Journal of Inclusive Methodology and Technology in Learning and Teaching
ISSN 2785-5104
Anno5 n.4 (2025)

EDIZIONI UNIVERSITARIE ROMANE
editoria scientifica dal 1952

Rethinking IEP design through AI: towards a dialogic ecology of school inclusion

Emanuela Zappalà[1]*, Lucia Campitiello[2], Umberto Bilotti[3], Stefano Di Tore[4] and Maurizio Sibilio[5]

[1] Dipartimento di Scienze Umane, Filosofiche e della Formazione, Università degli Studi di Salerno; ezappala@unisa.it
[2] Dipartimento di Scienze del Patrimonio Culturale, Università degli Studi di Salerno, Salerno, Italia, lcampitiello@unisa.it
[3] Dipartimento di Scienze Umane, Filosofiche e della Formazione, Università degli Studi di Salerno, Salerno, Italia, ubilotti@unisa.it
[4] Dipartimento di Studi Politici e Sociali, Università degli Studi di Salerno, Salerno, Italia, sditore@unisa.it
[5] Dipartimento di Scienze Umane, Filosofiche e della Formazione, Università degli Studi di Salerno, Salerno, Italia, msibilio@unisa.it
* Correspondence: ezappala@unisa.it

Abstract: The integration of generative Artificial Intelligence in the school context represents a paradigm shift in the role of technology in educational design and inclusive processes. This paper explores the potential of a generative chatbot, developed at the "Teaching Learning Centre for Education and Inclusive Technologies – Elisa Frauenfelder Laboratory" (University of Salerno), as a dialogic and dynamic scaffolding tool (Rizzo, Legrenzi, 2025) to support teachers in writing Individualized Educational Plans and adapting inclusive activities. The project is grounded in constructivist and sociocultural theories, viewing AI not as a substitute for human expertise but as a mediational and metacognitive partner that fosters reflection, collaboration, and inclusivity. Built on a Retrieval-Augmented Generation (RAG) architecture, the chatbot enables personalized interaction, transparency, and user feedback. The research follows a mixed-methods design including prototype testing, implementation with future support teachers, and pilot classroom studies. The study argues that the educational value of AI lies not on automation but in its ethical and dialogic integration. By promoting explainability and co-design, teachers and students may understand, adapt, and humanize AI, transforming it into a space for collective learning and inclusive innovation.

Keywords: Artificial Intelligence; Chatbot; co-design; Explainability; Dialogic Learning

1. Introduction

The integration of generative artificial intelligence (AI) and chatbots in the classroom is reshaping the field of instructional design and educational inclusion. Diverging from previous Learning Management Systems and Virtual Learning Environments, generative AI represents not only a tool but a paradigmatic shift in teaching and learning. These systems enable the possibility to produce content, maintain dialogue and dynamically adapt to learners' needs, directly transforming the relationship between teachers, students, the learning environment and knowledge itself.

This shift allows for the creation of personalized, flexible and interactive learning pathways where teachers take the role of architects of educational experiences, consciously and metacognitively guiding interaction with the chatbot and using it to reflect on how to design inclusive educational activities with reasonable accommodations (G.U., 2024). Consequently, the adoption of IA chatbot itself goes beyond the mere integration of new tools, because it also requires a complete rethinking of the relationships between teachers, students and subject contents (OECD, 2025). Nevertheless, this potential has some challenges because the integration of AI in education requires those who work in the educational field to reconsider teaching methods, epistemological beliefs and ethical limits, as well as their perceptions and attitudes. In fact, the success of AI also depends on educators' willingness to recognize its pedagogical value, trust its functionality and meaningfully include it in real teaching practice. Without this acceptance, the technology risk is marginal or even causes problems (Hazzan-Bishare, Kol & Levy, 2025; Nazaretsky et al., 2022; Viberg et al., 2024). As highlighted by Sibilio (2025), advanced AI systems, such as deep learning architectures and generative models, from a user's perspective operate as unintelligible "black boxes". They generate outputs (such as decisions, recommendations or texts) without making the underlying reasoning immediately clear. In educational contexts, this opaqueness may sometimes challenge trust since students and teachers may find it difficult to rely on or critically engage with AI-generated suggestions or assessments (Besio, Pinnelli, Sibilio, 2025; Pedro et al., 2019). The absence of transparent reasoning prevents the use of AI as a truly formative tool, as incomprehensible outputs tend to be accepted passively rather than foster reflective and critical thinking. This concern aligns with current European policy priorities, particularly the AI Act (articles 4 and 50; European Commission, 2024), which emphasizes the need for transparency, intelligibility and human supervision in high-impact technological applications.

