Strategies of Intelligent Tutoring Systems to Engage Students in Online Learning Before LLM Approaches

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ABSTRACT

Context: Several studies have investigated the integration of Intelligent Tutoring Systems (ITS) in education. However, there is still a gap in understanding approaches that promote student engagement in online learning. **Problem**: The literature lacks specific analyses that clarify the role of ITS in supporting student engagement in online learning environments, particularly before the advent of Large Language Models (LLM). **Solution**: This study analyzes the (inter)national literature to identify indicators of ITS contributions to student engagement, focusing on solutions implemented prior to the adoption of LLM. **ITS Theory**: The research is grounded in ITS theory by addressing ITS as mediating tools in online learning interactions, emphasizing their potential for enhancement through novel technological approaches. **Method**: Relevant articles from the literature were selected and reviewed to map themes addressed by ITS, identify the main types of solutions, and evaluate their implications for future ITS designs. **Summary of Results**: The results highlight the themes explored by ITS, the primary solutions developed, and their implications. Among the 15 studies analyzed in the Brazilian context, they also emphasize the potential of combining earlier and current solutions while maintaining the crucial role of human tutors in the teaching-learning process. **Contributions and Impact on ITS**: This study advances the ITS field by offering theoretical and practical insights for designing ITS that integrate traditional and modern approaches. By focusing on the relationship between ITS and student engagement, the research contributes to the development of tools that enhance online learning effectiveness and foster better interactions between students, systems, and human tutors.

CCS CONCEPTS

• Applied computing • Education • E-learning

KEYWORDS

Intelligent Tutoring Systems, engagement, student e-learning, Large Language Models.

1 INTRODUCTION

The transformation brought about by the integration of Artificial Intelligence (AI) technologies has been the subject of years of research and applications across various contexts and domains [1-7]. Intelligent Tutoring Systems (ITS) represent AI applications in education, designed to provide a personalized learning environment with recommendations, guidance, and immediate feedback that fosters greater student autonomy [8]. With the advent of Large Language Models (LLMs), applications such as ChatGPT [9-11] and Google Gemini [11], have emerged as advanced examples of LLM-based approaches. However, despite numerous studies exploring how ITS can leverage these models to deliver personalized and engaging teaching and learning environments [11], there remain significant limitations in understanding how ITS effectively support student engagement [12-14]. Specifically, there is a lack of clear guidelines to inform the design process, often leading to ITS approaches that inadequately involve key stakeholders in solution specification. At this point, it is argued that user involvement in the design process is critical, as has been widely adopted in other domains [15-16]. Whereas, before the advent of LLMs, ITS had already established well-defined theoretical and methodological frameworks, enabling the formulation and resolution of specific problems without reliance on advanced language models and focusing on task-specific applications. Research in Natural Language Processing (NLP) and symbolic AI had long addressed fundamental issues such as knowledge extraction, ontologies, and rule-based learning, which justifies the continued investigation of these approaches without the immediate integration of generative models. This, in turn, allows for future discoveries regarding the potential contributions of such models to upcoming ITS developments.

Thus, this study aims to map the themes explored, strategies implemented over the years, and trends adopted prior to the emergence of LLM-based approaches, with a particular focus on the Brazilian education context and the key implications of ITS for enhancing student engagement in teaching and learning processes. Consequently, the objective of this research is to examine the strategies documented in the literature, focusing on work conducted before the advent of LLM-based approaches to the development of tutoring systems aimed at engaging students. It also seeks to highlight the possibilities for collaboration between human tutors and emerging ITS. To achieve this goal, methodological criteria were applied to select relevant studies from the literature (Section 2).

2 REVIEW METHOD AND PROTOCOL

To review studies featuring ITS solutions that focus on student engagement in online learning contexts [17], a process flow (Figure 1) was developed, comprising the following stages: planning, execution, and reporting [18].

