Global Journal of Engineering and Technology Advances

eISSN: 2582-5003

Cross Ref DOI: 10.30574/gjeta

Journal homepage: https://gjeta.com/

(Review Article)

Managing Information Volatility and Density in Academic and Vocational Guidance: Modeling a RAG-based Chatbot for Guidance Counselors in Morocco

Rachid Chelouah * and Mohamed Khaldi

Research team in Computer Science and University Pedagogical Engineering Higher Normal School, Abdelmalek Essaadi University, Tetouan; Morocco.

Global Journal of Engineering and Technology Advances, 2026, 26(01), 041-049

Publication history: Received on 27 November 2025; revised on 03 January 2026; accepted on 06 January 2026

Article DOI: https://doi.org/10.30574/gjeta.2026.26.1.0005

Abstract

In the Moroccan educational landscape, characterized by the rapid expansion of training programs and the extreme volatility of regulatory norms, guidance counselors are facing an increasing cognitive load. The real-time mastery of administrative information (ministerial memos, procedures, admission thresholds) often conflicts with the mental availability required for the counseling relationship. While generative Artificial Intelligence offers promising prospects for assistance, standard Large Language Models (LLMs) suffer from factual hallucinations and data obsolescence, making them unsuitable for critical professional use.

This article proposes a conceptual modeling of a mobile AI assistant specifically designed for guidance counselors. Through a comparative analysis methodology, we demonstrate the superiority of the Retrieval-Augmented Generation (RAG) architecture over Fine-Tuning for managing dynamic knowledge updates. The proposed model couples a generic LLM with a vector database of regulatory documents, thereby ensuring reliability, source traceability, and a significant reduction in the practitioner's extrinsic cognitive load. This work contributes to the Design Science Research (DSR) field by offering a robust architectural framework for the transition toward a human-AI symbiosis in educational guidance.

Keywords: Academic and Vocational Guidance; Cognitive Assistant; RAG (Retrieval-Augmented Generation); LLM (Large Language Models); Cognitive Overload; Information Volatility

1. Introduction

Educational and vocational guidance has undergone a profound transformation over the last decade, marked by a shift from a traditional matching model to the Life Design paradigm (Savickas et al., 2009). This paradigmatic evolution places the individual at the heart of a continuous adaptation process within a fluid knowledge society (Guichard, 2013). However, this empowerment of the individual faces an extreme densification of training offers and a proliferation of educational pathways and regulatory constraints, creating a true informational labyrinth (Sampson et al., 2020). In this context, information becomes a critical resource, but its volatility; characterized by frequent changes in ministerial memos and procedures; makes it difficult for a human operator to master alone.

This increasing complexity creates a major challenge for practitioners in the field. Guidance counselors frequently operate under conditions of mobility and urgency, facing a dispersion of information sources ranging from paper documents to non-indexed digital circulars. This fragmentation generates significant operational friction: during interviews, the counselor must often interrupt the relational dynamic to conduct factual documentary research, thereby increasing their cognitive load (Sweller, 2011). This tension between the need for empathetic listening and the

* Corresponding author: Rachid Chelouah

requirement for encyclopedic technical expertise risks reducing the overall effectiveness of the guidance process (Watts, 2013).

In response to these challenges, the integration of Artificial Intelligence (AI) offers new perspectives. While educational research has historically focused on the student through intelligent tutoring systems (Holmes et al., 2019), a transformative potential lies in developing tools for professionals. The emergence of Large Language Models (LLMs) now enables advanced natural language processing (Kasneci et al., 2023). However, to mitigate the risks of hallucinations inherent in these models, coupling them with knowledge bases through the Retrieval-Augmented Generation (RAG) technique has become essential (Lewis et al., 2020). This hybrid architecture allows for the design of reliable Cognitive Assistants, capable of supporting counselors in accessing regulatory knowledge (Deng et al., 2024), thereby freeing up time for the human dimension of guidance.