Pedagogically, this implies that learners and teachers should be enabled to understand the logic, limits and ethical implications of the AI systems with which they interact (European Commission, 2024; Floridi, 2022). Making the internal mechanisms of AI explicit, therefore, becomes a form of educational challenge since it may allow the users to question how algorithms represent knowledge, whose values they embed and which perspectives they exclude (Long & Magerko, 2020; Sibilio, 2025; Pedro et al., 2019; Zanetti et al., 2020). In this sense, the goal is not merely to use technology, but to humanize it, to transform AI from an invisible setup into an object of inquiry, interpretation and co-design. Promoting AI explainability in education means equipping both the teachers and the students with critical tools to analyze how a model works, why it elaborates certain responses, and which filters or datasets influence its reasoning.

Based on these premises, this study offers a theoretical analysis of how a generative chatbot, developed at the University of Salerno's Teaching Learning Centre for Education and Inclusive Technologies' Elisa Frauenfelder Laboratory, may serve as a dialogic tool and dynamic support for teachers and students. In fact, the framework of this project is built upon dialogue among several influential thinkers. Each contributor may offer a different lens to reflect how AI may be designed and implemented as an educational assistant. The project aims to support teachers in designing inclusive learning activities and Individualized Education Plans with the support of a generative chatbot, while simultaneously engaging them in the process of developing their own chatbots. In doing so, teachers may critically examine the interplay between data, model and output, but also understand that ethical principles and pedagogical purposes stem not from the technology itself, but from the intentional agency of its human designers and users.

2. Theoretical framework

Chatbots, also known as "conversational agents", are software applications designed to simulate text-based dialogues with users by providing automatic responses to their input. During its initial development, in the 1980s and 1990s, early conversational bots, such as Eliza (Weizenbaum, 1966) and A.L.I.C.E. (Wallace, 2009), could engage in dialogue through pre-programmed answers. These types of "unintelligent" bots used to have predefined dialogues, including questions and potential replies; nevertheless, they often comprehended just a limited range of ideas pertinent to their purpose.

In contrast, contemporary conversational agents make use of advances in artificial intelligence, especially natural language processing and machine learning, enabling them to emulate human conversation with remarkable fluidity and contextual awareness. Their ability to learn through human contact (Mateos-Sanchez et al., 2022; Kuhail et al., 2023) transforms them into adaptive interlocutors capable of supporting more complex communicative and cognitive functions.

Since the early 1970s, within the educational field and particularly in higher education, chatbots have also been adopted, but as Conversational Pedagogical Agents (CPAs) (Laurillard, 2013). These CPAs aim to engage learners in a dialog-based conversation using AI (Gulz et al., 2011), acting as tutors, coaches or learning companions by using several communication styles and adaptive personalization strategies that respond to learners' needs fostering engagement, motivation and inclusion (Chhibber & Law, 2019; Fiorucci, & Bevilacqua, 2024; Hobert, & Meyer von Wolff, 2019; Kuhail et al., 2023; Martinez-Requejo, 2024; Ruiz Lázaro et al., 2024; Yusuf, Money, & Daylamani-Zad, 2025). Thus, CPAs gradually reshaped the educational ecosystem because their integration not only gradually influenced both teaching and learning practice, but it also raised the need to create new forms of agency (Floridi, 2022) through which teachers and students interact. As Paul Mason (2019) observes, "we have modified our environment so radically that now we must modify ourselves to survive within it" (p. 202). Therefore, the adoption of CPAs created new cognitive and relational environments that educators and learners had to learn to inhabit consciously and critically. In this sense, the emergence of AI represented, and it is still valid, not merely a technological evolution, but an ontological transformation of our learning ecosystems. Lévy (1996) would say that it is still necessary to move from artificial intelligence toward collective intelligence, to move from *cogito* to *cogitamus* (p.37) so that "our societies coordinate through a virtual world of meanings that our minds inhabit in shared ways, while our organisms actually interact with the physical world" (Lévy & Feroldi, 1999, p. 17). Thus, AI becomes not only a tool but also a space of shared meaning, where human minds cohabit and collaborate through virtual mediation. Consequently, in the educational field, rather than replacing human expertise, AI should act as a dialogical mediator and a cognitive–metacognitive scaffold, actively supporting the construction of knowledge (Rizzo & Legrenzi, 2025).

