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Emerging technologies in higher education assessment and feedback practices: A systematic literature review☆

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ABSTRACT

The use of Emerging Technologies, such as Artificial Intelligence (AI), Learning Analytics (LA) and Extended Reality (XR) applications, in higher education has proliferated in recent times, as these technologies are considered to have a significant impact on the future of postsecondary teaching and learning. We wanted to find out the emerging technologies used in computing education, its evaluation and effectiveness, and limitations and gaps for future research. We carried out a Systematic Literature Review study on the use of Emerging Technologies in higher education computing education to identify the state of the art in the use of these three groups of technologies for assessment and feedback practices. After systematic search and filtering from a search pool of 3038 studies published between 2016 and 2021, we selected 38 articles for detailed meta-analysis. Our findings reveal that 71% of the reviewed studies are journal articles, 50% studies focus on learning analytics, and the majority of the studies employ quantitative approaches. The results from this systematic review suggest that XR technologies have received least attention to date in computing education (amongst the emerging technologies considered for the review) and there is a lack of frameworks for design, evaluation and use of emerging technologies in higher education. The findings of this review will be beneficial for researchers and educators to obtain an in-depth understanding of the main areas of application of emerging technologies in higher education computing education, an inventory of emerging technology tools used for assessment and feedback, effectiveness indicators, and evaluation approaches that have been used. For evidence-based guidance on future assessment and feedback practices using emerging technologies, we also present a brief research agenda, drawing attention to the need to trial more XR, focus on formative assessment and feedback practices, better understand impact of human-centric issues and take more thoughtful consideration of ethics in the use of emerging technologies in computing education.

1. Introduction

Educational technologies have been used in higher education for many years and the use of Emerging Technologies (ETs) in education – such as artificial intelligence, extended reality technologies such as virtual reality – has proliferated in recent times. In an education specific context, Veletsianos (2010) defines emerging technologies as "tools, technologies, innovations, and advancements utilised in diverse educational settings to serve varied education-related purposes", and lists its characteristics as follows: (1) they may or may not be new technologies; (2) they change rapidly so are always in a state of 'coming into being'; (3) they go through cycles of hyped expectations; (4) they are in a continuous state of being understood and researched; and (5) they have potential for transforming social practices. The use of ETs in higher education is increasing; however, little systematic work exists that considers the use and effectiveness of a range of ETs such as Artificial Intelligence (AI), Learning Analytics (LA) and Extended Reality (XR) applications in higher education assessment and feedback domain. This study is a systematic literature review (SLR) that seeks to identify the state of the art in the use of ETs in higher education and systematically review, classify and synthesise research related to the use of ETs in higher education assessment and feedback practices between 2016 and 2021, to capture the latest developments in the educational applications of ETs.

Assessment and feedback are critical to learning. Means et al. (2014) explain the role of online assessments as follows: to determine if a student is ready for new content, tell system how to support the student (adaptive instruction), provide student or teacher with information about learning state, input to grade, identify students at risk of failure.

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Feedback is defined as "information about the gap between the actual level and the reference level of a system parameter which is used to alter the gap in some way" (Ramaprasad, 1983, p. 4). Nicol and Macfarlane-Dick (2006) discuss feedback as external and internal — external feedback that delivers information to students about their learning that provides opportunities to students to generate internal feedback to close the gap between their goals and the current performance. Eminent researchers such as Hattie and Timperley (2007), Shute (2008) and Narciss (2013) have proposed guidelines on aspects of the feedback process such as feedback delivery models, types, timing and characteristics of good feedback practice. Despite the key role assessment and feedback plays in student learning, it is claimed that students are generally dissatisfied with assessment and feedback experiences in their learning journeys. For example, Swiecki et al. (2022) summarises several issues with transitional assessment practices: they are perceived as burdensome, provide discrete snapshots of student performance at the given time, often inauthentic in the context not related to real-world and not tailored to students' diverse backgrounds. Assessments are fraught with several other limitations: they cause stress and grade anxiety, do not offer enough choice, do not engage students and poor assessment literacy (understanding of requirements, rubrics) makes it hard for students to interpret. There are also concerns with subjective marking and inter-marker differences, involving weeks-long wait for feedback, scalability of quality feedback causing instructor workload issues, assessment design presents limited opportunities to amend work after feedback that disempowers students and affects student motivation adversely (Tsai et al., 2021; Leite and Blanco, 2020; Lee, 2021; Pardo et al., 2019; Lim et al., 2020).

As the use of ETs in higher education increases, it is important to understand the opportunities and challenges these technologies present in the area of assessment and feedback to unlock the full potential of ETs and address the current challenges outlined in the above paragraph. A lack of understanding of the use and impact of ETs for student learning places higher education at the risk of falling behind in meeting the needs of contemporary learners. In this context, this SLR aims to provide a meta-analysis of the studies, identify the main areas of application, study results and measures of effectiveness, and areas for future research for ETs in higher education assessment and feedback practices. The protocol adopted in this SLR follows Kitchenham (2004)'s procedures for performing systematic reviews.

After searching and filtering from six key databases, we collated 38 primary research studies on ETs in higher education assessment and feedback practices between 2016 and 2021. The main contributions of this review are:

- Meta-analysis of the studies: ET types, application domains and research approaches employed in the studies;
- An inventory of contemporary ET tools being used for higher education assessment and feedback practices;
- Classification of evaluation approaches of ET interventions and identification of key indicators of effectiveness;
- Research agenda for future research into the use of ETs in higher education assessment and feedback practices based on the themes and gaps identified from the reviewed literature.

The findings from this SLR will help educators, practitioners and researchers better understand the application approaches and effectiveness of ETs to make informed decisions about its use in their assessment and feedback practices. It will provide guidance to researchers on the gaps and limitations of current research to focus their future research efforts.

2. Background and related work

The following section provides background information on ETs and discussion of related work from literature on the use of ETs in higher education assessment and feedback domain.

2.1. Definitions: Emerging technologies

Table 1 lists the definitions of the key technologies that are the focus of this SLR.

2.2. Related work and reviews

The use of ETs to enhance assessment and feedback practices has been an area of interest for researchers for a long time. Gikandi et al. (2011) attempted to identify key themes and findings related to online formative assessment in higher education by reviewing 91 articles in higher education spanning the last two decades in 2011. They discussed issues of validity, reliability and dishonesty, and assessment characteristics such as immediate feedback, promoting equitable education and engagement with critical learning processes. The focus of the review is to explain key terminology and build themes relating to online assessments, different to this SLR's review focus on the use of technology to support assessments. Souza et al. (2016) evaluated assessment tools and their characteristics for programming assessments in 49 studies considering the different assessment approaches used (such as instructor-centred, student-centred and hybrid) and its strengths and weaknesses. This SLR also did not look into specific technologies used for assessments as we do and classified assessment types such as manual, automatic and semi-automatic. In 2018, Febriani and Abdullah (2018) conducted a SLR on formative assessment tools in a blended learning environment between 2012 to 2018 and categorised assessments based on research approaches such as (quantitative, qualitative or mixed), assessment tool types and specialty. The classification approach for assessment tools as manual, automatic and semi-automatic was similar to Souza et al. (2016), with added groupings for assessment specialisation tools such as software testing, quizzes and computer based testing. Some of the groupings did not appear to be mutually exclusive and no ETs were explicitly considered for this review paper.

Zawacki-Richter et al. (2019) systematically reviewed 146 papers related to AI applications in higher education between 2007 and 2018. They analyse the publication patterns, AI applications and ethical approaches in the areas of learning and teaching, administration and academic support areas, not specifically on assessment and feedback practices that this review seeks to analyse. Most recently, Cavalcanti et al. (2021) systematically reviewed 63 studies on automatic feedback in online learning environments between 2009 and 2018 to understand approaches and techniques used for automatic feedback generation. The review differentiates from ours as the scope was broad to include all e-learning environments including Massive Online Open Courses which are not included in our review.

In terms of AR/VR use, systematic reviews have focussed on AR learning experiences for K-12 education settings (Santos et al., 2013), not higher education. Radianti et al. (2020) systematically reviewed immersive VR applications for higher education in terms of design elements and its mapping to learning content and application domain between 2016 to 2018. They also provide an overview of other SLRs related to VR use in construction engineering (Wang et al., 2018), evacuation, training and research (Feng et al., 2018), skills acquisition (Jensen and Konradsen, 2018) and Merchant et al. (2014) that reviewed desktop-based VR technologies as assessment tools factoring in studies until 2011 — all with a different domain application, aspects of ETs or year range, considered in our SLR. Martin et al. (2020) pressed for a need for a systematic review on emerging learning environments and technologies.

To our knowledge, no SLR has been conducted to date on AI, LA and XR technologies collectively in higher education. The three groups of technologies have been identified as the key ETs and practices likely to have a significant impact on the future of postsecondary teaching and learning within the highly regarded EDUCAUSE Horizon reports over the years (EDUCAUSE, 2019, 2020, 2021). Our SLR maintains a specific focus on assessment and feedback practices in higher education

Table 1
Key terms and definitions of emerging technologies.

Emerging technology	Definition
Artificial Intelligence (AI)	"Computers which perform cognitive tasks, usually associated with human minds, particularly learning and problem-solving". (Baker et al., 2019, p.10) They explain that AI is an umbrella term to describe a range of technologies and methods, such as natural language processing, machine learning, neural networks, or an algorithm.
Learning Analytics (LA)	"The measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" — Society for Learning Analytics Research (SOLAR). SOLAR (2022)
Extended Reality Technologies (XR)	Extended Reality (XR) technologies is an umbrella term that includes all descriptive forms of AR, VR and MR. (Chang et al., 2019) VR refers to "the technological hardware that creates the dimensions of experience affording different levels of vividness and interactivity in an immersive or para-reality environment" or "artificial simulations, usually recreation of a real-life environment, that enhance an imagery reality or situation" (Tham et al., 2018, p. 180). Heim (1993) lists the seven elements of VR as simulation, immersion, artificiality, interaction, telepresence, full-body immersion and communications. AR is broadly defined as "a situation in which a real world context is dynamically overlaid with coherent location or context sensitive virtual information" (Klopfer and Squire, 2008, p. 205). MR can be defined as the blending of the physical world and digital world (Milgram and Kishino, 1994)

Table 2
Research questions of this study.

RQ	Research question
RQ1.1	What is the current state of research studies on ETs in higher education assessment and feedback practices?
RQ1.2	What types of ETs are used in higher education assessment and feedback practices?
RQ1.3	Which application domain (assessment, feedback or both) have been the focus of studies dealing with ETs?
RQ1.4	Which research approaches (quantitative, qualitative, mixed) have been used to examine the use of ETs in higher education?
RQ1.5	What are the main areas of application of ETs in higher education assessment and feedback practices?
RQ1.6	What are the ET based tools, techniques and/or concepts being employed in higher education assessment and feedback domain?
RQ1.7	What are the indicators of effectiveness and evaluation approaches used in studies employing ETs in assessment and feedback practices?

technology, computing and/or engineering units as a differentiating aspect. The year range 2016 to 2021 was chosen to capture the latest developments in the educational applications of ETs.

This SLR aims to identify the state of the art in the use of ETs and systematically review, classify and synthesise primary research studies related to ETs in higher education (HE) assessment and feedback practices between 2016 to 2021. It seeks to collect evidence on the evaluation approaches and effectiveness indicators used in ET studies so we consider this review to be a part of the evidence-based effort to guide research and practice in this domain. The findings of the review will be beneficial for researchers and educators to obtain an in-depth understanding of the main ET application areas in HE assessment and feedback and also presents an inventory of ET tools used in assessment and feedback and measures of effectiveness employed to be able to make informed decisions on the use of ETs. Recommendations for further research on ETs in higher education are proposed that might be useful for edtech and education researchers in the area.

3. Study design

This paper presents a systematic literature review (SLR), a form of secondary research study, defined by Kitchenham (2004) as "a means of identifying, evaluating and interpreting all available research relevant to a particular research question, or topic area, or phenomenon of interest". The protocol adopted in this review follows Kitchenham (2004) procedures for performing systematic reviews. Kitchenham (2004) determines the following three stages in a systematic review employed to perform this review: planning the review; conducting the review; and reporting the review. In the planning phase, the need for a review was established through an exploratory literature review and reviewing other SLRs in the field (Section 2.2). The first author prepared a detailed review protocol documenting the rationale for the review, establishing the research questions, strategies and criteria for paper search, selection, quality assessment, extraction and synthesis, covered in Sections 3.1, 3.2 and 3.4. The rigour of systematic search process reduces the likelihood of incomplete searches and biases in literature selection process.

3.1. Research questions

The following key research question (RQ) guided the search and selection process of our review:

RQ: What is the state of the art in the use of emerging technologies in higher education for assessment and feedback practices?

