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Speaking of transparency: Are all Artificial Intelligence (AI) literature reviews in education transparent?

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Keywords

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transparency assessment.

Abstract

Literature reviews are considered a core research approach in developing new theories and identifying trends and gaps in a given research topic. However, the transparency level of literature reviews might hinder the quality of the obtained findings, thus limiting their implications. As transparency is one of the core elements when implementing Artificial Intelligence (AI), this study assesses the transparency level of literature reviews on AI in education. Specifically, this study used a systematic review to collect and analyze information about reports of methodological decisions and research activities in 61 literature review papers. The obtained findings highlighted that 51.9% of the conducted reviews on AI in education are descriptive. Additionally, the transparency level of the conducted literature reviews was low; 40% of the reviews were in Q1 and 32% in Q2. Particularly, the quality assessment step had the lowest transparency level. The findings of this research can advance the educational technology field by underscoring the methodological gaps when conducting a literature review on AI in education and hence enhance the transparency and trustworthiness of the obtained findings.

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Introduction

Since 2000, the term 'Technology-enhanced Learning' (TEL) has appeared more frequently in the educational landscape (Al-Ataby, 2020). A complex and intertwined relationship arose between education and technology, and the use of technology in education evoked pedagogical, social, political, and economic effects (Guilherme, 2017) In other words, the technology-intensive 21st century carries various educational implications. Specifically, the use of technology in learning and teaching can effectively facilitate the accomplishment of teaching tasks, improve learning outcomes, and increase classroom interaction and communication. The last 30 years, the advent of Artificial Intelligence (AI) technology penetrated the educational domain as well (Tahiru, 2021), and Artificial Intelligence in Education (AIED) emerged as a developing research field. In AIED, a machine is designed to mimic a human system to support human learning and teaching (Tahiru, 2021; Conati et al., 2018). Therefore, AIED has cognitive, adaptive, decision-making, problem-solving, modelling, and other capabilities to help perform different educational tasks more effectively, including reviewing and grading students' assignments, providing flexible and personalized learning experiences, and implicitly modelling students' profiles (Chen et al., 2020a; Essalmi et al., 2017; Pan et al., 2021; Tlili et al., 2022a).

To provide comprehensive insights into AI's use in education, several literature reviews have been conducted (e.g., Ouyang et al., 2022; Wang et al., 2023). Such studies are intended to provide a holistic perspective by analyzing the approaches and synthesizing the research findings across scholarly papers. Rowe (2014) stated that review papers can be grouped into four categories based on the type of contribution to theory, namely, describing, understanding, theory testing, and explaining a phenomenon (see Table 1).

Regardless of the category of a given review paper, a transparent, as well as a systematic process, among other factors, contributes to the formation of high-quality review papers and the production of new perspectives on the research field. Therefore, transparency is described as a meticulous and thorough reporting of methodological choices made during the review process (Templier & Pare, 2018). Explicit disclosure may strengthen the work and its conclusions' credibility. Further, it also helps to ensure the internal and external reliability of the review processes. Transparency creates methodological rigour and repeatability of studies. Its importance in scientific research is increasingly emphasized across disciplines in the social and natural sciences (Tuval-Mashiach, 2017; McIntosh et al., 2017). Paré et al. (2016) further highlighted two limitations of non-transparent literature reviews: (1) lack of clarity when discussing the methodology of the study and (2) structural constraints of the publishing environment on producing extensive information regarding systematicity in the process of research.

Motivated by this background, and since transparency has been also one of the key dimensions that should be considered when implementing AI in general or in education particularly (Tlili et al., 2021; Larsson & Heintz, 2020), this study answers the following research question: *What is the transparency level of the conducted literature reviews on AI in education?* Specifically, this study conducts a systematic review to identify literature reviews on AIED in the literature, and then assess their transparency level following the Rowe (2014) and Pare et al. (2016) classification and transparency assessment metrics in review articles. In other words, this present study analyzes how transparent the authors from the literature were when adopting a given methodology for their literature reviews on AIED. The findings of this study can contribute to the AIED field by highlighting the transparency gaps of the conducted AIED literature reviews, hence consider them in the future when conducting a literature review. This can ensure more reliable, reusable and trustworthy findings on AIED that can advance the field. Despite the importance of the topic, no previous research, to the best of our knowledge, has conducted a similar analysis.

Table 1. The classification of review papers and their contributions to the theory.