In this regard, as stated by Sibilio (2025), only a systemic pedagogical framework may support identifying pedagogical risks of uncritical use and the "invisible" pervasiveness of these systems both in the educational setting and in everyday life. Such a framework should address the key challenges of explainability and knowledge transparency, valuing AI within education without being overpowered by it. To address this purpose, fostering AI explainability would require equipping teachers and students with critical tools to analyse how a model works, why it elaborates specific answers and which filters or datasets influence its reasoning. For example, it would be useful to understand and learn how to build a chatbot, to concretely explore the relationship between data, model and output, recognizing how ethical intentions and educational purposes emerge not from the technology itself but from the agency of those who design and use it. In this perspective, transparency and co-design become essential pedagogical strategies for cultivating digital agency and ensuring that AI remains a means for teaching and learning, not its substitute.

Within this evolving epistemological perspective, constructivist and sociocultural theories provide valuable interpretive frameworks for understanding AI's educational potential. In particular, Piaget's constructivism encourages active learning, where students co-author their educational paths. According to Piaget, "the primary purpose of education in schools should be to create men and women capable of doing new things, not simply repeating what other generations have done" (in Rizzo & Legrenzi, 2025, p.140). Thus, the introduction of generative AI into schools isn't simply the adoption of new technology; it's an opportunity to profoundly rethink the way we learn and teach.

Moreover, Piaget states that comprehension and knowledge are not merely transmitted but actively constructed through the reorganization of mental structures through interaction and problem-solving. Therefore, AI may support this cognitive process, providing challenging scenarios and also scaffolding, so that it would stimulate and motivate the learner to reorganize their thinking. But, as highlighted by Dewey when talking about experiential learning and reflective action in democratic communities (Dewey, 1938), while designing a generative chatbot, it would be important to situate learning within meaningful, collaborative and participatory contexts. Actually, among the key challenges in education, Dewey identifies the need to question the assumption that all experiences are inherently or equally educative (1986, p. 13). He argues that not every experience contributes to growth; some may even become "mis-educative", hindering further development or distorting understanding. Likewise, an experience may be pleasant or engaging without necessarily fostering meaningful learning. For experience to be truly educative, it should be integrated within a coherent and reflective framework, enabling continuity and the construction of foundations for future learning. So, when considering the integration of generative AI in classrooms, it is important to avoid automatically considering it as formative or beneficial simply because it provides engagement or interaction. In fact, it would lead to "mis-educative experience" where the students would passively accept the opaque outputs offered by the chatbot. On the contrary, explainable AI would align with Dewey's conception of meaningful experience because it would enable both learners and educators to interrogate how the system arrives at its conclusions, to evaluate its assumptions and to integrate these insights into broader conceptual frameworks.

Furthermore, as emphasized by Vygotsky (1978), learning occurs through mediated interaction, in the space between independent performance and guided potential. Within this view, Vygotsky's Zone of proximal development theory may offer grounds for an interpretation of AI as a mediation tool that may foster learners' growth from current to potential competence levels. The importance of recognizing diverse cognitive profiles and strengths is outlined by Gardner's theory of multiple intelligences (1983). Taking it into account, a generative AI chatbot, by design, may be capable of producing several adaptations of the same content, thus supporting differentiated instruction. For example, a historical concept may be presented as a narrative account, a conceptual or mental map or a role-playing activity, depending on the learner's profile and preferences. In addition, it is important to consider how socio-cultural practices influence and inspire digital platforms (Gallese, Moriggi, Rivoltella, 2025). In fact, as stated by Simondon (1958), technology produces new forms of relationship between people, between things and between people and things. It establishes a network of interactions that reshapes the way individuals perceive and inhabit the world (Gallese, Moriggi, Rivoltella, 2025, p. 29). As highlighted by several neuroscientific studies on technology-mediated social practices, technology provides an essential lens for understanding intersubjectivity and the development of the self in today's trans-aesthetic and hyperconnected world. It not only mediates communication and experience but also influences cognitive development, adaptive capacities and the construction of reality (Gallese, Moriggi, Rivoltella, 2025).