The key question had seven sub-questions (listed in Table 2) to guide the data extraction and synthesis. The motivation and rationale for the questions are discussed in Section 4.

3.2. Identifying the relevant literature

The following databases were included in research in discussion with the review team:

(1) IEEE
(2) ACM
(3) Wiley
(4) Francis and Taylor
(5) ERIC
(6) SpringerLink

The chosen databases have a rich repository of information technology, computing, engineering and other software engineering focussed publications as well as education focused papers on the topic.

3.2.1. Search strategy for primary studies

A concept map (Table 3) was created to determine the concepts to be included in the search string. In consultation with the university librarian and review team, alternative concept terms and synonyms were considered for each concept and then combined using Boolean operators AND and OR to establish search strings. AND was used to link key search concepts, OR to link alternative search terms and wildcard character asterisk * for searching multiple characters. For example — pedagog* searches for pedagogies, pedagogy, pedagogical etc.

3.2.2. Refining the search string

The finalised search string is as follows and search adaptations for each database are listed in Appendix A:

(learning OR "higher education" OR tertiary OR universit* OR education OR teaching OR instruction OR pedagog*) AND (assess*

Table 3
Concept table used for systematic literature review search.

Concept	Alternative search terms	Search string
Higher Education	Tertiary Education, Learning, Education, University	learning OR "higher education" OR tertiary OR universit* OR education OR teaching OR instruction OR pedagog*
Assessment and Feedback	Assessment, Evaluation, Examination, Feedback	assess* OR exam* OR evaluat* OR feedback
Emerging Technologies	Artificial Intelligence, Learning Analytics, Augmented Reality, Mixed Reality	"Artificial intelligence" OR "AI" OR "learning analytics" OR reality OR "virtual reality" OR "mixed reality" OR "augmented reality" OR "emerging technologies" OR "emerging technology"

Table 4
Exclusion criteria table.

Exclusion criteria code	Exclusion criteria description
E01	Papers that relate to ETs in other domains e.g. K-12, MOOCs, vocational training
E02	Application areas other than higher education assessment and feedback e.g. student orientation, library services
E03	Papers relating to units related to other than technology, computing or engineering e.g. such as nursing, biology, medicine
E04	Papers relating evaluation of teaching performance or teacher training
E05	Papers focusing on ETs other than AI, LA, XR
E06	Papers focusing solely on technical aspects of ETs such as underlying models or algorithms
E07	Other reasons such as: Teaching about ETs instead of use for assessment and feedback); no English translation found; article inaccessible through library service
E08	Systematic Literature Reviews, scoping reviews, or other secondary studies
E09	Other grey literature e.g. thesis, workshops, blogs, web articles, posters, book reviews, commentary on articles etc.

OR exam* OR evaluat* OR feedback) AND ("Artificial intelligence" OR "AI" OR "learning analytics" OR reality OR "virtual reality" OR "mixed reality" OR "augmented reality" OR "emerging technologies" OR "emerging technology")

3.3. Paper selection criteria

Downloaded papers were saved in EndNote software folders where an automatic followed by manual duplication was performed to ensure only one copy of paper was retained so as not to bias the data. The most complete study was used where there were multiple versions of the same publication. As specified in the search strings in Appendix A, the year range for the search was scoped from 2016 to 2021. This was done to capture the latest developments in the educational applications of ETs. The year range was based on the year of acceptance of the studies, not year of publication. As a result, two papers Kochmar et al. (2022) and Zheng et al. (2022) were included as primary studies in the meta-analysis as the acceptance year for both studies was in 2021 and the studies got published in an issue in the following year 2022. Fig. 1 shows the process with an initial search pool of 3038 studies obtained through search from the six databases as follows: Springer (2032), ERIC (448), ACM (181), IEEE (142), Wiley (118) and Taylor & Francis (117).

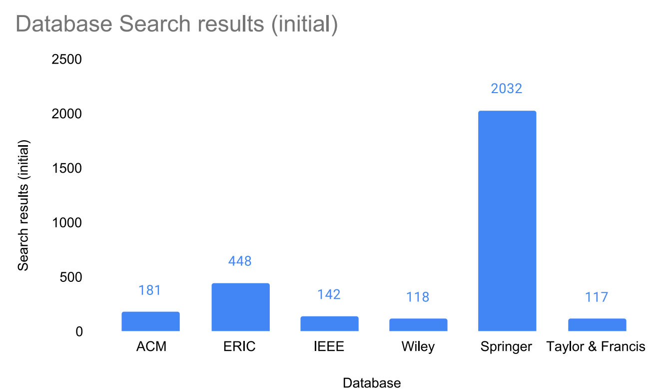

Fig. 1. Database search results.

3.3.1. Inclusion/exclusion criteria

The selection of the studies was governed by an inclusion/exclusion criteria as listed in Table 4. As listed in the table, there were nine exclusion codes developed for each of the criteria and any paper that met any of the listed criteria was excluded from the selection process with the appropriate exclusion code recorded against each paper as the reason for exclusion.

3.3.2. Filtering the papers

Fig. 2 shows the flowchart for the filtering process. A two-tiered filtering process was used. In the first pass, the exclusion criteria was applied based on titles, abstracts and conclusions resulting in removal of 2837 articles. Then, in the second pass, full papers were read and quality assessed for inclusion, resulting in exclusion of 73 studies yielding 38 studies (listed in Appendix B). A tri-colour colour coding system was used: Green (relevant), Red (not relevant) and Orange (to-be-discussed) papers. The author team reviewed the exclusion criteria and codes together for any Red papers before those were excluded. For the Orange papers, each member of the review team would independently assess the paper against the inclusion/exclusion criteria and then discuss as a team to determine if the Orange paper was included (mark as Green/relevant) or excluded (mark as Red/not relevant). Any disagreements were resolved with group consensus.

3.4. Data extraction strategy

Following on from the paper selection, inclusion/exclusion and filtering process discussed in Section 3.3, information from the papers was captured in a google sheet to answer the review questions. In the first instance, the first author conducted a pilot extraction and then fine-tuned the design of the extraction form with the review team. The data extraction form used to extract data from the 38 primary studies included the following sections as listed below, and was cross-checked by the co-authors for accuracy and completeness throughout the data extraction phase. The main sections of the data extraction form along with specific data fields that were populated for each included study are as follows:

- general information (paper title, authors, year, publication type and venue)
- focus of study (aim and motivation, application domain)
- use of Emerging Technology (ET used, working tool/technique/concept), and
- research methodology and research outcomes (evaluation findings, effectiveness indicators, benefits, limitations)

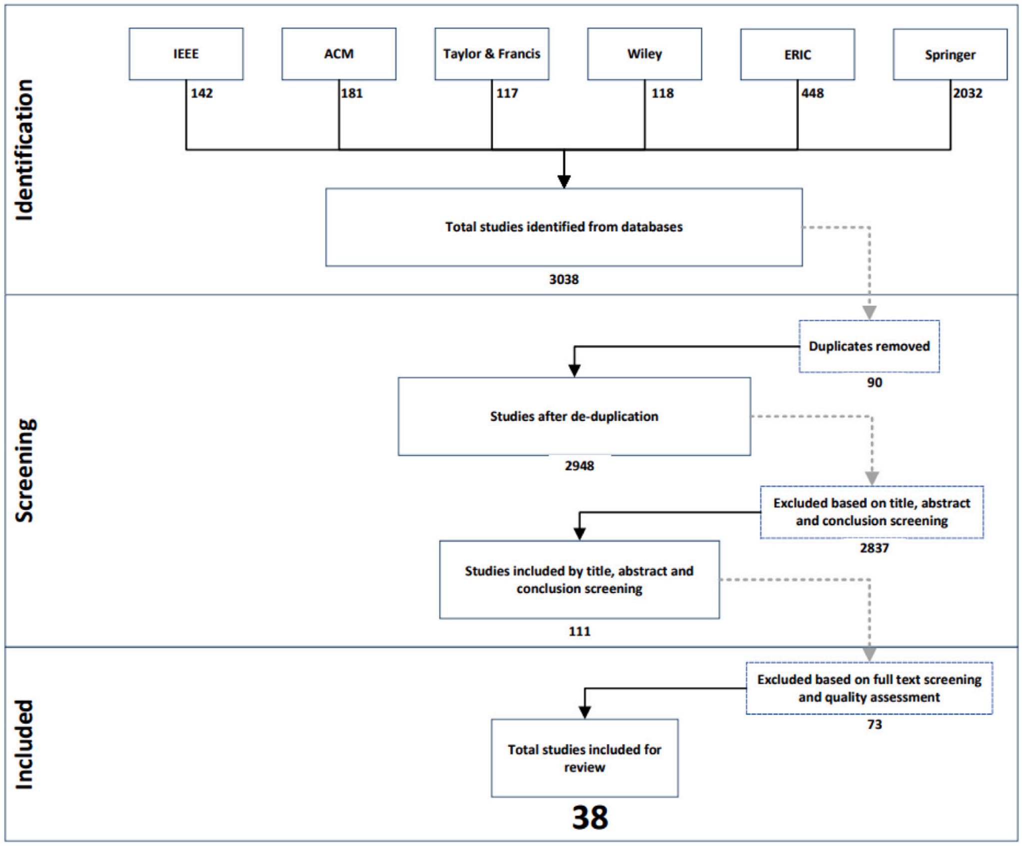

Fig. 2. Study filtering process.

- ethical issues and future directions identified

Appendix C contains a detailed table listing the included studies in the systematic review with a summary of the key characteristics corresponding to the data fields from the extraction process described in this section.

4. Results and analysis

This section contains the results of the systematic review described in accordance with the research questions. A meta-analysis technique, defined by Pigott and Polanin (2020), p. 24) as “a set of statistical techniques for synthesising the results of multiple studies.”, was employed to synthesise results from 38 studies.

RQ 1.1 What is the current state of research studies on ETs in higher education assessment and feedback practices?

Of the 38 articles included in our analysis in the year range 2016 to 2021, 71% were published in journals (n = 27) and 29% (n = 11) originated from conferences, as shown in Fig. 3. As shown in Fig. 4, research interest in use of ETs for assessment and feedback has picked up in recent years with the highest numbers of publications in 2020. In terms of publication count across different databases, highest publications are from Springer journals (n = 12) and ACM (n = 10) followed by ERIC (n = 7), Wiley (n = 5), Taylor and Francis and IEEE (n = 2), as shown in Fig. 5.

RQ 1.2 What types of ETs are used in higher education assessment and feedback practices?

Our review shows 50% (n = 19) studies employed Learning Analytics, 9 studies (23%) used AI tools and only 3 studies used XR technologies (including simulations). 5 studies used LA in conjunction with AI applications, for example, study by Cen et al. (2016) employed machine learning techniques with electronic data mining and Wang and

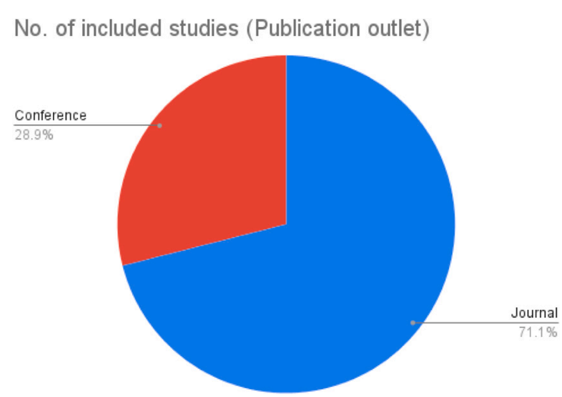

Fig. 3. Number of included studies (publication outlet).

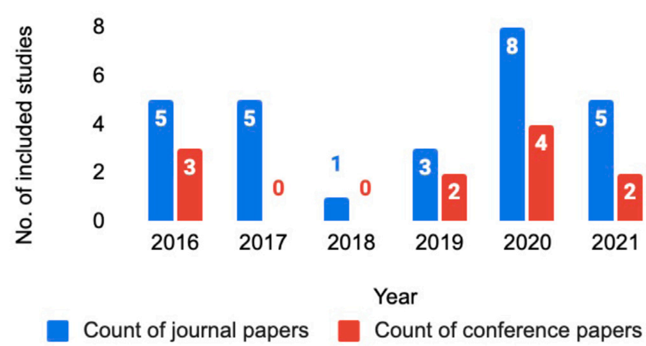

Fig. 4. Number of included studies according (year 2016–2021).

