with predictive feedback where educators can be early warned about students at risk of failure (e.g. Arnold & Pistilli, 2012). In addition, the use of LA for feedback helps educators to receive recommendations through automatic feedback for better pedagogical interventions (e.g. Azcona et al., 2019; Sedrakyan et al., 2016). Selected studies also suggested that feedback based on LA is positively correlated with educators' time management strategies and satisfaction (e.g. Iraj et al., 2020; Pardo et al., 2019; Shibani et al., 2020).

For students, LA-supported feedback provides a wider range of services compared to educators. Reviewed studies showed that feedback based on LA informs students how they are doing (e.g. Hunt et al., 2021), provides them with personalized feedback given their learning activities (e.g. Pardo et al., 2019), and based on these self-observations they are able to adjust and adapt their learning process in accordance with their learning needs (e.g. Gibson et al., 2017). These services provided by LA help students to become more

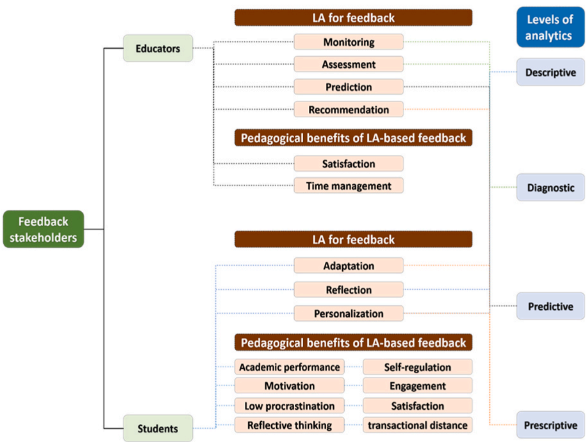

Fig. 3. Relations among feedback stakeholders, LA objectives, and analytics levels.

self-regulated learners (e.g. Tsai et al., 2021), and increase their motivation for learning engagement (e.g. Lewis et al., 2021; Sun et al., 2019) can result in the less transactional distance in online learning environments (e.g. Yilmaz & Yilmaz, 2020). LA-based feedback provides weekly reports on students learning activities and progress (e.g. Tempelaar et al., 2018) and also has a reminder system that helps students to be more focused and less procrastinated (e.g. Lim et al., 2020). In addition, reviewed studies showed that mentioned LA-based feedback services not only encourage students to trust more in their confidence and self-efficacy (e.g. Tsai et al., 2021) but also assist them with improving their reflective thinking skills (e.g. Yilmaz, 2020) which is due to the evidence-based and real-time information provided by LA-based feedback.

Moreover, this figure illustrates that LA services are provided at different levels of analytics according to Gartner Analytics Ascendancy Model (GAAM) (Eriksson et al., 2020; Maoz, 2013). For example, while at the descriptive level, LA-based feedback provides reflections on students learning activities and learning progress, at the diagnostic level, LA-based feedback serves educators with monitoring students' activities and assessing them by spotlighting the anomalies, similarities, and differences in their learning activities. Another example, at the predictive level, is to predict students' retention or dropout by using data mining methods. This implies that predictive feedback is expected to be provided at the predictive level. Furthermore, LA-based recommendations and personalized feedback typically refer to LA at the prescriptive level.

5. Discussion

In this study, we systematically surveyed the current state of LA-based feedback systems in higher education. Our review confirmed that the four core elements of LA system development as outlined hypothetically by Chatti et al. (2012) can guide systems that seek to draw on LA to deliver the more effective provision of feedback.

Our review revealed that while data usage varied, LA for feedback projects most commonly drew on learning data, confirming that most projects sought to collect data more about the student learning process, rather than about educators, or the teaching process. Additional data types employed - demographic, assessment, and academic history data – are also 'about students', confirming that most LA for feedback work is student-focused and seeks to serve students as the primary stakeholders. Even where educators were identified as stakeholders of LA-based feedback systems, the ultimate goals are almost exclusively student-focused. This means that even if analytics are delivered to teachers, their goal is to support student learning as it is indicated in the definition of LA that the goal of LA is to support and improve students' learning. This finding is in line with the prior studies that highlight the importance of the core role of students in LA application (Banihashem & Macfadyen, 2021; Ferguson, 2012; Gašević et al., 2015, 2016).