In line with these considerations about the mutual influences, Bakhtin's notion of dialogism (1981) stresses that meaning emerges through the interplay of multiple voices and perspectives. According to the author, the self and the other do not exist as separate entities but as a relation of similarity and difference that emerges also through dialogue (Baxter, 2011). Bakhtin envisages every act of speech or meaning as relational, situated within a continuous "chain of speech communion" (Bakhtin, 1981, p. 93). Each utterance both responds to previous voices and anticipates future ones, making meaning a result of ongoing interaction rather than individual expression. Through what he terms "dialogic overtones" (Bakhtin, p. 92), every utterance carries traces, echoes, and expectations shaped by the multiplicity of voices that precede and surround it. Transposed into the educational domain, this means that the chatbot should not provide univocal answers, but rather sustain dialogic exchanges, promote reflection, and enable students to encounter alternative viewpoints.

Lastly, McLuhan (1964) and de Kerckhove (1997) conceptualize media as extensions of human faculties. In fact, McLuhan considers all media as extensions of some human faculty (psychic or physical) and it supports the idea that they may function as an extension of human cognition and communication, not as an external or autonomous system. In this sense, for example, there are several assistive AI technologies, including speech recognition, automatic translation and multimodal synthesis tools, that function as sensory extensions to foster accessibility and participation for students with SEN.

Moreover, De Kerckhove's notion of the "connected mind" extends Marshall McLuhan's work because it emphasizes that digital media interconnect human minds into shared cognitive systems:

"We are beginning to share not only information but also awareness. The connected mind is a collective form of intelligence that grows through interaction and feedback" (De Kerckhove, 1997, p. 17).

In line with this point of views, it may place chatbots as an extension of teachers' and students' cognitive and communicative abilities within a shared knowledge network where collaboration may create a new form of collective intelligence. This reframes AI not as an automation but as an augmentation.

But, at the same time, all these perspectives require that AI systems remain explainable and transparent, allowing teachers and learners to understand how knowledge is represented, processed and delivered, but also so that they can critically engage with its outputs, question its assumptions and use it consciously as a learning partner rather than as an unquestioned authority.

In conclusion, the chatbot evolves from a mere technological tool into a dynamic teaching ecosystem. Actually, it may mediate learning, as Vygotsky suggested; it may stimulate active cognitive construction, following Piaget's ideas; and it may also differentiate learning pathways according to different types of intelligence, following Gardner's theory of multiple intelligence. Chatbot may foster dialogical interaction, as emerging through the interplay of voices (Bakhtin, 1981) and extend cognition within a connected environment, as theorized by McLuhan and de Kerckhove.

In this integrated perspective, the chatbot becomes not only a digital artifact but a pedagogical co-agent, a mediator of reflection, co-design and inclusion within an evolving ecology of human–AI collaboration.

3. Methodology

Based on this framework, the project pursues two central objectives:

1. support for inclusive education through the design of adaptive learning activities and IEPs that respond to diverse needs.
2. Promotion of dialogical teaching practices, where the chatbot acts as a partner in the co-construction of knowledge.

To achieve these purposes, the research will employ a mixed-methods approach, articulated in several phases, each addressing complementary questions.

3.1. Phase 1: Design and initial testing

The first phase focused on the development of a generative chatbot to assist teachers in designing individualized, ICF-based educational plans from an inclusive perspective. The AI system will undergo both an alpha- and beta-testing with two groups of students: first-year students enrolled in Sciences of Motor Activities, Sports and Psychomotor Education (within the Special Didactics course) and third-year students in Educational Sciences attending the Inclusive Technologies course. These trials will serve both for debugging purposes and for refining the chatbot's core features. Before using the chatbot, students will attend an introductory session on inclusive technologies in educational settings. To foster cooperation, a conscious and reflective use of the chatbot, students will be organized into small collaborative groups and asked to co-author a report on UDL, drawing from shared instructional materials and selected reference texts. In a subsequent step, each group will be tasked with creating its own AI-based chatbot specialized in UDL, using the collaboratively produced materials as its knowledge base. Students will then examine and evaluate their chatbot's responses, providing structured feedback to improve its accuracy and pedagogical coherence.

