Recommendations for the Design of a Customer Service Web Application for SMEs with Multimodal and Omnichannel Intelligent Agent

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Abstract: Currently, many small and medium-sized enterprises (SMEs) in Peru face difficulties in providing continuous, efficient, and personalized customer service due to technical, budgetary, and human resource limitations. This article proposes a set of 10 recommendations for designing a SaaS-type web application that implements an intelligent multimodal and omnichannel agent, based on Deep Learning and Natural Language Processing (NLP), with the objective of automating and optimizing customer service operations in the SME environment. The recommendations are based from a targeted review of 37 scientific articles and 18 commercial applications, the recommendations were organized into three categories: (i) technical infrastructure and architecture of the web application, (ii) interface, configuration, and SME experience, and (iii) conversational AI and end-customer experience. To illustrate their applicability, the design of a web application is presented a platform with the proposed recommendations. Additionally, an experiment was conducted with 25 subjects to measure satisfaction with the web application designed according to the proposed recommendations, yielding positive results. This proposal seeks to bridge the technological gap that limits the competitiveness of small businesses.

Keywords: SMEs, intelligent agent, Deep Learning, Natural Language Processing, customer service, omnichannel, multimodal.

1 Introduction

Artificial intelligence has revolutionized business communication, particularly through conversational agents that provide immediate and contextualized assistance using Natural Language Processing, transformer models, and multimodal inputs such as text, voice, and image [1][2][3]. These technologies enhance customer experience, reduce costs, and enable 24/7 operations [4][5][6]. However, small and medium-sized enterprises (SMEs), especially in emerging economies such as Peru, face critical barriers: lack of technical talent, limited digital infrastructure, and insufficient guidance for AI integration [2][9][10]. This gap is alarming considering that SMEs represent 99.6% of Peru's business fabric and generate more than 88% of formal employment [42], while 82% of customers abandon companies due to poor service [43] and 73% of SMEs fail to increase sales due to lack of automation [44]. Although 23% implement basic chatbots, most lack advanced capabilities such as intent analysis, emotional understanding, training with proprietary documents, or unified response across WhatsApp, Telegram, Messenger, and email [43]. This reality demands technical solutions that democratize access to conversational AI for SMEs. This article proposes a set of 10 recommendations for designing a SaaS-type web application that implements an intelligent multimodal and omnichannel agent, optimized for SMEs. The recommendations are derived from a targeted review of 37 scientific articles and 18 commercial applications demonstrating the use of omnichannel agent system characteristics and are grouped into three blocks: (i) technical architecture and infrastructure of the web application, such as the use of R1 (domain-scalable microservices) and R2 (autonomous system monitoring); (ii) configuration and usage experience by SMEs in the web application, such as the use of R3 (clear and persuasive landing page), R4 (frictionless federated authentication), R5 (simple web dashboard), R6 (omnichannel connection from panel), R7 (agent training with documents), and R8 (multichannel customer tracking); and (iii) intelligent interaction with end-user customers, such as the use of R9 (personalization through RAG and generative AI) and R10 (intent and emotion detection for adaptive responses). To illustrate their applicability, an illustrative example of a web application design called Omnisapientes is presented—a SaaS platform based on the proposed recommendations that enables SMEs to integrate multiple service channels, upload business documents, train generative AI models such as Mistral 7B, and automate customer service through a conversational agent that responds in a personalized, empathetic, and contextual manner. Additionally, an experiment was conducted with 25 subjects to measure satisfaction with the web application designed according to the proposed recommendations, yielding positive results. This proposal seeks to democratize access to advanced conversational technologies and bridge the digital gap that limits the competitiveness of small businesses in Latin America. This article is structured as follows: Section 2 reviews related work on the proposed recommendations. Section 3 presents the definition of the proposed recommendations. Section 4 designs an illustrative example of the web application. Section 5 shows early validation. Finally, Section 6 presents conclusions, limitations, and future research directions.

