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Educational and administrative AI-based conversational agents in Virtual Learning Environments (VLEs/LMSs): a Systematic Literature Review

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Abstract: This Systematic Literature Review aims to analyze current trends regarding educational and administrative AI-based conversational agents integrated into Virtual Learning Environments/Learning Management Systems (VLEs/LMSs). The review describes existing solutions and examines empirical evidence of their effectiveness. Methodologically, the study applied PRISMA 2020 guidelines to 42 studies selected from 234 records retrieved across seven databases (2022–2026). Findings reveal a clear shift from rule-based chatbots to systems utilizing Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG). Most existing implementations consist of small-sample pilot projects focused primarily on tutoring, feedback, administrative support, and

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student engagement. While results regarding effectiveness are generally favorable, methodological heterogeneity and a lack of longitudinal studies limit the generalizability of these findings.

Keywords: Conversational agents; Artificial Intelligence; Virtual Learning Environments.

Agentes conversacionais educacionais e administrativos baseados em inteligência artificial em Ambientes Virtuais de Aprendizagem (AVAS/LMS): uma Revisão Sistemática da Literatura

Resumo: O objetivo desta Revisão Sistemática de Literatura é analisar as tendências sobre agentes conversacionais educacionais e administrativos baseados em Inteligência Artificial integrados a Ambientes Virtuais de Aprendizagem/Learning Management System (LMS). A revisão descreve as soluções existentes e examina as evidências empíricas de efetividade. Metodologicamente, o estudo aplicou as diretrizes PRISMA 2020 a 42 estudos selecionados a partir de 234 registros recuperados em sete bases (2022-2026). Os estudos mostram uma mudança clara de *chatbots* baseados em regras para sistemas com Large Language Models (LLM) e Retrieval-Augmented Generation (RAG). A maior parte é composta por pilotos com amostras pequenas, voltados sobretudo a tutoria, feedback, suporte administrativo e engajamento. Há resultados favoráveis quanto à efetividade, mas a heterogeneidade metodológica e a falta de estudos longitudinais limitam a generalização.

Palavras-chave: Agentes conversacionais; Inteligência Artificial; Ambientes Virtuais de Aprendizagem.

Agentes conversacionales educativos y administrativos basados en inteligencia artificial en entornos virtuales de aprendizaje (EVAS/LMS): una Revisión Sistemática de la Literatura

Resumen: El objetivo de esta Revisión Sistemática de la Literatura es analizar el estado del arte sobre agentes conversacionales educativos y administrativos basados en IA integrados a EVAs/LMS. La revisión describe las soluciones existentes y examina las evidencias empíricas de efectividad. Se aplicaron las directrices PRISMA 2020 a 42 estudios seleccionados entre 234 registros recuperados en siete bases (2022–2026). Los estudios muestran un cambio claro de chatbots basados en reglas a sistemas con LLMs y RAG. La mayoría son pilotos con muestras pequeñas, dirigidos sobre todo a tutoría, retroalimentación, apoyo administrativo y compromiso. Hay resultados favorables en cuanto a efectividad, pero la heterogeneidad metodológica y la falta de estudios longitudinales limitan la generalización.

Palabras clave: Agentes conversacionales; Inteligencia Artificial; Entornos Virtuales de Aprendizaje.

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1 INTRODUCTION

Virtual Learning Environments (VLEs) have become central infrastructure in online education, and the rapid advancement of Artificial Intelligence (AI) — particularly Large Language Models (LLMs) — has opened new possibilities for automating and personalizing pedagogical mediation. Educational conversational agents, supported by these technologies, are being proposed as a large-scale mediation tool in platforms such as Moodle, Canvas, and Blackboard.

Despite the growth of scientific production at this intersection, literature remains fragmented. Some reviews focus exclusively on educational chatbots, others are restricted to LLMs in the classroom, and others focus on Moodle without encompassing the broader range of VLEs/Learning Management Systems (LMSs). In this direction, the absence is noted of a consolidated overview regarding the techniques employed, the pedagogical goals addressed, the modes of integration into LMSs, and the empirical evidence of effectiveness.

This Systematic Literature Review (SLR) seeks to address this gap. The objective is to analyze trends regarding educational and administrative AI-based conversational agents integrated into VLEs/LMSs, taking Moodle as a primary, though not exclusive, reference. The analysis describes existing solutions and examines the empirical evidence of their effectiveness within the 2022–2026 timeframe.

The article is organized into six sections. Section two presents the theoretical background guiding the review. Section three details the methodology in accordance with PRISMA 2020. Section four presents the results and discussion addressing the six research questions. Section five lists future research directions. Section six concludes the study.

2 THEORETICAL BACKGROUND

This section presents the four conceptual pillars guiding the review: Virtual Learning Environments (VLEs/LMSs) and their central role in online education; Massive Open Online Courses (MOOCs) and the challenge of large-scale pedagogical mediation; chatbots and conversational agents as a potential response to this challenge, along with the systematization of the technological generations that characterize them; and Artificial Intelligence applied to education, highlighting Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG).

2.1 Virtual Learning Environments and Learning Management Systems

Virtual Learning Environments (VLEs) and Learning Management Systems (LMSs) are digital platforms that organize online course delivery within a single institutional space: content, activities, synchronous and asynchronous communication, assessment, and analytics. In Brazil, Moodle predominates as an open-source software adopted by the majority of public universities and distance education programs. In the international market, Canvas and Blackboard hold equivalent positions.

The consolidation of VLEs/LMSs has progressed through three main waves: course organization around content delivery and discussion forums (1990s–2000s); social learning tools, mobile accessibility, and learning analytics (2010s); and, from 2020 onward, AI integration and conversational support—a wave significantly accelerated by the COVID-19 pandemic. Despite these advancements, the traditional VLE/LMS model replicates an asynchronous content delivery structure in which human mediation is inherently constrained by scale. This point, central to the core argument of this review, was further amplified by the rise of MOOCs and has driven the development of conversational agents as a solution for automated mediation.

2.2 MOOCs and the Challenge of Large-Scale Mediation

Massive Open Online Courses (MOOCs) consolidated from 2008 onward through platforms such as Coursera, edX, and Udacity, bearing the promise of democratizing access to higher education via open courses with thousands of enrollees. The xMOOC model, closely following the logic of scaled lecture-based instruction, came to dominate commercially, bringing its central problem into sharp focus: the absence of pedagogical mediation at scale. Completion rates between 5% and 15% (Jordan, 2015) were interpreted as symptoms of a framework in which students remain isolated in the face of video lectures and automated quizzes.