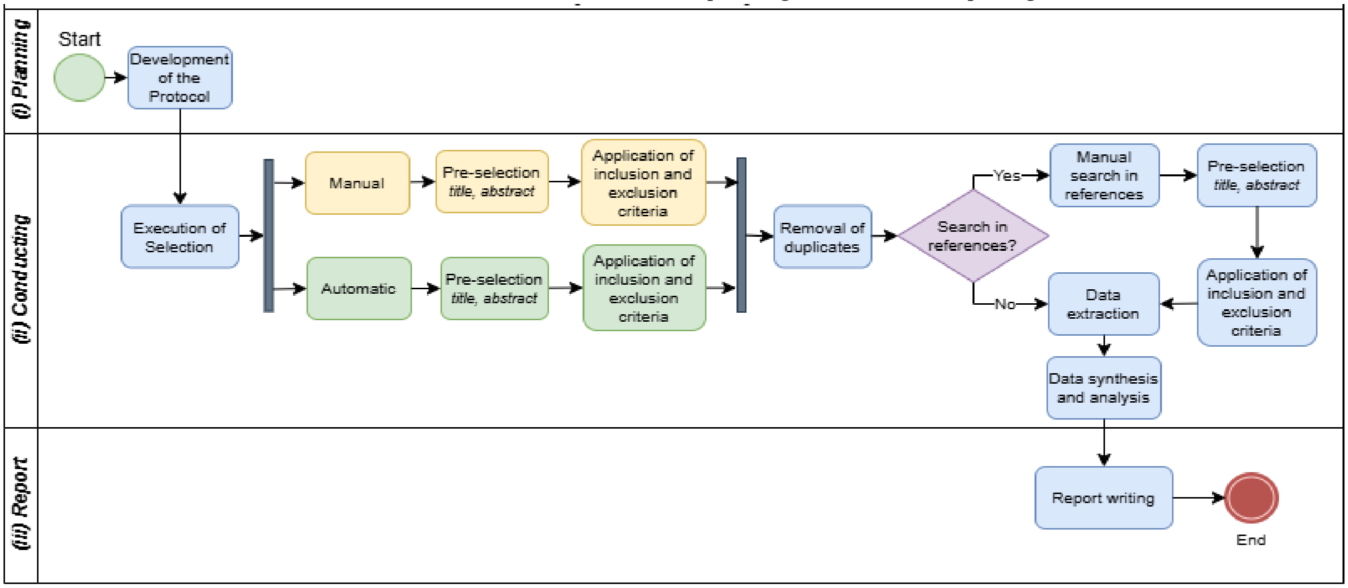

Figure 1: Activity Flow for Study Review.

The study review process follows (Figure 1) a structured methodology comprising three key phases: Planning, Conducting, and Reporting. Initially, a study protocol is developed, defining objectives, criteria, and methods. The Conducting phase involves selecting studies based on predefined criteria, evaluating them for inclusion or exclusion, removing duplicates, and performing a reference search to identify additional relevant sources. In the Reporting phase, data is extracted, analyzed, and synthesized to address the research question, culminating in comprehensive results that the methodology, findings, and implications of the review. This systematic approach ensures rigor, transparency, and reliability in study evaluations. Searches were conducted using indexed study resources, following techniques and procedures structured into stages as defined in the following sections (Sections 2.1, 2.2, 2.3, and 2.4).

2.1 Motivation, Objective, and Research Questions

Tracking student engagement is not an easy task, especially when it comes to online learning [19-20]. This is because it is challenging to understand how students interact and what keeps them engaged [21]. Intelligent tutors have been helping to analyze student engagement indicators, but there is still a general lack of understanding about how these solutions are developed and adopted, even in the most current approaches. To better understand the strategies of intelligent tutors used before the advent of LLM-based approaches, the following question was posed: "What strategies were employed by tutoring systems to promote engagement in online learning in tutoring contexts before the advent of LLM approaches?" In seeking an answer to this question, a review of studies in the literature can help achieve the following objectives: (i) to understand which intelligent tutoring approaches were being adopted in technologies with features that could be applied to online learning; (ii) to understand the main challenges faced in engaging students in online-mediated learning; (iii) to identify the different types of intelligent tutors and gaps where further studies are needed; (iv) to map the evidence from studies on intelligent tutors aimed at promoting student engagement in online learning prior to the emergence of LLM approaches. To achieve these objectives, Research Questions (RQs) were raised to guide data extraction, bibliometric analysis, synthesis, and presentation of the results: **RQ1**: *"What educational contexts were addressed by studies on Intelligent Tutoring Systems (ITS) aimed at engaging students?"* **RQ2**: *"How were ITS being developed to engage students in online learning?"* **RQ3**: *"What were the main types of ITS being created to engage students in online learning?"* **RQ4**: *"What are the limitations and possibilities for the evolution of ITS* *to support engagement in online learning?"* **RQ5**: *"What themes were being associated with ITS to engage students in Brazilian online learning?"*.

2.2 Sources and Data Collection

The following factors were considered: (i) availability of studies for consultation on the Web; (ii) availability of indexing databases capable of performing searches based on specified keywords; (iii) free access to the full-text documents of the primary studies. The data collection followed the methodology of Song and Wang [22] and Cuéllar-Rojas *et al*. [23], defining indexing databases as sources: Scopus, ACM Digital Library, IEEE Xplore® Digital Library, and Web of Science. The search utilized widely used keywords such as "intelligent tutoring systems" and "engagement," along with their respective synonyms ("adaptive educational system," "adaptive learning systems," "constraint-based tutors," "cognitive tutor," "autotutor," "student modeling," "knowledge tracing") and ("learner engagement," "school engagement"). These keywords and synonyms were reviewed considering aspects present in the literature related to the keywords and aligned with the research question's purpose, aiming to minimize errors and return the maximum number of studies on the topic. The searches were limited to studies published up until November 2022 (the month and year of the release of ChatGPT, the first widely known approach for the adoption of LLM models launched by OpenAI), with the search string formed by the keywords connected to their respective synonyms, as follows:

("intelligent tutoring systems" **OR** "adaptive educational system" **OR** "adaptive learning systems" **OR** "constraint-based tutors" **OR** "cognitive tutor" **OR** "autotutor" **OR** "student modeling" OR "knowledge tracing") **AND** ("engagement" **OR** "learner engagement" **OR** "school engagement")