Moreover, recognizing that attitudes significantly influence adoption, an additional questionnaire will be administered before the creation of the chatbot to explore their habits, opinions and perceptions of AI's usefulness, usability and adaptability in

IEP development. For this aim, an adaptation of the technological acceptance and usability scale (UTAUT; Venkatesh et al., 2003) will be adopted.

3.2. Phase 2: Iterative redesign and broader implementation with future support teachers

Based on the outcomes of the first phase, the chatbot will be redesigned and optimized, integrating user feedback and performance data. This phase also includes:

1. the involvement of future support learning teachers enrolled at a continuous professional development specialization course at the University of Salerno. This phase will focus on the design of adaptive learning activities and IEPs, analyzing the challenges teachers encounter at different stages of the IEP development process.
2. The exploration of teachers' general attitude towards using generative AI.
3. A post-intervention survey evaluating shifts in perception and intention to use AI tools.
4. A second redesign phase to enhance usability, pedagogical alignment, and inclusivity.

Additionally, focus groups and semi-structured interviews will complement the quantitative data, offering nuanced insights into perceived opportunities, concerns, and contextual variables (such as school culture, available resources, prior experiences with technology).

Insights gained will help customize the chatbot to align with actual workflows, user needs, and ethical standards.

3.2. Phase 3: Pilot studies

The next steps include a pilot study in a few classrooms, utilizing qualitative interviews and participatory observation to explore how teachers interact with AI. This will lead to a wider deployment across multiple schools to gather quantitative data on pedagogical sustainability, effectiveness, and inclusivity.

By outlining these research directions, the project aims to foster participatory models, ongoing professional development opportunities and pedagogical guidelines for involving students in the co-design and evaluation of AI-based educational tools. The expected value of this approach lies not in the technology itself but in thoughtfully integrating it into educational design. Within this framework, the teacher remains a metacognitive guide and designer of learning experiences, transforming each AI-mediated interaction into an opportunity for significant personal and collective growth.

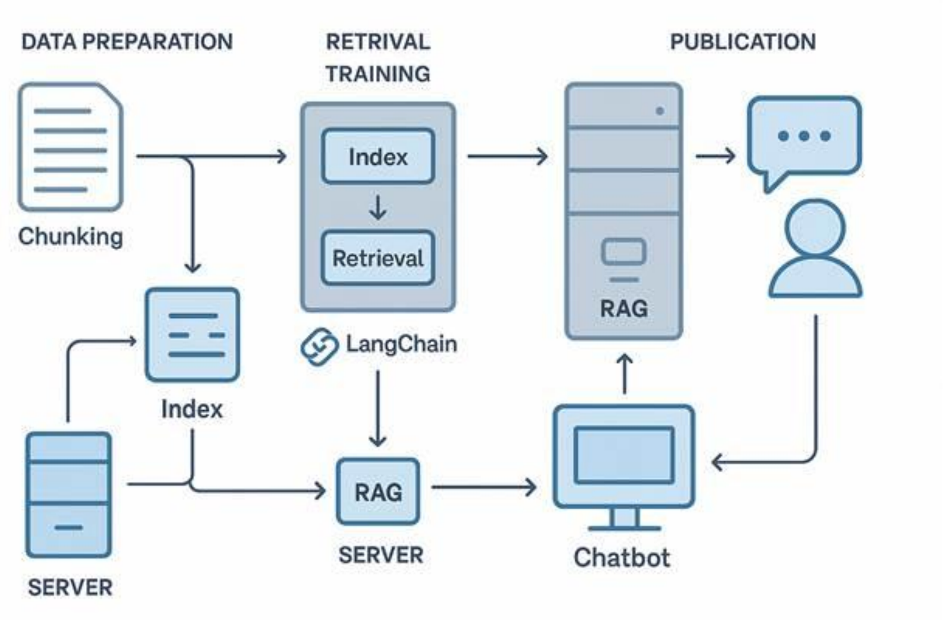
4. Design and development of the Artificial Intelligence Platform