Overarching goal (Adopted from Rowe, 2014)	**Types of literature reviews commonly accepted goals, and frequently researched questions (Adopted from Paré et al., 2016)**
Describing	*Narrative review:* A narrative review summarizes what has already been reported/published on a specific topic and what do we know or have discovered about this topic? *Descriptive review:* A descriptive review analyses the trends or patterns in available theories, hypotheses, techniques, or conclusions.
Understanding	*Scoping review:* A scoping review provides a broad overview of scientific knowledge on a particular topic. This form of review also permits identifying the gaps in the literature as well as future potential research directions. *Critical review:* A critical review is a critical evaluation that identifies flaws, contradictions, disagreements, or inconsistencies on a certain topic.
Testing theory	*Meta-analysis:* A meta-analysis is a method of combining statistical data from main quantitative research to provide relevant findings on a given issue. *Qualitative systematic:* A qualitative systematic literature review compiles statistical/empirical data on a certain topic and displays it in a narrative style. *Umbrella review:* The umbrella review examines and combines the qualitative systematic reviews and meta-analyses to produce the highest level of proof.
Explaining	*Theoretical review:* A theoretical review helps to develop new logical structure and framework by extending current ideas. The study objectives are stated, although there are usually no formal research questions. *Realist review:* A realist review determin[es] what works for whom, under what conditions, in what areas, and also how.

Method

This study assesses the transparency of the conducted literature reviews on AIED. To identify these literature reviews, the recommended reporting items for systematic reviews and meta-analyses (PRISMA) criteria were followed (Page et al., 2021). A PRISMA technique is one of the standardized peer-reviewed methodologies that employ a guideline checklist to ensure the quality and reliability of the revision process.

Search strategy and selection criteria

An extensive search was undertaken in the following databases, namely: Web of Science, Scopus, Taylor & Francis, and Science Direct, IEEE Xplore, as they are very popular in the field of educational technology (Tlili et al., 2022b; Wang et al., 2023). Particularly, the following search string was used: (AI OR Artificial Intelligence OR machine learning OR deep learning or natural language processing) AND (education OR learning) AND (literature review OR systematic review OR meta-analysis or state-of-art). The search query was applied to titles and abstracts, and the search keywords were partially adopted from Zawacki-Richter et al. (2020). After searching the appropriate databases, two authors individually analyzed the extracted papers by titles, abstracts, and textual on the inclusion and exclusion criteria reported in Table 2. During this phase, to reach a final consensus, disagreements between the authors were resolved through discussion or arbitration by a third author who has experience in AI research.

Table 2. Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
Journal article	Conference proceedings, dissertations, novels, book series, and book chapters
Literature review	Not a literature review article or an article that does not explain how the literature review was conducted.
Papers focusing on AI in education	Papers not focusing on AI or discussing AI, not in education
Accessible online Papers in English	Not accessible online Papers not in English

The search yielded a total of 1,367 articles, where 1,330 articles remained after removing duplicates. The screening of titles and abstracts resulted in the removal of 1,009 articles. The remaining 321 papers were considered and assessed as a full text. 260 of these articles failed to meet the criteria for inclusion. As a result, 61 research articles were suitable to be included in this study (see Table 3).

Table 3. 61 included studies in this systematic literature review.