2.3 Selection of Primary Studies

To initially filter the articles (in both automatic and manual searches) related to the theme of this study, a pre-selection process was conducted (reading titles and abstracts) of the primary articles returned. If the article did not correlate with the topic, it was excluded from further stages of the review. In the automatic searches, search strings and information retrieved from databases were utilized. In contrast, the manual search involved navigating through results and databases to identify relevant studies. Subsequently, Inclusion Criteria (IC) were applied: **IC1**: Articles proposing the use of Intelligent Tutoring Systems (ITS) for engaging students. **IC2**: Studies published until November 29, 2022 (one day before the launch of ChatGPT). **IC3**: Studies written in English or Portuguese. Additionally, the following Exclusion Criteria (EC) were applied to exclude studies that met any of the following conditions: **EC1**: Works written in languages other than English or Portuguese. **EC2**: Not accessible on the web. **EC3**: Duplicates: if the same study was available from different sources, only the first version was considered. **EC4**: Duplicate studies: similar studies were considered, but only the most recent and/or comprehensive version was included. **EC5**: Exclusion of gray literature (non-scientific evidence). **EC6**: Exclusion of incomplete documents, such as abstracts, drafts, or presentation slides. **EC7**: Studies related to ITS that are not specifically concerned with student engagement in online learning. The data collection was conducted by one researcher and reviewed by other members of the research team, who evaluated the inclusion and exclusion criteria as described.

2.4 Data Extraction and Analysis

The search options available in each database were used to apply the search string, which led to the retrieval of primary studies (Figure 2): Scopus (331 studies), ACM (605 studies), IEEE Xplore (51 studies), and Web of Science (195 studies). Using the platforms' own resources, the research was limited articles in English and Portuguese. After the pre-selection, application of inclusion and exclusion criteria, and removal of duplicates, a total of 330 studies were obtained. From these, the following information was collected: title, abstract, authors, context, methodology, problem statement, proposed solution, and applications.

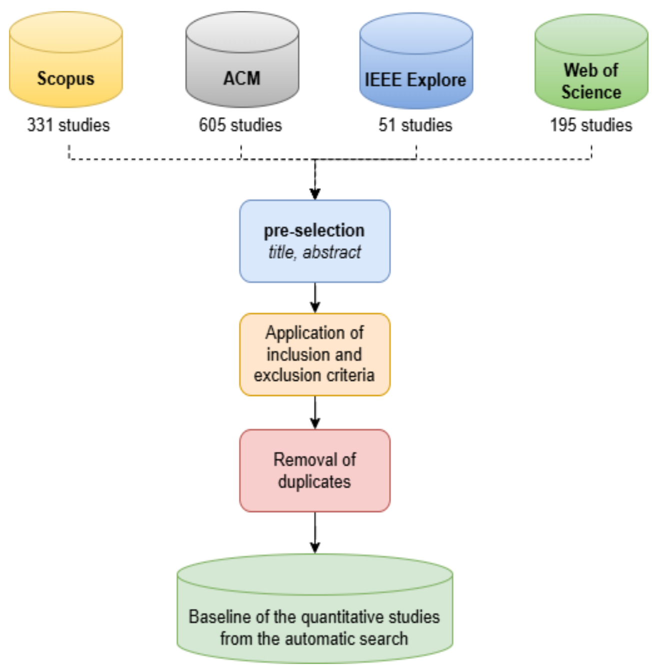

Figure 2: Flow of Search and Study Results for Review.

To analyze the resulting studies, approaches were used to provide insights into the past, present, and future possibilities of intelligent tutors supporting student engagement in online learning. In this phase, descriptive statistical analysis of co-citation (past), bibliographic coupling (present), and co-word analysis were employed to guide future research in emerging technologies. Table 1 presents the strategies adopted in the search for answers to the research questions.

Table 1: Relationship between Research Questions, Method, Analysis Tool, and Justification.

RQ	Technique	Tools	Justification
RQ1	Descriptive	Spreadsheets	Present the distribution of studies by year, authors, citations, countries/regions, journals, contexts, and educational levels adopted.
RQ2	Descriptive	Spreadsheets	Present how the research areas on ITS correlate.
RQ3	Co-word Analysis	VOSviewer	Form clusters of co-occurrence of keywords that represent the adopted themes.
RQ4	Burst Detection	VOSviewer	Present the co-cited references with a map of the most recent arrangement of thematic trends.
RQ5	Thematic Groups	CiteSpace	Present the themes of the references with the type of node: titles, abstract, and keywords, cosine strength, scope by slices, and g-index criteria.

Note: RQ - Research Questions.