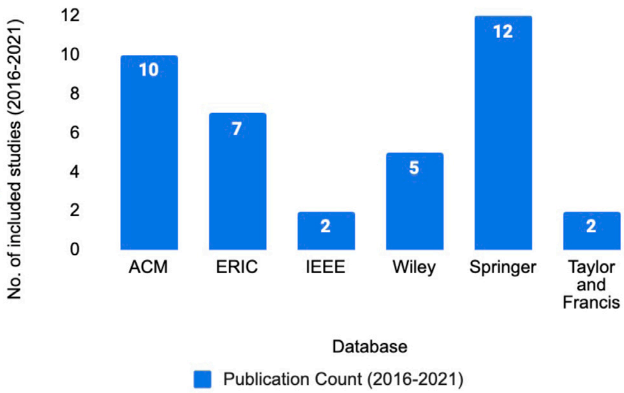

Fig. 5. Number of included studies (publication databases).

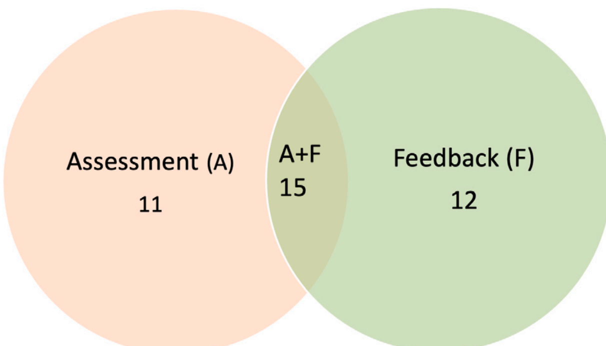

Fig. 6. Application domain of the 38 included papers.

Han (2021)'s study focused on learning analytics dashboard based in iTutor. It is noteworthy that no studies employed analytics with XR tools and only 1 study used recommender systems as well as learning analytics in remote lab and simulation (Gonçalves et al., 2018).

RQ 1.3 Which application domains (assessment, feedback or both) have been the focus of studies dealing with ETs?

60% studies (n = 23) related to assessment or feedback with 11 studies focussing on Assessments and 12 studies on feedback as shown in Fig. 6. In the assessment domain, studies focussed on adaptive assessments (Doble et al., 2019; Bendaly Hlaoui et al., 2016), self-regulated learning assessment (Cerezo et al., 2020), collaborative assessments (Cen et al., 2016) and peer assessment (Pinargote-Ortega et al., 2021). Examples of feedback-focussed studies included personalised feedback (Kochmar et al., 2022), simulation feedback (Taher et al., 2017), automatic feedback from autograders or based on natural language processing (Perikos et al., 2017; Leite and Blanco, 2020), learning analytics based feedback (Tsai et al., 2021; Lim et al., 2020, 2021; Matcha et al., 2019). 40% studies (n = 15) considered both assessment and feedback such as automatic assessment and feedback in intelligent tutoring systems (ITS) (Gerdes et al., 2017; Grivokostopoulou et al., 2017) and range of feedback types such as performance, meta cognitive and visual analytics based feedback on formative assessments (Villamañe et al., 2016; Martin et al., 2020; Guo and Kim, 2020).

RQ 1.4 Which research approaches (quantitative, qualitative, mixed) have been used to examine the use of ETs in higher education?

Table 5 lists studies corresponding to the research approaches. Quantitative methods dominate analysis with $\tilde{7}5\%$ (n = 28) studies employing quantitative measures such as effect size and study power (Hooshyar et al., 2016; Nyland et al., 2017), correlation (Doble et al., 2019), cluster analysis (Tempelaar, 2020) and graphs and charts (Ribeiro et al., 2019). 10 studies used mixed methods such as student perceptions collected through questionnaires, self-reports (Taher et al., 2017; Lim et al., 2021) in addition to quantitative analysis. Drey et al. (2020) proposed a mix of experience based measures for their proposed VR based educational game such as mental effort, player experience, usability SUS score and self-assessment questionnaires. No study employed solely qualitative methods for analysis.

RQ 1.5 What are the main areas of application of ETs in higher education assessment and feedback practices?

This question aims to understand the targeted assessment and feedback areas with ET applications. Our review categorised studies into 5 main application areas as listed below with sub-categories within automated feedback (listed in Table 6 — number of studies corresponding to application areas represented in Fig. 7. Additionally, we have graphically presented these mappings of assessment and feedback areas (on the y-axis) mapped to Emerging Technologies (AI, LA, XR, AI + LA) in Fig. 8. Bubble size shows number of studies in each category.

a. Automatic Feedback - It was a strong developing research area with 18 studies related to feedback in ITS (2), simulation feedback (2), automatic feedback in the form of hints and/or messages (7), feedback presentation (3), feedback preferences (1) and student perceptions and sense-making of learning analytics based feedback (3). Provisioning automatic feedback via hints and/or messages was explored in 7 studies. Perikos et al. (2017) explored the role of hints for adaptable programming tutor. Kochmar et al. (2022) investigated the efficacy of hints with Wikipedia-based explanations as data-driven automated, personalised feedback. Lee (2021) complemented an auto-grader's dynamic hints with detailed personalised feedback and a live anonymous scoreboard while Drey et al. (2020) used VR system's tracking capabilities to generate adaptive dynamic hints based on player behaviour and progress. Study by Buckingham Shum et al. (2016) looks into natural language processing to provide real-time formative feedback on draft reflective writing and Pardo et al. (2019) consider the use of quasi-immediate personalised feedback messages to provide quality feedback at scale. Leite and Blanco (2020) compare the impact of computer and human generated feedback on student outcomes in a programming course.

Two studies looked at feedback in ITS — Gerdes et al. (2017) considered natural language feedback within Ask-Elle ITS and Hooshyar et al. (2016) examined the influence of different feedback types on student knowledge acquisition in an ITS. Two studies considered simulation feedback — Taher et al. (2017) gauged the effectiveness of simulation based and hands-on feedback mechanism on student learning and Ruiz et al. (2020) discuss feedback-enriched simulation environment (FENIkS) for user-interface design learning. Villamañe et al. (2016) and Martin et al. (2020) deal with presentation of learning-analytics based feedback in the form of visualisations for formative and summative assessments, and enhancing rubric-based formative assessments respectively. Wang and Han (2021) use learning analytics dashboard to provide behavioural and procedural data (textual feedback, learning suggestions, warning info) in addition to outcome data. Nguyen et al. (2016) combined learner disposition data with data from other digital systems to examine students' feedback preferences and a group of studies focussed on student perception, sense-making and/or experiences of learning-analytics based personalised feedback (Lim et al., 2020, 2021; Tsai et al., 2021).

b. Personalised assessment and assessments for individualised instruction - 7 studies related to assessment for individualised instruction. Nyland et al. (2017) assessed knowledge gaps using transaction level student log data. Three studies assessed the impact of ETs for competency assessment — Menchaca et al. (2016) for project management skills using LA text mining and analysis; Ochoa and Dominguez (2020) for oral presentation skills using automated feedback and Ribeiro et al. (2019) assessed motivation using an AI based case based reasoning approach. On personalised assessment, Gonçalves et al. (2018) used LA and recommender system based approach to offer recommendations on class resources to students during the test and Grivokostopoulou et al.

Table 5
Studies corresponding to research approaches.

Research approach	Included study examples
Quantitative (28)	Hooshyar et al., 2016; Cen et al., 2016; Nyland et al., 2017; Cerezo et al., 2020; Chou and Zou, 2020; Perikos et al., 2017; Kochmar et al., 2022; Grivokostopoulou et al., 2017; Doble et al., 2019; Bendaly Hlaoui et al., 2016; Pardo et al., 2019; Wang and Han, 2021; Ochoa and Dominguez, 2020; Tempelaar, 2020; Ruiz et al., 2020; Gonçalves et al., 2018; Tsai et al., 2021; Leite and Blanco, 2020; Sharma et al., 2020; Matcha et al., 2019; Villamañe et al., 2016; Ribeiro et al., 2019; Nguyen et al., 2016; Guo and Kim, 2020; Azevedo et al., 2019; Omer et al., 2020; Pinargote-Ortega et al., 2021; Chango et al., 2021
Qualitative (0)	Nil
Mixed Methods (10)	Gerdes et al., 2017; Lim et al., 2020, 2021; Lee, 2021; Drey et al., 2020; Menchaca et al., 2016; Buckingham Shum et al., 2016; Taher et al., 2017; Zheng et al., 2022

Table 6
Studies corresponding to assessment and feedback application areas.

Assessment & feedback application area	Included study examples
Personalised assessment/assessment for individualised instruction	Nyland et al., 2017; Menchaca et al., 2016; Ochoa and Dominguez, 2020; Ribeiro et al., 2019; Tempelaar, 2020; Gonçalves et al., 2018; Grivokostopoulou et al., 2017
Assess self-regulated learning	Cerezo et al., 2020; Chou and Zou, 2020; Matcha et al., 2019; Guo and Kim, 2020
Assessment Design	Ruiz et al., 2020; Perikos et al., 2017; Kochmar et al., 2022; Lee, 2021
Automated Feedback	Feedback in intelligent tutoring systems (Gerdes et al., 2017; Hooshyar et al., 2016); Simulation feedback (Taher et al., 2017; Ruiz et al., 2020); Automatic feedback as hints and/or messages (Perikos et al., 2017; Kochmar et al., 2022; Lee, 2021; Drey et al., 2020; Buckingham Shum et al., 2016; Pardo et al., 2019; Leite and Blanco, 2020); Feedback presentation (Villamañe et al., 2016; Martin et al., 2020; Wang and Han, 2021); Feedback preferences (Nguyen et al., 2016); Student perception and experience of feedback/ Feedback literacy (Tsai et al., 2021; Lim et al., 2020, 2021)

(2017) used interactive visualisations to assess students' understanding of applied algorithms.

c. Assessment of self-regulated learning (SRL) - 4 studies focussed on examining students' SRL, 3 of those using LA based processes. Cerezo et al. (2020) employed text-mining through forum-supported collaborative learning to assess SRL. Chou and Zou (2020) examined the impact of external feedback from the OLM on students' internal SRL processes and feedback. Matcha et al. (2019) used process mining to examine students' pre-class activities such as readings completed and considered association with learning-analytics based feedback and academic performance. Only Guo and Kim (2020) investigated the influence of metacognitive monitoring feedback on students' self-efficacy in relation to learning material comprehension in an AR environment.

d. Assessment Design - 4 studies focussed on assessment design aspects. Azevedo et al. (2019) evaluated quality of multiple-choice questions using LA to build randomly generated tests in Moodle learning management system and Doble et al. (2019) measured reliability for adaptive assessment in ITS. Bendaly Hlaoui et al. (2016) presented an adaptive e-assessment (test generation, selection, feedback generation and test process) based on learner profile ontology and behavioural data.

e. Assessment of effort and/or performance - 5 studies related to prediction of students effort or performance such as emotional state based on multi-modal data to determine time for preventive/prescriptive feedback (Sharma et al., 2020), cognitive performance in higher level programming based on cognitive learning analytics framework (Omer et al., 2020) and prediction of group performance and insight into dynamic of interactions within group for individual student performance evaluation (Gerdes et al., 2017). Tempelaar (2020) used digital footprints and trace variables such as problems solved, correctness of responses, use of scaffolds etc. to create student profiles.

RQ 1.6 What are the ET based tools, techniques and/or concepts being employed in higher education assessment and feedback domain?

This question seeks to build an inventory of all ET based tools, techniques and/or concepts mapped to specific assessment and feedback application types in the studies. Table 7 summarises this mapping. We identified from each study — the tool(s) they developed and/or used, and the assessment and/or feedback application areas(s) these tools were used on. We categorised the assessment-focused tools based on types of assessments. These include: Collaborative assessment (Cen et al., 2016); Peer Assessment (Pinargote-Ortega et al., 2021); Content knowledge (Chango et al., 2021; Azevedo et al., 2019); Skills assessment (Ochoa and Dominguez, 2020); Adaptive assessment (Doble et al., 2019; Bendaly Hlaoui et al., 2016). Studies such as Lim et al. (2020, 2021), Cerezo et al. (2020) and Chou and Zou (2020) relate to SRL. We classified tools that specifically focus on feedback using the following categories. These include: Formative Assessment (Hooshyar et al., 2016); Automated Natural Language Feedback (Perikos et al., 2017); quasi-immediate feedback (Pardo et al., 2019); process-oriented feedback (Wang and Han, 2021); learning analytics-based feedback (Tempelaar, 2020); tool-graded vs human-graded feedback (Leite and Blanco, 2020); prescriptive and preventative feedback (Sharma et al., 2020); personalised feedback (Matcha et al., 2019); feedback preferences (Nguyen et al., 2016); simulation feedback (Taher et al., 2017); real-time feedback (Zheng et al., 2022) and meta-cognitive monitoring feedback (Guo and Kim, 2020).