No.	Author	Title
1	Hannan & Liu, 2023	AI: new source of competitiveness in higher education
2	Su et al., 2023	Artificial intelligence (AI) literacy in early childhood education: The challenges and opportunities
3	Banihashem et al., 2022	A systematic review of the role of learning analytics in enhancing feedback practices in higher education
4	Bilgic et al., 2022	Exploring the roles of artificial intelligence in surgical education: A scoping review
5	Chu et al., 2022	Artificial intelligence-based robots in education: A systematic review of selected SSCI publications
6	Dai & Ke, 2022	Educational applications of artificial intelligence in simulation-based learning: A systematic mapping review
7	Kirubarajan et al., 2022	Artificial Intelligence and Surgical Education: A Systematic Scoping Review of Interventions
8	Laupichler et al., 2022	Artificial intelligence literacy in higher and adult education: A scoping literature review
9	Maier & Klotz, 2022	Personalized feedback in digital learning environments: Classification framework and literature review
10	Murtazaet al., 2022	AI-Based Personalized E-Learning Systems: Issues, Challenges, and Solutions
11	Su & Yang, 2022	Artificial intelligence in early childhood education: A scoping review
12	Su et al., 2022	A meta-review of literature on educational approaches for teaching AI at the K-12 levels in the Asia-Pacific region
13	Tan et al., 2022	A systematic review of artificial intelligence techniques for collaborative learning over the past two decades
14	Xia et al., 2022	Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education
15	Xu & Ouyang, 2022	A systematic review of AI role in the educational system based on a proposed conceptual framework
16	Zafari et al., 2022	Artificial Intelligence Applications in K-12 Education: A Systematic Literature Review
17	Ahmad et al., 2021	Artificial intelligence and its role in education
18	Alamri & Alharbi, 2021	Explainable Student Performance Prediction Models: A Systematic Review
19	Aslam et al., 2021	Feature Evaluation of Emerging E-Learning Systems Using Machine Learning: An Extensive Survey
20	Balaji et al., 2021	Contributions of machine learning models towards student academic performance prediction: A systematic review
21	Bozkurt et al., 2021	Artificial intelligence and reflections from educational landscape: A review of AI studies in half a century
22	González-Calatayud et al., 2021	Artificial intelligence for student assessment: A systematic review
23	Hahn et al., 2021	A Systematic Review of the Effects of Automatic Scoring and Automatic Feedback in Educational Settings
24	Huang et al., 2021	A Review on Artificial Intelligence in Education
25	Hwang & Chang, 2021	A review of opportunities and challenges of chatbots in education
26	Hwang & Tu, 2021	Roles and research trends of artificial intelligence in mathematics education: A bibliometric mapping analysis and systematic review
27	Kabudi et al., 2021	AI-enabled adaptive learning systems: A systematic mapping of the literature
28	Kahn & Winters, 2021	Constructionism and AI: A history and possible futures
29	Kharbat et al., 2021	Identifying gaps in using artificial intelligence to support students with intellectual disabilities from education and health perspectives
30	Klyuchnikov et al., 2021	Some Aspects of Ai-Technologies in Education
31	Lee et al., 2021	Artificial Intelligence in Undergraduate Medical Education: A Scoping Review
32	Liang et al., 2021	Roles and research foci of artificial intelligence in language education: an integrated bibliographic analysis and systematic review approach
33	Liu & Afzaal, 2021	Artificial Intelligence (AI) and Translation Teaching: A Critical Perspective on the Transformation of Education
34	Luan & Tsai, 2021	A Review of Using Machine Learning Approaches for Precision Education
35	Maghsudi et al., 2021	Personalized Education in the Artificial Intelligence Era: What to Expect Next
36	Ng et al., 2021	Conceptualizing AI literacy: An exploratory review
37	Nigam et al., 2021	A Systematic Review on AI-based Proctoring Systems: Past, Present and Future
38	Sekeroglu et al., 2021	Systematic literature review on machine learning and student performance prediction: Critical gaps and possible remedies
39	Sousa et al., 2021	The Potential of AI in Health Higher Education to Increase the Students' Learning Outcomes
40	Tahiru, 2021	AI in education: A systematic literature review
41	Tang et al., 2021	Trends in artificial intelligence-supported e-learning: a systematic review and co-citation network analysis (1998–2019)
42	Vázquez-Cano, 2021	Artificial intelligence and education: A pedagogical challenge for the 21st century
43	Zhai et al., 2021a	A Review of Artificial Intelligence (AI) in Education from 2010 to 2020

44	Zhai et al., 2021b	A Meta-Analysis of Machine Learning-Based Science Assessments: Factors Impacting Machine-Human Score Agreements
45	Zhang & Aslan, 2021	AI technologies for education: Recent research & future directions
46	Alfaro et al., 2020	A Review of Intelligent Tutorial Systems in Computer and Web based Education
47	Chen et al., 2020a	Artificial Intelligence in Education: A Review
48	Chen et al., 2020b	Application and theory gaps during the rise of Artificial Intelligence in Education
49	Du et al., 2020	Educational data mining: a systematic review of research and emerging trends
50	Guan et al., 2020	Artificial intelligence innovation in education: A twenty-year data-driven historical analysis
51	Sapci & Sapci, 2020	Artificial intelligence education and tools for medical and health informatics students: Systematic review
52	Voskoglou & Salem, 2020	Benefits and limitations of the artificial with respect to the traditional learning of mathematics
53	Yufeia et al., 2020	Review of the application of artificial intelligence in education
54	Zhai et al., 2020	Applying machine learning in science assessment: a systematic review
55	Ferro et al., 2019	Innovative trends in implant dentistry training and education: A narrative review
56	Soofi & Ahmed, 2019	A Systematic Review of Domains, Techniques, Delivery Modes and Validation Methods for Intelligent Tutoring Systems
57	Winkler-Schwartz et al., 2019	Artificial Intelligence in Medical Education: Best Practices Using Machine Learning to Assess Surgical Expertise in Virtual Reality Simulation
58	Zawacki-Richter et al., 2020	Systematic review of research on artificial intelligence applications in higher education - where are the educators?
59	Chassignol et al., 2018	Artificial Intelligence trends in education: a narrative overview
60	Pappas & Drigas, 2016	Incorporation of Artificial Intelligence Tutoring Techniques in Mathematics
61	Athanasios & Ioannidou, 2012	Artificial intelligence in special education: A decade review

Following the PRISMA guidelines, the study selection process is presented in Figure 1.

