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Bibliometric analysis and systematic literature review of the intelligent tutoring systems

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This study is a literature review with educational evaluation mediated by intelligent tutoring systems (ITS) as its central axis seeking to establish state of the art on implementations executed in the last 20 years and their impact on the evaluation process. The PRISMA methodology was applied for the literature review; the studies were included using the R software and bibliometric techniques with a general search equation that allowed access to all ITS production in Scopus. Subsequently, with the help of artificial intelligence, text mining was used to identify topics of interest in the scientific community, followed by further filtering. Finally, the selected full texts were analyzed using the NVivo software to extract emerging challenges in the field, obtaining 163 full texts for analysis. Among the main findings, the primary purpose of evaluation in ITS was summative, peer and self-evaluation did not have the same level of importance as hetero evaluation, and ITS focus was quantitative. All of this allowed us to conclude that the analyzed texts did not implement a holistic perspective and therefore evidenced the need to establish a framework for constructing an ITS using current technologies that integrate the mentioned variables.

KEYWORDS

tutoring system, bibliometric analysis, literature review, text mining, educational innovation

Introduction

According to Álvarez de Zayas (2010), assessment is a systemic, holistic, and dialectical process, or, in other words, a complex process. However, this conception of evaluation does not always correspond to what those involved in educational processes put into practice. For example, in higher education, it is common that the preferred instrument for collecting information is the exam (Gibb et al., 2011). It is also common to confound evaluating with grading, measuring, correcting, classifying, or examining and focusing on the quantitative aspects (Álvarez, 2001). Although the grading process is related to evaluation and provides valuable data for decision-making (refer to Figure 1), it needs to be complemented with multiple instruments that integrate qualitative and continuous aspects that allow transforming classroom dynamics, not only at the end of the academic periods. In other words, they must be aligned with the true meaning of

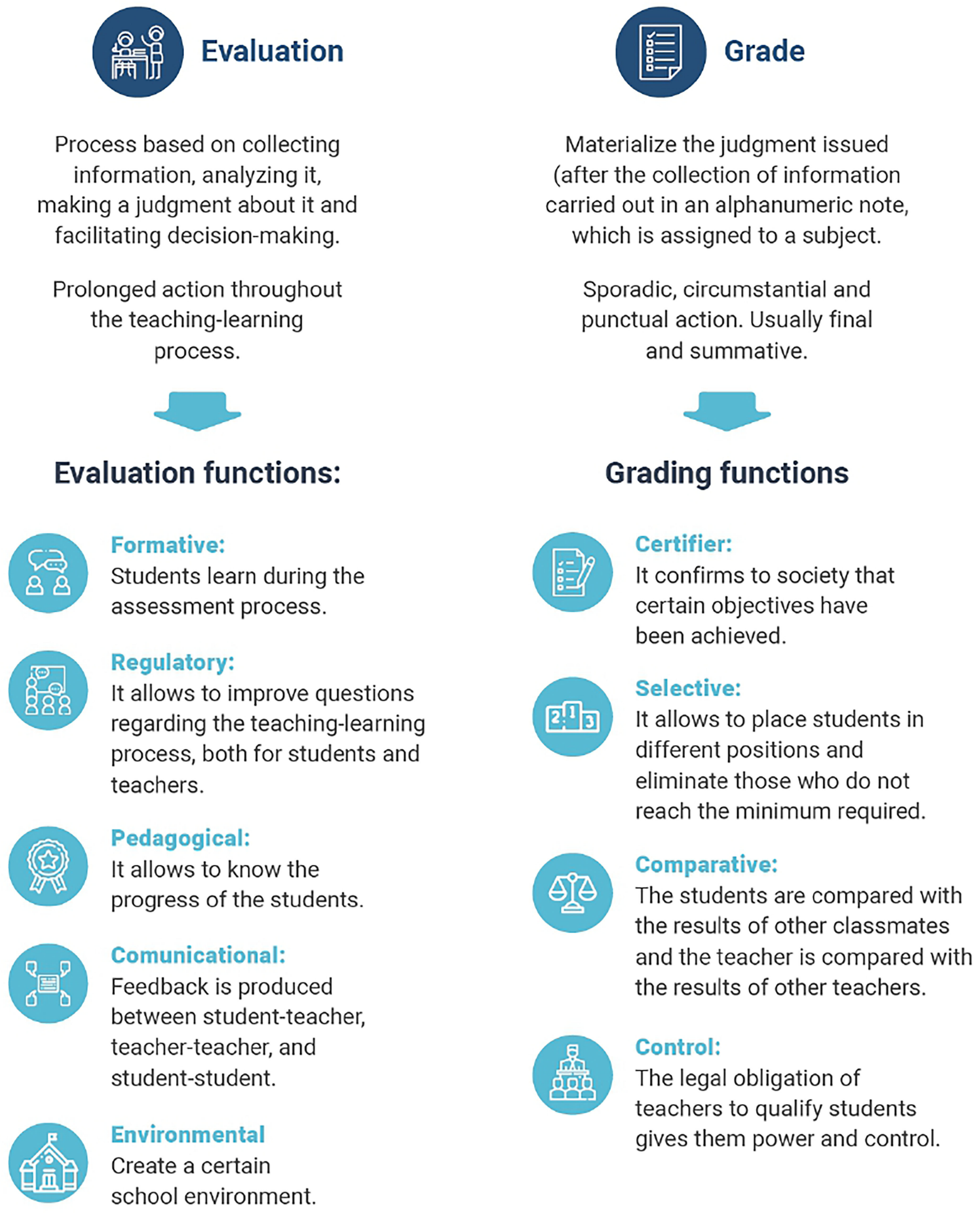

FIGURE 1
Evaluating and grading process. Adapted from Hamodi et al. (2014).

evaluation—a formative, regulatory, pedagogical, and communicative tool (Carless and Boud, 2018).

This situation can be better understood if we consider the different objectives of evaluation, i.e., it can be diagnostic, formative, or summative. In the diagnostic case, decisions can be made based on the student's starting level, adjusting methodologies, and monitoring strategies. In formative evaluation, the focus is on the learning process and, therefore, the acquisition of competencies; this implies, in most cases, the constant intervention of the teacher or, as will be explained in this study, the teacher supported by technology. Finally, the summative evaluation usually takes place at the end of the process and serves as a control. It is usually related to quantitative assessments that provide relevant information for decision-making for students and teachers. Furthermore, in relation to the holistic character of these evaluation objectives, the teacher must move among all three of them constantly (Chufama and Sithole, 2021; Rehhali et al., 2022; Sudakova et al., 2022).

In the case of basic sciences, the misinterpreted evaluation focused on results aggravates the problems of performance, grade repetition, and, in some cases, drop out. For example, according to Castillo-Sánchez et al. (2020), one of the leading causes of repetition in the first mathematics course is low academic performance in the first partial exam.

Introductory science courses are conventionally graded through exams, with the percentage distribution depending on the university. For example, in the Mathematics School at the National University of Colombia, there are three midterms of 25, 30, and 30%, respectively, and a short exam of 15% (Cuéllar Rojas, 2013). This implies that the student receives feedback on his learning process only in some specific moments and not in all classes.