1.1. Problem Statement

The contemporary practice of guidance counseling faces a structural limit inherent to human cognition: the management of cognitive overload. According to Cognitive Load Theory (Sweller, 2011), working memory has a limited capacity. However, the counselor finds themselves in a permanent "dual task" situation: they must simultaneously maintain empathetic active listening; a process costly in attentional resources; and retrieve complex, evolving administrative information from long-term memory (Wickens, 2008). This resource conflict creates saturation that inevitably degrades one of the two performances: either the quality of the relationship diminishes, or the technical accuracy of the response erodes.

This phenomenon results in informational latency. The inability to provide a reliable response *in situ* forces the practitioner to defer their answer or interrupt the exchange to consult external materials. These disruptions weaken the working alliance (Horvath & Greenberg, 1989), an essential component of counseling effectiveness, by introducing a technical distance into a human interaction. The challenge is therefore not only logistical but deeply relational: how to secure factual expertise without sacrificing psychological presence?

In this perspective, the hybridization of human and artificial intelligence appears to be a promising resolution. Rather than aiming for the automation of guidance, the relevant approach is that of human-machine symbiosis (Licklider, 1960; Jarrahi, 2018), where AI acts as a cognitive extension. The specific use of Retrieval-Augmented Generation (RAG) architecture allows the burden of memorization and regulatory monitoring to be delegated to the machine (Lewis et al., 2020). By acting as a dynamic external memory queryable in natural language, the system relieves the counselor of the intrinsic load associated with information retrieval.

Consequently, the central research question guiding this study is: How can the integration of a RAG-based cognitive assistance system optimize the information retrieval process, thereby reducing latency and mental load, while preserving or even reinvesting the cognitive availability necessary for the relational dimension of the profession (Molenaar, 2022)? The goal is to evaluate whether this technological cognitive offloading effectively translates into a requalification of the counseling act toward tasks with higher human added value.

1.2. Research Questions

The tension observed between the need for sharp regulatory expertise and the cognitive overload inherent in counseling practice highlights a lack of suitable technological solutions. Given this observation, our research is guided by the following central question:

"What information system architecture can reconcile the generative power of Artificial Intelligence with the factual reliability required by the regulatory framework of educational guidance?"

This central inquiry is broken down into two sub-questions that will guide our modeling:

- **RQ1 (Architectural Dimension):** In what ways does the Retrieval-Augmented Generation (RAG) approach constitute a theoretically superior response to Fine-Tuning for handling the volatility of administrative information?
- **RQ2 (Interactional Dimension):** How can human-computer interaction be modeled so that the assistant acts as a transparent cognitive extension, minimizing technological intrusion during the counseling interview?

Addressing these research questions requires bridging two distinct but complementary disciplinary fields: cognitive psychology and information systems engineering. Indeed, the modeling of a relevant assistant cannot rely solely on technical feasibility; it must be anchored in a human-centered approach to meet the ergonomic constraints of the profession (Shneiderman, 2022).

Consequently, this theoretical framework will be structured around three fundamental axes. First, we will mobilize Cognitive Load Theory (Sweller, 2011) to characterize the nature of the informational frictions encountered during guidance interviews. We will then analyze the state of the art of generative AI in education, highlighting its potential but, more importantly, its intrinsic limitations, notably the phenomenon of factual hallucination (Ji et al., 2023). Finally, we will present the theoretical foundations of the Retrieval-Augmented Generation (RAG) architecture (Lewis et al., 2020), which we identify as the technological cornerstone for resolving the paradox between conversational fluidity and regulatory rigor.

Research Objectives

In order to address the aforementioned research questions, the general objective of this study is to propose a theoretical and architectural modeling of a Mobile Cognitive Assistant dedicated to guidance counselors.

Specifically, this study aims to achieve three operational objectives:

- **Analyze the limitations of standard Large Language Models (LLMs)** within the critical context of school administration, particularly the risks associated with hallucinations and data obsolescence.
- **Design hybrid technical architecture (coupling LLMs and RAG)** specifically tailored for managing dynamic documentary corpora (memos, circulars, procedures, etc.), ensuring information traceability and freshness.
- **Define the ergonomic specifications** of a mobile conversational interface that respects cognitive load constraints, allowing for consultation without disrupting the working alliance with the student.