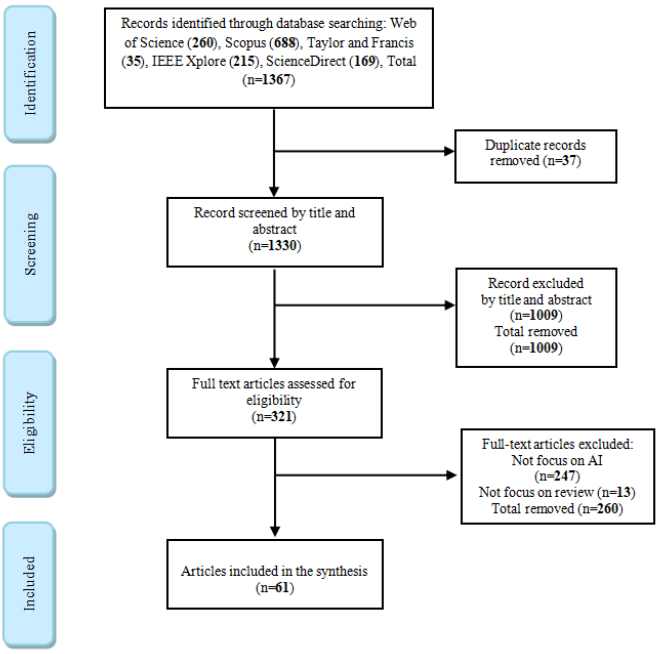

Figure 1. PRISMA Flowchart of the systematic review process.

Coding scheme

To assess the transparency of each identified literature review (among the 61 studies), this study uses the recommendation by Paré et al. (2016) on transparency and systematicity, which includes 17 questions split into six categories (see Table 4). Each paper was coded according to the information on the transparency characteristics to assess the level of its transparency. Specifically, for each question in Table 4, if the information exists, "Y" standing for "Yes" was assigned; otherwise, "N" standing for "No" was assigned. Particularly, all items with value = "Y" were counted and divided by the number of items in their group to calculate the transparency level in each group (e.g., for S01, we divided by 3, for S02, we divided by 4, for S04, we divided by 2, etc.). The researchers grouped the subtotal by the set of groups (six groups) throughout the assessment schema to calculate the overall assessment level. The data-gathering procedure was carried out throughout the article to reduce the risk of incomplete information, which is not mentioned in the methodology section. To reduce the opportunity for bias, an electronic data extraction form was designed (Tlili et al., 2022b), where two coders filled it in according to the coding scheme (see Table 5). To further ensure the reliability of the coding results, weekly meetings during the whole coding process were organized between the coders to discuss their coding progress, where disagreements were discussed and resolved by consensus.

Table 4. Transparency assessment in review articles (Paré et al., 2016).

Review steps to be assessed	Elements to be assessed in each step
S01 – Review planning	1. Are the objectives of review articles well argued? 2. Is the review type and procedures well described and justified in the study? (For reviews articles, use established frameworks or recommendations.) 3. Is the procedure or protocol described and publicized?
S02 – Search strategy	4. Is the search technique (for example, databases with coverage dates) well-defined? 5. Are the criteria for inclusion and exclusion explicitly mentioned? 6. Is there a complete electronic search technique for at minimum one database? (search terms & keywords) 7. Is there information about reference management tools and techniques, as well as other research processes?
S03 – Study selection	8. Is there a description of the screening and selection processes of the study mentioned? 9. Are there enough details about the included studies? 10. (if applicable) Is there a list of excluded studies, together with the reasons for the exclusion mentioned? 11. Is there a flow diagram depicting the study selection process?
S04 – Quality assessment	12. Are the results of each study's quality assessment presented? 13. Is there a description of the methods for integrating assessments into analyses?
S05 – Data extraction strategy	14. Are the methods and processes for data extraction mentioned? 15. Are the data extracted forms or items presented?

S06 – analysis and interpretation strategies	16. Are the main constructs or desired outcomes stated? 17. Are the analysis and synthesis methods explained and justified?