The data were analyzed using CiteSpace v6.1.6 and VOSviewer v1.6.18. In the co-word analysis, the keywords from the authors in each study were used. The generated maps utilized term extraction from the titles and abstracts of the studies. The counting method is expressed by the minimum occurrence of a given term with 10 (ten) other terms. Out of 20,304 terms, 701 reached the threshold. For each of the 701 terms, a relevance score was calculated, and based on this score, the most relevant terms were selected. The default selection was 60% of the most relevant terms. Clusters (groups) of themes were formed based on the main strategies for constructing the maps. The analyses of Brazilian studies in CiteSpace were conducted with the following parameters: data collection period from 2011 (availability of studies) to 2022 (before LLM approaches), slice per year, node type of title, abstract, and keywords, cosine of the link, scope by slices, and criteria with g-index [24], modified in each slice to include nodes with a scale factor of $k = 25$.

3 RESULTS AND DISCUSSION

When analyzing the studies by year, a reference was found that dates back to 1994 [25]. There has been a growing number of publications, especially since 2008, reaching 32 studies in 2022. Bibliometric analysis allows us to assess the trends and changes in knowledge about the topic over time [26]. The United States, the United Kingdom, and Canada were the leading countries in conducting studies in this thematic area, enabling us to evaluate the differences and similarities in the results obtained in different geographical contexts. Brazil ranked 11th. The authors (Graesser, A.; D'Mello, S.; Mitrovic, A.) had the most publications. The fields of Computer Science (47.0%), Social Sciences (17.9%), and Mathematics (14.9%) had the highest percentages of publications, allowing us to evaluate how the topic was addressed across different fields of study (Figure 3). As anticipated in research question RQ1.

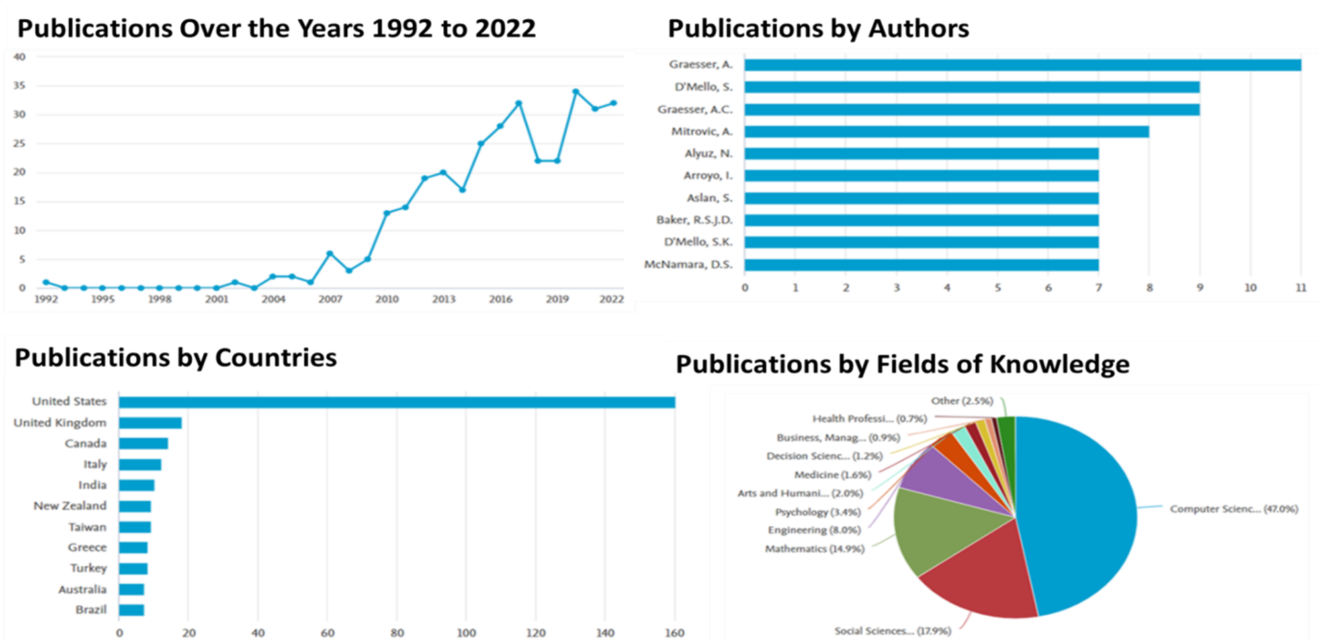

Figure 3: Studies on ITS and engagement in online learning.

The studies on Intelligent Tutoring Systems (ITS) for student engagement were grouped around three main themes (Figure 4): [blue] interaction: Fundamental for the learning and development of students, especially in the context of online learning. This theme highlights the importance of interactive environments where students can engage actively with the content and the system. [red] gamification: Utilized game elements (points, rewards, and challenges) to motivate students, promote collaboration, and encourage teamwork. This approach focuses on increasing student engagement through game-based dynamics. [green] algorithms: Employed computational tools and resources to analyze aspects such as emotion and attention levels in order to maintain engagement. This theme underscores the use of advanced algorithms to monitor and respond to students' emotional and cognitive states. These three themes reflect the diverse strategies used in ITS to enhance student engagement in online learning environments.