1.3. Theoretical Framework and State of the Art

The modeling of a reliable and effective cognitive assistance system for guidance counselors cannot rest on mere technological intuition. Instead, it requires a solid theoretical foundation capable of articulating the cognitive challenges of the profession with the capabilities and limitations of contemporary Artificial Intelligence technologies, ultimately identifying the technical architecture best suited for operational synthesis. This theoretical framework is structured around three interdependent pillars.

First, we will rely on Cognitive Load Theory (Sweller, 2011) and shared attention models to precisely model the "dual task" burden experienced by the counselor. This first axis allows us to qualify the nature of the human problem: informational friction that parasitizes limited attentional resources, to the detriment of the counseling relationship.

Second, we will examine the landscape of Large Language Models (LLMs) and generative AI. While their conversational potential is undeniable, we will analyze their structural limitations; notably factual hallucination (Ji et al., 2023) and knowledge obsolescence; which make them unsuitable in their current state for a critical regulatory domain. This critical examination is essential to dismiss naive solutions and identify the technical constraints that must be overcome.

Finally, we will present the Retrieval-Augmented Generation (RAG) paradigm introduced by Lewis et al. (2020). We will demonstrate how this hybrid architecture constitutes the theoretical and practical response for reconciling the conversational fluidity of LLMs with the requirements of reliability and information freshness. RAG acts as a dynamic and searchable external memory, thus offering a mechanism for cognitive externalization directly aligned with the needs identified by the first theoretical pillar.

The originality of our approach lies precisely in the convergence and systematic articulation of these three fields. Indeed, it is at the intersection of cognitive psychology, information systems analysis, and knowledge engineering that the modeling of an assistant emerges, not as an automaton, but as a true symbiotic extension of human expertise within the specific context of Moroccan educational guidance.

1.4. Cognitive Load in Helping Professions

The practice of guidance counseling occurs within a permanent dual-task context. According to Cognitive Load Theory (Sweller, 2011), human working memory has a limited processing capacity. When a counselor conducts an interview, their cognitive resources are primarily allocated to the intrinsic load of the task (understanding the student's request, analyzing their psychological profile).

However, searching for administrative information (procedures, admission thresholds, dates, etc.) imposes a parasitic extraneous load. The dispersion of information sources forces the practitioner to divert their attention from the student to navigate complex interfaces. This phenomenon, known as the split-attention effect (Ayres & Sweller, 2014), degrades the quality of active listening. According to Wickens (2008), this mental overload inevitably leads to a decline in performance or factual errors. Therefore, the ergonomic challenge of an assistant is not merely utilitarian, but cognitive: it involves externalizing the memorization of facts to free up the mental space necessary for empathy and human judgment.

1.5. Generative AI and its Limitations in a Regulatory Context

The advent of Large Language Models (LLMs), such as GPT-4 or Llama, offers unprecedented natural language processing capabilities, enabling fluid interactions similar to human conversation (Brown et al., 2020). However, their raw application in a critical administrative domain faces two major obstacles:

- **Factual Hallucination**: LLMs are probabilistic models rather than truth-based databases. When they do not know an answer, they tend to generate information that is plausible but false (Ji et al., 2023). In the field of educational guidance, inventing an application deadline is an unacceptable error.
- **Knowledge Obsolescence (Cut-off date)**: An LLM's knowledge is frozen at the date its training ended. However, regulatory information is volatile (a ministerial memo can be issued at any time). Constant retraining of the model (Fine-Tuning) is technically cumbersome and economically unviable for daily updates (Ouyang et al., 2022).

1.6. The RAG Paradigm as a Cognitive Augmentation Solution

The integration of generative AI into guidance counseling faces a major epistemological and technical hurdle: the reliability of factual knowledge. As highlighted by Ji et al. (2023), Large Language Models (LLMs) are prone to "hallucinations" when queried about specific data absent from their training set. For a guidance counselor in Morocco, using a standard LLM presents a risk of obsolescence, as ministerial memos and pre-registration procedures evolve annually, surpassing the knowledge cut-off of pre-trained models.