To assess the transparency level among the six criteria/ dimensions (see Table 4), the following information in Table 5 was coded. This information can help to provide comprehensive and deep insights related to the 17 items within the six steps (see Table 4).

Table 5. Coding scheme.

Code	Rationale, definitions, and examples
Article keywords	Author's article keywords
Electronic databases	The name of the database or the name of the electronic scientific index
Keywords and search terms	Authors' use of keywords and search terms
Years included	Years of studies included
Audience	Practitioners, researchers, policymakers, researchers, not stated, etc.
Type of primary sources	If the authors have mentioned: Conceptual/theoretical paper, Empirical – qualitative/quantitative, literature review, critical paper, bibliometric, mixed methods.
Number of studies	The total number of included reviewed articles.
General purpose	The author's purpose, intention, or aim for the article.
Research questions or Hypothesis	(If applicable) The author's research topics, hypotheses, or proposals
Review paper	"Y" if the authors clearly declared that their paper was a review paper
Author's review paper type	(if mentioned) the review type selected
Coders' review paper type	Review types assigned by coders
Scope of the research question	"N" means the scope is narrow; "B" means the scope is broad
Search strategy	Including representational, comprehensive, iterative, purposeful, and selective.
Articles explicitly mention the selection processes	"Y" is yes, "N" is no
Quality appraisal	"Y" means that the article is systematically screened for relevance and authenticity; "N" means that the article is not systematically screened
Nature of primary source	Contains meta-analysis, systematic analysis, qualitative, quantitative, and conceptual
Search method, which includes databases and timelines with a clear description	"Y" means that the article explicitly mentioned the search method; "N" means that the article did not
The disclosure of inclusion and exclusion criteria	"Y" if the article clearly listed the inclusion and exclusion criteria; "N" if the article did not
Tools and methods used to manage bibliographic materials	"Y" if the article clearly listed the methods used; "N" if the article did not
Revealing the list of the profile of included articles	"Y" if the article mentioned the list of included articles; "N" if the article did not
Revealing the list of the profile of excluded articles and the reasons for exclusion	"Y" if the article mentioned the excluded articles and the reasons of exclusion list; "N" if the article did not
Thorough information reporting on quality assessment results for specific sources	"Y" if the article detailed quality assessment results; "N" if the article did not
Information reporting on the quality assessment method	"Y" if the article assessed the quality of reviewed studies by collecting and analyzing data to demonstrate that a given study met the standards; "N" if the article did not
Data extraction techniques and methodologies reported	"Y" if the article reported on what methods and techniques were used to extract the data; "N" if the article did not
Disclosure of specific items or data extraction forms for structured data collection	"Y" if the article reported specific items or forms for data extraction; "N" if the article did not
Principal constructs or outcomes of interest mentioned	"Y" if the article detailed the principal constructs or outcomes; "N" if the article did not
Methods of analysis and synthesis described and justified	"Y" if the article detailed the analysis method with justifications; "N" if the article did not

Results and discussion

Descriptive summary of the AIED systematic reviews

Table 6 shows the goal of the included 61 literature reviews on AIED. These articles were published between 2012 and 2023. Additionally, based on the overarching goal of a literature review (Table 1), 57.36% of the AIED reviews had a primary purpose of describing a phenomenon with little or no addition to the theory (Rowe et al., 2012), as 54.09% of them were descriptive, while only 3.27% were narrative. Table 6 shows that the second highest type of review article is the critical review (31.14%) which comes under understanding. In contrast, review paper types other than descriptive and critical reviews are underrepresented, calling for more research in this context to cover those less applied types of literature review. It is noteworthy that the descriptive type's dominance probably stems from the relatively recent history of AI technologies. It is also important to note that the novelty effect of AI technologies expectedly urges researchers to investigate the phenomenon through descriptive review designs (Johnson et al., 2022). However, this tendency creates an imbalance and is a potential drawback to gaining a deeper understanding of AIED.

Table 6. The classification of systematic review articles (type and year) 2012–2023.