Belloni (2009) pointed out that personalization without intentional mediation fragments learning; in MOOCs, this risk manifested in an extreme form. Garrison, Anderson, and Archer (2000) argue, in the Community of Inquiry framework, that online learning depends on the articulation among social, cognitive, and teaching presences, an articulation that large-scale MOOCs tend to compromise. The resulting operational question is whether it is possible to restore personalized

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mediation at scale without multiplying the teaching staff, and conversational agents emerge as a potential response.

2.3 Chatbots and Conversational Agents as a Response to the Absence of Mediation

Conversational agents (chatbots, virtual assistants, intelligent tutors) are systems that interact with the user in natural language and can offer pedagogical and administrative support in a scalable manner. In VLE/LMS contexts, they occupy the space left by the absence of sufficient human mediation: they answer conceptual and operational questions, offer formative feedback, guide study trajectories, and support administrative tasks (enrollment, deadlines, platform navigation).

The technical evolution of these systems can be organized into three overlapping generations, along with a fourth (hybrid) approach that has recently gained traction. Each generation offers a distinct trade-off between control (predictability, cost) and flexibility (coverage, adaptation). Box 1 synthesizes this contrast.

Box 1 – Comparative synthesis among technological generations of conversational agents

GERAÇÃO	TÉCNICAS PREDOMINANTES	FUNÇÕES TÍPICAS	PONTOS FORTES	LIMITAÇÕES
1ª — Regras e NLP clássico	Dialogflow, Rasa, intents/entities, FSM, Bag of Words	FAQ, suporte administrativo, navegação no LMS	Previsibilidade, baixo custo, latência baixa	Pouca flexibilidade lexical, manutenção contínua
2ª — ML, grafos e adaptativos	Random Forest, GNN, RL, TF-IDF, k-means	Recomendação, adaptação por perfil	Personalização orientada por dados	Demanda massa de dados, opacidade decisional
3ª — LLM e RAG	GPT-4/4o, Llama, Gemini, LangChain, Chroma/FAISS	Tutoria conceitual, feedback adaptativo	Fluência, cobertura, contextualização	Custo, risco de alucinação, dependência de curadoria
Híbrida (regras + LLM)	Roteamento determinístico + LLM + RAG, orquestração (n8n, LangChain)	Combinação de tutoria e administrativo	Compromisso entre controle e flexibilidade	Complexidade arquitetural e operacional

Source: prepared by the authors based on research data.

The pedagogical perspective supporting the use of these agents finds support in Vygotsky (1991): the agent can act as a more knowledgeable other, offering cognitive scaffolding within the

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Zone of Proximal Development. Moore (1993), through the Theory of Transactional Distance, suggests that adaptive interaction reduces the perception of pedagogical distance. This theoretical framework guides the empirical analysis presented in the results section.

2.4 Artificial Intelligence Applied to Education

Artificial Intelligence (AI) in education encompasses a broad set of techniques: supervised and unsupervised machine learning, natural language processing (NLP), knowledge graphs, reinforcement learning, and, more recently, Large Language Models (LLMs) based on the Transformer architecture (Vaswani et al., 2017). The combination of these techniques in educational systems initiated a period of intense experimentation between 2022 and 2026, the timeframe adopted in this review.

LLMs such as GPT-4, Llama, and Gemini answer questions from practically any domain in fluent language, but they can hallucinate, that is, generate plausible yet incorrect responses, which is critical when the target audience is a student in training. Retrieval-Augmented Generation (RAG) mitigates this problem: the system retrieves excerots from a database of curated documents (slides, textbooks, course materials) and includes them into the prompt, so that the response remains anchored to the official source. RAG became standard practice in educational solutions from 2024–2025 onward.

The articulation among VLEs/LMSs as infrastructure, conversational agents as an interface, and LLMs with RAG as the engine defines the object of this review. The subsequent sections describe the methodology adopted and the findings on how this articulation has been implemented and evaluated in recent literature.

3 METHODOLOGY

The research follows the guidelines of Kitchenham and Charters (2007) and Kitchenham et al. (2010) for systematic reviews in software engineering, the PRISMA 2020 recommendations (Page et al., 2021), and methodological guidance from the Cochrane Collaboration (Higgins et al., 2022). A Systematic Literature Review (SLR) identifies, evaluates, and synthesizes primary studies based on a pre-defined protocol. The difference compared to Systematic Mapping lies in the analytical depth, involving quality assessment and evidence synthesis.

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The protocol was defined prior to the search process and encompasses: objectives, research questions, search strings adapted for each database, inclusion and exclusion criteria, the selection process according to PRISMA, quality assessment, and data extraction forms. The questions follow a descriptive-evaluative framework: separating the mapping of what exists from the empirical analysis of what works. Three tools supported the execution of this work and ensured traceability; their detailed description is provided in Section 3.6.

For each included study, the extraction form recorded a standardized set of variables organized into four main blocks: (i) bibliographic identification (authors, year, country, and publication type); (ii) agent characterization (name, type as pedagogical, administrative, or hybrid, functions performed, and target audience); (iii) technical dimension (AI techniques and models employed, use of RAG, VLE/LMS platform, and form integration); and (iv) evaluative dimension (methodological design, sample size, instruments and metrics used, such as TAM, SUS, NASA-TLX, and performance tests, as well as main reported results). These variables feed directly into the syntheses in Box 2 and 3 and the analysis per research question.

The variable integration method with the VLE/LMS was coded into five categories: native plugin, when the agent code is installed directly within the LMS and accesses its data internally; integration via REST API, when an external agent communicates with the platform through authenticated calls; decoupled *middleware*, when microservices and orchestrators mediate between the agent and the platform; embedded *widget* or *iframe*, when only the agent interface is incorporated into course pages; and conceptual proposal, when the architecture is described without functional implementation. This coding standardizes the analysis for RQ1 and allows comparing the degree of coupling among solutions.

3.1 Objective and research questions

The objective is to analyze trends in AI-based educational and administrative conversational agents integrated into VLEs/LMSs, taking *Moodle* as the primary, though not exclusive, reference. The analysis describes existing solutions and examines empirical evidence of their effectiveness. Six research questions (RQs) guided the study, as listed in Box 2.