To overcome these limitations, we propose a modeling based on the Retrieval-Augmented Generation (RAG) architecture. Introduced by Lewis et al. (2020), RAG transforms the LLM into a reading-comprehension system rather than a mere probabilistic generation engine. The fundamental principle lies in splitting the process into two stages: a retrieval phase and a generation phase. This mechanism anchors AI responses in a verified and real-time updated documentary corpus, thereby ensuring the veracity of the information transmitted to guidance counselors.

From a knowledge engineering perspective, the choice of RAG over Fine-Tuning (re-training) is justified by the volatility of Moroccan regulatory information. While Fine-Tuning requires significant computational resources and freezes knowledge at a specific point in time, RAG allows for instantaneous updates through simple vector indexing of new documents (PDFs, circulars). This dynamism directly addresses the "information freshness" requirement identified in our non-functional requirements (Glinz, 2007).

From the standpoint of ergonomic psychology, this architecture supports Sweller's Cognitive Load Theory (2011). By acting as an external working memory, the RAG chatbot relieves the counselor of the task of rote memorization of thresholds and dates. By reducing the extraneous load associated with searching for information across disparate sources, the tool enables the professional to reallocate their cognitive resources toward the relational dimension and the complex analysis of student profiles, thus fostering the Life Design posture advocated by Savickas (2009).

1.7. Scientific Positioning of the Study

The analysis of existing literature reveals a marked dichotomy. On one hand, research on AI integration in educational settings focuses primarily on personalized learning for students or pedagogical support for teachers (Gocen & Aydin, 2020; Holmes et al., 2019). On the other hand, while recent reviews of RAG architecture validate its theoretical capacity to secure factual knowledge (Gao et al., 2024), these studies often remain decontextualized and do not address the professional specificities of guidance services.

Consequently, there remains a clear research gap concerning the specific technological instrumentation for guidance counselors. The unique constraints faced by these practitioners—defined by Sampson et al. (2020) as a constant navigation through an "informational labyrinth" requiring permanent updates—have not yet been the subject of a dedicated RAG modeling. Our study aims to fill this void by proposing a mobile assistance architecture, custom-tailored to meet this dual requirement of regulatory reliability and professional mobility.

Identifying these cognitive and technical (RAG) constraints now necessitates a methodological framework capable of transforming these theoretical principles into a functional artifact: this is the objective of the Design Science Research (DSR) approach presented below.

2. Methodology

To address the challenge of hybridizing human expertise and artificial intelligence, this study is situated within the Design Science Research (DSR) paradigm. According to Hevner et al. (2004), DSR aims to create and evaluate innovative artifacts (models, methods, systems) to solve identified organizational problems.

Our methodological approach follows the sequential process defined by Peffers et al. (2007), structured here into four distinct phases:

2.1. Phase 1 : Problem Identification and Domain Analysis

The first step consists of defining the practical relevance of the problem. We conducted a **narrative literature review (Vom Brocke et al., 2009)** intersecting the fields of guidance psychology and software engineering. This analysis allowed us to isolate two critical variables that justify the design of a new tool:

- **Informational Friction:** The mismatch between current (static) search tools and the volatility of regulatory data.
- **Mobility Constraint:** The need for guidance counselors to access information outside of a fixed workstation.

2.2. Phase 2 : Definition of Solution Objectives

Based on the previous analysis, we established the Non-Functional Requirements (NFR) of the target system, according to Glinz's (2007) classification. To be theoretically valid, the proposed model must satisfy three criteria:

- **Information Freshness:** The system must allow for near-instantaneous updates of the knowledge base without requiring the costly retraining of the neural model (Lewis et al., 2020).
- **Cognitive Load Reduction:** The interface must minimize interaction effort, prioritizing natural language over complex navigation menus (Shneiderman, 2022).
- **Mobile Interoperability:** The architecture must be compatible with the constraints of mobile devices (latency, display), justifying the use of native technologies such as Android/Jetpack Compose.