In order to conduct an initial experimentation with university students at the University of Salerno, an artificial intelligence engine was developed and conceived as an experimental platform aimed at providing information and educational support on the topic of Universal Design for Learning (UDL). The platform was designed to enable the creation and customization of educational chatbots capable of interacting with users and delivering context-aware responses based on specific teaching materials (Huang et al., 2025). The artificial intelligence engine is based on a Retrieval-Augmented Generation (RAG) architecture (Lewis et al., 2020), whose workflow includes the phases of data preparation (document chunking and indexing), retrieval training through LangChain for indexing and retrieving relevant content, and publication through a chatbot interface that enables interaction with the end user. Specifically, the system accepts documents in various formats (e.g., .pdf, .txt), which may be ingested, processed, and segmented into coherent informational units (chunks) through a semantic extraction and structuring pipeline. Subsequently, these chunks are transformed into vector embeddings generated with BGE models and indexed to allow efficient information retrieval. During user interaction, the system identifies the most relevant chunks based on similar metrics and reranking processes, dynamically reconstructing a reliable informational context that enables the selected language model (LLM), based on DeepInfra/OpenAI architectures, to generate an appropriate response. This approach mitigates typical LLM issues such as hallucinations and outdated knowledge by integrating external retrieval mechanisms (Gao et al., 2023). The platform includes a feedback module that allows users to record evaluations and modifications, with the purpose of improving the knowledge base and the overall quality of the responses. Additionally, it supports the publication of static chat sessions exportable in HTML format, which can be assigned to specific projects or user groups. From an architectural perspective, the system is multi-tenant, with knowledge management structured for users and for projects. Authentication is handled through login and JWT tokens, while the server-side component is implemented using FastAPI and exposed through a Nginx/Apache reverse proxy to ensure security, scalability, and modularity of the service.

4.1. Architecture of the model of Retrieval-Augmented Generation

The artificial intelligence engine is based on a multi-tenant pipeline designed for dynamic knowledge management and personalized interaction through Large Language Models (LLMs). The system is structured across three main layers: the user-facing frontend, the application backend, and external LLM providers. Users can access the dedicated interface through a web browser, authenticate through JWT-based login, and subsequently upload files in .pdf or .txt format, or configure project-specific parameters. Requests are handled by a reverse proxy (Nginx/Apache), which manages TLS termination, rate limiting, and routing to the main backend services developed in FastAPI. Within the platform, the backend constitutes the operational core of the system, orchestrating all functions required for the correct processing flow and response generation. It manages user authentication and project handling in a multi-tenant environment, ensuring an isolated and customized workspace for each user. Authentication is carried out through the use of JWT tokens. The backend also manages the upload and parsing of documents, enabling text extraction and accurate semantic interpretation. Once extracted, the content undergoes a semantic chunking process, which segments the text into coherent blocks of configurable size (expressed in tokens) to optimize the subsequent information retrieval phase. To provide a semantic representation of these blocks, the system adopts the BAAI/bge-m3 model to generate embeddings, that is, vector representations that allow the calculation of textual similarity. The generated indices are stored locally in CSV format and temporarily cached in Redis to speed up access and search operations. The reranking phase of the retrieved results is performed using the BAAI/bge-reranker-v2-m3 model, which reorders the selected content based on its degree of relevance to the user's query, thereby improving the accuracy of the responses. The RAG-based chat module represents the core of user interaction, dynamically constructing the prompt by combining the most relevant text fragments with the user's query, thus enabling the language model to generate coherent and context-aware answers. Furthermore, the system integrates a feedback loop that records user evaluations and content modifications, enabling incremental learning and continuous refinement of the knowledge base. Finally, the platform includes a Publisher module that allows the generation of static HTML files and the deployment of customized chatbots, which can be accessed even without authentication, facilitating broader dissemination of the projects. All status updates (upload, parsing, embedding) are streamed to the client in real time through Server-Sent Events (SSE) on the /progress endpoint. The content processing within the platform follows a structured end-to-end workflow designed to ensure semantic consistency and the progressive optimization of the responses generated by the artificial intelligence system. The process unfolds across six interconnected phases. First, the user accesses the platform through authentication and initiates the ingestion and parsing phase. In this stage, the uploaded files (PDF, TXT, or other supported formats) are analyzed and converted into raw text. At the same time, semantic elements such as titles, paragraphs, and tables are detected and normalized. The second phase involves chunking, during which the extracted text is segmented into coherent informational units (sentences or short sections). This operation preserves internal semantic relationships and prepares the content for efficient indexing and retrieval. The third phase concerns embedding generation and indexing. Each chunk is converted into a numerical vector using the BGE-m3 model, enabling semantic representation of the content. These vectors are stored within searchable indices, which are loaded into RAM to accelerate retrieval operations. Next is the retrieval, reranking, and prompt construction phase. When the user submits a query, it is converted into an embedding and compared with the indexed vectors. The most relevant results are then reranked and assembled into a structured prompt, which is sent to the language model. The fifth phase is response generation, in which the system queries the selected model and receives a response via streaming. The output is subsequently post-processed: redundant elements are removed, Markdown formatting is applied, and the final response is delivered to the user interface. Finally, a phase of feedback and incremental learning is included. The user can evaluate, modify, or enrich the generated responses. These interactions are recorded and, when appropriate, used to update the embeddings and regenerate the index, thereby progressively expanding the chatbot's knowledge base. Once the testing phase is completed, the user can proceed with project publication. The platform generates a static HTML version of the chatbot, preserving all configured settings, such as the selected language model, source documents, and generation parameters (temperature, max tokens, etc.). This version acts as a "frozen snapshot" of the project, featuring a lightweight interface and fixed parameters that cannot be altered by the end user, while still relying on the original server-side pipeline. From a security standpoint, access to restricted functions is regulated through JWT-based authentication and user-level project isolation. The reverse proxy manages CORS, rate limiting, and protection against unauthorized access. The backend records structured logs containing requests and feedback outcomes, ensuring traceability and auditability. The architecture is designed to be scalable and future-proof, as indices initially stored in CSV format can be migrated to more efficient formats (such as Parquet or Feather) or to dedicated vector databases (e.g., FAISS, Chroma, Qdrant), thus enabling approximate searches via Approximate Nearest Neighbors (ANN) algorithms. The overall workflow, from project creation to chatbot publication, can be summarized as follows: 1) project creation; 2) document upload, parsing, and chunking; 3) embedding generation, indexing, and caching; 4) chatbot testing and parameter tuning; 5) feedback collection and system optimization; 6) publication, static HTML generation, and URL sharing. In this way, the platform ensures coherence and full traceability throughout the entire knowledge generation process and operates as a dynamic system capable of evolving through continuous user interaction.