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Box 2 – Research questions of the SLR

ID	QUESTÕES DE PESQUISA
QP1	Quais tipos de agentes conversacionais educacionais e administrativos baseados em IA foram propostos ou integrados a AVAs/LMS, incluindo o Moodle como principal exemplo?
QP2	Quais técnicas, modelos e abordagens de Inteligência Artificial são utilizados nesses agentes conversacionais?
QP3	Quais funções e objetivos (pedagógicos ou administrativos) esses agentes desempenham nos AVAs/LMS?
QP4	Quais estudos realizam avaliação empírica do uso desses agentes em contextos educacionais mediados por AVAs/LMS?
QP5	Quais evidências de efetividade são reportadas pelos estudos avaliativos sobre o uso desses agentes?
QP6	Quais lacunas, limitações e tendências de pesquisa são identificadas na literatura?

Source: prepared by the authors.

3.2 Search strategy and sources

The strategy combined four conceptual axes linked by the Boolean operator AND. Within each axis, synonyms were joined by the OR operator. The axes were: (1) Conversational Agent (*chatbot*, *conversational agent*, *virtual assistant*, *pedagogical agent*, *intelligent tutor*, *dialogue system*); (2) Artificial Intelligence (*artificial intelligence*, *machine learning*, *natural language processing – NLP*, *large language model – LLM*); (3) VLEs/LMS (*virtual learning environment*, *learning management system*, *LMS*, *AVA*, *Moodle*); and (4) Education (*education*, *teaching*, *learning*, *ensino*, *aprendizagem*). The timeframe covered 2022 to 2026, including publications in English, Portuguese, and Spanish.

The general string was (Axis 1) AND (Axis 2) AND (Axis 3) AND (Axis 4). As an example, the final string applied to the *Scopus* database was:

```
TITLE-ABS-KEY ( ( chatbot OR "conversational agent" OR "virtual assistant" OR "pedagogical agent" OR "intelligent tutor" OR "dialogue system" ) AND ( "artificial intelligence" OR "machine learning" OR "natural language processing" OR NLP OR "large language model" OR LLM ) AND ( "virtual learning environment" OR "learning management system" OR LMS OR AVA OR Moodle ) AND ( education OR teaching OR learning ) ) AND PUBYEAR > 2021 AND PUBYEAR < 2027
```

The same logical structure was adapted to the syntax of each database. In *Web of Science*, TITLE-ABS-KEY was replaced with TS=, and quotation marks were retained for compound

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expressions. In the *ACM Digital Library*, fields were explicitly specified as [Title] and [Abstract]. In *ERIC* (via *EBSCOhost*), native descriptor and title filters were used. For national databases (*BDTD*, *Portal de Periódicos CAPES*, and *SciELO*), the terms were translated into Portuguese (*chatbot*, *agente conversacional*, *assistente virtual*, *tutor inteligente*, *inteligência artificial*, *aprendizagem de máquina*, *processamento de linguagem natural*, *ambiente virtual de aprendizagem*, *AVA*, *Moodle*, *educação*, *ensino*, *aprendizagem*) and applied to the title, abstract, and keyword fields. Across all databases, the four-axis structure and the use of AND between axes and OR between synonyms were maintained, adjusted only for the syntactic specificities of each platform.

The searches were conducted across seven databases (Table 1). In *SciELO*, the manual search utilized simplified combinations executed separately, followed by screening based on title and abstract.

Table 1 – Results by database

BASE DE DADOS	REGISTROS
Scopus	65
Web of Science	23
ACM Digital Library	1
BDTD	5
ERIC	11
Portal de Periódicos CAPES	16
SciELO	113
TOTAL	**234**

Source: prepared by the authors using research data.

3.3 Selection criteria and review procedure

The inclusion criteria (IC) were: studies addressing conversational agents or *chatbots* in educational contexts (IC1); studies using or proposing AI techniques in the agent (IC2); studies related to *Moodle* or comparable LMS/VLEs (IC3); published between 2022 and 2026 (IC4); articles in English, Portuguese, or Spanish (IC5); and primary studies (IC6). The exclusion criteria (EC) were: duplicates (EC1); articles without full text available (EC2); secondary or tertiary studies, such as other reviews, surveys, or mappings (EC3); articles without an AI component, including *chatbots* based

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solely on simple rules (EC4); studies outside the educational context (EC5); and extended abstracts, editorials, tutorials, and presentations without a full article (EC6).

It is important to distinguish what criterion EC4 excludes from what was retained in the review. By "simple rules," we mean systems with fixed, manually coded responses (static decision trees, menus, and predefined answers), without any learning or language processing component. These were excluded. In contrast, first-generation studies employing structured *NLP* and dialogue frameworks — *Dialogflow*, classic *Rasa*, finite state machines (*FSM*), and simple *NLP* techniques (such as *Bag of Words* and intent classification) — were included, as they contain an AI component (intent recognition, classification, or natural language processing) that satisfies criterion IC2.

Title and abstract screening and eligibility assessment through full-text reading were conducted with the support of *Rayyan*, configured in blind mode to ensure reviewer independence. The inclusion and exclusion criteria were systematically applied at each stage: each record received a decision (include, exclude, or hold) from each reviewer and, in cases of exclusion, the corresponding reason. Disagreements were logged directly within the platform and resolved through consensus among the authors during review meetings; when immediate consensus was not reached, a third author served as an arbitrator. This procedure, aligned with the guidelines of Kitchenham and Charters (2007) and reinforced by Higgins et al. (2022), reduces selection bias and enhances process reproducibility.

3.4 Selection process

The selection process followed the four PRISMA stages (Identification, Screening, Eligibility, and Inclusion), as shown in Figure 1.

Identification: 234 records were retrieved from the seven databases (*Scopus*: 65; *WoS*: 23; *ACM*: 1; *BDTD*: 5; *ERIC*: 11; *CAPES*: 16; *SciELO*: 113). All records were imported into *Rayyan* in *BibTeX*/*RIS* format. Automatic deduplication removed 50 duplicates, leaving 184 unique records for screening.

Screening: the 184 records underwent title and abstract analysis in *Rayyan*, resulting in 91 exclusions (EC5: 35; IC1: 19; EC3: 19; EC6: 10) and 93 articles selected for full-text reading.