2 State of Art

This section reviews related work on the design of intelligent multimodal and omnichannel conversational agents for customer service in small and medium-sized enterprises (SMEs). The TLR approach was selected to synthesize design patterns from both academic and commercial sources, appropriate for extracting actionable recommendations. This method allows inclusion of grey literature alongside peer-reviewed articles, essential for emerging technologies where innovation occurs in both academia and industry. This was accomplished through a Targeted Literature Review (TLR), a non-systematic and informative review that aims to retain only significant references to minimize bias. The proposed recommendations for designing an intelligent multimodal and omnichannel agent system for customer service in SMEs are based on research work collected from the Scopus bibliographic database. The search string used in this work is as follows: ("omnichannel" AND "multimodal" AND "intelligent agent" AND "SMEs" AND "NLP" AND "Deep Learning" AND "customer service" AND "web application"). The inclusion criteria are: topics related to the use of natural language processing and Deep Learning in conversational agents, application of multimodal and omnichannel strategies in digital services, and studies applicable to the context of small and medium-sized enterprises. The exclusion criteria are: topics unrelated to customer service, articles older than two years—due to the rapid evolution of the multimodal intelligent agents field and the need to maintain technological currency of the state of the art studies without the use of multiple interaction channels or multimodal inputs, and research focused exclusively on large corporations. The initial Scopus search yielded 60 articles. After applying inclusion/ exclusion criteria, 15 core articles were selected. Snowballing (citation analysis) identified 22 additional studies, totaling 37 articles. Additionally, 18 commercial platforms were analyzed using criteria: (i) AI/NLP capabilities, (ii) multi-channel support, (iii) public documentation, and (iv) SME-oriented features. The research works were divided into two groups: (i) implementation of omnichannel and multimodal strategies in intelligent assistants, and (ii) application of natural language processing (NLP).

2.1 Implementation of omnichannel and multimodal strategies in intelligent assistants

Pursnani et al. [15] developed Floodplain Manager AI, a system based on large language models (LLMs) that combines text and image inputs, such as FEMA flood maps, with the objective of assisting decision-making in territorial planning. They employed a distributed architecture based on microservices and a vector query system (ChromaDB), evaluating its performance comparatively against other environmental information platforms. The results indicated a significant improvement in the precision and contextualization of responses, achieving 97% accuracy in specialized queries. This approach proved effective in handling multimodal data and highly adaptable to other contexts. Chen et al. [14] investigated the impact of different post hoc explainability strategies on user trust and acceptance of recommendations in conversational agents. Through three experimental studies, they analyzed the effect of interface type (voice vs. text), decision type (hedonic vs. utilitarian), and consumer style (intuitive vs. rational) on the perception of transparency and utility of the assistant. The results indicated that explanations aligned with context and user style increase trust, especially in multimodal interfaces. This study provides valuable evidence on how response personalization and adaptation to interaction channels strengthen the effectiveness of intelligent assistants in omnichannel digital services. Karunanayake [13] explored the transformative impact of next-generation artificial intelligence systems called agentic AI in the healthcare sector. The study highlights how these agents, powered by multimodal large language models (MLLMs), integrate textual, visual, and clinical data to offer contextual, autonomous, and scalable solutions. Through examples such as AgentClinic and VoxelPrompt, the article demonstrates that conversational agents with adaptive capabilities can assist in tasks such as diagnosis, patient monitoring, and clinical decision-making with improved precision and efficiency. Boudin et al. [12] propose a multimodal model capable of predicting both the position and type of feedback during a conversation, using prosodic, morphosyntactic, and gestural signals from the interlocutor. The study introduces a detailed taxonomy of feedback—generic and specific—and identifies subtypes based on the affective load of the main speaker's discourse, known as emotional valence (positive or negative), as well as the status of information (new or known). The results showed that integrating multiple modalities significantly increases the model's precision and its ability to interpret context. Although their application was conducted on a French corpus of natural conversations, the authors highlight the transferability of their approach to human-computer interaction contexts, especially in virtual agents. Vinarti et al. [11] designed I-Mun, a system that combines an informative chatbot on Telegram with scheduled reminders sent via WhatsApp. The system aimed to inform parents about their children's vaccination schedule, using multiple channels in a complementary manner. The combination of automated reminders with conversational interaction proved effective in improving calendar adherence. This proposal represents a functional case of using omnichannel strategies in intelligent assistants, applicable to business contexts where personalization and multichanneling are necessary. Key patterns emerged: microservices enable scalability [15], multimodal inputs improve understanding [13][14], and omnichannel requirescentralization [11][15].