However, given this approach, it is difficult to avoid the question: How can an evaluation process that overcomes these difficulties be implemented in courses with many students? This question has already been addressed, although not resolved. Digital technologies offer the educational community a wide range of ways to collect information, such as interactive videos, simulations, and surveys (Torres Mancera and Gago Saldaña, 2014)—all of which may be configured to be assessed automatically without requiring excessive teacher time. However, if these tools were implemented, the evaluation process would continue without solving the fundamental evaluative aspect. What decisions are to be made with the data? Or, even more complex, how to analyze these data?

One of the favorable environments for these implementations is the intelligent tutoring system (ITS). It is possible to transition from exam-centered grading to one that draws on multiple instruments. In this context, the student receives constant cognitive and metacognitive feedback. As mentioned earlier, formative assessment is a crucial element for learners' success. It involves three agents, namely, the teacher, the peers, and the learner himself/herself. Although formative assessment is not new, it has been limited in contexts where the number of students exceeds the teacher's physical capacity to accompany each of them. There are other tools that the teacher can use to compensate for this deficiency, such as self-assessment and peer assessment, which have a broader scope. This learning process involves students using the aforementioned metacognitive process to evaluate their learning outcomes (Schildkamp et al., 2020; Shemshack and Spector, 2020).

The main task of an ITS is to evaluate students' knowledge acquisition throughout the education process. In general, aAdaptive ITS provides learning environments in which all relevant information about students is kept and used to guide them (Lemke, 2013; Tan and Chen, 2022).

Intelligent tutoring system uses artificial intelligence principles and methods, for example, neural networks, to make inferences and learn autonomously. This characteristic enables ITS to be adaptive, since it alters its structure, functionality, or interface for the user and their needs (Anohina, 2007).

Intelligent tutoring system has different configurations according to the application context, but four modules stand out in educational courses, namely, (1) the pedagogical module, (2) the student module (diagnosis), (3) the expert module, and (4) the communications module. These modules are complemented by the models created from the data they provide, which are represented in blue (refer to Figure 2A).

This structure integrates naturally with massive courses, favoring learning environments with lesser teacher interaction. Student and teacher interactions using these modules produce large volumes of mixed data. Unfortunately, this information is difficult to analyze on a massive scale. Considering that Massive Online Course has exceeded 180 million students (Shah, 2020) and that the number of participants per course easily exceeds 1,000 in some of them (Kaser and Gütl, 2016), these figures justify mass-grading strategies, with which it is possible to achieve constant and automatic feedback, minimizing the interaction with the tutor and turning the student into the protagonist of the learning process. However, the amount of data generated by this constant interaction grows exponentially and quickly, exceeding the human capacity to analyze them and make decisions that are not always quantitative.

This system responds to qualitative questions about each student, as specific as:

1. Which of the concepts covered in class require further study?
2. What are the performance levels in the fundamental competencies of the course from the first class?
3. What methodological adjustments are required in the course to favor the student process?
4. What curricular adjustments are necessary to favor the development of the competencies offered by the course?

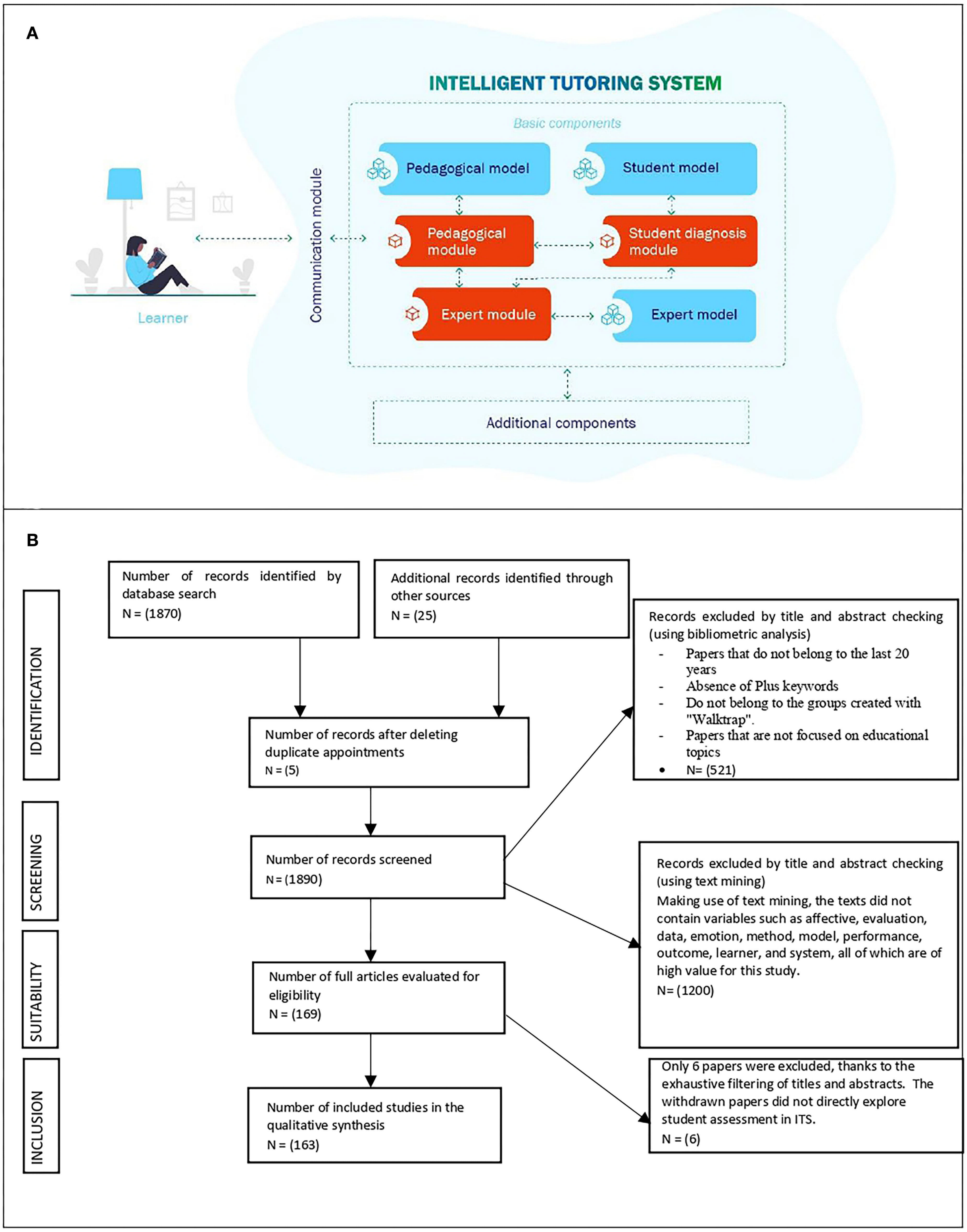

FIGURE 2
(A) ITS Basic components. Adapted from Anohina (2007) and Al-Hanjori et al. (2017) and **(B)** the process of PRISMA for data collection and analysis.

5. What feedback do teachers and students require to make decisions that favor the acquisition of the competencies offered by the course?

Furthermore, all aspects related to the individual process of the subjects are complex even for a conventional number of students, since the evaluative processes of this level of personalization require an investment of time on behalf of the educational actors that do not correspond to the implementation model (maximizing the number of participants, minimizing tutors).

These tasks for massive groups require an intelligent data processing system that learns from the data and acts as a virtual master, performing accurate decision-making evaluations. However, the approaches to this problem are still under development. Fundamental variables have been considered (Rajendran et al., 2019; Torres-Madroñero et al., 2020). For example, students' self-regulation or motivation has been included in some ITS. However, aspects such as diagnostic, formative, and summative evaluation have not been considered together. Therefore, a systematic review was conducted to identify and evaluate articles that propose implementations of evaluation systems using machine learning techniques for massive volumes of data.