RQ 1.7 What are the indicators of effectiveness and evaluation approaches used in studies employing ETs in assessment and feedback practices?

This question aims to assist educational practitioners gain an understanding of the evaluation approaches and indicators used in the appraisal of ETs. We found that there are 3 main evaluation approaches that influenced the choice of indicators: (a) Tool performance; (b) Student performance (comparison studies); and (c) Student perceptions and attitudes. These are summarised in Fig. 9. Tool performance includes metrics such as prediction accuracy, accuracy of feedback models, efficacy of hints, accuracy comparison against human experts, system usage metrics or performance comparison to other tools. These allow educations to measure the effectiveness of the ET tools deployed on learning and feedback activities, as summarised in Table 7. Studies categorised in the Student Performance approach used pre and post knowledge tests, assessment outcome, correct answers, test scores or results on quizzes and exams. These are used by teachers to help gauge how well ET tools assist student learning outcomes. Studies using Student Perception and Attitudes use self-reports, questionnaires or interviews to collect student perception and/or attitudinal data. These are used by teachers to assess how well ET tools are received and accepted by students.

Table 8 lists the effectiveness indicators reported for each study. 19 studies considered tool performance for evaluation employing accuracy prediction (Cen et al., 2016; Omer et al., 2020), comparison with human annotators or markers (Perikos et al., 2017; Kochmar et al., 2022; Grivokostopoulou et al., 2017; Menchaca et al., 2016), tool output (Sharma et al., 2020) and system usage metrics (Lee, 2021). 11 studies considered one or more student performance indicators.

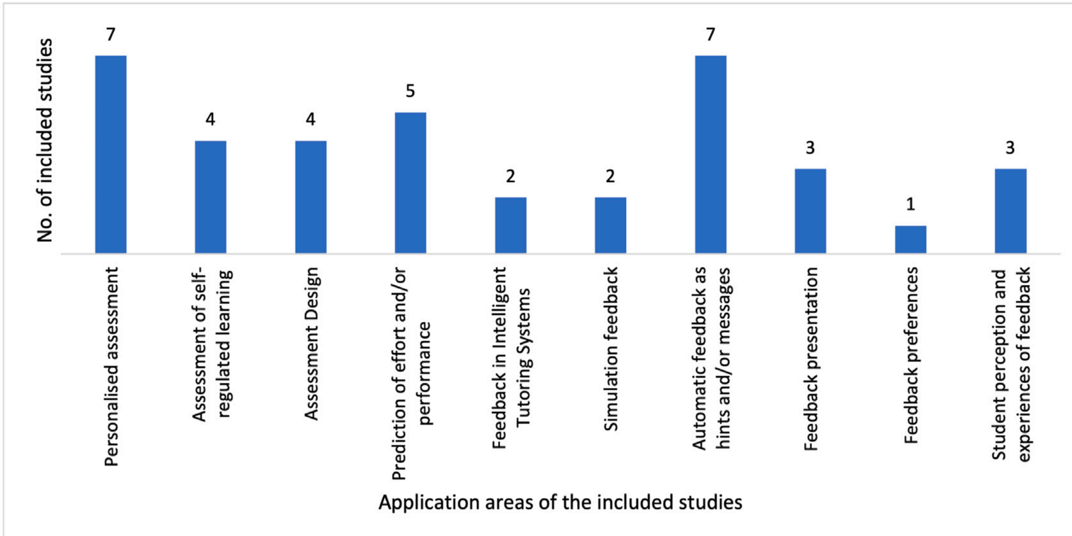

Fig. 7. Application areas of the 38 included papers.

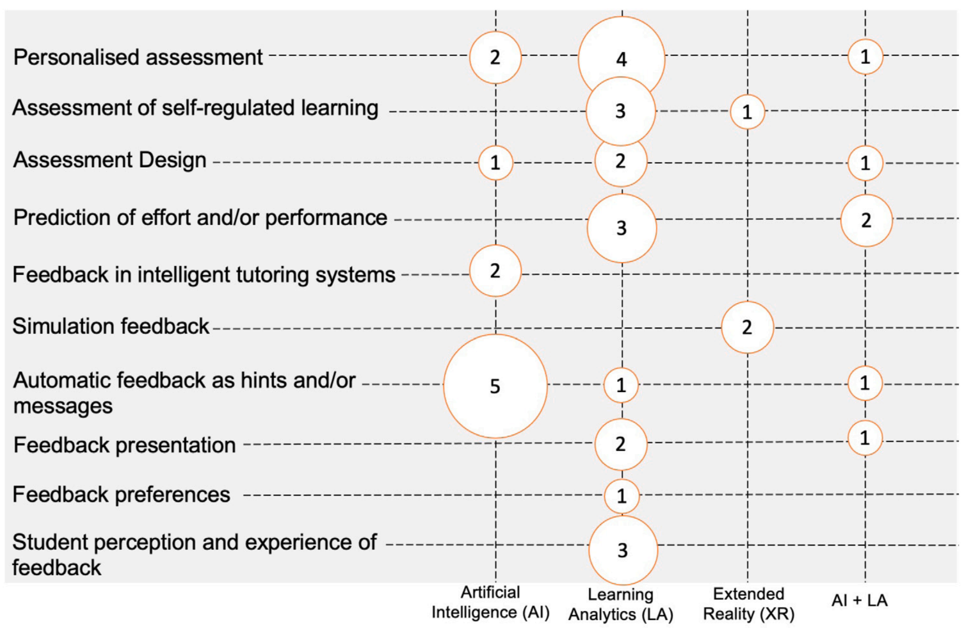

Fig. 8. Mapping of assessment and feedback to type of ET.

These included assessment outcome (Bendaly Hlaoui et al., 2016; Pardo et al., 2019; Leite and Blanco, 2020; Guo and Kim, 2020), pre and post knowledge tests (Hooshyar et al., 2016) and comparing student performance in different learning conditions (with/without system) (Ruiz et al., 2020) or system v/s human or hands-on conditions (such as Taher et al., 2017; and Ochoa and Dominguez, 2020).

Table 9 groups effectiveness indicators according to evaluation approaches. It categorises indicators related to tool performance together such as tool evaluation or performance, system feature uptake, comparison with human teachers, analysis of student, task errors or effort and other metrics and measures (such as fitness metric and conditional standard error). Indicators such as assessment outcome (such as test scores or proportion of correct answers) and comparison of student learning by system and human tutors are grouped in student performance approach. Indicators the capture student perceptions (such as enjoyment, satisfaction or attitudes) and student sense-making or adaption of learning processes in response were categorised as student perception and attitudes. 10 of the primary studies used student self-reports to gauge student perceptions of the tools. 4 of these studies, such as Lim et al. (2021) and Nguyen et al. (2016), used these measures on their own. The other 6 studies, such as Pardo et al. (2019) and Bendaly Hlaoui et al. (2016), used these measures in conjunction with student performance and/or tool performance evaluation measures.

5. Findings and recommendations

5.1. Summary of findings

A summary of findings from the synthesis of the reviewed research studies is presented below.

5.1.1. Motivation to use emerging technologies

The major intent of integrating ETs that emerged from the synthesis was to analyse learning performance of students to develop more personalised support in a timely manner and alleviate teacher workloads.

Table 7
An inventory of ET tools mapped to specific assessment and feedback applications are compiled in the table below.

Study	Tool	Assessment & feedback application
Hooshyar et al. (2016)	Solution-based ITS (SITS)	Formative assessment with different feedback types - Immediate Elaborated Feedback (IEF), No Immediate Elaborated Feedback (NIEF) for comparison
Cen et al. (2016)	Collaborative learning environment (CLE) platform	Collaborative assessments - assessment of individual contribution in group collaborative assessments; collaborative learning- group performance prediction and group composition
Nyland et al. (2017)	Hidden Event Log for Individual Observation System	Online assessment
Cerezo et al. (2020)	Inductive Miner Algorithm	Self regulated learning assessment
Chou and Zou (2020)	Open Learner Models for Self-Regulated Learning	Self regulated learning assessment
Perikos et al. (2017)	NLtoFOL system (natural language (NL) sentences into first-order logic (FOL) formulas)	Automatic feedback (natural language feedback)
Gerdes et al. (2017)	Ask-Elle intelligent tutor	Automated programming assessment; Automatic feedback
Kochmar et al. (2022)	Personalised feedback model is used in Korbit, a large-scale dialogue-based ITS	Personalised feedback model in Intelligent Tutoring System
Grivokostopoulou et al. (2017)	Artificial Intelligence Teaching System (AITS)	Automatic assessment
Doble et al. (2019)	ALEKS (Assessment and LEarning in Knowledge Spaces) software - PPL Placement, Preparation and Learning	Adaptive assessment
Bendaly Hlaoui et al. (2016)	Cloud-AWAS (Cloud Adapted Workflow e-Assessment System)	Adaptive e-assessment
Pardo et al. (2019)	Education data mining and learning analytics for feedback	quasi-immediate personalised feedback messages (for courses with large student cohorts)
Wang and Han (2021)	Learning Analytics Dashboard (LAD)	Process-oriented feedback
Ochoa and Dominguez (2020)	Automatic Presentation Feedback System (shortened to RAP due to its Spanish acronym)	Assessment of oral Presentation Skills
Lim et al. (2021)	OnTask system	Personalised Learning analytics based feedback
Tempelaar (2020)	Learning Analytics based assessment and feedback	Feedback on assessment as learning (test-steered e-learning); Learning Analytics based feedback
Ruiz et al. (2020)	FENIkS - Feedback enriched simulation environment	Knowledge assessment as per different cognitive levels (understand, apply, analyse, evaluate); Instructional Feedback (formative)
Gonçalves et al. (2018)	Learning Analytics and Recommender System	Personalised Assessment
Lee (2021)	Grading System	Real-time dynamic hints + personalised instructor feedback + live anonymous scoreboard
Tsai et al. (2021)	OnTask tool	Learning analytics based feedback
Drey et al. (2020)	VR-based educational game Social Engineer (HTC VIVE platform)	Real-time progress assessment in a VR-based educational game
Leite and Blanco (2020)	Autograder (autograding automatic feedback)	Tool-graded feedback comparison with human assisted feedback
Sharma et al. (2020)	Hidden Markov Models (HMMs) and the Viterbi algorithm for behavioural pattern discovery (using logs and physiological data)	Prescriptive/Preventative Feedback
Matcha et al. (2019)	Process Mining - First Order Markov models (FOMMs) and the pMineR R package for data analysis. Agglomerative Hierarchical Clustering based on the Ward's algorithm (for pattern extraction of how individual students used the identified learning tactics)	Learning analytics based feedback; personalised feedback
Menchaca et al. (2016)	Automatic analysis and exploratory techniques. Technological tools to mine student activity-Gantter, Microsoft Project and Google Calendar. Pentaho Kettle data integration system	Learning analytics based feedback; Competency assessment
Buckingham Shum et al. (2016)	Xerox Incremental Parser (XIP). Academic Writing Analytics (AWA) educational user interface onto XIP	Reflective writing assessment; Formative Feedback
Villamañe et al. (2016)	RubricVis application (using Visual Learning Analytics techniques)	Formative Assessment; Visual Learning Analytics based feedback
Ribeiro et al. (2019)	Case Based Reasoning approach (computerised framework grounded in AI techniques)	Motivation assessment
Lim et al. (2020)	Learning Analytics-based software called OnTask	Personalised feedback; Self-regulated learning
Nguyen et al. (2016)	Learning Analytics trace data	Feedback preferences (to what extent feedback preferences mediate the relationship between learning dispositions and academic performance)
Martin and Ndoye (2016)	Learning Analytics data visualisations (Tableau for quantitative data analysis and IBM's ManyEyes visualisations)	Formative and summative (comprehension type, reflection, discussion board and project based); Performance feedback (+ time and effort feedback); feedback based on combining data from different information elements
Taher et al. (2017)	Simulation based labs, simulation feedback	Simulation feedback
Guo and Kim (2020)	Augmented Reality AR environment - Holo lens and NFER (near-field electromagnetic ranging (NFER) systems)	Metacognitive monitoring feedback
Azevedo et al. (2019)	Learning Analytics (Drivers used ODBC, MS ExcelTM and VBA)	Assessment - Multiple Choice Questions
Omer et al. (2020)	Framework for cognitive learning analytics	Programming Assessments
Zheng et al. (2022)	LA based real-time feedback approach (based on deep neural network to improve CSCL approach)	Real-time feedback
Pinargote-Ortega et al. (2021)	Supervised machine learning approach (text mining for sentiment analysis)	Peer assessment
Chang et al. (2019)	Attribute selection and classification ensemble algorithm	Post-test domain content knowledge

Table 8
Effectiveness indicators for emerging technology enabled assessment and feedback studies in higher education.