In summary, from this group of works, it can be affirmed that there is consensus regarding the utility of integrating multimodal and omnichannel strategies in intelligent assistants to improve user experience, adaptability, and contextual precision, as evidenced by Pursnani et al. [15], Chen et al. [14], and Vinarti et al. [11]. Furthermore, studies such as those by Karunanayake [13] and Boudin et al. [12] reinforce the relevance of incorporating diverse inputs (text, voice, gestures, images) in conversational models to achieve greater naturalness and contextual interpretation.

2.2 Application of NLP and Deep Learning in Conversational Agents

Olujimi and Ade-Ibijola [3] conducted a systematic review on current Natural Language Processing (NLP) techniques employed in automating responses to customer queries. They identified that deep learning-based models, such as transformers, exhibit significantly superior performance in intent classification and response generation compared to rule-based systems. However, the authors emphasize that ambiguous interactions, the need for prolonged contextual understanding, and emotional recognition remain persistent technical limitations in most current systems. McAllister et al. [4] proposed an interdisciplinary research agenda aimed at improving chatbot systems through the incorporation of more adaptive and empathetic capabilities. They highlight that, despite advances in conversational efficiency, many systems lack mechanisms to interpret emotions, mental states, or complex user intentions. They also emphasize the need for conversational models that learn from experience and interact with greater naturalness and sensitivity. Zhang and Luo [1] proposed an artificial intelligence-based personalization framework designed specifically for SMEs. This framework uses NLP to adapt responses to particular customer needs, enabling more personalized interaction. The study demonstrated its effectiveness in improving user experience but also identified technical difficulties associated with model training and integration with limited enterprise infrastructures. Badghish and Soomro [2], through the application of the TOE (Technology-Organization-Environment) framework, evaluated the factors that condition AI adoption in customer service processes in small businesses. The authors conclude that, while SMEs recognize the value of implementing intelligent conversational agents, they face significant structural barriers such as lack of technical talent, tight budgets, and scarce technological infrastructure to support these solutions. Critical gaps include emotional recognition [3][4], training complexity [1], and infrastructure requirements [2], motivating SME-focused recommendations. As a conclusion regarding the works considered in this category, it can be affirmed that there is consensus regarding the potential benefits of intelligent conversational agents based on NLP and deep learning in optimizing customer service processes, as evidenced by Olujimi and Ade-Ibijola [3] and Zhang and Luo [1]. Nevertheless, technical and organizational barriers that hinder their adoption are also identified, especially in the context of SMEs, as proposed by Zhang and Luo [1] and Badghish and Soomro [2]. Likewise, McAllister et al. [4] highlight critical gaps related to the lack of emotional sensitivity and limited adaptive capacity of current models.

3 Definition of recommendations for Application Design

This section defines a set of 10 recommendations for designing a SaaS (Software as a Service) web application, whose objective is to offer multiple small and medium-sized enterprises (SMEs) a customer service solution through an intelligent agent with multimodal capabilities (text, voice, image) and omnichannel features (WhatsApp, Telegram, Facebook, Instagram, email), powered by generative artificial intelligence (Mistral 7B model). The recommendations were developed from a documentary analysis of 37 scientific articles and 18 applications. The procedure for developing the recommendations consisted of identifying scientific articles that described the design, implementation, or evaluation of intelligent conversational systems applied to SMEs, extracting recurring technical patterns, architectural approaches, omnichannel integration strategies, and natural language processing with deep learning. These elements were organized and systematized as technical recommendations applicable to the design of the proposed system. Each recommendation is presented with the prefix "R" followed by a sequential number (R1, R2, R3, etc.). The set is organized into three technical blocks, which correspond to the main axes of the proposed web application: (i) Design of the multimodal and omnichannel intelligent agent web application; (ii) Functional components for SME-oriented web applications; and (iii) Interaction of the AI agent with SME customers. The formulated recommendations are detailed below.