Methodology

Method

This systematic review was conducted based on the preferred reporting items for systematic reviews and meta-analyses (PRISMA) proposed by Moher et al. (2015). Figure 2B displays the process of PRISMA for data collection and analysis.

Research questions

This systematic review responds to the following research questions:

- RQ 1: What is the ITS primary evaluation purpose?
- RQ 2: What is the main evaluating agent (in evaluation processes)?
- RQ 3: What is the main approach used in the selected ITS?
- RQ 4: Is the ITS evaluation process implemented holistically?

Search strategy

With the search equation *intelligent tutoring*, the following results presented in Table 1 were obtained. However, it is crucial to remember that this general equation is only considered since it was expected to obtain new filtering criteria that will lead to a more refined equation.

TABLE 1 Characteristics of the data.

Main information about data	
Timespan	1979↔2021
Sources (Journals)	618
Documents	1,890
Average citations per document	21.12
Document types	
Article	1,890
Authors	
Authors	3,819
Authors collaboration	
Single-authored documents	322
Documents per author	0.495
Authors per document	2.02

A total of 1,890 results were found in Scopus, covering 42 years of academic production. The texts considered were articles published in specialized journals, although it is recognized that this field of knowledge has important dissemination through conferences. However, due to the objective of the study to identify structured knowledge with an important level of depth, conference papers were not included in this analysis. Thus, a total of 3,819 authors were considered in this initial search.

Academic production began in 1979; in 2014, it reached its maximum (105 papers), and since 2016, such production has slightly decreased (Figure 3A).

Figure 3B shows that the largest source of texts was the *International Journal of Artificial Intelligence in Education*, classified in Q1. Figure 3C shows the top five most-cited journals in relation to ITS. The journal *Computers and Education* stands out with a total of 4,814 citations.

The main authors by total citations in the chosen period are presented in Figure 3D. For example, Kenneth R. Koedinger, professor of human-computer interaction and psychology at Carnegie Mellon University, is the founder and current director of the Pittsburgh Learning Science Center, with 2,112 citations.

The data represented in Figure 4 are the KeyWords Plus count. They were generated from words or phrases that frequently appear in the articles' references but do not appear in the article's title. Using R and the Bibliometrix plugin, it is possible to obtain them. KeyWords Plus enhances the power of cited reference searching by looking across disciplines for all articles with commonly cited references.

Garfield claimed that Keywords Plus terms could capture an article's content with greater depth and variety (Garfield and Sher, 1993). However, Keywords Plus is as effective as Author Keywords in the bibliometric analysis of the knowledge structure

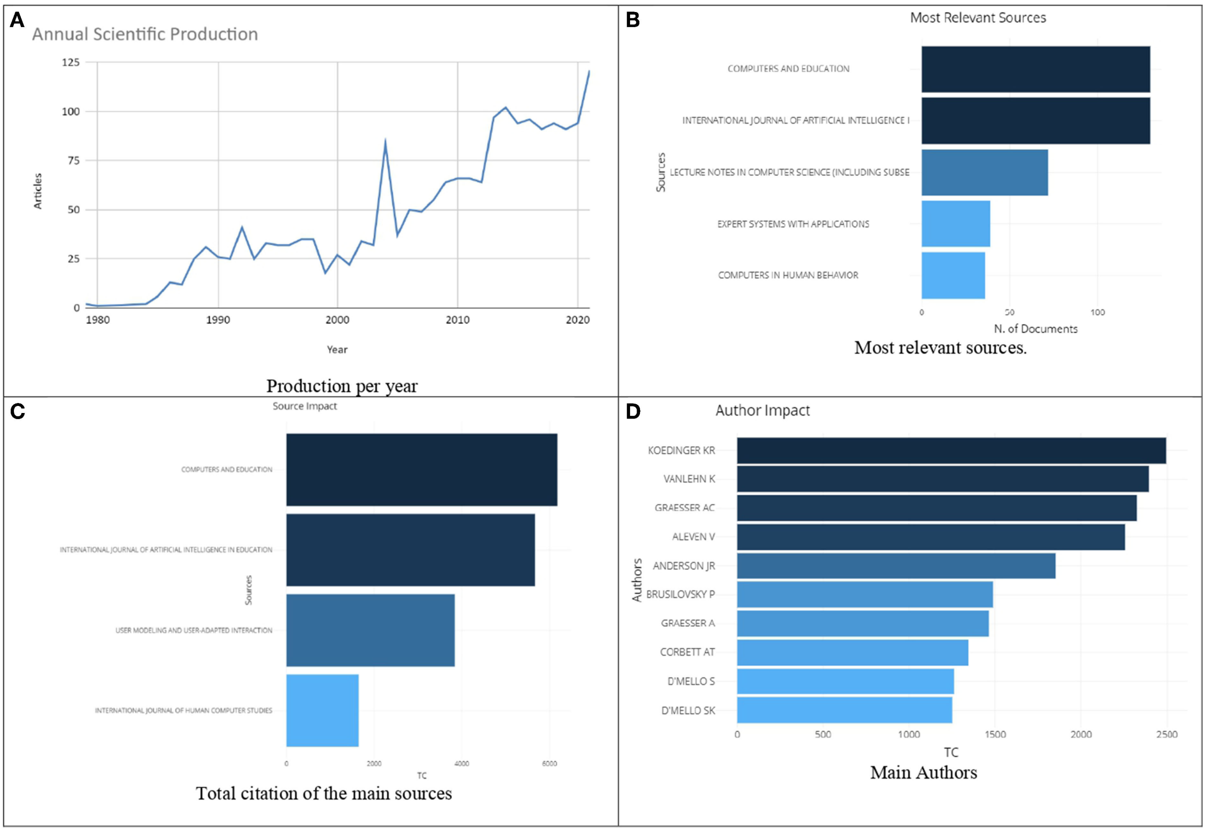

FIGURE 3
(A) Production per year, **(B)** Most relevant sources, **(C)** Total citation of the main sources, and **(D)** Main Authors.

of scientific fields, but it is less comprehensive in representing an article's content (Zhang et al., 2016).

In Figure 4, computer-aided instruction is the main topic, representing 17% of the frequencies examined in the text references. Finally, for the elaboration of Figure 5, it was considered that co-occurrences could be normalized using similarity measures such as the Salton cosine, the Jaccard index, the equivalence index, and the strength of association (van Eck and Waltman, 2009).

The selected algorithm was the strength of the association since it is proportional to the relationship between the observed number of co-occurrences of objects i and j and the expected number of co-occurrences of objects i and j under the assumption that the occurrences of i and j are statistically independent.

For the grouping strategy, "Walktrap" was selected as one of the best alongside "Louvain" (Lancichinetti et al., 2010). The graph is interpreted by considering the following characteristics:

- Centrality/periphery (position).
- Dimension of the bubble (number of citations).
- Strength of relationships (links).
- Clusters (and density).
- Bridges.

The colors represent the groups to which each word belongs. In this case, there are three groups. In the first one, colored in red, the theme of computer-aided instruction is dominant in citations. Citation is not the central theme in the green one but relationships, that is, Expert Systems relating topics of interest such as artificial intelligence. Finally, the third group, colored blue, seems to be a subgroup of the first one focused on educational issues.