The [**blue**] **interaction** (Figure 4) theme was addressed by establishing completeness with the development of social skills, emotions, attention levels, gestures, confidence, and individual differences. In this case, the studies focused on interactions across different paradigms (tutoring, tutor, and peer agents) that affected children's emotional development, including tutors with characteristics of social robots [27-28]. Emotions were linked to attention, affecting how students learned and directly connected to motivation. In this context, the studies explored how ITS used algorithms (e.g., fuzzy) to improve recommendation accuracy [29]. Analyzing or assessing students' emotions (through expressions, spoken or written dialog interactions) to mediate new interactions, reduce feelings of loneliness, and increase student motivation, especially when activities were designed to involve collaboration and teamwork [30-32]. To understand student trust, particularly when they were encouraged to share their ideas, knowledge, and skills, facial expressions and gestures were explored to enhance the experience [31].

Individual differences were also explored, with perceived patterns of difficulties where tutors familiarize themselves with the way of interacting with students to appropriately adjust the teaching process [32]. Overall, students' interactions in online learning can be complex, varied, with different goals and expectations. The ITS examined in these studies aim to streamline interactions by employing algorithmic strategies, often reducing or eliminating human involvement. However, research suggests that while ITS can enhance human capabilities, minimizing human presence may hinder the development of complex cognitive skills, such as knowledge construction, intellectual growth, and engagement [33]. In response to and as anticipated in research question RQ4.

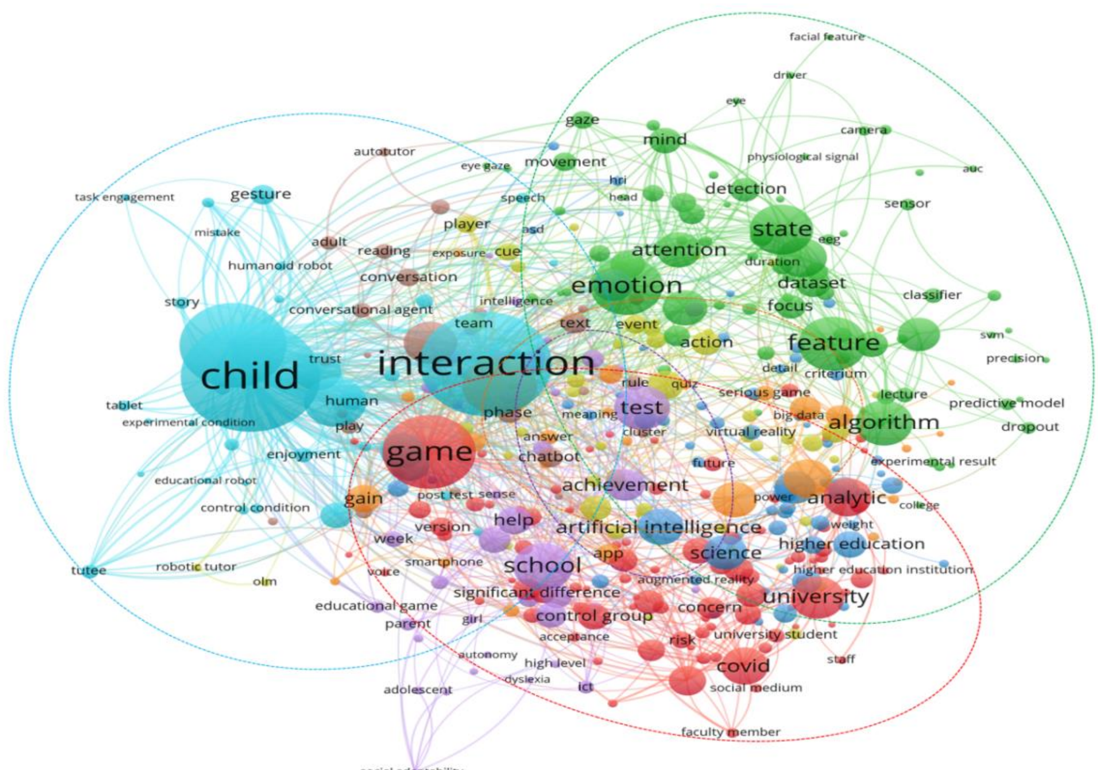

Figure 4: VOSviewer: thematic groups on ITS to engage students.

Gamification [**red**] (Figure 4) was approached as a playful way of learning that can improve engagement and learning outcomes in technology-supported learning environments [34]. In online learning, engagement indicators [levels of interaction - with contact rates and mutual communication; assessment - with likes; sharing - with the number of times materials were distributed to other students; reach - with the number of students who studied the subject; comments - with students' collaboration regarding doubts and discussions] can be used to assess students' involvement and motivation, providing insights into performance that assist in decision-making. However, due to concerns about screen time and its potential deficits in terms of social interaction, engagement was proposed through mixed learning experiences (physical and/or digital) [35]. In other cases, scaffolding strategies [36], were used, which involve collecting and providing support to students while they learn, with evidence-centered design based on cognitive evidence over time or task time behaviors [37]. These strategies featured granularity (providing progressively less support), adaptability (according to individual skills), collaboration (active student involvement to minimize difficulties), and process focus (rigor in the process, generous with the results). This aligns with Vygotsky's sociocultural theory of development, where the ITS could operate in the zone of proximal development by providing certain scaffolds, but the interesting part is combining this with peers and human instructors [38].