3.1 Recommendations for the Design of the Multimodal and Omnichannel Intelligent Agent Web Application

R1: Implement a microservices architecture for the web application backend. Recent work supports microservices-based backend architectures for SME customer service applications. In the work of: (i) Costa et al. [16] identify that customer service digitization requires technical structures adjusted to operational constraints, highlighting that microservices enable modular and scalable solutions adapting to progressive growth without compromising stability. (ii) Ewim et al. [17] propose a customer-centered framework where each microservice is optimized by specific function and deployed under load balancers, improving efficiency and resource distribution. (iii) Radicic and Petković [18] argue that SME structural heterogeneity demands distributed architectures that decouple critical components, increasing maintainability, flexibility, and efficiency. (iv) Wang et al. [19] demonstrate that SMEs adopting modular architectures achieve greater innovation capacity through microservices as digital evolution enablers. Consequently, adopting a distributed architecture based on microservices decoupled by functional domain, orchestrated through an API Gateway, operating under load balancing and structured under a multitenant model is recommended. In conclusion, this architecture maintains operational integrity, guarantees horizontal scalability, and ensures logical isolation of each SME user—essential factors for efficient SaaS platform deployment in high concurrency contexts with SME technical limitations.

R2: Incorporate autonomous monitoring mechanisms and operational continuity in intelligent web applications for SMEs. Scientific articles highlight that autonomous monitoring plays a role analogous to the nervous system: continuously supervising internal functioning, detecting anomalies, and immediately activating correction mechanisms. In the work of: (i) Alabi et al. [6] defined that in low technical capacity environments, automated platforms must incorporate permanent supervision mechanisms capable of proactively detecting failures and activating responses without human intervention. (ii) Hussain and Rizwan [10] emphasize that SME operational sustainability depends on functional autonomy the system's ability to operate and recover without constant supervision. In the application: (iii) IBM [25] proposes that AI systems include intelligent supervision modules functioning as internal control centers, executing corrective measures according to predefined policies. (iv) Dharmaraj and Pandian [45] recommend implementing mechanisms allowing restart of only the failing system part without affecting other operations. In conclusion, SME-oriented intelligent applications should integrate an autonomous monitoring module responsible for continuously evaluating internal service status, detecting operational errors, activating automatic selective recovery processes, and ensuring sustained availability, this architectural strategy maintains service continuity in environments with scarce technical infrastructure, favoring reliability and scalability of AI-based solutions.

3.2 Recommendations on Functional Components of Web Applications for SMEs

R3: Design landing pages including AI capabilities. Scientific articles supporting the design of landing pages (websites that showcase a product for users to take action: buy, register, or request more information) for web applications focused on SMEs interested in adopting intelligent conversational agents were analyzed. In the work of (i) Al-Shafei [21] identified that anthropomorphism in design, such as the use of avatars or friendly facial expressions, increases the perception of closeness and trust toward AI-based systems, especially in environments where the end user is new to technology. (ii) Mafra et al. [22] validated, through systematic review, that landing pages with clear hierarchical structure, benefit-oriented messages, and attractive visual components increase small businesses' willingness to explore conversational solutions. (iii) Aboelmaged et al. [23] noted that to capture initial interest from an SME, it is essential that the graphical user interface shows both current and potential AI capabilities through an accessible narrative that avoids technical complexity. In conclusion, it is recommended to implement an initial landing page that combines anthropomorphic design (through illustrations of the intelligent agent with friendly appearance), clear benefit structure (such as 24/7 assistance and no-code automation), and a section of interactive demonstrations by industry, where each video or simulation shows how the system resolves real queries. this visual, persuasive, and contextualized strategy reduces cognitive friction, improves product understanding, and significantly increases adoption intention by companies exploring AI-based SaaS solutions for the first time.

R4: Generate trust through simplified authentication mechanisms. Scientific articles on federated authentication design and user menus in web applications focused on SMEs were analyzed, identifying critical UX/UI (user experience and interface) elements. In the work of: (i) Li et al. [24] demonstrated that federated authentication systems significantly reduce entry barriers for business users. (ii) Ali et al. [27] established that simplified login interfaces improve technology adoption in small businesses. (iii) Al-Shafei [21] confirmed that social authentication processes increase trust and usability in business SaaS applications. In the application (iv) Fuselab Creative [26] identified that user-friendly authentication processes and clear notifications constitute fundamental elements for generating trust in secure SaaS interfaces, especially critical for SMEs evaluating technology adoption. In conclusion, federated authentication design for SMEs should implement: simplified social authentication (Google, Microsoft, Facebook) that reduces access friction, and transparent notification systems that generate user trust during the login process.