The search string was as follows: TITLE-ABS-KEY (*intelligent tutoring system*) AND [LIMIT-TO (DOCTYPE,"ar")] AND [LIMIT-TO (PUBYEAR,2021) OR LIMIT-TO (PUBYEAR,2020) OR LIMIT-TO (PUBYEAR,2019) OR LIMIT-TO (PUBYEAR,2018) OR LIMIT-TO (PUBYEAR,2017) OR LIMIT-TO (PUBYEAR,2016) OR LIMIT-TO (PUBYEAR,2015) OR LIMIT-TO (PUBYEAR,2014) OR LIMIT-TO (PUBYEAR,2013) OR LIMIT-TO (PUBYEAR,2012) OR LIMIT-TO (PUBYEAR,2011) OR LIMIT-TO (PUBYEAR,2010) OR LIMIT-TO (PUBYEAR,2009)

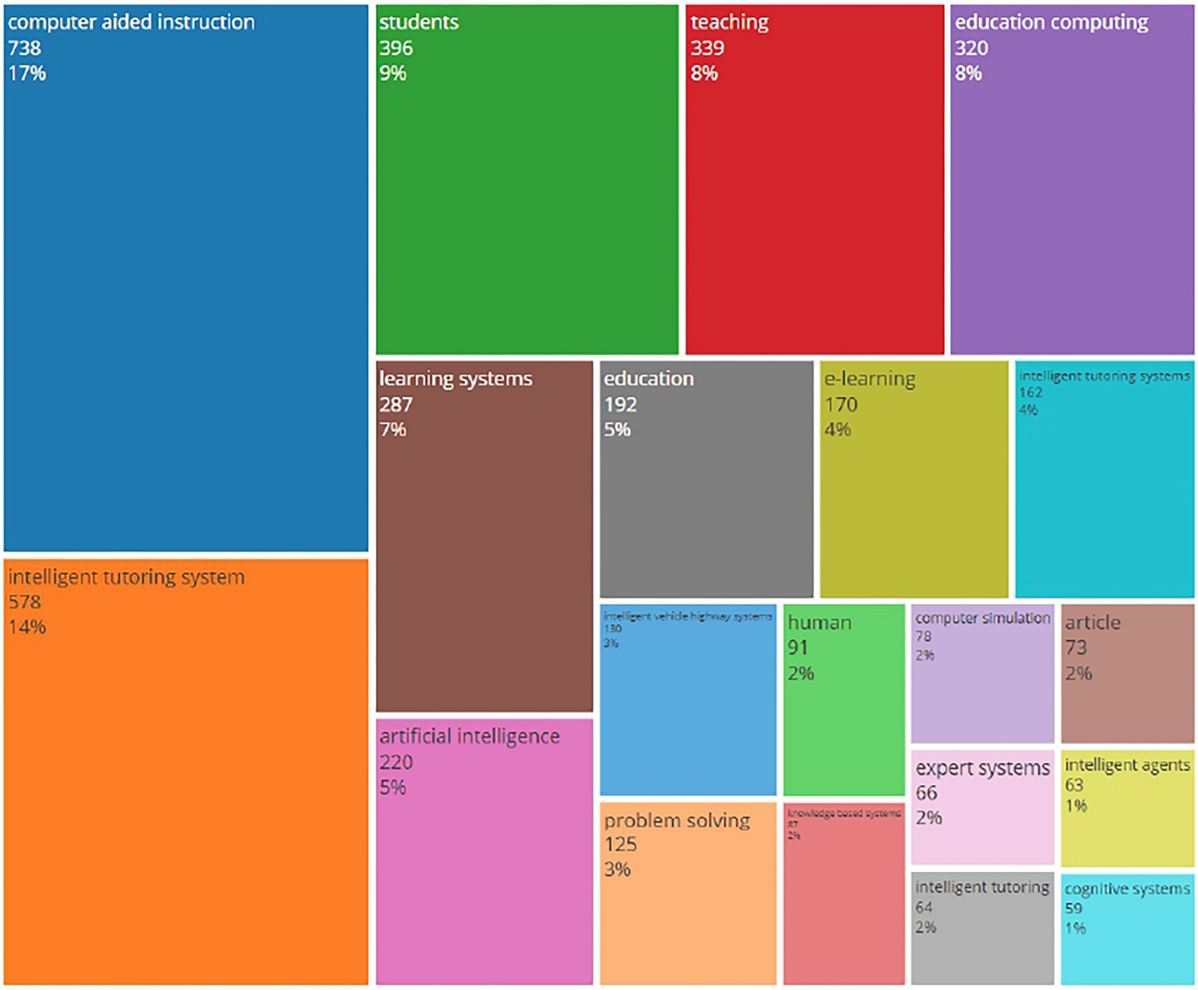

FIGURE 4
Percentage of participation based on Keywords Plus.

OR LIMIT-TO (PUBYEAR,2008) OR LIMIT-TO (PUBYEAR,2007) OR LIMIT-TO (PUBYEAR,2006) OR LIMIT-TO (PUBYEAR,2005) OR LIMIT-TO (PUBYEAR,2004) OR LIMIT-TO (PUBYEAR,2003)].

Text mining

Although the bibliometric analysis found the authors and journals with the most impact in the specific field and the possible thematic fields based on the analysis of the Keywords Plus and the classification of these in groups, it was necessary to perform additional analysis to identify more specific thematic groups, for which the Software KNIME (Berthold et al., 2009) was used.

Figure 6A shows the scheme under which the database downloaded from Scopus was processed. Data were previously filtered from 2003, when a production peak occurred, which is of interest. Finally, in this analysis, all the abstracts of the selected papers were considered.

Figure 6B shows the workflow developed in KNIME, with which it was possible to analyze 1,369 abstracts and extract the hidden thematic structure, identifying the topics that best describe a set of documents.

Table 2 describes each item presented in Figure 6B.

After going through this process, the algorithm returned all the selected terms, which were classified into five topics from the 1,369 abstracts; each topic required interpretation. However, the focus of the analysis was to determine if some of them were related to the category of interest: evaluation.

The program interface allowed the analyst to explore the five topics, as shown in Figure 7.

For example, topic_0 contains the terms game, instruction, intelligent, language, reading, skill, strategy, study, and system.