Overarching goal	Percentage	Literature review type	12	13	14	15	16	17	18	19	20	21	22	23	Total	%
Describing	57.36%	Narrative	0	0	0	0	0	0	1	1	0	0	0	0	2	3.27
		Descriptive	0	0	0	0	1	0	0	3	6	17	5	1	33	54.09
Understanding	31.14%	Scoping	0	0	0	0	0	0	0	0	0	3	2	1	6	9.83
		Critical	1	0	0	0	0	0	0	0	4	8	0	0	13	21.31
Testing theory	8.19%	Meta-analysis	0	0	0	0	0	0	0	0	0	2	3	0	5	8.19
		Qualitative systematic	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Explaining	3.27%	Theoretical	0	0	0	0	0	0	0	0	0	2	0	0	2	3.27
		Total	1	0	0	0	1	0	1	4	10	32	3	0	61	100%

Transparency assessment of the literature reviews

This section assesses the transparency criteria of each step (the six steps, see Table 4) of the reviewed articles. Each step is discussed in a subsequent section, while the overall transparency level is discussed in the final section.

Developing a review plan (S01)

This section assesses the transparency of the step of developing a review plan. The most important aspects of guaranteeing systematicity are planning the strategy, identifying the problem, proclaiming the purpose and research questions, and selecting and explaining the review type (Paré et al., 2016). Creating a review plan further improves the review process's systematicity and serves as the foundation for more extensive reporting of methodological decisions made during the study process (Templier & Pare, 2018). As demonstrated in Table 7, 81% (n = 50) of the review articles explicitly mentioned the targeted audience (researchers, practitioners, policy-makers, teachers, analysts, and students). Particularly, more than 70% of the reviewed articles centred on teachers as the audience when discussing AIED. Further, as shown in Table 6, 100% (n = 61) of the reviewed articles clearly stated their objectives or purposes by explicitly mentioning the research questions or hypotheses. Additionally, 81% (n = 50) of the studies clearly mentioned the scope of the research question (see Table 7).

We classified the literature reviews according to the type and breadth of their research questions based on their stated objectives and research questions (when available). All articles (n = 61) declared explicitly that their work was a review paper (i.e., the authors stated directly that their study was a review paper) and the authors' review paper type. However, only 50% (n = 31) of the articles mentioned the coders' review paper type (review types assigned by coders). Additionally, in the studies included, justifications for the review type selection were not identified. Furthermore, in the descriptive reviews, the authors stated their review objectives, types, and protocols at higher rates than in narrative, critical, scoping, or meta-analysis reviews. The use of explicit frameworks and guidelines for undertaking a literature review helps to explain some of these findings (Snyder, 2019).

Based on the above results, it is very important that authors put more attention on the rationale for choosing to conduct one type of literature review and not the other based on the research questions to be answered. For instance, if the authors want to measure the impact of a specific educational intervention, conducting a meta-analysis would be the most adequate type for this objective. Adding such information could increase the transparency of the conducted literature review, and help readers understand the ultimate goal of conducing a given literature review generally, and on AIED particularly.

Searching the literature (S02)

As shown in Table 7, 55% of the articles reported their search methods, which include databases and timelines with a clear description. Specifically, 75% of the articles reported the review period, and 81% of the articles reported the search queries. Additionally, all articles (100%) reported the electronic databases used to identify the research corpus. Particularly, when analyzing the mentioned electronic databases (in all 61 articles), Scopus (n = 25) was the most preferred electronic database to identify and review AIED papers, followed by Web of Science (n = 15), Science direct (n = 15) and IEEE Xplore (n = 6). However, only 45% of the articles explicitly reported the search queries used during the process of building a research corpus, and only 8% of the articles reported the tools and methods used to manage bibliographic materials.

Table 7. Results of the coded information for transparency assessment.

Code	Total	Percentage
Article keywords	59	96%
Electronic databases	61	100%
Keywords and search terms	28	45%
Years included	46	75%
Audience	50	81%
Type of primary sources	58	95%
Number of studies	48	78%
General purpose	61	100%
Research questions or hypotheses	50	81%
Review paper	61	100%
Author's review paper type	58	95%
Coders' review paper type	31	50%
Scope of the research question	55	90%
Search strategy	46	75%
Articles explicitly mention the selection processes	46	75%
Quality appraisal	34	55%
Nature of primary source	45	73%
Search method, which includes databases and timelines with clear description	34	55%
The disclosure of inclusion and exclusion criteria	43	70%
Tools and methods used to manage bibliographic materials	5	8%
Revealing the list of the profile of included articles	31	50%
Revealing the list of the profile of excluded articles and the reasons for exclusion	21	34%
Thorough information reporting on quality assessment results for specific sources	5	8%
Information reporting on the quality assessment method	4	6%
Data extraction techniques and methodologies reported	10	16%
Disclosure of specific items or data extraction forms for structured data collection	36	59%
Principal constructs or outcomes of interest mentioned	37	60%
Methods of analysis and synthesis described and justified	36	59%

Based on the above results, it is seen that authors should elaborate more in terms of the used search keywords to conduct their systematic reviews on AIED. This is crucial, especially for a complex topic like AIED, where several technologies (e.g., deep learning, machine learning, natural language processing) and techniques (e.g., learning analytics, prediction and modelling) can be used interchangeably with AIED. Besides, it is seen that less attention has been put by authors to elaborate on the used tools to manage their bibliographic materials, and this could be because these tools are more managerial and do not impact the research quality in any way.