R5: Optimize spatial understanding and operational efficiency through information architecture patterns. Scientific articles on intuitive UI navigation design for SaaS dashboards aimed at SMEs integrating omnichannel conversational agents were analyzed, identifying information architecture patterns and critical usability elements that optimize spatial understanding and operational efficiency. In the work of: (i) Costa & Silva [28] developed a dashboard procedure oriented toward improving productive team performance, establishing that dashboard development for SMEs must consider the level of business quality maturity and information systems, with information architecture adapted to small business particularities being a critical element for successful implementation. (ii) Moertini [29] confirmed that SME digital ecosystems require specific interactive components that facilitate socio-technical adaptation, where human capital in digital talent and government support constitute main restrictions for business information system adoption. In the application (iii) Octet Design [30] established that dashboards aimed at small businesses should prioritize simplicity and ease of navigation, incorporating user research and usability testing to ensure that functionalities extract actionable insights without cognitive overload. (iv) Raw Studio

[31] validated that responsive design with mobile-first architecture is essential for SMEs where multi-device access represents a critical operational need, with personalization and intuitive interfaces being determining factors for successful business adoption. In conclusion, intuitive dashboard design for SMEs should implement consistent global navigation with a maximum of 12 main categories (grounded in cognitive load principles [7] and adaptive interface design [8] that establish working memory limitations and optimal information architecture) adapted to the business technological maturity level, establish simplified visual hierarchy that prioritizes critical metrics without overwhelming technical complexity, incorporate interactive components that facilitate gradual socio-technical adaptation considering digital human capital limitations, and design responsive mobile-first architecture with contextual personalization.

R6: Facilitate simple and centralized omnichannel integration from the dashboard. Scientific articles and applications on omnichannel connection interface design for SaaS dashboards aimed at SMEs were analyzed, which allow connecting multiple communication channels (WhatsApp, Telegram, Messenger, Email) with intelligent agents through token/API configuration from a centralized interface. In the application: (i) VIMOS [32] established that WhatsApp API constitutes a critical platform for SMEs where authentication token configuration should facilitate direct connection with conversational AI systems, allowing intelligent agents to automatically respond to end-customer queries through simplified configuration interface. (ii) D7 Networks [33] confirmed that tools like Gallabox allow SMEs to manage multiple channels (WhatsApp, Telegram, Messenger) from the same dashboard, integrating token/API insertion forms per channel, which automatically link with virtual assistants without requiring technical knowledge. (iii) Octet Design [30] recommended that dashboards for small businesses should be structured in clear visual categories, where one of them is channel configuration, allowing direct credential administration, connection activation, and data editing from a unified and understandable environment. In the work of: (iv) Alabi et al. [6] proposed an omnichannel experience framework for SMEs based on dashboards that allow orchestrating the connection between channels and AI systems, validating that integration should focus on simple interface for API authentication from the same entry point. In conclusion, omnichannel dashboards designed for SMEs should offer a clear and hierarchized interface that centralizes channel configuration, allowing direct insertion of authentication tokens or credentials for WhatsApp, Telegram, Messenger, and Email. In conclusion, this interface should facilitate automatic connection with intelligent agents from a single control point, without requiring technical knowledge, and allow each channel to be activated, edited, or managed from an intuitive visual structure.

R7: Allow agent training with SME documents. Scientific articles on knowledge center design for dashboards were analyzed, which facilitate AI loading and training through business documents, identifying knowledge base management interface patterns and critical usability elements that optimize the process of feeding intelligent agents with specific business knowledge. In the work of: (i) Kedi et al. [34] through scientific study demonstrated that AI chatbot integration in SME marketing platforms requires robust knowledge bases fed by business documents, where content upload interfaces allow training conversational agents with specific product and service information to improve automated customer interaction. In the application (ii) MDPI

Research [35] confirmed that SMEs adopt AI technologies mainly Machine Learning and Natural Language Processing, being fundamental that training interfaces allow loading technical documentation, product manuals, and business FAQs to create specialized knowledge bases that feed intelligent conversational systems. In the application (iii) Intercom [36] established that chatbots equipped with structured knowledge bases require quality content where SMEs can upload technical documents, business policies, and operational procedures, with drag-and-drop interfaces being critical elements to facilitate AI training process without advanced technical knowledge. (iv) Zendesk [37] validated that 2024 AI knowledge base platforms incorporate generative capabilities that allow creating expanded content from basic business documents, where SMEs can upload simple bullet points and the system generates complete responses to train conversational agents. In conclusion, knowledge center design for SMEs should implement document upload interface through drag-and-drop supporting multiple formats (PDF, Word, Excel, CSV) allowing feeding specific business knowledge base, incorporate automatic categorization system that organizes uploaded documents by query type and product to optimize AI agent training, establish generated response preview where SMEs can validate how AI agent will interpret business documents before activating training, and design monitoring dashboard showing knowledge base effectiveness metrics through analysis of queries successfully resolved by trained AI agent.