Regarding **algorithms** [**green**] (Figure 4), some of the strategies included Machine Learning algorithms, which analyzed data about students' progress to identify patterns and trends. Multiple approaches, primarily ensemble classifiers [39], were employed. These allowed tutoring related to content and activities [40], based on recommendations (about students' preferences), classification (highlighting important content), natural language processing (already present to understand and respond to questions in dialogues), optimization (finding correlations between subjects), clustering (grouping students and content by similarities), regression (to track levels of interactions and predict dropouts and dilatory behavior), neural networks (also present, to process large sets of data), and decision trees (to track behavior patterns).

3.1 Strategies of ITS before LLM to engage students

When analyzing the strategies of the studies for ITS solutions developed before the LLM approaches, focused on engaging students in online learning (Figure 5), the studies primarily adopted algorithms such as SVM (Support Vector Machine) [41]. The tutoring approaches were generally conversational (human conversation simulations) or autotutors (with characteristics of a "digital twin" directed at the "tutee" receiving the tutoring) [27]. The devices used included tablets to access virtual learning objects, with one study addressing techniques and narrative tips through a tutoring chatbot that could be employed. However, in this case, the "Wizard of Oz" technique was used [42]; cameras, which helped recognize students' emotions in images or videos [42]. Despite being previously addressed in earlier studies [43-45], both in On-Task (online tasks mediated virtually) or Off-Task (offline tasks mediated locally) [46-47]; and hardware resources - for communication between devices (infrared, camera, capacitive touch) and the ITS itself [48], even assessing the sense of smell in students [49]. As anticipated in research question RQ2 and RQ3.

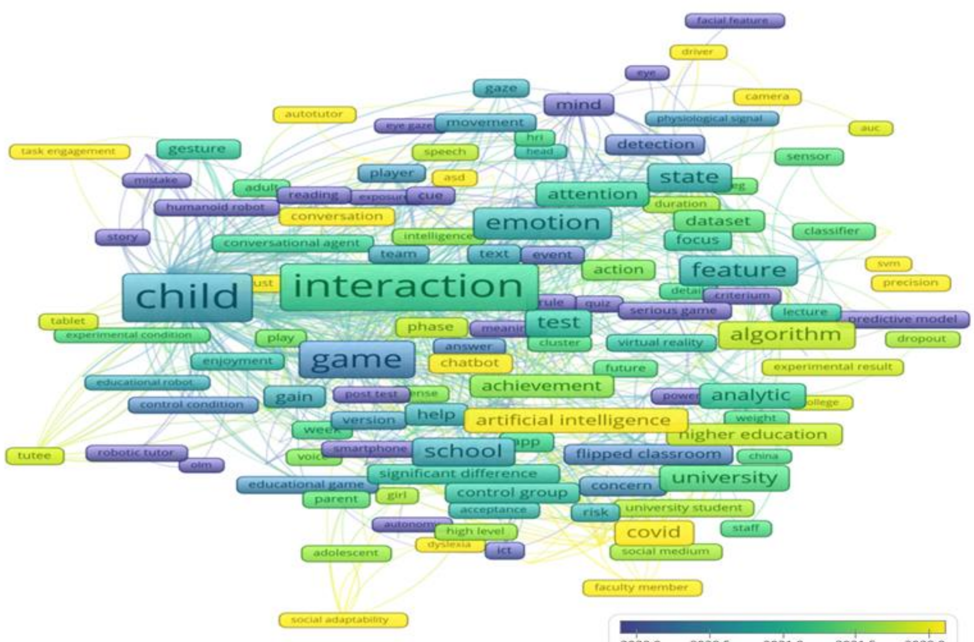

Figure 5: VOSviewer: Groups over the years (before LLM approaches).

The resources were primarily addressed in dealing with some student disorders [50]. The pandemic drove the rapid adoption of ITS solutions in remote and hybrid learning, underscoring the demand for adaptive and personalized experiences. However, despite greater reliance on these technologies, innovation in engagement and interactivity remained limited, leaving a persistent research gap post-pandemic. During the Covid-19 pandemic, ITS approaches focused on monitoring gestures, interests, and understanding motivation in performing activities. To measure the effectiveness of AM models, the use of precision and accuracy as statistical indicators stands out. Even in more recent research, there are few studies addressing the improvement of human-computer interactions [51]. This could be overcome, in our view, by involving human tutors and students in the design process of ITS. Interested in understanding the Brazilian educational context, the next section (Section 3.2) highlights studies conducted in Brazil.