We found that different LA methods were employed in the selected feedback studies, however, data mining methods were the most commonly employed in LA-based feedback systems. This finding is supported by prior studies that highlight the key role of data mining methods in LA use (Chatti et al., 2012; Siemens& Baker, 2012). Despite the undeniable role of data mining methods in LA projects, It is worth noting that many projects employed multiple methods. For example, data mining was used alongside information visualization methods, to develop systems to warn students they were at risk of failure (Baneres et al., 2019). Or data mining methods were used alongside text mining methods and information visualization methods to explore students' perceptions of their self-evaluation in order to the early-stage prediction of academic failure (Yu et al., 2018).

We observed that while the use of LA can simply make the provision of feedback possible, more detailed, and better personalized - especially for large classes – LA also makes it possible to provide a wider range of feedback, with different purposes, and achieving a range of positive outcomes. In other words, using LA to support feedback goes far beyond simply making feedback manageable for busy, overworked educators. It can also permit the provision of better, more diversified, and better-customized feedback to learners to help them acquire and develop additional learning strategies and skills. These findings imply that LA role in the improvement of feedback practices in higher education have not been tightened to feedback itself, but also has evolved beyond our first anticipation based on our proposed model.

Finally, our analysis showed that LA has served educators and students in different ways at different levels. While for educators, LA mainly provided insights into tracking students learning activities for timely intervention, assessing students learning progress, and early identifying students' who are at risk, LA mostly supported students to be informed about how they are doing, reflect on their own learning process to adapt their learning based on the learning needs. These findings suggest that for educators, LA was mainly used at diagnostic and predictive levels, while for students, LA was employed at descriptive and prescriptive levels.

As we reported findings for the core elements of LA systems, now, we map these elements together and propose our evidence-based conceptual framework to guide the use of LA for feedback practices (Fig. 4).

6. A conceptual framework to guide the use of LA for feedback practices in higher education

Based on our findings on the four key aspects of LA systems for feedback practices in higher education, we now propose an evidence-based conceptual framework for the role of LA in feedback practices within higher education contexts (see Fig. 4). The suggested conceptual framework not only gives an overall picture of the current state of LA implementation to empower feedback practices in higher education but also entails indications regarding how to guide LA use for feedback purposes in higher education settings.

According to our proposed framework, we suggest that a critical first step to guiding LA application for feedback practices is to determine whether an LA feedback system is desired to serve educators or students. The feedback services that LA provides for educators are different than the feedback services for students. For example, the feedback provided by LA for educators tends to focus on both improving teaching strategy and performance (e.g., Herodotou et al., 2019) and monitoring students' learning processes and

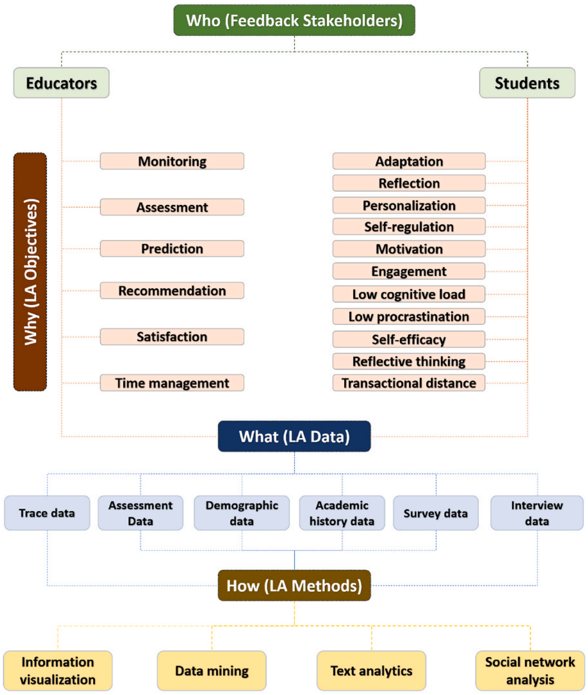

Fig. 4. The evidence-based conceptual framework for the role of LA in feedback practices.