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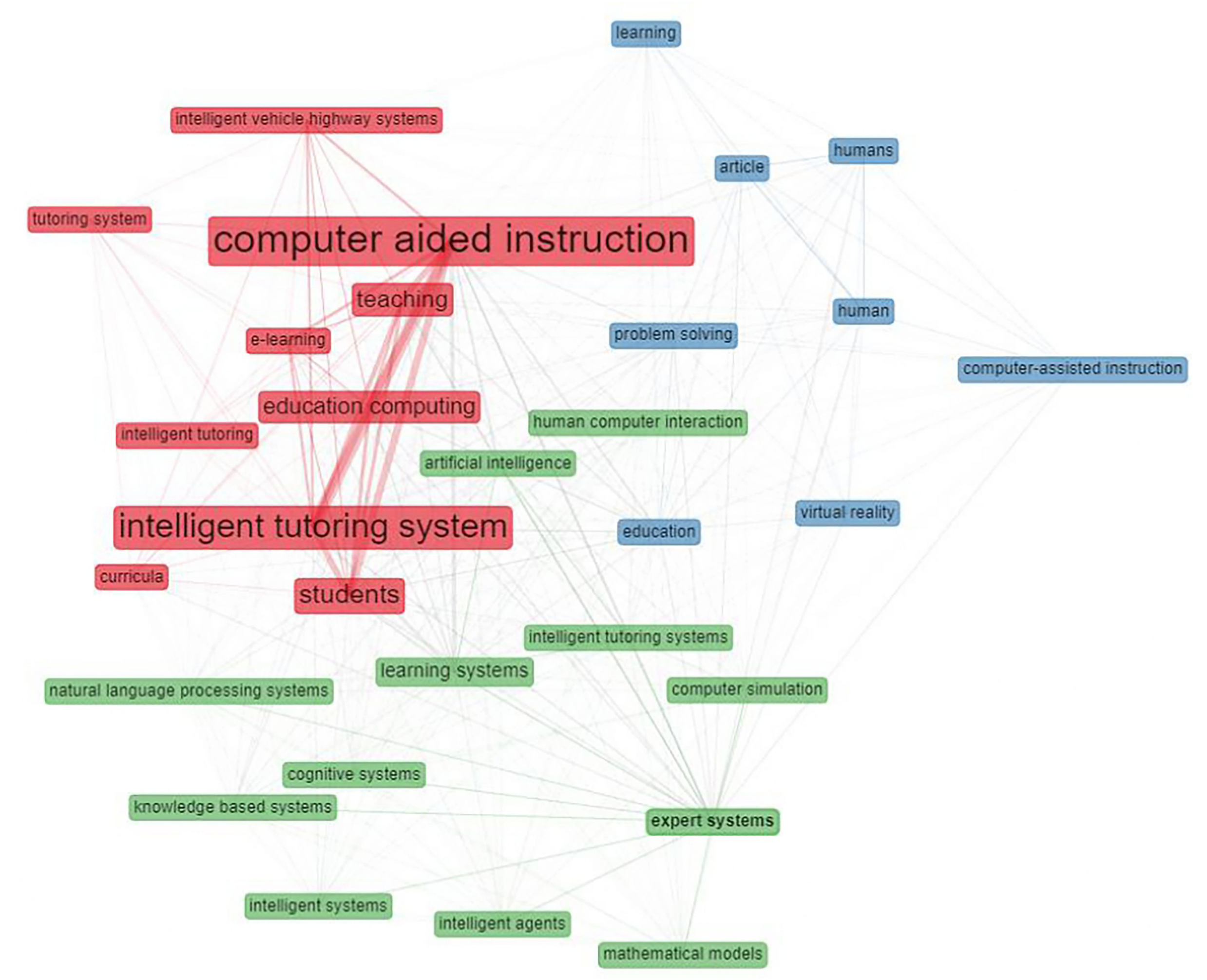


FIGURE 5
Co-occurrence of words in Keyword Plus from all sources.

In the "document" column, the text and the contribution weight for each of the terms were displayed.

The topic_3, represented in yellow in Figure 8, emerges naturally among the analyzed abstracts. The terms that compose it are affective, assessment, data, emotion, method, model, performance, result, student, and system, all of which have high values for this studio.

Data extraction

The results with high values were used as the selection criteria to link the full texts analyzed in NVivo in the next phase. From the text mining of the emerging group represented in Figure 9A, 163 papers were selected. It is essential to consider that the weight of the term *assessment* is not high compared to the other terms identified in topic_3 and even less compared to the total number of identified terms, as shown in Figure 9B.

Results

In this section, a year-wise representation is given in Figure 10.

These results were characterized by research questions posed earlier in this study. The variables of selected studies are presented in Table 3.

- Q1: What is the main purpose of the evaluation in these ITS?
- Q2: What is the main evaluating agent (in evaluation processes)?
- Q3: What is the main approach used in the selected ITS?

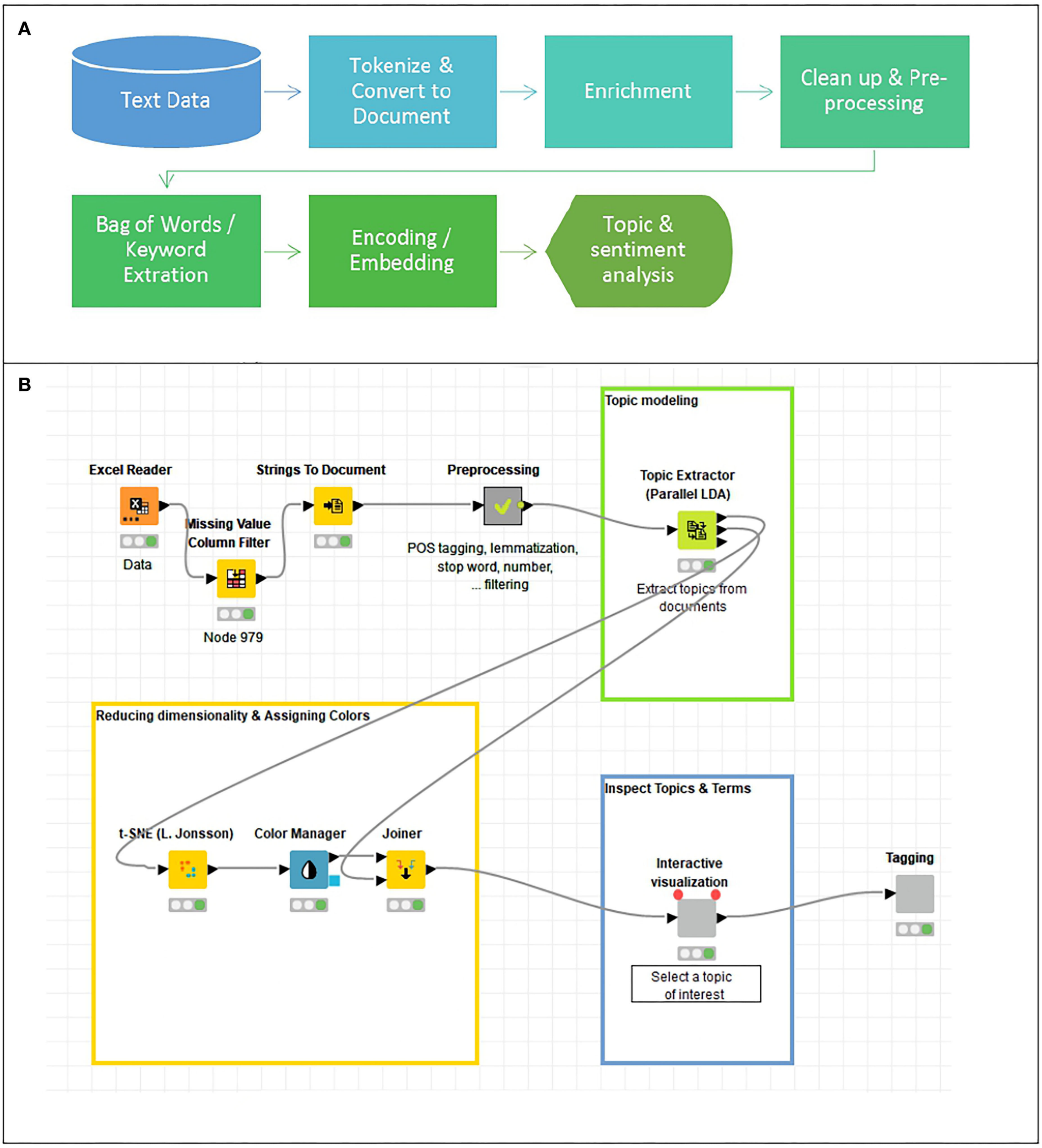


FIGURE 6
(A) Co-occurrence of words in a flow-diagram and **(B)** Co-occurrence of words in Keyword Plus from all sources.