Eligibility: the full-text reading of the 93 articles resulted in 51 exclusions, 20 of which were due to EC2 (full text unavailable); the remaining reasons, detailed in Figure 1, focused on IC3 (lack of actual integration with LMS/VLEs), EC3, IC4, IC1/IC2, and EC4.

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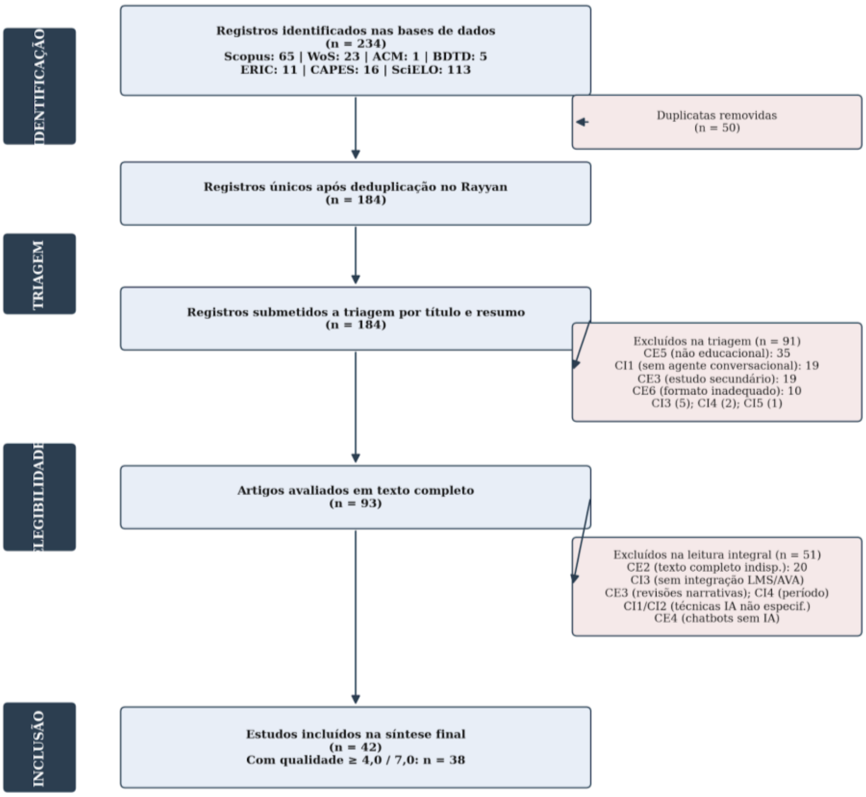
Inclusion: the remaining 42 studies underwent quality assessment. Of these, 38 achieved a score of ≥ 4.0 on a scale from 0 to 7, which was the threshold adopted for acceptable quality. Following Higgins et al. (2022), the four studies with lower scores were not excluded, but were categorized as having a high risk of bias and received reduced weight in the evidence synthesis.

Figure 1 – PRISMA flow diagram of the review



Source: prepared by the authors, based on PRISMA 2020 guidelines (Page et al., 2021).

3.5 Quality assessment

Each included study was evaluated across seven criteria on a scale from 0 to 1 (0 = No, 0.5 = Partially, 1 = Yes): clarity of objectives (QA1); methodological appropriateness (QA2); agent description (QA3); specification of AI techniques (QA4); description of VLE/LMS integration (QA5); presentation of evidence (QA6); and discussion of limitations (QA7). The scores of the 42 studies ranged from 2.0 to 7.0, with a mean of 5.46.

The 4.0 threshold corresponds to approximately 57% of the maximum score and was adopted to ensure a minimum level of methodological rigor. This choice accompanies standard practice in

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systematic reviews, which adopts thresholds between 50% and 60% of the maximum score when using scales that combine yes, partially, and no responses (Kitchenham; Charters, 2007). In line with Higgins et al. (2022), studies below this threshold were not automatically excluded, but retained in the descriptive synthesis with reduced interpretative weight—an approach that preserves transparency, avoids losing marginal evidence, and allows the reader to evaluate the relative robustness of each finding. In this case, 38 studies reached the threshold; 4 were classified as having a high risk of bias (E03 with 3.0; E10 and E11 with 3.5; E43 with 2.0) and were treated with this additional caution. The maximum score of 7.0 was awarded to López-Goyez, González-Briones, and Demazeau (2026, E04); *MoodleBot* by Neumann et al. (2025, E12) scored 6.8.

3.6 Tools and software used

The study utilized three complementary software applications, one for each main phase. In Phase 1, *Parsifal* (Freitas, 2013), a free tool for planning systematic reviews in software engineering, was used to document the protocol: research questions, search strings, inclusion and exclusion criteria, and selected databases. In Phases 2 and 3, *Rayyan* (Ouzzani et al., 2016), a free screening platform featuring collaborative tools and machine learning features, received the 234 records, performed automatic deduplication (removing 50 duplicates), and supported title and abstract screening; all decisions and rationale were logged directly within the platform. *Zotero* (Corporation for Digital Scholarship, 2024) was used across all phases to organize references by database and generate the bibliography list. Table 3 summarizes this division of responsibilities.

Table 3 – Software used in conducting the SLR

SOFTWARE	FINALIDADE	FASE DO FLUXO
Parsifal	Definição do protocolo, questões, strings, critérios	Fase 1 — Planejamento
Rayyan	Importação, deduplicação, triagem com IA, classificação	Fases 2–3 — Busca e Triagem
Zotero	Gestão de referências, organização por base, citações	Todas as fases

Source: prepared by the authors.

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4 RESULTS AND DISCUSSION

The following results analyze the 42 studies included in the final synthesis, organized by the six research questions. Table 4 provides an overview of the selected studies.