outcomes to make real-time educational interventions (e.g., Persico & Pozzi, 2015), while LA feedback for students is mostly focused on their own learning performance to provide personalized feedback and to help them with regulating their learning (e.g., Pardo et al., 2019; Sedrakyan et al., 2020). Without this understanding, it will be difficult to make proper use of LA systems for feedback purposes in higher education.

In the second step, it is critical to determine what is the goal of using LA tools for feedback activities. Is LA used for providing reflections on students' learning performance for educators or is it used for providing personalized feedback for students? Defining the recipient of the LA and the goal of the use of LA would make it clear what kind of data should be captured and analyzed (Chatti et al., 2012). That is to say that although LA is, of course, a data-oriented field of study, we suggest placing data in the third position, after stakeholders and objectives. This represents the critical recognition that for LA-based feedback systems to be meaningful and relevant, data collection must be guided by a foundational understanding of whom the LA feedback system is intended to serve, and for what purpose. If we do not know who are the LA stakeholders and what are the pedagogical reasons for LA application, then, we cannot expect to collect the required and appropriate data (Banihashem & Macfadyen, 2021). This finding is supported by the LA scholars who indicate that objectives of the use of LA play a key role in determining what types of data are needed to collect by LA (Chatti et al., 2012).

To give an example here, if LA seeks to serve educators with the purpose of early recognizing students at risk of academic failure as warning feedback, it is expected that data regarding students' "performance" such as their final grades, mid-term scores, assignments, and completion of the summative exercises are collected, while if LA serves for students as a reflection to inform them about how they are doing, it is intended to use "learning activities" data such as number of the posts added in the discussion forum, time spent on watching the course videos, and the level and type of interactions with their peers.

Flowing on from this, the choice of analytic method must necessarily be guided by the objectives of the LA-based feedback system or project and the nature of the data available. For example, projects with rather different goals of, on the one hand, using LA-based feedback to promote student reflection on their learning strategies, and on the other hand, using LA-based feedback to predict students at risk of dropout, need to adopt very different analytic methods at different analytics levels. Therefore, we suggest placing LA methods after the data capture step. This hierarchy of steps incorporated into our conceptual framework is in line with the findings of prior studies (e.g. Banihashem et al., 2022; Chatti et al., 2012; Elias, 2011, pp. 1–22; Clow, 2012).

7. Limitations and suggestions for future research and practice

We acknowledge some limitations of this review. First, our review was limited to empirical studies for sake of reporting only authentic findings, and we recognize that some noteworthy reviews and conceptual papers may have been missed. Second, while we feel that our selected set of literature databases covers the most relevant publications, Although later on, we did complementary research to see if new studies can be found and nine new studies were added, we acknowledge that we may have missed studies not indexed in our selected databases. Third, it is also important to acknowledge that there is a publication bias which means that research with null findings is often not published (Larrabee Sønderlund et al., 2019). For these reasons, our findings should be interpreted with the usual amount of caution. Fourth, while this study expands our understanding of how feedback in higher education is influenced by LA, it does not investigate LA-based feedback studies in any K-12 educational contexts. Our findings may therefore not be generalizable to all modes of educational contexts. Certainly, this leaves room for future work investigating how LA-based feedback in higher education may differ in its use and impact compared to K-12 educational environments. In this study, we did not provide information on identifying the gaps regarding the feedback features and purposes that have not been addressed by LA in higher education. We also did not investigate the effect size of different types of data to see which certain type of data can more support feedback activities in higher education settings. For future studies, we suggest exploring this.