- Q4: Is the ITS evaluation process implemented holistically?

To answer these questions, three pillars were considered, namely, each selected paper's purpose, agent, and evaluation approach. Using the NVivo program (NVivo, 2020), a case has been created for each. Subsequently, the percentages of their presence in the selected complete papers have been identified with a search matrix. Finally, considering that a proper holistic evaluation uses all the pillars comprehensively, the holistic column has been completed, with the finding that none of the studies possess the simultaneous presence of all the sub-variables. Table 4 summarizes the results and identifies whether the study was holistic or not. The continuation of Table 4 is presented in Annex A.

Next, we present each research question and its results.

- Q1: What is the main purpose of the evaluation in these ITS?

According to the data found, the primary purpose of the evaluation is summative; that is, most of the evaluation sections in the ITS analysis tried to establish reliable balances of the results obtained, focusing on the collection of information and the elaboration of instruments that allow reliable measurements of the knowledge to be evaluated at the end of a teaching-learning process.

- Q2: What is the main evaluating agent (in evaluation processes)?

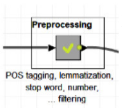
The main evaluating agents were those external to the student or their peers; that is, hetero evaluation was prioritized. This is consistent with the purpose found in question 1. Most ITS identify gaps or "weak spots" that need to be reinforced before moving forward with the program and design redress activities aimed at the group or individuals who require it.

- Q3: What is the main approach used in the selected ITS?

The main approach was quantitative, which makes sense since smart tutors use data to achieve process automation. However, qualitative approaches were evidenced to a lesser extent, and in some cases, both were used due to the technological development that allows emotional interpretation and the participants' language.

- Q4: Is the evaluation process implemented in ITS holistic?

TABLE 2 Item description of KNIME workflow.

Image	Name	Description
	Excel reader	It allows incorporating a database obtained from Scopus in Excel format.
	Missing Value Column Filter	This node removes all columns from the input table that contain more missing values.
	Strings to Document	It converts the specified strings to documents. For each row, a document will be created and attached to that row.
	Preprocessing	This is a metanode, which groups several nodes responsible for multiple tasks, including Part of Speach tagging, lemmatization, stop word, number, filtering. Inside this metanode are the elements shown in Figure 6B.

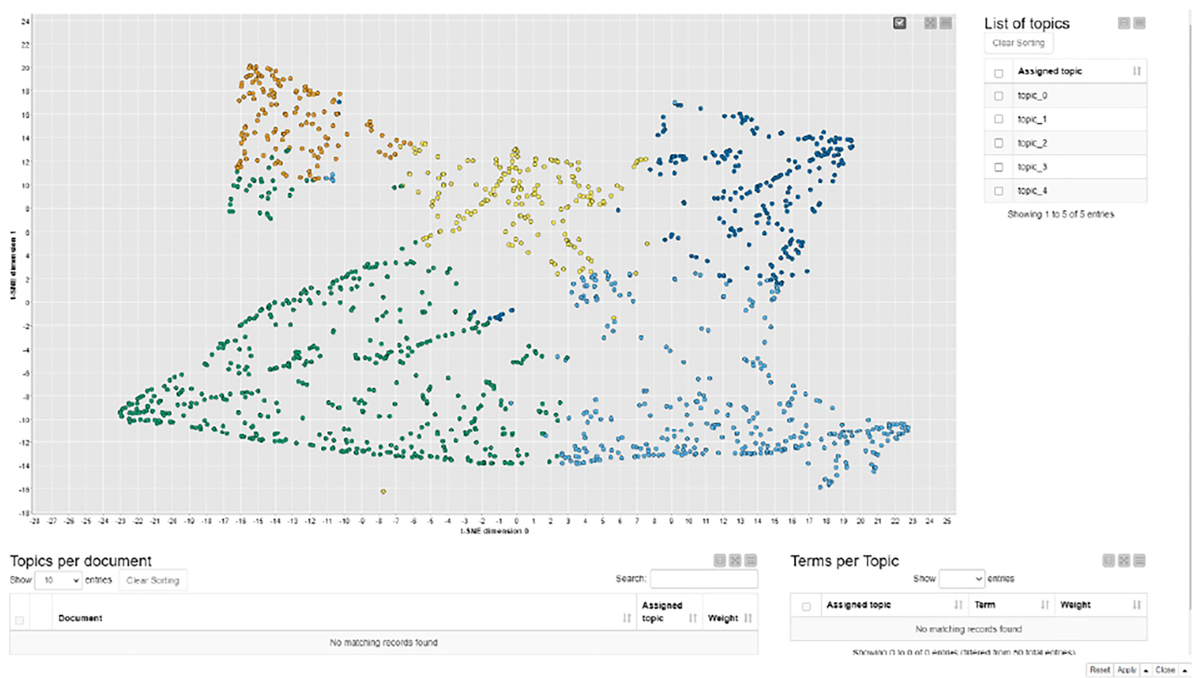


FIGURE 7
Inspect topics and terms.

FIGURE 8
Inspect topics and terms exploration.

To answer this question, the criterion was the following: in each of the selected papers, diagnostic, formative, and summative evaluation elements were sought. Whether the STI used hetero evaluation, peer review, or self-assessment was also tracked. Furthermore, it was determined whether it integrated qualitative and quantitative approaches. All this accounted for a holistic assessment that favors deep learning. Texts that met all these criteria would be classified as holistic.

Under the criteria applied, it is possible to affirm that holistic designs were not found in the analyzed texts. Mainly, special attention is required for the diagnostic and formative evaluations. Furthermore, it is also necessary to encourage the participation of other agents in the evaluation processes of ITS, specifically peer evaluation and the participation of other actors, such as the family. Finally, the mixed approach can enrich the reading of the process; the qualitative evaluative aspects in ITS are a technical challenge; however, these can be included through professionally trained bots.

Emerging challenges

Based on Table 4, it was possible to identify the analysis foci and propose the following challenges.