Study	Indicators for evaluating effectiveness
Hooshyar et al. (2016)	knowledge acquisition, perception of enjoyment, preference of feedback during game based assessment
Cen et al. (2016)	prediction accuracy of group performance
Nyland et al. (2017)	comparison of error data (average no. of errors in process v/s final solution); frequency of errors (comparison) and patterns of error over time
Cerezo et al. (2020)	fitness' evaluation metric
Chou and Zou (2020)	The correlation of the students' internal SRL processes and feedback and learning performance
Perikos et al. (2017)	difference in learning in different learning conditions; comparison of student learning by system v/s human tutors
Gerdes et al. (2017)	accuracy and perceived usefulness of the feedback from ITS; student experience with ITS feedback
Kochmar et al. (2022)	solution verification (agreement with human annotators); hint efficacy (student success rate estimated as their ability to answer the posed question correctly after being provided with a hint); accuracy of different formative feedback models
Grivokostopoulou et al. (2017)	evaluation of Artificial Intelligence Teaching System AITS; compare assessment mechanism against expert (human) tutor
Doble et al. (2019)	correlation between actual and simulated scores, conditional standard error of measurement CSEM and consistency of actual and simulated scores
Bendaly Hlaoui et al. (2016)	assessment outcome, learner satisfaction
Pardo et al. (2019)	self-reported student satisfaction with the quality of feedback, and academic performance in the midterm exam
Wang and Han (2021)	prior knowledge relating to post-test scores (for learning analytics dashboard group and analytics report group)
Ochoa and Dominguez (2020)	statistical analysis on different dimensions of oral presentation, subsequent assessment by human experts
Lim et al. (2021)	students perceptions and affective responses to personalised LA based feedback
Tempelaar (2020)	student profiles and use of learning activities (in digital learning environments) - cluster analysis
Ruiz et al. (2020)	test scores/errors without and with the system
Gonçalves et al. (2018)	correct answers
Lee (2021)	latency from submission to scoreboard; student feedback, no. of hints unlocked by students, no. of commits pushed by students (for a hint, after a hint), no. of commits instructor commented on
Tsai et al. (2021)	student experience improvement based on tool feedback (boxplot); perceived feedback importance v/s student experience (mean values); relationship between attitudes to feedback to self regulation and self-efficacy (silhouette analysis for clustering + Weight of Evidence method)
Drey et al. (2020)	learning measures - self-assessment questionnaire, pre and post knowledge test for learning evaluation;experience- player experience, mental effort, usability
Leite and Blanco (2020)	Results on quizzes and exam questions
Sharma et al. (2020)	cognitive aspects of learning and effort displayed by students identified using multimodal physiological data
Matcha et al. (2019)	association between the personalised feedback and the effective strategies
Menchaca et al. (2016)	teachers' rating of tool, percentage similarity between teacher and LA assessments
Buckingham Shum et al. (2016)	accuracy (confusion matrix) of the parser and cross-validation of 'shallow' marked system annotations by human annotators
Villamañe et al. (2016)	radar plot-graphs, bar and line charts to visually represent feedback
Ribeiro et al. (2019)	representation of motivation subscales and cognition using worm graphs, and motivation using line graphs
Lim et al. (2020)	students sense-making of personalised LA feedback and how student adapt their SRL processes in response
Nguyen et al. (2016)	students' preferred feedback modes (examined feedback preferences as mediators between their learning dispositions and academic performance)
Martin and Ndoye (2016)	visualisations of analytics from online assessments
Taher et al. (2017)	effect on student learning (effect of simulation and hands-on instructional strategies AND feedback types in simulation on student learning - quant and qual measures)
Guo and Kim (2020)	participants' confidence level and test scores
Azevedo et al. (2019)	Difficulty and Discrimination Indexes (measures to check for consistency and reliability in MCQs for fairer assessment design)
Omer et al. (2020)	prediction accuracy range (found to be better than other related work)
Zheng et al. (2022)	knowledge map analysis to measure knowledge elaboration and knowledge convergence
Pinargote-Ortega et al. (2021)	compared the concordance between the score the SVM model (sentiment score) automatically obtained with that the annotator (sentiment polarity) gave of each of the data set's activities through the Kappa, Pearson, and Spearman coefficients
Chang et al. (2019)	performance of learning algorithm

As more education continues to be digitised and hybrid modes of physical and online education continue to be used, research interest in eliciting information about students learning behaviours and their emotions, cognition, metacognitive processes from their use of the ET mediated education systems seems to be growing. This is evident from the findings in RQ1.2 that show a great concentration of studies in the area of LA and its use in conjunction with other systems such as ITS.

5.1.2. Effectiveness of AI enabled assessment and feedback systems

Bringing together the findings from the analysis in RQ 1.5–RQ 1.7, it can be inferred that provisioning of feedback within ITS has generally been found to be effective. Studies reported a positive effect on student knowledge acquisition in ITS with the use of feedback (Hooshyar et al., 2016) and worked-out examples (Gerdes et al., 2017). However, studies such as Leite and Blanco (2020) and Ochoa and Dominguez (2020) reported better learning effectiveness of AI applications with human-in-the-loop. AI assessment applications such as Lee (2021) showed promising results in higher throughput (higher number of marking review cycles) and Hooshyar et al. (2016) showed strong relationships between the assessment done by system and human markers The results seem promising to influence educators decision making regarding the adoption of these tools and imply investigation of more human-in-the loop AI approaches.

5.1.3. Effectiveness of LA enabled assessment and feedback systems

Applications employing LA showed positive results in uncovering knowledge gaps in students' learning (Nyland et al., 2017), advancing student learning with adaptive e-assessment tools (Bendaly Hlaoui et al., 2016), ensuring fair and reliable assessment design (Azevedo et al., 2019). Studies reported higher accuracy range with LA tools than previous related work in examining learners' cognitive propagation on related programming concepts (Omer et al., 2020) and more active student engagement and satisfaction with LA based personalised feedback (Lim et al., 2021; Tsai et al., 2021). Promising results have also been reported for LA in interesting applications such as effort prediction using multimodal data (Sharma et al., 2020), student profile building (Tempelaar, 2020) and SRL (Chou and Zou, 2020).

5.1.4. Effectiveness of XR enabled assessment and feedback systems

In the limited number of XR application studies, mixed results were reported on the effectiveness of student learning. Some studies reported positive effects in terms of number of errors, active observation with feedback-enriched simulation (Ruiz et al., 2020) and improved test scores with the use of a metacognitive monitoring tool in an AR learning environment (Guo and Kim, 2020). However, analysis in Taher

Table 9
Effectiveness indicators corresponding to the evaluation approaches used for the included studies.

Evaluation approaches	Types of effectiveness indicators used in the included studies
Tool performance	***Tool evaluation or performance***: evaluation of Artificial Intelligence Teaching System, accuracy of the parser using confusion matrix, prediction accuracy range, accuracy of group performance, performance of learning algorithm, solution verification, hint efficacy, accuracy of feedback models; ***System feature uptake***: no. of hints unlocked by students, no. of commits pushed by students for a hint or after a hint, no. of commits instructor commented on; ***Comparison with human teachers***: comparison of assessment mechanism against expert (human) tutor, percentage similarity between teacher and LA assessments; ***Analysis of students, task errors or effort***: Student profiles and cluster analysis for use of learning activities in digital learning environments,Representation of cognitive aspects of learning and effort displayed by students identified using multimodal physiological data, latency from submission to scoreboard, cross-validation of ‘shallow’ marked system annotations by human annotators,comparison of error data; patterns of error over time; ***Metrics and Measures***: fitness’ evaluation metric, measures to check for consistency and reliability for fairer assessment design (such as Difficulty and Discrimination Indexes),conditional standard error of measurement
Student performance	***Assessment outcome***: Test scores or errors (such as midterm exam, quiz),test scores/errors without and with the system, proportion of correct answers; ***Student preferences***: preference of feedback during game based assessment; difference in learning in different learning conditions; Participants’ confidence level,knowledge map analysis to measure knowledge elaboration and knowledge convergence; ***Comparison of assessment by human tutors***: statistical analysis on different dimensions of assessment (such as oral presentation) and subsequent assessment by human experts, comparison of student learning by system v/s human tutors
Student perception and attitudes	***Student perception***: perception of enjoyment; learner satisfaction, self-reported student satisfaction with the quality of feedback, student experience improvement based on tool feedback (boxplot),perceived feedback importance v/s student experience (mean values),attitudes to feedback to self regulation and self-efficacy (silhouette analysis for clustering + Weight of Evidence method); ***Student sense-making***: students sense-making of personalised LA feedback and how student adapt their SRL processes in response, relationship between students’ preferred feedback modes (examined feedback preferences as mediators between their learning dispositions and academic performance)

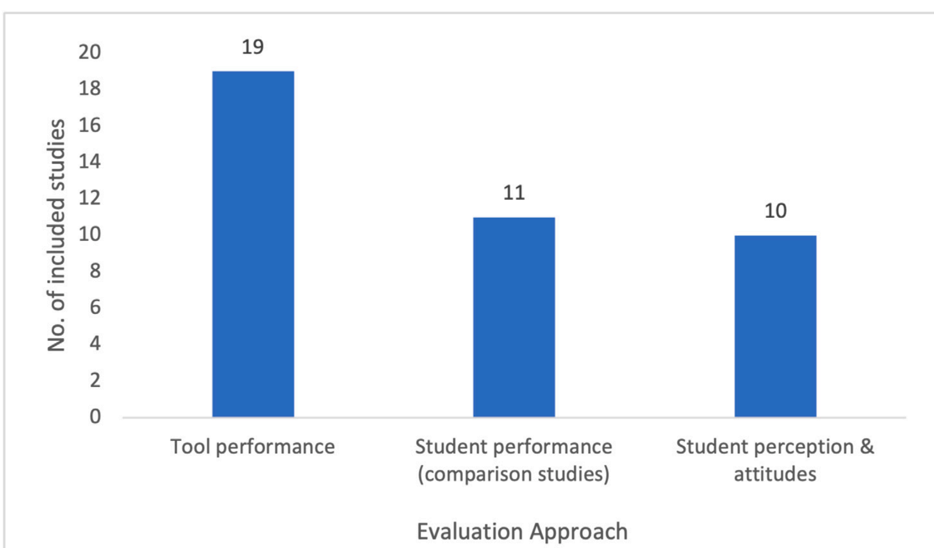

Fig. 9. Evaluation approaches for the included 38 studies.

et al. (2017) found that simulation by itself is not very effective in promoting student learning as compared to hands-on approach in learning of circuit design and application courses. It was found to have only a marginal effect on student learning. The findings may be useful for educators considering hybrid instructional approach using simulation and hands-on approach and exploring more XR applications as a low-cost and flexible training platform in a range of disciplines and learning contexts.

5.1.5. Study approaches for emerging technology enabled assessment and feedback systems

Findings in RQ 1.4 indicate higher concentration of studies employing quantitative analysis approaches. The authors draw attention to the need to employ more qualitative and/or mixed study approaches to understand the rich and complex context of learning and teaching and stakeholders such as student perceptions of the task, assessment method, nature of the assessment and their attitude towards ET to

Table A.1
Search string adaption employed for each database.

Database	Type of search	Search string adaptation
IEEE	Advanced Search	Search filter - title only; Publications - Journals and Conferences; Year range- 2016 to 2021
ACM	Advanced Search	Search filter - title, Publications - Proceedings and Journals; Year range- 2016 to 2021
Wiley	Advanced Search	Search filter - title
Taylor & Francis	Advanced Search	Search filter - title; Year range- 2016 to 2021
ERIC	Advanced Search	Limit to: Title search; peer-reviewed; Custom range: 2016 to 2021; Source type: Conference papers and proceedings OR Scholarly Journals
SpringerLink	Search by journal	Search string: assess* OR exam* OR evaluat* OR feedback; Year range: 2016–2021 The following 7 databases related to the topic were identified in SpringerLink- International Journal of Artificial Intelligence in Education, International Journal of Educational Technology in Higher Education, Journal of Computing in Higher Education, Journal of Computers in Education, Educational Technology Research and Development, Technology, Knowledge and Learning, International Journal of Computer-Supported Collaborative Learning

provide a deeper understanding of the efficacy of the technology and how it impacts learning outcomes for students. Incorporating teachers' perceptions and voice in addition to student feedback to get a fuller picture of the impact of ETs is also suggested. in higher education assessment and feedback practices.

5.2. Suggested future areas of study

After analysing and synthesising the literature findings and gaps, the following recommendations are being made for future research and exploration.