2.3. Phase 3 : Design and Development of the Model

This phase constitutes the core of our contribution. We adopted a component-based modeling approach (Bass et al., 2012) to design a hybrid architecture. Our design methodology contrasts two theoretical approaches:

- **The Fine-Tuning approach:** Re-training models on a specific corpus.
- **The RAG (Retrieval-Augmented Generation) approach:** Dynamic context injection.

The modeling process relies on the Unified Modeling Language (UML) to formalize the interactions between the user (the counselor), the mobile interface (Frontend), and the inference engine (Python Backend). This formalization allows for the validation of the data flow logic prior to any physical implementation.

The culmination of this architectural reflection is presented in Figure 1, which details the technical organization of our artifact.

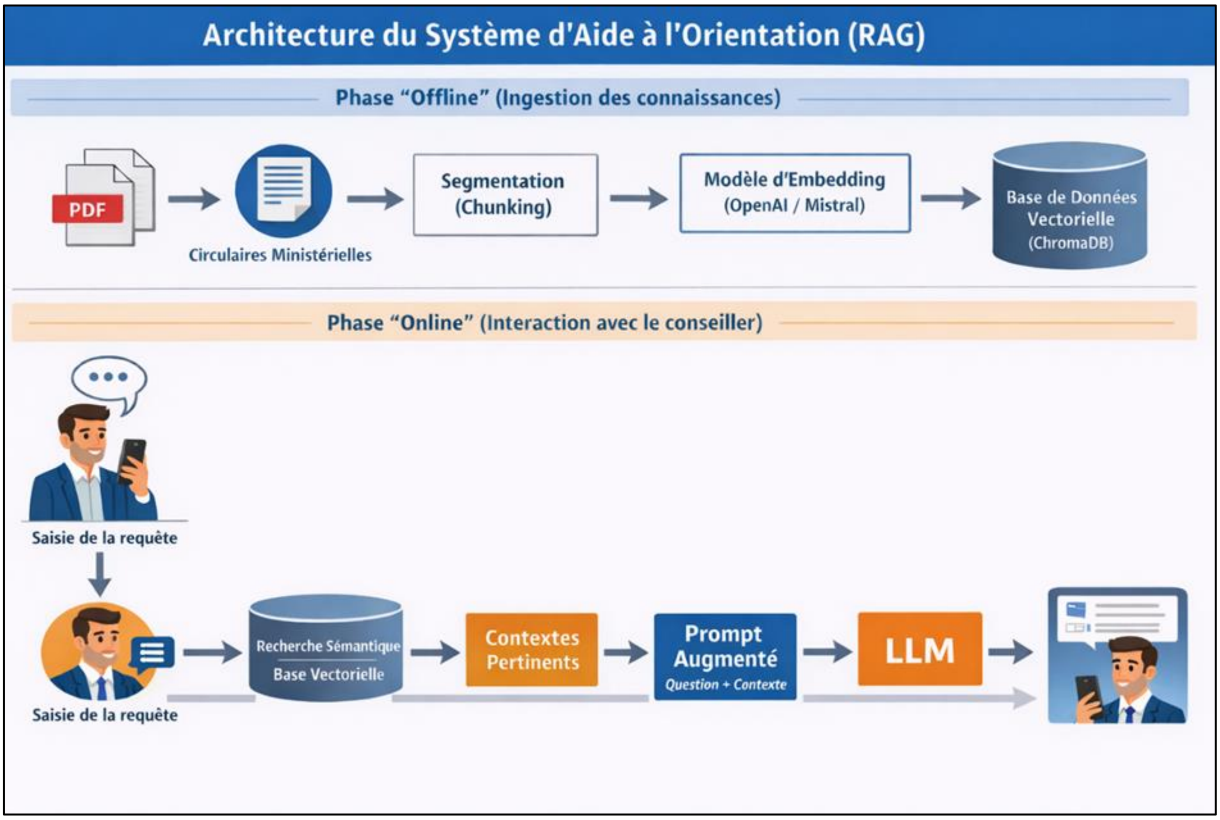

Figure 1 Guidance Support System Architecture (RAG-based)