Table 4 – Studies included in the final synthesis

ID	REFERÊNCIA	ANO	PLATAFORMA		ID	REFERÊNCIA	ANO	PLATAFORMA
E01	Chamnankij ;Naowanich; Tumthong	2026	LMS genérico		E34	Armas	2025	Moodle
E02	Hu; Yu; Hsieh	2025	Moodle		E35	Puertas; Mariscal-Vivas; Martínez-Requejo	2023	Canvas
E03	Lutfiani et al.	2023	Moodle		E37	Lee; Rew	2025	LMS institucional
E04	López-Goyez; González-Briones; Demazeau	2026	Moodle		E40	Allen; Naeem; Gill	2024	QMPlus (VLE)
E05	Yang et al.	2025	LMS próprio		E41	Vinutha et al.	2025	LMS próprio
E07	Serrano Franco	2025	Web standalone		E43	Ahmed et al.	2024	LMS
E08	Sandra et al.	2024	Moodle		E44	Han	2026	Moodle
E09	Nozhovnik et al.	2023	Smart Sender		E45	Babou et al.	2024	Moodle
E10	Klayklueng; Chatwattana	2025	LMS genérico		E46	Sowmya et al.	2025	Edusphere
E11	Snekha; Ayyanathan	2023	LMS próprio		E47	Costagliola et al.	2025	CLUE LMS
E12	Neumann et al.	2025	Moodle		E48	Macías et al.	2024	Moodle
E13	Chen; Anyanwu	2025	Moodle		E50	Kaiss; Mansouri; Poirier	2023	Moodle
E14	Moraes Neto; Fernandes; Amiel	2022	Moodle		E51	Rasanjani; Anuradha	2024	Moodle
E15	Dahal et al.	2025	Moodle (LXP)		E52	Paunovic; Uyar; Tanic	2023	Moodle
E16	Lytridis; Tsinakos	2025	Moodle		E54	Eltahir; Babiker	2024	Moodle
E17	Sedrakyan et al.	2024	Canvas		E55	Abid et al.	2024	LMS instit. (MyU)
E18	Mzwri; Turcsányi-Szabó	2025	Canvas		E56	Mehnen; Pohn	2024	Moodle
E21	Sabar et al.	2024	Moodle		E58	Simmons; Holanda; Silva	2025	Moodle
E25	Villegas-Ch;	2024	Moodle		E60	Gao et al.	2024	VR (DataliVR)

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ID	REFERÊNCIA	ANO	PLATAFORMA		ID	REFERÊNCIA	ANO	PLATAFORMA
	Govea; Gutierrez							
E29	Vu et al.	2026	Moodle (conceit.)		E66	Alvarado; Guerrero; Serón	2023	CAVE-like VR
E30	Gutierrez; Villegas-Ch; Govea	2025	Moodle		E70	Lecon	2024	LMS genérico + VR

Source: prepared by the authors using research data.

4.1 RQ1: What types of AI-based educational and administrative conversational agents have been proposed or integrated into VLEs/LMSs, including *Moodle* as the primary example?

The temporal distribution of the 42 studies confirms the recent acceleration of the field: 1 study in 2022, 7 in 2023, 14 in 2024, and 16 in 2025; the 4 studies from 2026 reflect only the beginning of the year, when the search was concluded. The literature is geographically dispersed across more than 25 countries, with recurring contributions from Germany (4 studies), India (3), and an Ibero-American axis bringing together Spain, Ecuador, and Brazil. Brazil appears in 3 studies (E14, E34, E58).

Box 2 accounts for the frequency of the primary AI techniques across the 42 studies. *LLMs* appear in 25 studies (60%), followed by *RAG*, present in 18 (43%). First-generation approaches (*Dialogflow*, *Rasa*, *FSM*, and classic *NLP*) are limited to 6 studies (14%), and reinforcement learning to 4. These figures quantify the technical shift of the field: generative AI, absent in the earliest works within the timeframe, has come to support the majority of solutions.

Box 2 – Frequency of primary AI techniques across the 42 studies.

TÉCNICA / ABORDAGEM	ESTUDOS (N)	% DO TOTAL
LLMs (GPT, Llama, Gemini, Claude etc.)	25	60%
Retrieval-Augmented Generation (RAG)	18	43%
Regras / NLP clássico (Dialogflow, Rasa, FSM)	6	14%
Machine Learning / grafos (RF, GNN, k-means)	5	12%
Aprendizado por reforço (RL)	4	10%
Recursos multimodais / socioemocionais	3	7%

Source: prepared by the authors using research data.

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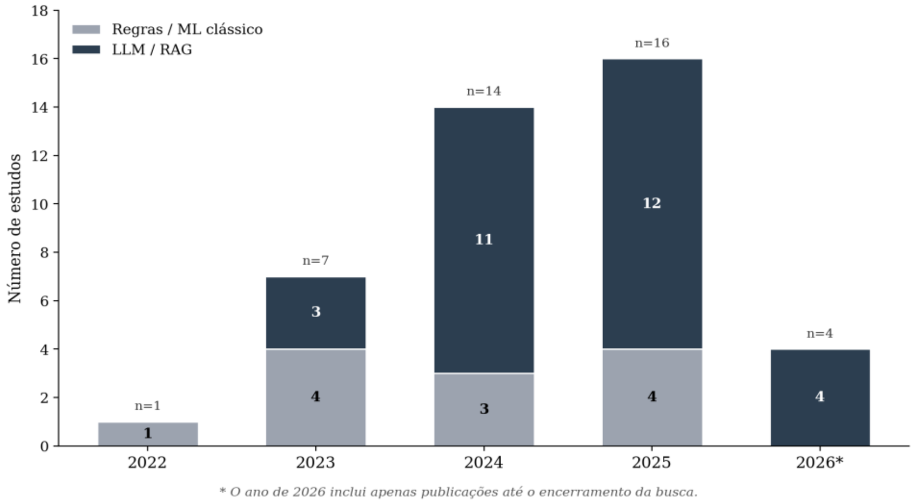
Figure 2 below highlights the technological transition during this period. In 2022 and 2023, rule-based approaches and classic *ML* (*Dialogflow*, *Rasa*) predominated; starting in 2024, systems with *LLM* and *RAG* account for the majority of publications, and by 2026 they represent all studies within the timeframe.

Figure 2 – Temporal evolution of publications by approach type (2022–2026)



Source: prepared by the authors using research data.

Regarding functional typology, the 42 studies cover everything from FAQ-based administrative assistants to multi-agent architecture featuring reinforcement learning and socio-emotional support. Pure pedagogical agents are the most frequent group (*TABOT*/*Master Socrates* in E02, *Q-Module-Bot* in E40, and *Learning Assistant Chatbot* in E44). Hybrid agents, which combine pedagogical and administrative functions, follow closely (*ELA Tutor* in E04, *MoodleBot* in E12, *Ask ME Assistant* in E18, and *NAJEH* in E55). Purely administrative agents are a minority (*AIMT Agent* in E16 and *CRM Chatbot* in E11).