5.2.1. Use cases with XR technologies

The review yields XR technologies are significantly under-explored in higher education and limited use cases explored its potential such as with simulations (Taher et al., 2017) and metacognitive feedback in an AR environment technologies (Guo and Kim, 2020). Grivokostopoulou et al. (2017) discuss the crucial role of visual animations and interactivity for learning subjects like search algorithms. XR technologies have affordances such as immersion, presence, 3D visualisation etc. that seem to offer promising directions to track user behaviour and assess progress (Drey et al., 2020) and feedback enriched simulation environment for teaching user interface design skills (Ruiz et al., 2020). Therefore, a suggested research area is development of XR technology use-cases in higher education to demonstrate opportunities and boundaries of use of these technologies in assessment and feedback.

5.2.2. Need for frameworks for design, evaluation and use of emerging technologies

A lack of relevant frameworks for design, evaluation and/or use of ETs in higher education is evident in the literature. For example — Matcha et al. (2019) point out the need for a holistic framework for personalised analytics-based feedback adoption. Also, there is a lack of guidelines to guide assessment and feedback design using ETs and a need to establish evaluation frameworks including (but not limited to) guidelines, criteria and/ metrics for evaluating the effectiveness of ETs. The authors deem it important that studies consider not only assessment scores but also qualitative changes in student learning such as deeper understanding of content, enhancement in critical thinking and higher order skills to determine indicators to capture the intended learning impact of ET tools. Incorporating qualitative approaches with the inclusion of both teacher and student voices to better situate the context, purpose, instructional and approaches and assess the impact of ET enabled interventions is strongly suggested.

5.2.3. Need for more research in the use of emerging technologies for formative assessments and feedback

A recommendation of this review is to trial the use of ETs in formative assessments due to benefits formative assessments offer in terms of immediate feedback, opportunities for intervention and adaptation of learning strategies (Martin et al., 2020; Nyland et al., 2017). Kochmar et al. (2022) identify the need for development of models capable of explanatory formative feedback as a future direction). The useful role of visualisations (Nyland et al., 2017) and visual analytics (Cerezo et al., 2020) for feedback has also been discussed in the review. To enhance feedback quality in ITS environments, Gerdes et al. (2017) suggest data-driven techniques to provide hints and feedback, messaging similar to that of human tutors, and making feedback adaptable for different contexts. Kochmar et al. (2022) specifically consider aspects of auto hints for better personalisation such as granularity, complexity, level of transparency. The review yields the following areas (but not limited to) for future research using ETs: problem solving situations (Hooshyar et al., 2016), collaborative and group assessments (Cen et al., 2016; Lee, 2021), prose writing such as reflective writing Buckingham Shum et al., 2016, project management skills (Menchaca et al., 2016), presentation skills (Ochoa and Dominguez, 2020) and leadership and teamwork as suggested by Menchaca et al. (2016)

5.2.4. Investigate the impact of different feedback types and approaches in ET based learning environments

It is recommended that the role of feedback be explored in different ET-mediated learning environments. This aligns with Perikos et al. (2017)'s and Cerezo et al. (2020)'s suggestion to examine feedback effectiveness and impact of prompts on SRL behaviours across different educational systems and learning platforms. Future research needs to focus on determining conditions within ET-based learning environments in which different types of feedback are effective. Zheng et al. (2022) suggest exploring the use of real-time learning analytics based feedback approach and online discussion transcript analysis in collaborative learning environments. Another suggested feedback approach drawn from studies such as Ochoa and Dominguez (2020) and Leite and Blanco (2020) is for human graders to base their feedback on findings of automated systems for consistency or use system feedback as a 'reflection-inducing artefact' for students and teachers. Other related lines of suggested investigation the interplay of feedback with student learning profiles and knowledge gaps (Kochmar et al., 2022) and how students modify or adapt their learning strategies in response to system feedback (Matcha et al., 2019).

5.2.5. Better understanding of human-centric issues in the use of emerging technologies in assessment and feedback — learning behaviours, social context of learning and student participation

Student learning strategies are highly context-dependent and often cannot be directly observed in a learning environment as learning behaviours such as time spent on task, learning materials accessed etc. Nguyen et al. (2016). Kochmar et al. (2022) asks future researchers to look closely at student motivation, engagement and managing of emotional states as ITSs are increasingly used. As ET-mediated environments continue to rise, we believe that it is critical to explore social, technical and other contextual aspects in these environments to better understand aspects that forward or hinder student learning. The role of ET tools in monitoring and visualising learning behaviours was prominent in the review however, there is scope to understand learning and assessment strategies and behaviours more deeply (Matcha et al.,

Table B.1
Included studies in the review.

No	Code	Authors	Title
1	S1	Hooshyar et al. (2016)	A solution-based intelligent tutoring system integrated with an online game-based formative assessment: development and evaluation
2	S2	Cen et al. (2016)	Quantitative approach to collaborative learning: performance prediction, individual assessment, and group composition
3	S3	Nyland et al. (2017)	Transaction-level learning analytics in online authentic assessments
4	S4	Cerezo et al. (2020)	Process mining for self-regulated learning assessment in e-learning
5	S5	Chou and Zou (2020)	An analysis of internal and external feedback in self-regulated learning activities mediated by self-regulated learning tools and open learner models
6	S6	Perikos et al. (2017)	Assistance and Feedback Mechanism in an Intelligent Tutoring System for Teaching Conversion of Natural Language into Logic
7	S7	Gerdes et al. (2017)	Ask-Elle: an Adaptable Programming Tutor for Haskell Giving Automated Feedback
8	S8	Kochmar et al. (2022)	Automated Data-Driven Generation of Personalized Pedagogical Interventions in Intelligent Tutoring Systems [pre-print appeared 2021]
9	S9	Grivokostopoulou et al. (2017)	An Educational System for Learning Search Algorithms and Automatically Assessing Student Performance
10	S10	Doble et al. (2019)	A Data-Based Simulation Study of Reliability for an Adaptive Assessment Based on Knowledge Space Theory
11	S11	Bendaly Hlaoui et al. (2016)	Learning analytics for the development of adapted e-assessment workflow system
12	S12	Pardo et al. (2019)	Using learning analytics to scale the provision of personalised feedback
13	S13	Wang and Han (2021)	Applying learning analytics dashboards based on process-oriented feedback to improve students' learning effectiveness
14	S14	Ochoa and Dominguez (2020)	Controlled evaluation of a multimodal system to improve oral presentation skills in a real learning setting
15	S15	Lim et al. (2021)	Students' perceptions of, and emotional responses to, personalised learning analytics-based feedback: an exploratory study of four courses
16	S16	Tempelaar (2020)	Supporting the less-adaptive student: the role of learning analytics, formative assessment and blended learning
17	S17	Ruiz et al. (2020)	Learning UI Functional Design Principles Through Simulation With Feedback
18	S18	Gonçalves et al. (2018)	Personalized Student Assessment based on Learning Analytics and Recommender Systems
19	S19	Lee (2021)	Effectiveness of Real-time Feedback and Instructive Hints in Graduate CS Courses via Automated Grading System
20	S20	Tsai et al. (2021)	Feedback literacy -relations between student expectations of feedback and their experience with LA-based feedback
21	S21	Drey et al. (2020)	Towards Progress Assessment for Adaptive Hints in Educational Virtual Reality Games
22	S22	Leite and Blanco (2020)	Effects of Human vs. Automatic Feedback on Students' Understanding of AI Concepts and Programming Style
23	S23	Sharma et al. (2020)	Predicting learners' effortful behaviour in adaptive assessment using multimodal data
24	S24	Matcha et al. (2019)	Analytics of Learning Strategies: Associations with Academic Performance and Feedback
25	S25	Menchaca et al. (2016)	Using learning analytics to assess project management skills on engineering degree courses
26	S26	Buckingham Shum et al. (2016)	Reflecting on reflective writing analytics: assessment challenges and iterative evaluation of a prototype tool
27	S27	Villamañe et al. (2016)	RubricVis: enriching rubric-based formative assessment with visual learning analytics
28	S28	Ribeiro et al. (2019)	An artificial intelligence case based approach to motivational students assessment in (e)-learning environments
29	S29	Lim et al. (2020)	Students' Sense-Making of Personalised Feedback Based on Learning Analytics
30	S30	Nguyen et al. (2016)	What Learning Analytics-Based Prediction Models tell us about feedback preferences of students
31	S31	Martin and Ndoye (2016)	Using Learning Analytics to Assess Student Learning in Online Courses
32	S32	Taher et al. (2017)	A Comparative Study for Determining the Impact of Simulation-based, Hands-on and Feedback Mechanisms on Students' Learning in Engineering Technology and Computer Networking Programs
33	S33	Guo and Kim (2020)	Using Metacognitive Monitoring Feedback to Improve Student Learning Performance in a Real-Time Location-Based Augmented Reality Environment
34	S34	Azevedo et al. (2019)	Using Learning Analytics to evaluate the quality of multiple-choice questions
35	S35	Omer et al. (2020)	Cognitive Learning Analytics Using Assessment Data and Concept Map: A Framework-Based Approach for Sustainability of Programming Courses
36	S36	Zheng et al. (2022)	Effects of a learning analytics-based real-time feedback approach on knowledge elaboration, knowledge convergence, interactive relationships and group performance in CSCL [pre-print appeared 2021]
37	S37	Pinargote-Ortega et al. (2021)	Peer assessment using soft computing techniques
38	S38	Chang et al. (2019)	Improving prediction of students' performance in intelligent tutoring systems using attribute selection and ensembles of different multimodal data sources

2019; Cerezo et al., 2020) such as build student profiles, analyse motivation (Lee, 2021), use of SRL for learning personalisation within ITSs.

5.2.6. More thoughtful consideration of ethics in the use of emerging technologies

Only five studies explicit touch on ethical issues such as: careful selection of attributes relevant to learning processes (Cerezo et al., 2020), explainability of AI decisions (Cen et al., 2016), data privacy and consent (Menchaca et al., 2016), hint-abuse behaviour (Lee, 2021) and transparency and trust (Buckingham Shum et al., 2016). This lack of ethical consideration is consistent with Zawacki-Richter et al. (2019)'s study who also pointed to the lack of critical pedagogical reflection in AI based educational applications. More thought and consideration needs to be given to ethical issues such as attributes used, consent of stakeholders when collecting, using and analysing system traces of their data and how it is being used and more transparency in how automated graders make decisions with opportunities for users to contest decisions, engaging in dialogue and providing feedback on the performance and improvement of systems.

5.3. Threats to validity

A limitation of the study, as inherent to any SLR, is selection bias based on specific search strings and databases used. Year range has been chosen wisely however, limits the capture range of studies. The validity of conclusions is within the scope of these research boundaries. For rigour of review process, Kitchenham (2004)'s procedures for systematic reviews was followed. Search string formulation was iterative and based on an advanced search approach, and databases were chosen based on suitability and relevance to field, in conjunction with librarian and research team. An inclusion/exclusion criteria was rigorously followed with careful examination at each stage of the review such as noting reasons for inclusion/exclusion and quality assessment, resolution of conflicts or uncertainties with team consensus. Risk of any inadvertent errors in review process is acknowledged.

6. Conclusion

This study presented a systematic literature review of ET applications (AI, LA, XR) in higher education assessment and feedback domain

Table C.1
Included studies in the systematic review with a summary of the data fields from the extraction process.