Figure: Diagram of the operational workflow of the artificial intelligence engine based on the RAG (Retrieval-Augmented Generation) architecture.



5. Conclusions

The system presented was conceived primarily for educational and pedagogical purposes: to make the complex mechanisms underlying large language models (LLMs) understandable, to offer a user-controllable learning environment, and to support inclusive design processes, such as the creation of Individualized Education Plans (IEPs) and adaptive teaching activities, without replacing human expertise. Within this framework, AI is envisioned as a metacognitive and dialogic partner, capable of revealing its internal logic (data, models, filters, and limitations) and thereby fostering practices of co-design, reflection, and critical engagement.

At the core of this initiative lies the idea of humanizing AI, not as a rhetorical or anthropomorphic act, but as the recognition of its fundamentally socio-technical nature. AI does not exist independently of human intention: it emerges from networks of social, cultural, and professional relationships, from design decisions, data selection, institutional frameworks, and educational aims. In every context, it reflects the values and goals of those who create and employ them. To humanize AI therefore means to:

1. trace its outputs back to the chain of human choices and ethical assumptions that generate them (transparency and traceability);
2. reduce technological opacity, transforming interaction into a reflective learning process;
3. empower teachers and students to define the purposes, criteria, and limits of its use, thus cultivating AI literacy and critical agency.

This conception aligns both with the AI literacy framework proposed by Long and Magerko (2020), which emphasizes the ability to understand, question, and negotiate the behavior of AI systems, and with Floridi's (2022) vision of a human-centered AI ethics grounded in explainability, human oversight, and accountability as preconditions for ethical and educational use.

Ultimately, the platform goes beyond supporting inclusive planning and differentiated instruction: it performs a genuine unboxing of the AI black box, returning technology to its human and relational origins. In doing so, it promotes a critical and conscious engagement with AI by teachers and students alike, contributing to a dialogic ecology of inclusion in which technology and pedagogy co-evolve transparently, collaboratively, and in service of meaningful educational goals

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