In terms of maturity, 26 studies feature an implementation with empirical evaluation (experimental, quasi-experimental, survey, or case study), while the remaining 16 are architectural proposals, prototypes without evaluation, or proofs of concept. Among the studies with controlled experimental evaluation and complete technical description of the agent are the Empathic VLE agent by Armas (E34), developed at *USP*, which combines textual and facial emotion recognition in a real *Moodle* environment; the *ELA Tutor* (E04), a multi-agent architecture orchestrated by Q-learning and

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evaluated in *Moodle* 4.5.5 with 150 students; and *MoodleBot* (E12), integrated into *Moodle* using GPT-4 and *RAG*, and validated through manual fact-checking and *TAM* evaluation.

Moodle is the most frequent platform: it appears in 22 of the 42 studies (around 52%), confirming its centrality among open-source LMSs. *Canvas* appears in 3 studies (E17, E18, E35), *QMPlus* in 1 (E40), and proprietary institutional LMSs in 6 (E05, E11, E37, E41, E46, E47). Another 6 use environments outside the traditional LMS axis, such as VR/CAVE and messaging platforms (E02, E07, E09, E60, E66, E70), and were included with a qualification regarding criterion IC3: although they are not LMSs in the strict sense, they perform functions equivalent to those of a VLE (content delivery, tutor-student interaction, and learning mediation); the qualification indicates that generalization to conventional LMSs requires caution.

The forms of integration with VLEs/LMSs were divided into five categories: (i) native LMS plugins (E04, E08, E12, E30, E48, E52, E58); (ii) integration via REST APIs with token authentication (E18, E21, E25, E45, E51); (iii) decoupled middleware with microservices and orchestration, as seen in *ELA Tutor* (E04, using *Django* + *n8n* + *Docker*) and in Villegas-Ch, Govea, and Gutierrez (E25, using *Docker*/*Kubernetes* and *WebSockets*); (iv) widgets or iframes embedded via HTML (E50, E51); and (v) conceptual proposals without functional implementation (E01, E10, E17, E70).

These architectural choices have distinct practical implications. Native plugins offer direct access to course data, but couple the agent to the LMS version and hinder portability. Integrations via REST API and decoupled middleware favor independent maintenance and replacing the AI model without modifying the platform, at the cost of higher infrastructure complexity. Embedded widgets represent the path of least effort, though with limited access to student context. The predominance of plugins and APIs among empirically evaluated studies suggests that access to course context is a practical prerequisite for effective personalization. Five studies involve Brazilian authors or institutions (E14, E34, E58, and E54 and E29 in international collaborations), with notable highlights, due to evaluation in real-world environments, for the thesis by Armas (E34) at *USP* and the work by Moraes Neto, Fernandes, and Amiel (E14) on conversational analysis in *Moodle* forums.

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4.2 RQ2: What Artificial Intelligence techniques, models, and approaches are used in these conversational agents?

The 42 studies are distributed across the three generations of the reference framework (Section 2.3), with a strong concentration in the third. The first generation appears in E03, E07, E08, E11, E14, and E16, using *Dialogflow*, *Rasa*, *Bag of Words*, feed-forward networks, and finite state machines; the *AIMT Agent* (E16) exemplifies this non-*LLM* approach, featuring sub-second response times and zero calls to external APIs.

The second generation appears in E10, E14, E15, E25, and E51, employing *k-means*, *Random Forest*, *TF-IDF*, *Graph Neural Networks*, and *Reinforcement Learning*; the *LXP* by Dahal et al. (E15) combines *TF-IDF*, *GNN*, and *LLM+RAG* within a hybrid architecture.

The third-generation concentrates 25 of the 42 studies. More than the variety of models used — from GPT-4 and *Llama* to *Gemini*, *Claude*, and local models such as *Qwen2.5* — three movements summarize the trend the direction of the field. The first is the growing predominance of *LLMs* as the engine for agents, as confirmed by Figure 2. The second is the consolidation of *RAG* as a mechanism to mitigate hallucinations and anchor responses in curated course content: 18 of the 25 third-generation studies adopt some variant of *RAG*, typically utilizing vector databases (*Chroma*, *FAISS*, *PGVector*) orchestrated by *LangChain* or *LlamaIndex*. The third is the rise of hybrid and multi-agent architectures combining deterministic rules with generative AI, exemplified by *ELA Tutor* (E04), *MoodleBot* (E12), Han's dual-mode chatbot (E44), and the memory-augmented chatbot by Lee and Rew (E37).

Empirical analysis confirms the trade-off between control and flexibility discussed in the literature: first-generation solutions are predictable but offer limited coverage outside predefined intents, whereas third-generation solutions answer more questions, though they rely on *RAG* to maintain content accuracy in specialized domains (E04, E12, E37, E44, E47). Hybrid architectures address this bottleneck in 2025–2026 studies through adaptive routing between procedural and conceptual responses, such as the threshold-based confidence model used in *ELA Tutor* (E04).

4.3 RQ3: What roles and objectives (pedagogical or administrative) do these agents fulfill in VLEs/LMSs?

The objectives served by the agents fall into six categories, often combined within the same agent. Tutoring and learning support are the most common, present in over 30 studies (for instance, *MoodleBot* in E12, *Q-Module-Bot* in E40, *CLUE LMS* in E47, and *Socratic Playground ITS* in E05): the agents answer conceptual questions, offer adaptive explanations, and guide study paths. Automated feedback and formative assessment appear in E04, E07, E08, E12, E30, E35, E41, E47, E56, and E58, ranging from automated responses to feedback tailored to the student's cognitive and emotional state, as seen in the chatbot by Puertas, Mariscal-Vivas, and Martínez-Requejo (E35), which retrieves course PDFs from *Canvas* to generate assessments; and in the Empathic VLE agent (E34), which adapts feedback to emotions detected through facial recognition.