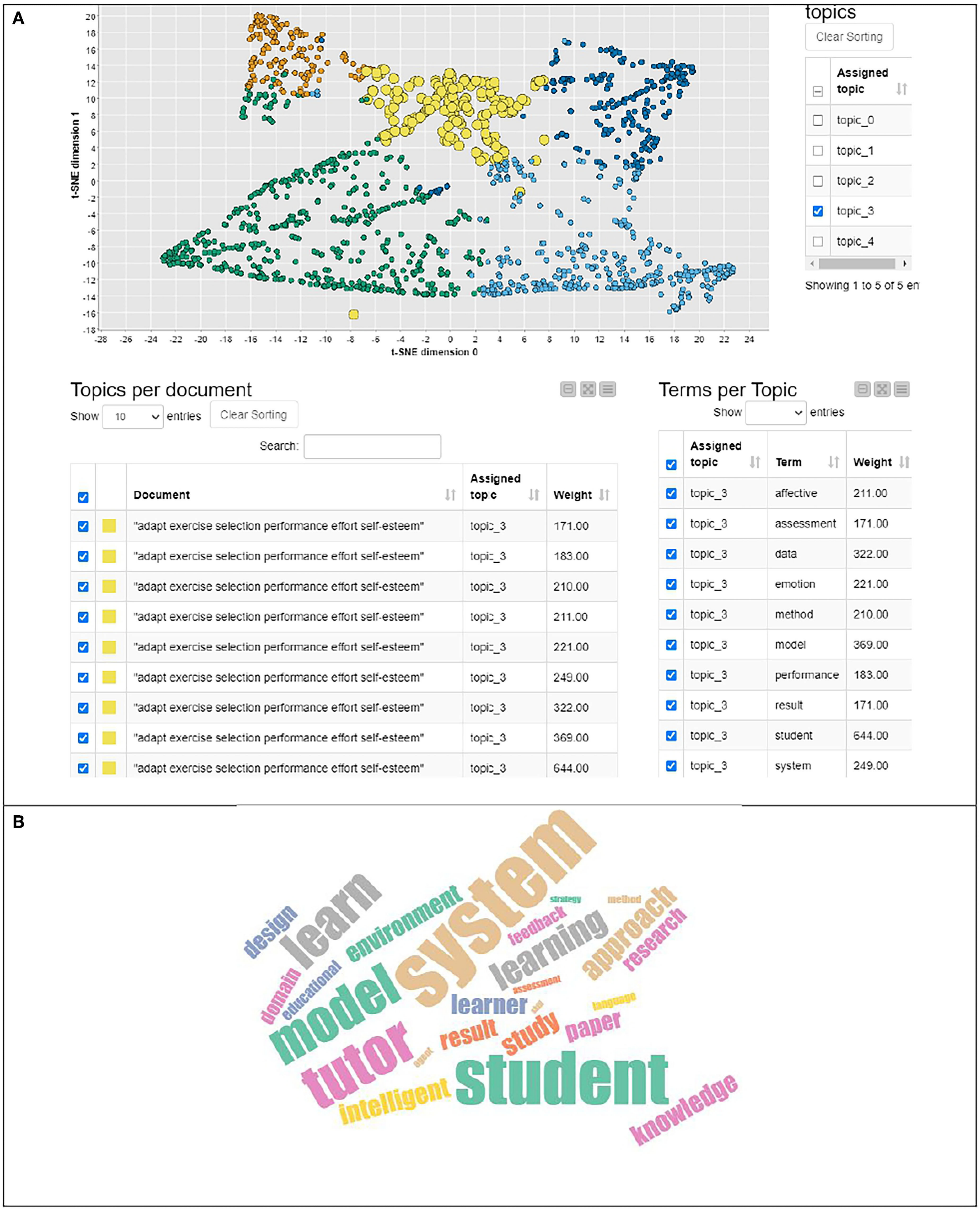


FIGURE 9
(A) Inspect topics and terms, highlighting topic 3, related to the assessment and **(B)** Inspect topics and terms as a word cloud.

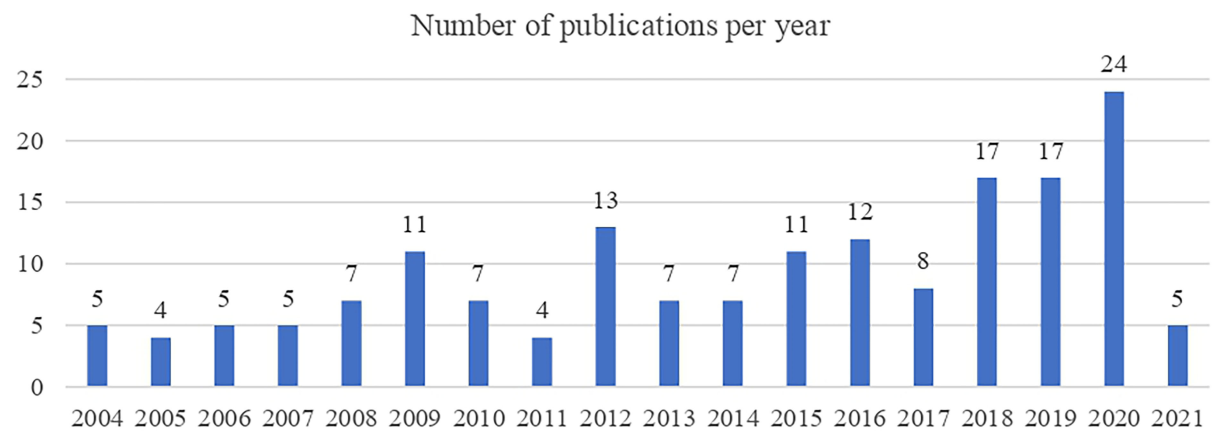


FIGURE 10
The number of publications per year.

TABLE 3 Analyzed variables.

Variables	
Purpose	Diagnostic evaluation
	Formative evaluation
	Summative evaluation
Evaluating agent	Self-assessment
	Co-evaluation
	Hetero evaluation
Approach	Qualitative evaluation
	Quantitative evaluation
Holistic	Yes
	No

Demonstrate the pedagogical value of scaffolding by intelligent tutors

According to Arevalillo-Herráez et al. (2017), to facilitate problem-centered instructional models, scaffolding is necessary, that is, contingent support from another more capable person who helped others solve complex problems and acquire valuable skills in doing so; these include deep content learning, argumentation skills, and problem-solving skills. Providing this type of coaching traditionally requires small groups and personalized training processes.

Using intelligent tutoring systems, it is possible to provide this support in large groups; however, the expected learning outcomes of scaffolding respond to different variables, such as cognitive, motivational, or metacognitive aspects. In the cognitive aspects, it has been found that intelligent tutoring systems favor noteworthy progress. However, the motivational and metacognitive aspects require further research to demonstrate their pedagogical value. This can be evidenced by the priority given in the selected full texts to evaluating summative aspects.

Link an efficient evaluation mechanism

Current trends indicate that online learning has become a vital learning mode; however, the analyzed texts did not identify a holistic evaluation mechanism.

The learning performance assessment assess what students learn during the process. It is usually summative or formative; however, both have been confused with the rating in some ITS, focusing on materializing a numerical value. This is clearly due to the learning framework in which each research is inscribed. However, to mobilize higher thinking skills such as problem-solving, critical thinking, or creativity (typical of deep learning), and according to the results found in Table 4, it is necessary to complement this approach with qualitative approaches.

Use multiple data sources

The fundamental challenges to address when considering an intelligent tutor are usually the data sources to feed the predictive models, which come from the summative assessment, such as the result of exercise A or the performance in unit B (Anderson et al., 2011). However, it is crucial to determine the pedagogical value of the actions that led to these results and their implications in predicting the participants' performance (Penumatsa et al., 2006).

The need to link e-learning environments with intelligent tutoring systems

In large-scale courses, for example, accurate and meaningful evaluation is a demanding task for tutors. Assessment of students' performance on exercises could delay the tutor's feedback to students for days or even weeks. Then, sometimes, tutors may have to reduce the number of assignments given to their students due to time constraints. Moreover, achieving accuracy is often challenging for subjective and objective reasons.

TABLE 4 Results.