Selecting studies (S03)

The selection process of articles provides important information on the sources used for interpretation and analysis, as well as the techniques used to pick these sources, by disclosing information about these aspects (Tricco et al., 2011). Consequently, it highlights the papers that are not relevant to the researchers' search interests. A

comprehensive and detailed screening approach decreases the risk of bias when it comes to including or excluding articles for further research. Researchers also give evidence on the usefulness of these studies for generating relevant results and addressing the study questions by giving thorough information about the included and excluded articles.

As presented in Table 7, 78% (n = 48) of the review articles mentioned the number of studies included in the review process. It is also critical for researchers and practitioners to have precise and organized information regarding exclusion methods since this allows them to assess the criteria's soundness and scientific rigour. Moreover, reporting inclusion and exclusion criteria provide insights that lead to generating research findings through reviewing the related literature and providing the base criteria for replicating the study and benchmarking the research process. Specifically, 70% of the articles mentioned their inclusion/exclusion criteria. 50% of the articles revealed the list of the profile of included articles, and just 34% of the articles provided information about the inclusion and exclusion criteria. Particularly, 50% (n = 31) of the publications presented the list of studies that were included and 45% (n = 28) of the studies graphically published data.

Inclusion/exclusion criteria are an important step to help readers understand how a given study might or might not be included within a given literature review. Based on the obtained results, it is seen that most studies did not elaborate on this step, as well as the final list of included studies. Consequently, this makes those conducted AIED literature reviews a black box, where it is not clear what was included and why. This also hinders understanding the obtained results, hence making full use of them to advance the AIED field, as the literature review input (i.e., included studies and how they are selected) is absent.

Assessing quality (S04)

This information can guarantee that only high-quality sources are obtained as a method of improving the quality of the findings and outcomes (Bandara et al., 2015). As shown in Table 7, only 8% of the articles thoroughly reported the quality assessment results for specific resources, and 6% of the articles reported information on quality assessment methods. On the other hand, 73% of the studies clearly mentioned the nature of the primary source. However, only 55% of the review studies mentioned the quality appraisal, where they compared the covered articles collectively. These findings are alarming, as assessing quality is related to the robustness of the research conducted.

Therefore, to increase the adoption and use of the obtained results given by some AIED literature reviews, the quality assessment should be highlighted. This is because researchers might always be hesitant to rely on some findings that they are not sure of their quality. This is even more pertinent in the AIED field as designing AI-based educational systems is very tricky and requires careful attention to not accidently harm (e.g., biased interventions) users (e.g., learners, educators) instead of supporting them.

Extracting data or key aspects from included studies (S05)

Whittemore et al. (2014) stated that the accurate reporting of individual research is vital to improving the quality of any knowledge synthesis technique. This aims to identify, organize, and carry out agreed-upon methods for collecting data from primary sources to mitigate the risks of omission, misclassification, or misrepresenting crucial information (Paré et al., 2016; Webster et al., 2002).

As shown in Table 7, only 16% of the articles reported their data extraction techniques and methods, whereas 59% of the articles disclosed the specific items or data extraction types for structured data collection. Furthermore, 95% of the reviewed articles included the items or information needed to extract data from their primary sources (e.g., descriptive, narrative, evidence-based qualitative, evidence-based quantitative, conceptual or theoretical paper, critical paper, bibliometric, mixed methods, or literature review). Some articles utilized a list of items to display this information (e.g., Al-Azawei et al., 2016), whereas others used structured approaches with more specific information (e.g., Arbaugh, 2014).

Based on the obtained results, authors should elaborate more on their extraction techniques, especially their coding scheme, to increase the replicability of their research (i.e., literature reviews) by others.

Synthesizing and interpreting data and formulating conclusions (S06)

As shown in Table 7, 60% of the studies indicated the major constructs or outcomes, while 59% described the analytical and synthesis methodologies. In both cases, the number of descriptive reviews outnumbered the remainder of the review articles.