ID	Publication Type	Study Aim	Motivation to use ET	ET used	Working Tool/Technique/Concept	Domain (Assessment/Feedback) & Application Area	Methodology	Evaluation- effectiveness indicators	Evaluation - summary of findings
S1	Journal	assess success of SITS on knowledge acquisition	find out advantages of using online formative assessmen tool	Intelligent Tutoring System	solution-based intelligent tutoring system (SITS) integrated with an online game-based formative assessment game	Formative assessment - Immediate Elaborated Feedback (IEF)	Quantitative	knowledge acquistion, perception of enjoyment, preference of feedback during game based assessment	positive effect of elaborate immediate feedback on student knowledge acquisition
S2	Journal	develop quantitative approaches to describe the characteristics of collaborative learning and assess their impact on learning performance	find detailed insight into the dynamics of interactions within the group to understand individual contributions	[AI] Extreme Learning Machine and Classification and Regression Trees [LA] Educational Data Mining (EDM) - data driven learning analytics	collaborative learning environment (CLE) platform	Collaborative assessments	Quantitative	prediction accuracy of group performance	high level of predictability of group performance based solely on the style and mechanics of collaboration; positive use-case of quantitative approaches to measurement, prediction and impact analysis in computer-supported collaborative learning.
S3	Journal	determine the degree to which the use of transaction-level data might better identify misconceptions and knowledge gaps that may not be identified through an analysis of the final answer	use transaction-level data to uncover and identify misconceptions persisting among students for one knowledge component - to facilitate better feedback and remediation in online instruction	[LA] transaction level data for assessments	Hidden Event Log for Individual Observation System or HELIOS	Online assessment	Quantitative	comparison of error data (average no. of errors in process v/s final solution); frequency of errors (comparison) and patterns of error over time	significant difference suggesting greater student knowledge gaps detected in transaction level data compared to final solution. Aggregated errors tended to spike on the second occasion and then remained somewhat constant in later lessons
S4	Journal	discover students' self-regulated learning processes during an e-Learning course by using Process Mining Techniques	e-Learning process can give rise to a spatial and temporal gap that poses interesting challenges for assessment of not only content, but also students' acquisition of core skills such as self-regulated learning	[LA] Educational Process mining	Inductive Miner Algorithm	Self regulated learning assessment	Quantitative	fitness' evaluation metric	inductive mining algorithm correctly reproduces students interactions on Moodle. (i.e. pass students followed logic of SRL and higher activity levels in forum supported collaborative learning as compared to fail students).
S5	Journal	explores the impact of external feedback from the OLM on students' internal SRL processes and feedback	explore how external feedback from OLM impact students internal SRL processes and feedback	[LA] Open Learner Models	Open Learner Models for Self-Regulated Learning (OLM-SRL) - an intelligent computer assisted learning system to offer SRL tools, based on based on the SRL-IE model to support SRL	Self regulated learning assessment	Quantitative	The correlation of the students' internal SRL processes and feedback and learning performance (relationship among external SRL tools, internal SRL processes, internal feedback, and external feedback)	students often had poor internal self-regualted processes including not setting appropriate target goals and external feecdback from open learning models assisted most students in monitoring their learning performance, goal-setting, strategy setting and outcome monitoring.
S6	Journal	present feedback mechanism (general framework for modeling assistance to students) and evlauation of effectiveness on student learning	converting natural language (NL) sentences into first-order logic (FOL) formulas in units such as Artificial Intelligence.	[AI] Intelligent Tutoring Systems/ AI in Education	NLtoFOL system (natural language (NL) sentences into first-order logic (FOL) formulas)	[Feedback] Automatic feedback (natural language feedback), natural language feedback sequences that grow from general to specific and can include statements on student's metacognitive state	Quantitative	difference in learning in different learning conditions; comparison of student learning by system v/s human tutors	introduced a general framework for modeling system assistance to students in an intelligent tutoring system (feedback grows from general to specific and can include statements on a student's metacognitive state) and found effectiveness at a similar level as that of human tutors (in 4th year students of AI class).
S7	Journal	design of a tutor that combines the incremental development of different solutions in various forms to a programming exercise with automated feedback and teacher-specified programming exercises, solutions and properties.	adaptable programming tutor that can provide hints and help students develop their programs incrementally with automatic feedback if they are on the right track	[AI] Intelligent Tutoring Systems/ AI in Education	Ask-Elle	[Assessment] Automated programming assessment, [Feedback] Automatic feedback, learning programming language Haskwell, Ask-Elle assessment tool	Mixed	accuracy and perceived usefulness of the feedback from ITS; student experience with ITS feedback	accuracy and perceived usefulness of the feedback -recognise nearly 82% and classify nearly 93% of all interactions, also no false positives, second, students highly value the worked-out examples from Ask-Elle and feedback more helpful for beginners than more advanced programmers
S8	Journal	propose a machine learning approach to generate personalized feedback in an automated way, which takes individual needs of students into account, while alleviating the need of expert intervention and design of hand-crafted rules	investigate how feedback in a large-scale ITS can be automatically generated in a data-driven way, how personalization of feedback can lead to improvements in student performance outcomes	[AI] Intelligent Tutoring Systems/ AI in Education	Personalized feedback model is used in Korbit, a large-scale dialogue-based ITS	[Feedback] Personalised feedback model in ITS	Quantitative	solution verification (agreement with human annotators); hint efficacy (student success rate estimated as their ability to answer the posed question correctly after being provided with a hint); accuracy of different formative feedback models	Personalised discourse feedback model achieved highest student success rate compared to random hints and shallow personalisation models. Human annotators agreed with system's assessment in 80.53% cases of solution verification and led to an average success rate of 60.47% at solving exercises on the platform
S9	Journal	introduce interactive step-based visualisations of algorthmic operations in ITS	use of interactive visualisations through interactive exercises can make learning more effective (active learning)	[AI] Intelligent Tutoring Systems/ AI in Education	Artificial Intelligence Teaching System (AITS), Automatic assessment unit consists of three main parts: the Error Detection Mechanism, the Automatic Marking Mechanism and the Feedback Mechanism.	Automatic assessment, learning using visualisations and interactive exercises	Quantitative	evaluation of Artificial Intelligence Teaching System AITS; compare assessment mechanism against expert (human) tutor	Strong positive relationship between automatic marker and human marker. Automated system accuractly estimated the mark category of the student answer in approximately 83% of the cases.
S10	Journal	eventual implementation of standard measures in the AIED community for examining reliability	no standard approach within the artificial intelligence in education (AIED) or intelligent tutoring system (ITS) literature for measuring reliability for adaptive assessments, concepts borrowed from phychometrics to outline procedure for reliability evaluation for ALEKS PPL assessment	[AI] Intelligent Tutoring Systems/ AI in Education	ALEKS (Assessment and LEarning in Knowledge Spaces) software - PPL Placement, Preparation and Learning	Adaptive assessment	Quantitative	correlation between actual and simulated scores, conditional standard error of measurement CSEM and consistency of actual and simulated scores	found high Pearson correlation (r=0.958) relating the assessed and simulated scores; student's score would lie within one CSEM of the assessed score approximately 68% of the time, where the student to re-take the assessment many times (without a change in the student's knowledge state).
S11	Journal	aims to put forward a set of techniques that can ensure the objectivity of peer assessment with mining text through sentiment analysis and detecting inaccuracy through fuzzy logic	uses soft computing techniques to reduce the professor's workload in the correction process, to assist professors in dealing with peer assessments where there is no consensus between graders (high score with problems identified in feedback or low score with no problems in written feedback)	AI	Supervised machine learning approach; text mining for sentiment analysis Python libraries + SPSS (for data analysis)	Peer assessment	Quantitative	compared the concordance between the score the SVM model (sentiment score) automatically obtained with that the annotator (sentiment polarity) gave of each of the data set's activities through the Kappa, Pearson, and Spearman coefficients	predictive models with classical ML, SVM was the best model with linear function. With modern ML, VE (S) outperformed SVM, but with higher computational costs; with the deep learning model, the prediction performance with Bi-LSTM was weaker, thus the sample size was small
S12	Journal	applying classifcation algorithms, feature selection algorithms, and ensembles to data gathered from a variety of sources in order to predict the students' fnal performance in the ITS.	personalised support to learner by understanding the learning process through resources	LA (Mulitmodal learning analytics, Educational data mining)	attribute selection and classification ensemble algorithm	Post-test domain content knowledge	Quantitative	performance of learning algorithm	J48, RandomTree and RepTree algorithms produced the best results, however, unable to fnd a single best algorithm that would win in all cases in the experiments.
S13	Journal	creating a learner profile ontology based on extraction data from e-assessment activities, file log and personal information,implementation of the adaptation process using cloud service environment and empirical evaluation	making e-assessment system adaptive as learners are distinct and present different knowledge levels, behaviours and preferences	[LA] Learning Analytics	Cloud-AWAS (Cloud Adapted Workflow e-Assessment System)	Adaptive e-assessment	Quantitative	assessment outcome, learner satisfaction	higher performance and answered more tests in an adaptive e-assessment system integrated with Moodle learning management system

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Table C.1 (*continued*).

S14	Journal	Using learning analytics to provide feedback at scale	issues with providing timely and meaningful feedback at scale and learning analytics can provide a novel solution	[LA] education data mining and LA	quasi-immediate personalised feedback messages based on education data mining and learning analytics	[Feedback] quasi-immediate personalised feedback (messages for courses with large student cohorts)	Quantitative	self-reported student satisfaction with the quality of feedback, and academic performance in the midterm exam	positive impact on student perception of feedback quality and on academic achievement; provision of personalised feedback messages in the 2015 edition had a small to medium positive effect on the midterm score.
S15	Journal	developed a learning analytics dashboard based on process-oriented feedback in iTutor, test effectiveness compared to product-oriented feedback and how students with different prior knowledge levels benefit	existing LAD instruments mostly target performance visualisation often in the form of outcome feedback, rather than process-oriented feedback and without providing support mechanisms to facilitate their interpretation and suggestion	[LA] Learning Analytics (educational data mining)	Learning Analytics Dashboard LAD	[Feedback] process-oriented feedback, behavioural and performance data automatically recorded during students' learning processes. Students are immediately able to access their individual LAD after each assessment	Quantitative	prior knowledge relating to post-test scores (for learning analytics dashboard group and analytics report group)	better learning effectiveness with the use of process feedback based learning analytics dashboard group than product-oriented analytics report and learning effectiveness was more pronounced in low-level prior student groups than medium or high level prior knowledge groups.
S16	Journal	conduct the first large-scale randomised controlled experiment in an authentic setting to test the effect that one of these sys-tems, RAP has on the oral presentation performance of entry-level higher education students	none of the automated feedback systems have been adequately evaluated in authentic settings (development of oral presentation skills is integrated into regular courses)	[LA] Multimodal Learning Analytics (MmLA)	Automatic Presentation Feedback System (shortened to RAP due to its Spanish acronym)	[Assessment] Oral Presentation Skills	Quantitative	statistical analysis on different dimensions of oral presentation, subsequent assessment by human experts	small but significant effect in oral presentation skills improvement when presentations were subsequently evaluated by human experts in a real-world setting. Different dimensions of oral presentations not affected equally by automated feedback.
S17	Journal	proposed a LA-based real-time feedback approach based on a deep neural network model to improve CSCL performance	real-time feedback is a major challenge of LA, and only quasi-immediate feedback has been provided to learners, students do not interpret and make use of LA results	[LA]	Learning analytics based feedback	LA based real-time feedback approach (based on deep neural network to improve CSCL approach)	Mixed	knowledge map analysis to measure knowledge elaboration and knowledge convergence	LA-based real-time feedback approach significantly promoted knowledge convergence, knowledge elaboration, interactive relationships and group performance.
S18	Journal	understand students' sensemaking of personalised, learning analytics-based feedback	how personalised feedback is perceived, interpreted and acted upon by stakeholders	[LA]	OnTask system	[Feedback] personalised Learning analytics based feedback	Mixed	students perceptions and affective responses to personalised LA based feedback	students were mostly engaged with their personalised feedback
S19	Journal	student profiles based on learning dispositions and analysis related to other dispositions and if dispositional differences could be neutralised	best facilitate students most in need of learning support, support to underperforming students by systematically analysing trace variables/digital footprints	[LA] Dispositional Learning Analytics	learning analytics based as	[Assessment] Assessment of, for and as learning - feedback on assessment as learning (test-steered e-learning), [Feedback] Learning Analytics based feedback	Quantitative	student profiles and use of learning activites (in digital learning environments) - cluster ananlysis	The intensity of using the e-tutorials, and the choice of what learning scaffolds to use, differ between students of the several clusters, although effect sizes are small.
S20	Journal	investigate benefits of feedback-enriched simulation environment (FENIkS) to teach UI design. Does the use of FENIkS improve the novice designers' learning of principles related to functional aspects of UI design?	teaching UI Design is challenging and pape trials the use of simulation environment to provide learning support by providing feedback on UI, its conceptual and presentation models.	[ET] Simulation	FENIkS - Feedback enriched simulation environment	[Assessment] Knowledge assessment as per different cognitive levels, [Feedback] Insructional Feedback (formative), Three types: immediate,visual feeback using a preview, and corrective feedback	Quantitative	test scores/errors without and with the system	students make fewer errors in UI design principles wirh FENIkS system support than without it and simulation allows students to be more active observers, experience errors and see effects of design choices.
S21	Journal	process based on learning analytics and recommender systems toward personalized student assessment	remote lab and simulation benefits - more interaction time with lab experiments when they are away to achieve haptic skills and instumental awareness, learners can deal with simulations without damaging or being monitored by someone.	[AI] Recommender system; [LA] Learning Analytics; [Other] Remote Labs and Simulations	Learning Analytics and Recommender System	[Assessment] Personalised Assessment	Quantitative	correct answers	better performance in calculus and simulations approaches when compared with hands-on and remote laboratories approaches. The analyses also provide support for the recommendation step allowing the configuration of a knowledge base
S22	Conference	Deliver personalised learning experience with the use of an auto-grader	difference between the grading environment and a student's local environment causes unexpected run-time errors at the time of grading, manual feedback not scalable and delayed	[AI] Automated evaluation (real-time dynamic hints)	Grading System	[Feedback] Real-time dynamic hints and personalised instructor feedback and live anoymous scoreboard, personalised	Mixed	latency from submission to scoreboard; student feedback, no. of hints unlocked by students, no. of commits pushed by students (for a hint, after a hint), no. of commits instructor commented on	latency between 3-7 mins from submission to scoreboard; instructor comments (45.5 reviews per student and 3 reviews per assignment per student). students pushed 1-3 commits to receive a new hint and unlocked 2-3 hints per assignment (max 8)
S23	Conference	examined students' experience of LA-based feedback, offered with the OnTask system, taking into consideration the factors of students'self-efficacy and self-regulation skills	insufficient research looking into relations between student expectations of feedback and their experience with LA-based feedback, inadequate delivery of effective feedback	[LA] LA-based feedback	LA-based feedback in tool called OnTask	[Feedback] LA based feedback	Quantitative	student experience improvement based on tool feedback (boxplot); perceived feedback importance v/s student experience (mean values); relationship between attitudes to feedback to self regualtion and self-efficacy (silhoutte analysis for clustering + Weight of Evidence method)	high satisfaction with the feedback received through OnTask (higher the appraciation for feedabck, more positive the experience with the tools)
S24	Conference	propose the concept of adaptive hints using progress assessment based on player behavior tracked through a VR-system's tracking capabilities	assess progress in educational games, leverage the real-time assessment for adaptive hint systems	[XR] VR	VR-based educational game Social Engineer (HTC VIVE platform)	[Assesment] real-time progress assessment in educational game	Mixed	learning measures - self-assessment questionnaire, pre and post knowledge test for learning evaluation; experience-player experience, mental effort, usability	design educational games that adapt to learners' needs. by find behavioral patterns for progress assessment and evaluate the effects of adaptive hints on player experience and learning outcomes (conceptual)
S25	Conference	current autograding systems did not provide ways to offer feedback at the level of granularity we desired	feedback from autograder unspecific and need for feedback to be more granular	[AI] Autograding automatic feedback	autograder	[Feedback] tool-graded feedback v/s human assisted feedback	Quantitative	Results on quizzes and exam questions	human assisted feedback in addition to auto grader automatic feedback more impactful than simply automatic feedback. course grade distribution revealed that students who received human-written feedback performed better overall and feedback about the syntax-logic relation may be a primary mechanism by which human feedback improves student outcomes
S26	Conference	classification of effort in an adaptive assessment context - student effort assessment based on multimodal data, proposes and evaluates an approach for timely classification of learners' effortful/effortless behaviour during an adaptive assessment activity	encoding relationship between effort and behavioural data, student effort on tasks not directly observable, pinpointing the moments to provide preventive/prescriptive feedback to the learners in real-time	[AI] adaptive self-assessment [LA] logs and physiological data (i.e., eye-tracking, EEG, wristband and facial expressions)	Hidden Markov Models (HMMs) and the Viterbi algorithm for behavioural pattern discovery	[Feedback] Prescriptive/Preventative Feedback	Quantitative	cognitive aspects of learning and effort displayed by students identified using multimodal physiologial data	focus on cognitive aspects of effort displayed by the students on learning - efficient encoding of effort and behavioural data
S27	Conference	examine the sequential and temporal characteristics of learning strategies and association with feedback, examining strategies that students adopt to complete pre-class preparation activities and association of academic performance and feedback with the students' preclass learning strategies	research into how students prepare for face-to-face sessions in a flipped classroom is under-explored (student's ability to self-regulate and impact of feedback towards the selection of learning strategies in flipped classrooms hardly present)	[LA] Process Mining Data analysis: first order Markov models (FOMMs) and the pMineR R package	first order Markov models (FOMMs) and the pMineR R package for data analysis	[Feedback] Learning analytics based feedback, personalised feedback	Quantitative	association between the personalised feedback and the effective strategies	found positive association between the personalised feedback and the effective strategies