As illustrated by the artifact modeling (Figure 1), the software design is segmented into two distinct processes:

- **The Offline Phase (Ingestion):** This workflow manages knowledge persistence. Ministerial circulars undergo semantic segmentation (Chunking) before being converted into vectors by an embedding model (OpenAI / Mistral). These vectors are stored in the ChromaDB database, creating a searchable semantic index.
- **The "Online" Phase (Interaction):** This workflow describes the guidance counselor's experience. The user's query triggers a similarity search. The system does not generate a response *ex nihilo*; instead, it constructs an "Augmented Prompt" by merging the question with the official context. The Large Language Model (LLM) then acts solely as a synthesis engine to deliver a sourced and secure response.

This architecture ensures that the system remains a reliable decision-support tool, minimizing the risks of hallucinations while respecting the practitioner's cognitive load through a direct and documented response.

2.4. Phase 4 : Demonstration and Descriptive Evaluation

Within the scope of this conceptual paper, the evaluation of the artifact does not rely on empirical experimental metrics, but rather on a descriptive evaluation as defined by Hevner et al. (2004). We conduct a theoretical comparative analysis, demonstrating through logical argumentation that the proposed RAG architecture offers structural superiority; in terms of update costs and hallucination reduction; compared to traditional monolithic architectures for the specific use case of educational guidance.

2.5. Evaluation Perspectives and Ethical Considerations

The conceptual modeling presented here naturally calls for a future validation and implementation phase. Beyond the comparative descriptive evaluation conducted in this article, the relevance and acceptability of the proposed "Cognitive Assistant" must be tested in the field. This section outlines a framework for future evaluation and addresses the fundamental ethical considerations raised by the introduction of an AI agent into the helping relationship.

2.6. Future Evaluation Protocol

Once prototyped, the evaluation of the artifact should adopt a mixed-methods approach, combining objective system performance metrics with subjective measures of user experience and perceived impact on practice. We envision a two-phase protocol:

2.7. Laboratory Evaluation (Performance & Reliability):

The evaluation of the prototype's performance and robustness will rely on several key technical metrics. First, factual accuracy will be rigorously measured using Recall and Precision indicators. This measurement will be conducted on a specific set of test questions, developed from a controlled corpus of regulatory documents, to assess the system's ability to retrieve relevant information and formulate it correctly.

Second, a hallucination robustness test will be conducted by subjecting the system to intentionally out-of-domain or misleading questions. The goal is to evaluate its propensity to recognize its limitations by responding appropriately—for example, with an "I don't know" or a request for clarification—rather than generating plausible but erroneous information. Finally, with a view toward real-world practical use, system latency will be evaluated. This response time measurement will be carried out under various mobile connection conditions, as this parameter is critical to ensuring fluid and non-intrusive interaction during face-to-face interviews with students.

2.8. *In situ* Evaluation with Practitioners (Perceived Usefulness & Cognitive Impact):

To assess the perceived usefulness and cognitive impact of the assistant, an *in situ* evaluation would be conducted with a cohort of guidance counselors through a user-testing protocol involving the prototype's deployment during simulated or real interviews, carried out with the participants' informed consent. Data would be collected using a mixed-methods approach, combining structured questionnaires and semi-structured interviews to measure several key indicators: the perceived reduction in mental workload using adapted scales such as the NASA-TLX; the concrete impact on interview fluidity, objectified by the frequency of interruptions for documentary research; the level of trust placed by the counselor in the system-generated responses; and the overall acceptability of the tool alongside the stated intention for its future integration into professional practice.