This result might reveal that it is always easier to elaborate on some descriptive analysis, while it is not the case when the analysis is more advanced. For instance, when discussing meta-analysis review papers, there is a need to go beyond the simple description of the process and elaborate on the motivation of selecting a given technique, for instance, related to measuring effect size (Cohen's d and Hedges' g) or publication bias based on the different samples or research methods used in each included study within the review process.

The overall level transparency (S07)

Table 8 summarizes the overall level of transparency of the 61 review articles on AIED arranged by type and quartiles, with Q1 being the highest and Q4 the lowest. Specifically, a study belongs to Q1 if its overall transparency level is between 76% and 100%, Q2 if its overall transparency level is between 51% and 75%, Q3 if its overall transparency level is between 26% and 50%, and Q4 if its overall transparency level is between 0% and 25%. When describing research efforts, the findings reflect various levels of transparency; 40% of the articles were in Q1 and 32% in Q2. This implies

that the transparency level of the conducted literature reviews on AIED is low. Therefore, future research should consider the transparency factor of the conducted literature reviews on AIED, as this may provide detailed insights about the field and positively impact the scientific community more broadly (Vom Brocke et al., 2018).

Additionally, descriptive review articles were in the top two quartiles (Q1 and Q2), while critical review articles (11 out of 13) were in the last quartile (Q4), implying that descriptive review articles have the highest transparency level while critical review articles have the lowest. Contrary to our findings, Castro-Gil and Correa (2021) found that the lowest transparency level was in descriptive literature reviews on blended learning in higher education.

Furthermore, Table 8 shows that step four "quality assessment" had the lowest transparency level. This implies that the reported reviews on AIED did not explicitly discuss the quality of the reviewed articles. Consequently, this might hinder the quality of the reported findings related to AIED. In this context, to ensure quality assessment when conducting review articles, several studies focused only on reviewing SSCI/SCIE or top journals in the field (e.g., Crompton & Burke, 2018; Hwang & Tsai, 2011).

Table 8. Studies fulfilling the transparency assessment items by type of review paper and quartile.

Review type and number of studies	Steps of the review process (S01–S06) and transparency assessment items (1–17)																	Quartiles				Total	%
	S01		S02					S03				S04		S05		S06		Q1	Q2	Q3	Q4		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17						
Descriptive	33	31	28	28	32	30	2	31	23	16	22	6	6	32	32	33	32	17	14	0	1	32	52.4
Narrative	1	1	0	0	1	0	0	1	0	0	0	0	0	1	1	1	1	0	1	1	1	3	4.9
Critical	3	2	3	2	2	2	0	1	1	0	1	0	0	1	1	1	1	0	1	1	11	13	21.3
Scoping	6	6	6	6	6	5	5	5	2	2	6	2	2	6	6	6	6	5	1	0	0	6	9.8
Meta-analysis	4	3	2	2	3	1	0	5	5	3	3	3	2	4	4	4	4	2	2	1	0	5	8.1
Theoretical	2	2	2	2	2	0	2	2	1	0	0	0	0	2	2	2	2	1	1	0	0	2	3.2
Total	49	45	41	40	46	38	9	44	39	21	32	11	10	46	46	4	46	40 %	32 %	4.9 %	22.95 %	61	100

Conclusions, implications, and limitations

This study conducted a transparency assessment of AIED review articles. The obtained findings showed that the transparency level is considerably low. Specifically, researchers should focus more on elaborating on the quality assessment of the reviewed articles, as well as the included and excluded articles.

The findings of this study can contribute to the educational technology field from different perspectives. From a theoretical perspective, this study can enrich the ongoing debate about the dimensions to consider for applying a transparent systematic review generally, and on AIED particularly. From a methodological perspective, this study presents how to conduct a transparency assessment of articles, as well as how to enhance the methodological part of a given literature review to obtain valid and reproducible research by others. From a practical perspective, this study can contribute to the AIED field by highlighting to researchers and practitioners the weaknesses of the conducted AIED literature reviews. Enhancing these parts can contribute to enhancing the quality of the obtained findings related to AIED, hence providing more insights to the working community on AIED, as well as providing evidence-based practices or making decision processes related to AIED.

Despite the solid ground of this study, it has some limitations that should be acknowledged. For instance, the covered literature review articles in this study might be limited due to the search queries and electronic databases used. Therefore, interested researchers can further complement the research presented in this study. Future research can focus on going beyond assessing the transparency level to analyze how the conducted literature reviews tackled AIED (e.g., from which perspective, the targeted stakeholders, education level and context, etc.). This might reveal the trends of AIED, as well as the gaps that researchers and practitioners should focus on in the future.

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