R8: Implement real-time multichannel visual customer tracking. Scientific articles on multichannel tracking interfaces for dashboards in SMEs were analyzed, components that allow tracking operational metrics such as number of customers served, query volume per channel, and unresponded users through WhatsApp, Telegram, Messenger, and Email from a centralized platform. In the application (i) Qualtrics [38] highlighted that these interfaces help detect operational bottlenecks through monitoring attention flows per channel. (ii) Sprinklr [39] demonstrated that omnichannel tracking requires real-time dashboards showing customer transitions between channels preserving attention continuity. (iii) ValueCoders [40] confirmed that SMEs need visual interfaces of interaction volume from initial contact to successful resolution. (iv) Coupler.io [41] validated that omnichannel reporting requires consolidation of multichannel operational metrics to generate complete view of attention performance. In conclusion, a unified timeline showing customer flow per channel with visual indicators of attended versus unattended volume should be implemented, real-time monitoring dashboard tracking number of queries received, resolved, and pending through graphs and counters, automated alert system identifying operational overload and notifying when intervention is required, and consolidated view allowing detailed navigation from general metrics to specific customer interactions maintaining multichannel operational history.

3.3 Recommendations for AI Agent Interaction with SME Customers

R9: Personalize responses using real SME information. These studies agree that, to generate useful responses adapted to each SME's context, it is necessary to combine document retrieval mechanisms with advanced generative models. (i) Zhang and Luo [1] proposed an AI-based personalization framework that adapts agent responses according to each company's internal data, highlighting that the key lies in adjusting content to business language and needs, (ii) Soudani et al. [20] explained that the use of semantic embeddings, stored in vector databases, allows retrieving relevant document fragments when the customer makes a query, which improves response coherence and relevance, (iii) McAllister et al. [4] noted that an effective conversational agent must combine information retrieval with text generation to respond in a contextualized, non-generic manner, and (iv) Vidivelli et al. [19] validated the use of models like Mistral 7B in SME contexts, highlighting their high performance and low cost for generating precise and sectorized responses. In conclusion, it is recommended to implement a hybrid architecture combining semantic embeddings, retrieval-augmented generation (RAG), and generative models like Mistral 7B. Example: if a technical services company uploads its warranty regulations and support processes to the platform, the system can, faced with a query like "How long does the warranty last for my equipment if it was repaired?", locate the exact paragraph of the document that responds (using embeddings + RAG), and generate a clear and adapted response (using Mistral 7B). This allows the AI to personalize its responses according to each SME's real content, optimizing precision, utility, and customer service experience.

R10: Adapt AI responses according to customer intention and emotion. Scientific studies explaining how a conversational agent can improve its response if it is capable of understanding what the customer means (intention), recognizing how they feel (emotion), and learning each time it converses were reviewed. (i) Olujimi and Ade-Ibijola [3] showed that modern models allow the agent to understand from the first message whether the customer wants help, wants to make a complaint, or has a query, (ii) McAllister et al. [4] explained that if the agent detects whether the customer is upset, confused, or in a hurry, it can respond more empathetically and appropriately, (iii) Hussain and Rizwan [10] emphasized that the best agents are those that learn over time, that is, they adjust their responses as they interact with more people, and (iv) Vidivelli et al. [19] highlighted that current models like Mistral 7B exist that allow combining these three capabilities without needing much technical infrastructure. In conclusion, it is recommended that the conversational agent in an SME be able to: Understand what the customer needs as soon as they start writing, identify whether the customer is angry, calm, or confused, and improve their way of responding with each new conversation. This allows attention to be faster, more human, and better adapted to each real situation.