2.9. Fundamental Ethical Considerations

The introduction of an algorithmic assistant into a profession rooted in human relationships and trust demands heightened ethical vigilance. Four major challenges emerge:

- **Responsibility and Human Agency (Human-in-the-Loop):** The system must be designed as a decision-support tool rather than a replacement. The final decision-making responsibility and professional judgment must imperatively remain in the hands of the counselor. The interface must avoid any phrasing that presents the AI's response as a verdict, instead always contextualizing it as sourced information.
- **Transparency and Explainability:** The principle of source traceability, inherent to the RAG architecture, is a major ethical asset. The counselor must be able to consult, with a single click, the specific passage of the regulatory document upon which the response is based. This transparency is necessary to maintain the user's expert control and to build trust.
- **Confidentiality and Data Protection:** The assistant will handle sensitive data (queries posed by the counselor, which may indirectly reveal elements of a student's situation). It is imperative that:
    - No conversational data is used to retrain general models.
    - All data is encrypted both in transit and at rest.
    - Data storage and processing comply with both local (Moroccan) and international (GDPR) regulations.
- **Bias and Fairness:** The documentary corpus, though regulatory, may contain historical or structural biases. The ingestion and indexing process must be supervised to avoid a biased representation of information. Furthermore, access to the tool must be designed so as not to create a new digital divide between practitioners based on their level of equipment.

2.10. Limitations and Future Research

This modeling presents certain limitations that open avenues for future research. On one hand, the proposed evaluation remains to be conducted. On the other hand, the system's success will depend on the quality and comprehensiveness of the **initial documentary corpus**, the creation and maintenance of which represent an organizational challenge in their own right. Finally, future research could explore the integration of more advanced reasoning modules concerning individual student pathways, always within a framework of assistance rather than automation.

In conclusion, the RAG approach stands as the most promising architecture for addressing the challenge of informational volatility. However, its successful deployment will be contingent upon a rigorous human-centered evaluation and adherence to strict ethical principles. These safeguards ensure that technology serves and strengthens, without altering, the essential relationship between the counselor and the student.

3. Conclusion

This research originated from a critical operational observation: the practice of school guidance counseling in Morocco is compromised by an insoluble cognitive tension between the necessity of mastering volatile, dense regulatory information and the requirement of psychological availability for the helping relationship. Faced with this paradox, existing technological solutions; particularly standard LLMs; prove inadequate due to their factual hallucinations and structural obsolescence.

To address this issue, we proposed the conceptual modeling of a Mobile Cognitive Assistant specifically designed for guidance counselors. The central contribution of this modeling lies in demonstrating the superiority of the Retrieval-Augmented Generation (RAG) architecture. By coupling a generic language model with a constantly updatable vector knowledge base, RAG provides an elegant and effective response to two field imperatives: absolute reliability (through source traceability and a drastic reduction in hallucinations) and information freshness (through simplified documentary corpus updates without costly retraining). This approach does not aim to automate counseling but to achieve a human-machine symbiosis, where AI acts as an external memory and facilitator, thereby freeing up the counselor's cognitive resources for the core of their profession: listening, empathy, and personalized guidance.

From a theoretical standpoint, this study contributes to filling an identified research gap by facilitating an unprecedented convergence between three disciplinary fields: cognitive psychology (Cognitive Load Theory to model the human problem), guidance sciences (Life Design and working alliance to frame relational needs), and information systems engineering (LLMs and RAG to design technical solutions). This interdisciplinary articulation is fundamental to moving beyond a purely techno-centric vision and anchoring innovation in professional realities.

On a practical level, the modeling provides a clear operational framework (supported by the DSR methodology and NFR specifications) for the future development of a prototype. The outlined mixed-evaluation perspectives and robust ethical considerations (responsibility, transparency, confidentiality) provide a roadmap for responsible implementation.

Finally, this research opens several major perspectives. It calls for a phase of prototyping and empirical validation with practitioners in the field. It also questions the evolving role of the counselor, whose expertise could shift toward higher-value tasks once the informational burden is lightened. In the long term, this paradigm of cognitive augmentation through RAG could inspire the development of similar assistants for other professions facing the dual demand of specialized technical expertise and human relations, such as legal professionals or social workers.