3.2 Brazilian studies before LLM and implications of ITS to engage students

The Brazilian studies (Appendix A), conducted before the advent of LLM, already highlighted chatbots, gamification, and learning analytics, in addition to discussing human-chatbot interaction, the use of virtual environments, and games to improve academic performance in various areas and educational levels. Some papers focus on specific populations, such as deaf children, the importance of interactions between students and teachers, and explore the use of simulated students (Wizard of Oz) to test new systems. Figure 6 presents thematic groups on ITS to engage students in Brazilian online learning.

Although few studies highlight the Brazilian context, positive evaluations can be observed regarding the effectiveness of ITS in improving student learning and engagement, such as adaptive learning systems (adjusting content and pace according to performance) [S02] [S12] [S13], conceptual design (involving student needs) [S02] [S04], data visualization (presenting information graphically or pictorially) [S03], educational robots (materializing the tutor physically in medical simulation) [S15], data mining (extracting useful information in collaborative learning contexts) [S12], involving the environment [S06], as well as classrooms or competitive online learning platforms [S04] [S05]. In response to and as anticipated in research question RQ5.

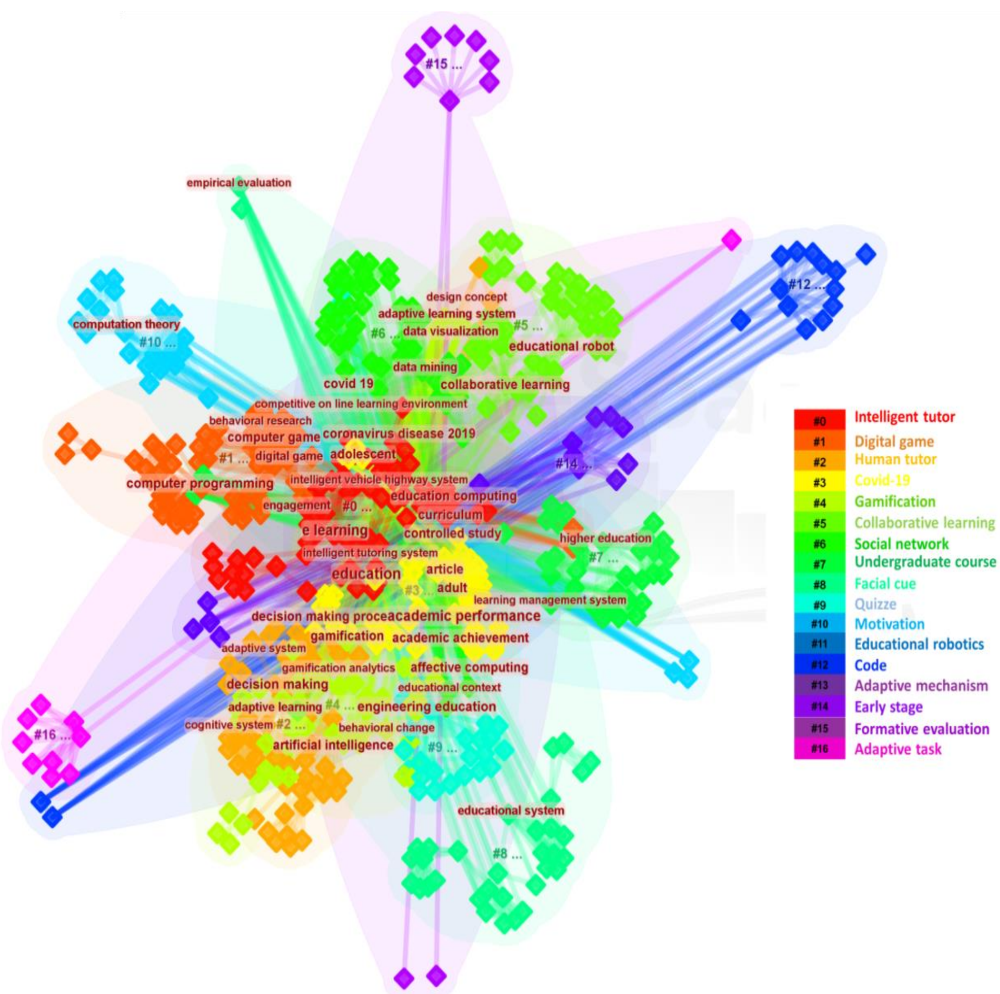

Figura 6: CiteSpace: Thematic groups for Brazilian studies.

With empirical evaluation strategy [S11], computational theory (analyzing the effectiveness of algorithms) [S13], behavioral research (focusing on behaviors) [S10]. Gamification (especially in the context of the coronavirus pandemic) [S04] [S05] [S07], to assist in decision-making (about learning methods) [S06] [S09], based on academic performance (knowledge levels) [S11], using analytics strategies (for discovering, interpreting, and communicating patterns, improving decisions and performance) [S03] [S04]. Cognitive systems and AI strategies were also adopted (imitating students' cognition) [S08], for behavioral change (thoughts, emotions, or actions) [S01] [S14].