Based on our findings and suggested conceptual framework, we suggest recommendations for future research. We found that different types of data such as demographic data and academic history data play a role in providing LA-based feedback services. However, we did not provide insights into how different categories of data are connected to different LA objectives and methods for feedback purposes in higher education. For future studies, we recommend taking steps forward and exploring specifically what kind of data and analytics method is needed for the particular purpose of LA-based feedback services. Especially, we suggest diving more into the interrelations and the effect size of different types of data, LA methods, and objectives with respect to the main stakeholders including students and educators.

In our conceptual framework, we provided an overview of the connections between different core elements of LA systems and how they are influencing each other. However, this explanation needs further exploration to see more detailed information regarding the interconnections and relationships among different LA data, objectives, and methods. For future studies, we recommend considering our conceptual framework as the starting point for further exploration of the interconnections of different core elements of LA systems. For example, building on our framework, for future studies we suggest separately investigating data types, analytics methods, and analytics levels for feedback as personalization and feedback as a recommendation. Or we suggest exploring the effect size of different data types and categories in different LA-supported feedback practices.

In our findings, we did not make a distinction between educator feedback and peer feedback and how differences between these two types of feedback may lead to different use of LA in higher education contexts. According to the literature, there is a difference between teacher feedback and peer feedback as teachers are more subject-matter experts with lots of feedback experiences and knowledge, and compared to students they need less support in providing feedback (Gielen et al., 2010; Paulus, 1999). Providing feedback for students causes a more cognitive workload compared to teachers (Noroozi et al., 2022). For future studies, we suggest separately investigating the role of LA-based feedback on educator feedback and peer feedback. In addition, our findings do not provide insights into the role of LA in features of feedback, for example how LA can influence affective, cognitive, and constructive features of feedback quality. We suggest taking steps forward and exploring how LA may impact feedback features.

Since our findings relied on higher education contexts, it would be interesting to do a similar review study in K-12 educational settings to see similarities and differences in the use of LA for feedback purposes. Comparing the results of these two review studies can provide a detailed understanding of LA role in enhancing feedback activities in different types of education.

Building on our findings, we also suggest recommendations for educational practice. For LA users in higher education to enhance feedback practices, we suggest first thinking of who is the recipient of LA-based feedback services and for what goals these services are going to be used. By defining who (stakeholder) and why (objectives) in LA-based feedback, it will be easier for the LA user to decide what data and what methods should be captured and used. Furthermore, in Fig. 3, we preliminary outlined the relations between feedback stakeholders, LA objectives, and levels of analytics. This figure can guide LA users regarding the level of analytics they should apply for different LA objectives. For example, if the LA user aims to provide recommendations for teachers, therefore, the level of analytics expected to be run is prescriptive.

8. Conclusions

In this systematic review, we made use of a well-known LA model that outlines four dimensions of LA (Chatti et al., 2012) to guide our thematic analysis and explore connections between these dimensions. In this way, we have developed a detailed overview of the current state of implementation of LA to improve feedback practices in technology-mediated learning environments. Furthermore, we have developed a framework that could guide both educational designers and also research scholars to implement LA for enhancing educators' and students' feedback practices in higher education. That being said, this review study provides insights into the role of LA in feedback practices in higher education and practically it contributes to extending our understanding of how LA tools can be used to support feedback practices in higher education. According to our findings and the suggested framework, it could be said that the effective and appropriate use of LA to empower feedback practices in higher education requires a clear understanding of the educators' and students' pedagogical needs for LA support, required data to meet these needs, and the proper choice of analytics. By following these steps, we can expect to see LA is delivered properly to support feedback. The findings of this study can also be used to guide future research in the field of LA and feedback in higher education regarding how LA dimensions differently or similarly should be connected in different types of LA-supported feedback activities. For example, it would be interesting to explore and compare the effect size of different types of data, analytics methods, and levels of analytics that work best for the feedback that is teacher-focused and the feedback that is student-focused.

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Data availability

Data will be made available on request.

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