Ultimately, this study advocates for a thoughtful, critical, and human-centered integration of artificial intelligence within the sensitive sector of guidance. It demonstrates that in the face of informational complexity, the most relevant solution is not to replace the professional with a machine, but to equip them with a reliable algorithmic companion designed to serve them and enable them to better exercise their own humanity.

Compliance with ethical standards

Disclosure of conflict of interest

The Authors proclaim no conflict of interest.

References

[1] Ayres, P., & Sweller, J. (2014). The split-attention principle in multimedia learning. In The Cambridge Handbook of Multimedia Learning.

[2] Bass, L., Clements, P., & Kazman, R. (2012). Software Architecture in Practice (3rd ed.). Addison-Wesley Professional.

[3] Brown, T., et al. (2020). Language Models are Few-Shot Learners. NeurIPS.

[4] Deng, Y., & Lin, Y. (2024). RAG for Education: Bridging the Gap between Large Language Models and Educational Knowledge Bases. International Journal of Artificial Intelligence in Education.

[5] Gao, Y., Xiong, Y., Gao, X., et al. (2024). Retrieval-Augmented Generation for Large Language Models: A Survey. IEEE Transactions on Knowledge and Data Engineering.

[6] Glinz, M. (2007). On non-functional requirements. Requirements Engineering, 12(1), 21-26.

[7] Gocen, A., & Aydin, F. (2020). Artificial Intelligence in Education and Schools. Research on Education and Media, 12(1), 13–21. DOI : 10.2478/rem-2020-0003.

[8] Guichard, J. (2013). Career guidance, education, and dialogues for a fair and sustainable human development. International Journal for Educational and Vocational Guidance, 13(1), 29-43.

[9] Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. MIS Quarterly, 28(1), 75-105.

[10] Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Center for Curriculum Redesign.

[11] Horvath, A. O., & Greenberg, L. S. (1989). Development and validation of the Working Alliance Inventory. Journal of Counseling Psychology, 36(2), 223–233.

[12] Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577-586.

[13] Ji, Z., Lee, N., Frieske, R., et al. (2023). Survey of hallucination in natural language generation. ACM Computing Surveys, 55(12), 1-38.

[14] Kasneci, E., Sessler, K., Küchemann, S., et al. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274.

[15] Lewis, P., Perez, E., Piktus, A., et al. (2020). Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. Advances in Neural Information Processing Systems (NeurIPS).

[16] Licklider, J. C. (1960). Man-Computer Symbiosis. IRE Transactions on Human Factors in Electronics, 1, 4-11.

[17] Molenaar, I. (2022). Towards hybrid human-AI learning technologies. European Journal of Education, 57(4), 632-645.

[18] Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C. L., Mishkin, P., ... & Lowe, R. (2022). Training language models to follow instructions with human feedback. Advances in Neural Information Processing Systems (NeurIPS), 35, 27730-27744.

[19] Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. Journal of Management Information Systems, 24(3), 45-77.

[20] Sampson, J. P., Osborn, D. S., & Kettunen, J. (2020). The Role of Information and Communication Technology in Career Development. In Career Development and Counseling: Putting Theory and Research to Work (3rd ed.). Wiley.

[21] Savickas, M. L., Nota, L., Rossier, J., et al. (2009). Life designing: A paradigm for career construction in the 21st century. Journal of Vocational Behavior, 75(3), 239-250.

[22] Shneiderman, B. (2022). Human-Centered AI. Oxford University Press.

[23] Sweller, J. (2011). Cognitive load theory. Psychology of Learning and Motivation, 55, 37-76.

[24] Vom Brocke, J., et al. (2009). Reconstructing the giant: On the importance of rigour in documenting the literature search process. ECIS 2009 Proceedings.

[25] Watts, A. G. (2013). Career guidance and orientation services in global perspective. In International Handbook of Career Guidance. Springer.

[26] Wickens, C. D. (2008). Multiple resources and mental workload. Human Factors, 50(3).