4 CONSIDERATIONS

Strategies adopted before the advent of LLM approaches to make learning more engaging and motivating were identified, such as interaction analysis, gamification, progress tracking, content customization, learning objectives, recommendations, rewards, and support to overcome difficulties. These strategies used student performance data to adapt teaching, provide personalized suggestions, and encourage engagement. The identified intelligent tutors supported the analysis of engagement indicators in online learning to offer continuous and progress-adjusted feedback. However, it is understood that, even with emerging approaches, they cannot replace social interaction and emotional support offered by human tutors. Therefore, it remains important to design models that complement human teaching and tutoring, rather than trying to replace it. STI solutions tend to prioritize machine learning algorithms over didactic-pedagogical and human factors, which can limit understanding and make interactions more artificial. It is important to emphasize that human tutors play a fundamental role in perceiving interpersonal factors and adjusting to students' individual needs. In this sense, it is still emerging to find design elements that promote cooperation between humans and AI, in order to propose a new generation of STI that aligns with generative Artificial Intelligence (AI) contexts and is more assertive in addressing challenges. Future possibilities for this study include mapping and reviewing articles aimed at incorporating STI approaches to engage students in online learning, conducted post-advent of approaches powered by large language models, such as ChatGPT [OpenAI], Gemini [Google], Copilot [Microsoft], LLaMA [Meta], among others. Can also explore, practical reports on projects or approaches, including technologies used, the number of students impacted, and the stakeholders involved. A practical analysis of the differences between national and international approaches could provide insights into their advantages, disadvantages, challenges, and recommendations for tutors and other participants. Additionally, the human-computer interaction aspects of the developed systems could be tested, clarifying the evidence highlighted by these systems based on the availability of additional ITS data.

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Appendixes

Appendix A - Studies Produced in Brazil Before LLM Models, on STI and Student Engagement.

#	Title	Authors	Year	Source
S01	A Proposal of Model of Emotional Regulation in Intelligent Learning Environments	Reis, H.M., Alvares, D., Jaques, P.A., Isotani, S.	2021	Informatics in Education
S02	How Should My Chatbot Interact? A Survey on Social Characteristics in Human–Chatbot Interaction Design	Chaves, A.P., Gerosa, M.A.	2021	International Journal of Human-Computer Interaction
S03	Using learning analytics in the Amazonas: understanding students' behaviour in introductory programming	Pereira, F.D., Oliveira, E.H.T., Oliveira, D.B.F., (...), Toda, A., Isotani, S.	2020	British Journal of Educational Technology
S04	Raising teachers empowerment in gamification design of adaptive learning systems: A qualitative research	Tenório, K., Dermeval, D., Monteiro, M., Peixoto, A., Pedro, A.	2020	Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in

				Bioinformatics)
S05	A Gamified Solution to the Cold-Start Problem of Intelligent Tutoring System	Pian, Y., Lu, Y., Huang, Y., Bittencourt, I.I.	2020	Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)
S06	Exploring navigation styles in a futurelearn MOOC	Shi, L., Cristea, A.I., Toda, A.M., Oliveira, W.	2020	Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)
S07	GaTO: An Ontological Model to Apply Gamification in Intelligent Tutoring Systems	Dermeval, D., Albuquerque, J., Bittencourt, I.I., (...), Silva, A.P., Vassileva, J.	2019	Frontiers in Artificial Intelligence
S08	AI and education: the importance of teacher and student relations	Guilherme, A.	2019	AI and Society
S09	Improving decision-making in virtual learning environments using a tracing tutor agent	Filho, A.H., Thalheimer, J.M., Dazzi, R.L.S., Santos, V., Koehntopp, P.I.	2019	ICEIS 2019 - Proceedings of the 21st International Conference on Enterprise Information Systems
S10	Conceptual framework to support a web authoring tool of educational games for deaf children	Dos Passos Canteri, R., García, L.S., Felipe, T.A., Oliveira Galvão, L.F., Antunes, D.R.	2019	CSEDU 2019 - Proceedings of the 11th International Conference on Computer Supported Education
S11	The use of a serious game and academic performance of undergraduate accounting students: An empirical analysis	Malaquias, R.F., Malaquias, F.F.O., Borges Junior, D.M., Zambra, P.	2018	Turkish Online Journal of Distance Education
S12	Engagement in digital games and web applications using adaptive matching-To-sample tasks in teaching reading	De Souza, G.N., Brito, Y.S., Lopes, D.F., (...), De Santana, A.L., Dos Santos Assuncao, F.	2017	2017 International Symposium on Computers in Education, SIIE 2017
S13	Implementation and use of Simulated Students for Test and Validation of new Adaptive Educational Systems: A Practical Insight	Dorça, F.	2015	International Journal of Artificial Intelligence in Education
S14	Tutorial Intervention's Affective Model Based on Learner's Error Identification in Intelligent Tutoring Systems	Ascari, S.R., Pimentel, A.R., Gottardo, E.	2021	International Conference on Intelligent Tutoring Systems
S15	Integração da interface phantom ao sistema tutor inteligente para o ambiente de simulação médica	Melo, J.S.S., Brasil, L.M., Panerai, C.E.B., da Silva, A.P.B.	2011	Brazilian Journal of Biomedical Engineering V. 27 (2) p. 98-109, 2011