	Paper	Purpose			Evaluating agent			Approach		Holistic
		A: Diagnostic	B: Formative	C: Summative	A: Hetero assessment	B: Peer assessment	C: Self-assessment	A: Qualitative	B: Quantitative	
1	Muldner and Burleson (2015)	16.67%	0%	83.33%	94.74%	0%	5.26%	0%	100%	No
2	Alqahtani et al. (2021)	0%	0%	100%	91.49%	0%	8.51%	0%	100%	No
3	Sanz Garcia et al. (2019)	0%	0%	100%	100%	0%	0%	4.35%	95.65%	No
4	Van Amelsvoort et al. (2013)	0%	0%	100%	100%	0%	0%	0%	100%	No
5	Zheng et al. (2019)	0%	42.65%	57.35%	100%	0%	0%	4.76%	95.24%	No
6	Gobert et al. (2015)	0%	22.22%	77.78%	52.47%	47.53%	0%	0%	100%	No
7	Anderson et al. (2011)	0%	0%	100%	100%	0%	0%	0%	100%	No
8	Anderson (2012)	0%	0%	100%	100%	0%	0%	0%	100%	No
9	Anderson et al. (2012)	0%	0%	100%	100%	0%	0%	0%	100%	No
10	Rus and Stefanescu (2016)	0%	33.33%	66.67%	100%	0%	0%	11.11%	88.89%	No
11	Paaßen et al. (2018)	0%	0%	100%	100%	0%	0%	0%	100%	No
12	Penumatsa et al. (2006)	0%	0%	100%	100%	0%	0%	1.96%	98.04%	No
13	Krivec and Guid (2020)	0%	2.63%	97.37%	100%	0%	0%	0%	100%	No
14	Whitehill et al. (2014)	0%	0%	100%	100%	0%	0%	0%	100%	No
15	Kuk et al. (2017)	8.33%	0%	91.67%	100%	0%	0%	0%	100%	No
16	Yang et al. (2009)	100%	0%	0%	100%	0%	0%	0%	0%	No
17	Olsen et al. (2020)	0%	0%	100%	50%	46.15%	3.85%	0%	100%	No
18	Kabanza and Rousseau (2005)	100%	0%	0%	100%	0%	0%	0%	0%	No
19	Snow et al. (2016)	0%	25%	75%	100%	0%	0%	10%	90%	No
20	Yang and Li (2018)	0%	5.26%	94.74%	65.06%	25.30%	9.64%	1.89%	98.11%	No
21	Jraidi and Frasson (2013)	0%	0%	100%	100%	0%	0%	0%	100%	No
22	Abbasi et al. (2010)	0%	0%	100%	100%	0%	0%	0%	100%	No
23	Abdi and Idris (2014)	17.65%	0%	82.35%	100%	0%	0%	0%	100%	No
24	Šarić-Grgić et al. (2020)	0%	0%	100%	100%	0%	0%	0%	100%	No
25	Mostow and Beck (2006)	0%	0%	100%	63.33%	36.67%	0%	16.67%	83.33%	No
26	Guzmán and Conejo (2005)	0%	30%	70%	74.74%	0%	25.26%	0%	100%	No
27	Alepis et al. (2008)	0%	0%	100%	100%	0%	0%	0%	100%	No
28	Khalfallah and Ben Hadj Slama (2017)	0%	0%	0%	0%	0%	0%	0%	0%	No
29	Chen et al. (2013)	0%	16.67%	83.33%	100%	0%	0%	0%	100%	No
30	Litman and Forbes-Riley (2006)	0%	0%	100%	100%	0%	0%	14.29%	85.71%	No
31	Nielsen et al. (2009)	0%	14.29%	85.71%	100%	0%	0%	0%	100%	No
32	Castillo et al. (2014)	0%	0%	100%	100%	0%	0%	0%	0%	No
33	Kaya et al. (2015)	0%	0%	100%	100%	0%	0%	0%	100%	No
34	Ting and Phon-Amnuaisuk (2012)	8%	4%	88%	100%	0%	0%	0%	100%	No
35	Moradi et al. (2014)	2.94%	17.65%	79.41%	74.51%	25.49%	0%	0%	100%	No
36	Moridis and Economides (2009)	0%	0%	100%	54.72%	0%	45.28%	35.29%	64.71%	No

Possible solutions to the emerging challenges

In the above discussion, several challenges were identified. To address them, the following research challenges are posed.

Understand and implement the difference between evaluating and grading

Intelligent tutoring systems require moving toward an interpretation of the numerical results, which allows for feedback as proposed by Daniel Wilson, director of the "Zero" project at Harvard University, who indicates that the feedback process consists of the following four ascending phases: clarify, value, express concerns, and make suggestions, which allows focusing on communication with the student in the construction of meaning toward the achievement of deep learning (Krechevsky et al., 2013). Currently, developments have focused on grading.

Designing a holistic framework

The theory of conscious processes, elaborated by Álvarez de Zayas (2010), is of a systemic, holistic, and dialectical nature, that is, complex. It presents a redefinition of the school as a space where teaching and systematization would eventually lead to the training process essentially. This is currently ratified by Schildkamp et al. and Shemchack and Spector, who agree that evaluation can be understood in a systemic, articulated, holistic, and dialectical manner (Schildkamp et al., 2020; Shemshack and Spector, 2020). Teachers need to move easily between diagnostic, formative, and summative approaches at the evaluation time. Focusing only on instruments that lead to a numerical assessment is not enough, since these results are important sources of information about teaching and learning processes, but they need to be complemented with peer or self-assessment tools that include aspects related to purpose, extension, evaluating agents, moments, approaches, and standards of comparison. These dialectically produced instruments favor cognitive and metacognitive processes.

Focus on the process, not just the outcome

To provide a solution to this aspect, ITS must move toward formative evaluation, which implies collecting, analyzing, and identifying student progress (learning monitoring) and reflecting, providing feedback, reorienting, and creating support strategies for students (pedagogical use of the results). The latter is a technological challenge, which implies training the ITS not only with quantitative data.

Implement learning analytics systems that impact the curriculum

When the evaluation process is done correctly, changes to the curriculum emerge naturally, enabling the student to access authentic deep learning. This line of research would imply establishing a framework that allows artificial intelligence to detect new learning goals for the students based on the analysis of mixed data.

Conclusion

The use of text mining was fundamental to extracting knowledge from a wide field of academic production. Other researchers in different fields can use the workflow adapted in KNIME to optimize reading time and focus attention only on the aspects of interest.

Based on intelligent tutors' research, it was possible to identify that progress has been made in detecting concepts that require further study in the constant feedback given to students and teachers in a personalized and automatic way. First, however, it is necessary to propose a framework that offers mixed feedback to students and teachers and facilitates decision-making based on implementing predictive methods, an evaluation that transcends the grading, which is possible due to the fusion between pedagogical and technological aspects.

Deep learning seeks to give meaning to new information; that is, it aims to incorporate critical perspectives on specific learning and, in doing so, favors its understanding to allow its long-term retention. Achieving it requires moving toward a complex evaluation that involves different evaluation forms, actors, moments, approaches, and analyses.

The ITS requires moving toward interpreting the numerical results, allowing communication with the student to focus on constructing meaning toward a holistic evaluation. This holistic evaluation includes the student's participation and peers' diagnostic, formative, and summative aspects. These changes will allow it to account for the depth of learning achieved.

Moving toward this type of evaluation involves analyzing quantitative and qualitative variables. Therefore, it is necessary to create a framework that allows artificial intelligence to integrate all these variables and effectively communicate its results. In other words, an ITS is required to assess and measure all variables related to deep learning and achieve a truly holistic assessment.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://docs.google.com/spreadsheets/d/1suQHtzhovtvXITp v-C_KCMSpoJbOudDz/edit?usp=sharing&ouid=103572763070360419912&rtpof=true&sd=true.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2022.1047853/full#supplementary-material

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