Administrative and institutional support appears in E01, E04, E07, E11, E12, E16, E18, E21, E37, E51, E52, E55, and E56. The agents assist with deadlines, course structures, LMS navigation, calendars, enrollments, and institutional FAQs. *NAJEH* (E55) and *AIMT Agent* (E16) cover the largest number of simultaneous administrative functions among the analyzed studies. The focus on engagement, motivation, and retention guides E09 (*Smart Sender*, with gamification), E34 (Empathic VLE agent, focused on reducing student-teacher transactional distance), E45 (a chatbot in African digital universities focused on dropout rates), and E54 (an AI tool suite integrated into *Moodle* for an instructional design course). Cognitive and affective adaptation represents a more recent research direction: E04 (Q-learning that adjusts pedagogical strategies), E30 (an emotionally intelligent adaptive assistant using *LSTM*, *VADER*, *TextBlob*, and Q-learning), E34 (multimodal Empathic VLE agent), and E50 (*LearningPartnerBot*, with adaptation through the Felder-Silverman Learning Styles Model). Collaborative learning and conversational analysis are concentrated in E14 (Moraes Neto; Fernandes; Amiel, 2022), which works on *Moodle* discussion forums, and in E02 (*TABOT*/*Master Socrates*), which offers cognitive scaffolding for information problem-solving (IPS) based on the Big Six framework.

The functional scope of these agents has been expanding. Systems have evolved from administrative FAQ chatbots to multimodal intelligent tutors capable of responding to the student's socio-emotional state. This trend aligns with a broader transformation of *Moodle* itself, which Dahal et al. (E15) describe as the transition from a traditional LMS to a Learning eXperience Platform (*LXP*).

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4.4 RQ4: Which studies perform empirical evaluations of the use of these agents in VLE/LMS-mediated educational contexts?

Of the 42 studies, 24 include empirical evaluation with students or instructors, in three groups: experimental or quasi-experimental with control groups (E02, E04, E05, E07, E08, E09, E13, E29, E30, E34, E50, E54, E60); surveys and mixed methods via *TAM*, *SUS*, *NASA-TLX*, and interviews (E12, E16, E17, E18, E21, E40, E44, E47, E51, E55); and log analysis in real environments (E14, with approximately 20,976 forum messages; E15, E25, E37, E44). Furthermore, 13 studies adopt experimental or quasi-experimental designs with a control group and inferential statistical testing, which allows attributing effects to the use of the agent: Hu, Yu, and Hsieh (E02), using *ANCOVA* and effect sizes η^2 up to 0.94; Chen and Anyanwu (E13), a controlled experiment in *Moodle* with *ANCOVA* with 83 students; Vu et al. (E29), a quasi-experiment with three groups ($n = 263$) in soft skills; Gutierrez, Villegas-Ch, and Govea (E30), a pre/post-test in *Moodle* with 30 students in critical reading comprehension; Eltahir and Babiker (E54), involving 110 participants in a postgraduate course in Education; and Han (E44), with 4,918 enrolled students, 1,349 chatbot sessions, and triangulation through an explanatory sequential mixed-methods design. The remaining empirical studies rely on perception surveys or log analysis, while the remaining 18 are limited to technical evaluations, expert validations, proofs of concept, or studies under development.

4.5 RQ5: What evidence of effectiveness is reported by evaluative studies on the use of these agents?

The evidence of effectiveness is distributed across three levels. At the first level is robust quantitative evidence. Hu, Yu, and Hsieh (E02) reported large effect sizes in need for cognition ($F = 50.02$; $p < 0.001$; $\eta^2 = 0.40$), performance ($F = 153.93$; $p < 0.001$; $\eta^2 = 0.67$), and information literacy ($F = 1{,}265.55$; $p < 0.001$; $\eta^2 = 0.94$). Sandra et al. (E08) obtained partial η^2 up to 0.653 in Toulmin-based argumentative writing. Chen and Anyanwu (E13) showed that the group using a chatbot in *Moodle* outperformed the group using a metacognitive approach (significant effect via *ANCOVA*). Vu et al. (E29) observed significant gains ($p < 0.001$) in 6 soft skills domains. Gutierrez, Villegas-Ch, and Govea (E30) reported an average increase of 32.5% in correct answers and an increase in the error correction rate from 60% to 84%. Eltahir and Babiker (E54) found post-test EG = 18.32 vs. CG = 15.31 ($t = 10.356$; $p < 0.001$). Rasanjani and Anuradha (E51) reduced average task completion time from 4.5 to 2.7 minutes, raised the resolution rate from 71% to 91%, and increased satisfaction from 3.6 to 4.4.

At the second level is mixed and acceptance evidence, which can be grouped into 4 analytical categories. In terms of user acceptance (measured by *TAM*), *MoodleBot* (E12) and *AIMT Agent* (E16) recorded high perceived acceptance, with the latter featuring response times under 1 second. In usability (measured by *SUS*), *CLUE LMS* (E47) achieved a score of 88.13, well above the threshold of 68 considered good in usability literature. Regarding cognitive load (measured by *NASA-TLX*), the same *CLUE LMS* (E47) registered 4.50, indicating low perceived mental demand. In operational performance and adoption, *Ask ME Assistant* (E18) reduced platform switching by 78% and student hesitation by 73%, with an average satisfaction rating of 4.65/5; *NAJEH* (E55) reached daily active usage of around 85% among 4,714 students and a 76% response rate on its survey (n = 3,581); and *Q-Module-Bot* (E40) was considered easy to use by 90% of stakeholders. This grouping shows that acceptance and usability are the most frequently reported dimensions, whereas cognitive load is still evaluated by relatively few studies.

At the third level is exploratory and perception-based evidence, which describe most of the remaining studies. These consist of technical validations (precision, F1, response time), heuristic evaluations by experts (E01 with IOC = 0.93; E10 with an average ≥ 4.6/5), or usability studies with very small samples (E47 with n = 4). These results help confirm technical feasibility and initial acceptance, but do not allow inferring actual educational impact. In the study by Eltahir and Babiker (E54), for example, the intervention is multi-component (ChatGPT + *Kahoot!* + *Studiosity*), which prevents attributing gains exclusively to the conversational agent.

The strength of this evidence is aligned with the methodological quality of the studies. First-level evidence comes from studies with an average quality assessment score above 6.0/7.0, all featuring a control group or pre- and post-intervention measurements; no robust quantitative evidence originates from a study classified as having a high risk of bias. At the opposite end, the 4 studies scoring below the 4.0 cutoff appear only at the third level, restricted to technical or heuristic validations. This alignment indicates that the field's most favorable conclusions are supported by the most rigorously designed studies, while also revealing that the high-rigor evidence base still represents only about one-third of the total sample.