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Table C.1 (*continued*).

S28	Conference	assessment of general competences, which constitutes key learning in engineering students and has thus been identified as a need that can be met by learning analytics	assessing the extent to which students have developed the project management skills	[LA] text mining and text analysis	technological tools that enable data about the student's activity to be properly mined and that they be equipped with a data structure to facilitate their subsequent analysis - Gantter, Microsoft Project and Google Calendar	[Feedback] Learning analytics based feedback, [Other] competency assessment	Mixed	teachers' rating of tool, percentage similarity between teacher and LA assessments	89.3% similarity of LA assessment with teachers; teachers rated the tool and contribution it can make positively
S29	Conference	designing a writing analytics application, detailing the methodology by which informally expressed rubrics are modelled as formal rhetorical patterns, a capability delivered by a novel web application	natural language processing may also help address the challenge of providing real time, formative feedback on draft writing	[AI] Natural Language Processing [LA] writing analytics	Xerox Incremental Parser (XIP)	[Assessment] Reflective writing assessment, [Feedback] Formative Feedback	Mixed	accuracy (confusion matrix) of the parser and cross-validation of 'shallow' marked system annotations by human annotators	iterative evaluation on an independently human annotated corpus, showing improvements from the first to second version
S30	Conference	presents some of the visualization capabilities provided by RubricVis, a system that uses Visual Learning Analytics techniques to enhance rubric-based formative assessment	visualisations can enrich formative feedback for students and teachers	[LA] Visual Learning Analytics	RubricVis, a system that uses Visual Learning Analytics techniques to enhance rubric-based formative assessment	[Assessment] Formative Assessment, [Feedback] Visual Learning Analytics based feedback	Quantitative	radar plot-graphs, bar and line charts to visually represent feedback	visual analytics techniques to represent feedback for rubrics-based formative feedback
S31	Conference	present computerized framework grounded on Artificial Intelligence techniques complemented with a Knowledge Representation and Reasoning method that considers unknown, incomplete or even self-contradictory data or knowledge in the motivational student's assessment	uncertainty issues associated to the students motivational assessment are not contemplated in the evaluation of the relation between students, courses in different learning and (elearning environments)	[AI] Artificial Intelligence based Case based reasoning	Case Based Reasoning approach (computerised framework grounded in AI techniques)	[Assessment] motivation assessment	Quantitative	representation of motivation subscales and cognition using worm graphs, and motivation using line graphs	can given insights on students motivation evolution throughout the course
S32	Journal	examined students' sense-making of learning analytics–based personalised feedback, how these map to subsequent self-described self-regulated learning processes	students face challenges in self-regulating learning, role of feedback in SRL is central however, challenges in personalising and providing feedback at scale.	[LA] Learning Ananlytics based feedback	LA-based software called OnTask •OnTask automates the collection of learner data from various sources (e.g., learning management system activity and engagement, assessment and attendance) to enable instructors to generate and send personalised feedback to all students in their course.	[Feedback] Personalised feedback, [Other] Self-regulated learning	Mixed	students sense-making of personalised LA feedback and how student adapt their SRL processes in response	instructor-mediated (perosonalised) feedback with dialogic elements preferred over highly visualised learner reports
S33	Journal	examine the use of preferred feedback modes in students by using a dispositional learning-analytics framework, combining learning-disposition data with data extracted from digital systems	examine the use of preferre	[LA] Dispositional Learning Analytics Framework	Learning Analytics trace data	[Feedback] Feedback preferences (to what extent feedback preferences mediate the relationship between learning dispositions and academic performance)	Quantitative	students' prerferred feedback modes (examined feedback preferences as mediators between their learning dispositions and academic performance)	Findings from analysing feeback preferences of 1062 students indicated that compared with hints, fully worked-out solutions demonstrated a stronger effect on academic performance and acted as a better mediator between learning dispositions and academic performance
S34	Journal	capture use of learning analytics in different types of assessments; identify learning analytics techniques and data measures for different assessment types in online courses, suggest techniques and analysis to provide feedback that could enhance both online teaching and learning	Online learning provides better opportunities to monitor learning, offer immediate feedback for corrective actions	[LA] Learning Analytics	learning analytics data (visualisations from learning management system- module access frequency, assessment access frequency, time spent and assessment scores).	[Assessment] Formative and summative (comprehension type, reflection, discussion board and project based), [Feedback] performance feedback and time and effort feedback, feedback based on combining data from different information elements	Mixed	visualisations of analytics from online assessments	more proactive approach to provide support and remediation to students based on structured and unstructured data from various online sources (done for 18 students)
S35	Journal	determine the Impact of Simulation-based, Hands-on and Feedback Mechanisms on Students' Learning; study the effects of simulation feedbacks on computer engineering students' declarative knowledge.	determine efffectiveness of simulations, recommendations for improving student learning through the use of simulation-based, hands-on, and feedback-based teaching methodologies	[Other] Simulation	first case: simulation; second case: feedback (Answer-Until-Correct)	[Feedback] Simulation feedback	Mixed	effect on student learning (effect of simulation and hands-on instructional strategies AND feedback types in simulation on student learning - quant and qual measures)	Learning - hybrid approach (combination of hand-on and simulation) perceived best instructional strategy for learning circuit design and applications - moderate effect on student learning; simulation based instructional strategy had a marginal effect on student learning compared to hands-on teaching strategy. Feedback - no advantage for simulated labs under any feedback condition over hands-on experiments; only simulated lab with AUC showed better results when compared with simulated labs with no feedback when it comes to improving declarative knowledge in learning of basic IT concepts.
S36	Conference	new guideline on how to develop more effective learning content in AR environments, use metacognitive monitoring feedback to improve student learning performance in a real-time location-based AR environment.	how the metacognitive monitoring feedback tool affects student learning behavior in AR environments	[VR, AR, MR] AR - HoloLens and near-field electromagnetic ranging (NFER) systems were combined to create a realistic AR environment	AR - Holo lens and NFER (near-field electromagnetic ranging (NFER) systems)	[Assessment] Questions (related to force and moment calculations), [Feedback] metacognitive monitoring feedback	Quantitative	participants' confidence level and test scores	significant higher test scores in the experimental group that used the tool than the control group. predictions using participant confidence judgments that students using the metacognitive monitoring feedback tool could be more accurate in their metacognitive judgments than students who did not receive the tool
S37	Journal	find appropriate forms of analysis of multiple-choice questions (MCQ) to obtain an assessment method, as fair as possible, for the students	quality control of MCQ questions in a bank of questions (to build randomly generated tests in Moodle)	[LA] Descriptive Learning Analytics	MS Excel	[Assessment] Multiple Choice Questions	Quantitative	Diificulty and Discrimination Indexes (meaures to check for consistency and reliability in MCQs for fairer assessment design)	Although Item Response Theory could not be applied as intended due to not having enough answers, the other value (Cronbach alpha > 0.8) indicated success as it indicated more consistency, reliability and more fairness in the test in general terms.
S38	Journal	a framework-based approach proposed for cognitive learning analytics on the concepts taught in initial level programming courses	less or no attention to assess learning at various cognitive levels of specific concepts,deficiencies in examining the effect of learners' cognitive performance on subsequent stages of the course	[LA] Cognitive Learning Analytics	[R] framework for cognitive learning analytics using assessment data in programming courses	[Assessment] Programming Assessments	Quantitative	prediction accuracy range (found to be better than other related work)	examined learners' cognitive propagation on related concepts using assessment data in initial level programming courses and identified prediction accuracy ranges (64.81% to 90.86%) which were better than those presented in most of the related work

between 2016 to 2021. While there has been an increase in AI and LA studies, the use of XR technologies seem to have received less attention in computing education. Although most ET tools were not without limitations, the review makes a strong case to support the efficiencies brought about by ET tools in assisting and complementing teachers and assessors. It is recommended that assessment and feedback be continued to be explored, targeting efforts towards formative assessments, and skills and competencies as areas of key focus, for future research with the use of ET tools. Suggested areas of future research are in the use of XR technologies for assessment, impact of feedback approaches in different ET mediated learning environments, deeper consideration of human-centric issues in the contexts in which the ET mediated learning operates and an explicit factoring of ethical and pedagogical approaches to inform the design, use and evaluation of ETs.

CRediT authorship contribution statement

Ruchi Sembey: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Visualization, Writing – original draft, Writing – review & editing. **Rashina Hoda:** Supervision, Validation, Writing – review & editing. **John Grundy:** Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Ruchi Sembey reports financial support was provided by Research Training Program Scholarship. John Grundy reports financial support was provided by Australian Research Council Laureate.

Data availability

Data will be made available on request.

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Appendix A. Search string in each database

The employed search string adaptations for each database are compiled in Table A.1.

Appendix B. Included studies in the review

The included studies in the review are compiled in Table B.1.

Appendix C. Included studies with summary of data fields

Included studies in the systematic review with a summary of the different characteristics corresponding to the data fields from the extraction process described in Section 3.4 (see Table C.1).

References

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