Comparison across approaches reveals both convergences and divergences. Acceptance findings converge: regardless of the technological generation, agents well integrated into the course

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workflow achieve high acceptance, as shown by *AIMT Agent* (E16, based on *Rasa*) and *MoodleBot* (E12, based on GPT-4). Learning outcomes diverge: significant performance gains are concentrated in studies with *LLM*/*RAG* and controlled experimental designs (E02, E13, E29, E30, E54), whereas first-generation agents primarily report operational gains, such as response time and resolution rates (E16, E51). This divergence suggests that pedagogical gains stem mainly from the generative capacity to adapt explanations; direct comparative studies across generations, which are still absent from the literature, would be required to test this hypothesis.

4.6 RQ6: What gaps, limitations, and research trends are identified in the literature?

A cross-sectional analysis of the 42 studies revealed recurring gaps. First, studies with small samples (generally under 100 participants) and short durations (2 to 12 weeks) predominate, making generalization difficult. Second, longitudinal evaluations across multiple institutions are rare, and almost none track cohorts over entire semesters. Third, methodological and metric heterogeneity (*SUS*, *TAM*, *ANCOVA*, *SUS* + *NASA-TLX*, ad-hoc precision and F1 metrics) prevents meta-analyses and direct comparisons. Fourth, 16 of the 42 studies are purely conceptual or at the proof-of-concept stage, indicating a field still undergoing technical consolidation.

Other limitations warrant attention. Ethical and privacy issues are cited but rarely explored in depth (E07, E18, E21, E25, E52, E55, E56), and discussions surrounding over-reliance and academic integrity remain scarce (E17, E52). Standardized metrics for hallucinations are lacking: only E12 and E58 report numbers (88% accuracy and a 5% hallucination rate). There is a dependence on specific languages, such as the Korean focus in Lee and Rew (E37), and non-*Moodle* LMS platforms are underrepresented (*Canvas* in three studies; *Blackboard* absent), which limits generalization to other institutional environments.

Regarding trends, six key developments stand out: the adoption of *RAG* on top of *LLMs* as the de facto standard in 2025–2026; the emergence of multi-agent architectures and agentic AI, such as the *ELA Tutor* (E04) with its Orchestrator Meta-Agent and specialized agents; the transition of *Moodle* toward a Learning eXperience Platform (*LXP*), proposed by Dahal et al. (E15); the incorporation of computational empathy and socio-emotional support (E04, E30, E34); the adoption of dual-mode chatbots that allow students to choose between free-generative and *RAG*-referenced modes (E44); and

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the pursuit of open-source and reproducible solutions (E12, E16, E45, E48, E58), utilizing local models such as *Qwen2.5* and *Llama 3.2* to reduce reliance on proprietary APIs.

5 FUTURE DIRECTIONS FOR NEW RESEARCH

Based on the identified gaps, five research directions emerge as priorities. The first is to conduct longitudinal and large-scale evaluations featuring larger sample sizes, multiple institutions, and full academic semesters, utilizing quasi-experimental designs with control groups and subgroup analyses. The second is to standardize metrics and evaluation frameworks that combine pedagogical (learning gains, engagement), technical (accuracy, latency, hallucination rate), and user experience dimensions (*SUS*, *TAM*, *NASA-TLX*); without this standardization, meta-analyses and direct comparisons will remain unfeasible.

The third is to deepen research into ethics and privacy: educational data protection (*LGPD*, *GDPR*), academic integrity, over-reliance on AI responses, and the deployment of *LLMs* in formative and summative assessments. The fourth is to expand multimodal, empathic, and multi-agent architectures, integrating voice, facial recognition, and learning styles along the lines of empathic agents (E04, E30, E34) alongside specialist coordination via reinforcement learning. The fifth focuses on hallucination detection and mitigation through fact-checking, semantic re-ranking, and response validation; the two-stage filters proposed by Lee and Rew (E37) and the hallucination rate monitoring by Simmons, Holanda, and Silva (E58) serve as key starting points.

6 FINAL CONSIDERATIONS

This Systematic Literature Review analyzed 42 studies on AI-based educational and administrative conversational agents integrated with VLEs/LMSs (2022–2026), selected from 234 records across 7 databases. The technical shift is clear: moving from rule-based chatbots (*Dialogflow*, *Rasa*) to systems powered by *LLMs* and *RAG*, and more recently, to multi-agent architectures with reinforcement learning and socio-emotional support. Agents primarily address tutoring, formative feedback, academic support, engagement, and cognitive and affective adaptation, with *Moodle* standing out as the dominant integration platform (approximately 52% of studies), followed by *Canvas*, proprietary institutional LMSs, and dedicated environments (VR, messaging apps).

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Findings regarding effectiveness are overall favorable: experimental evaluation studies demonstrate significant gains in academic performance, information literacy, satisfaction, engagement, and support efficiency. Even so, the prevalence of pilot projects with small sample sizes and methodological heterogeneity limits generalizability; the highest quality scores were awarded to López-Goyez, González-Briones, and Demazeau (E04, 7.0), Neumann et al. (E12, 6.8), and ten studies scoring 6.5.

Beyond the numbers, these findings carry key pedagogical implications. The agents reposition instructors rather than replacing them: taking on first-level tutoring and freeing faculty for higher-order mediation (Garrison; Anderson; Archer, 2000; Moore, 1993). Student autonomy expands when the agent provides cognitive scaffolding (Vygotsky, 1991), provided the pedagogical design encourages critical verification of responses. As for personalization, it yields consistent gains only when paired with curated content and intentional mediation; without these, it risks fragmenting learning and undermining its collective dimension (Belloni, 2009).

Three structural limitations warrant mention: linguistic and geographical bias, with research heavily concentrated in English and an under-representation of the Global South; the generative AI hype effect, which can inflate expectations and bias publication toward positive outcomes; and the low maturity of the field, characterized by a predominance of proofs of concept, small sample sizes, and an absence of longitudinal studies, all of which call for a cautious interpretation of the evidence.

Brazilian scholarship maintains a consistent presence, with Armas's (2025) thesis on the Empathic VLE agent at USP and the work of Moraes Neto, Fernandes, and Amiel (2022) in *Moodle* serving as examples of real-world environment evaluation; the next step is to advance toward controlled, longitudinal, and multi-institutional evaluations.

The identified gaps set a concrete agenda. It is hoped that this review serves as a reference for researchers and developers designing conversational agents for VLEs/LMSs with empirical rigor, ethical awareness, and pedagogical intentionality.

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