4 Illustrative Example with the Proposed Recommendations

This section presents an illustrative example of a web application that integrates the 10 proposed recommendations (R1 to R10) for designing a multimodal and omnichannel intelligent agent web application oriented toward customer service in small and medium-sized enterprises (SMEs). The example shows how these recommendations are implemented in the architecture, design, and functionality of a web application. This is a web application that allows SMEs to configure their own intelligent agent, integrate communication channels such as WhatsApp, Telegram, Messenger, Instagram, and Email, upload business documents, and automate 24/7 responses through a generative artificial intelligence engine. The web application combines voice, image, text, and document processing to understand customer intentions, detect emotions, and respond contextually through any connected channel. Below, each of the steps that an SME performs within the platform is illustrated, from registration to the final automated conversation with their customers.

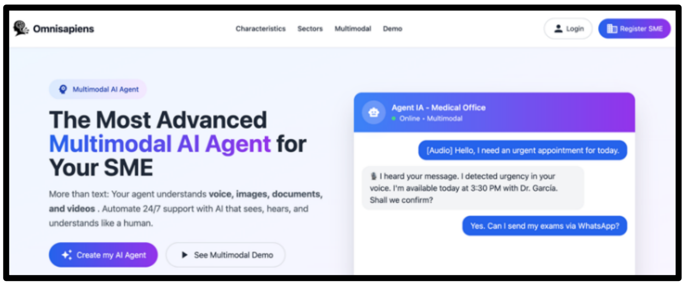

Fig. 1. Landing page of the application with federated authentication and interactive demo.

Figure 1 shows the web application landing page designed according to recommendations R3 and R10. It presents a clear, hierarchical, and visually friendly design (R3), ideal for capturing SME attention. In the upper right corner, it applies recommendation R4 through a federated authentication system that allows registration with email or accounts such as Google or Microsoft, facilitating entry without complications. Additionally, it includes an interactive demo that allows visualizing how the AI agent serves customers in a coherent and contextual manner (R10). This helps the SME easily understand the value of the web application and motivates them to adopt it.

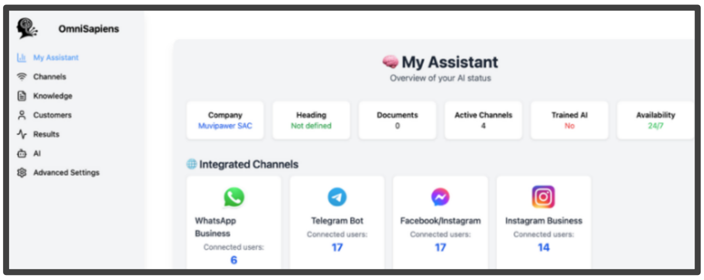

Fig. 2. Main agent dashboard with access to configuration and general status.

Figure 2 shows the "My Assistant" panel interface, where SMEs visualize their business profile and access the lateral menu with options to (i) configure channels, (ii) train the AI with documents, (iii) monitor customers, (iv) review statistics, and (v) log out. Recommendations R4 and R5 are implemented through simple external authentication and intuitive hierarchical design, R2 through training indicators and system status, and R9 with personalization based on uploaded data. This structure allows each SME to independently manage their agent from a visually accessible environment.

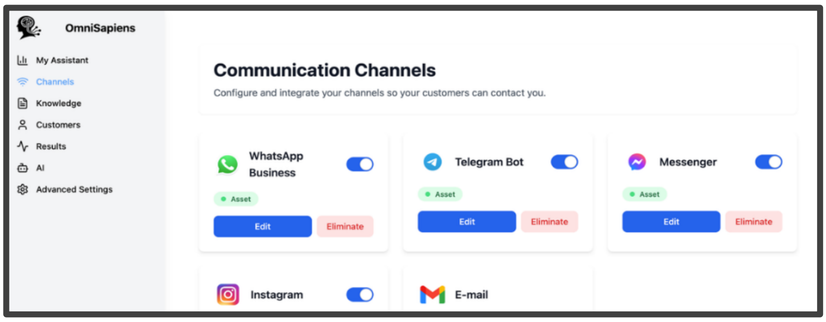

Fig. 3. The SME integrates its communication channels with the intelligent agent

Figure 3 shows the implementation of recommendation R6, allowing configuration of communication channels in a simple and intuitive manner. The SME can connect WhatsApp Business, Telegram Bot, Facebook Messenger, Instagram Business, and Email from initial "Configure" states, activating connection processes through tokens or credentials. This approach based on external APIs guarantees autonomy and security in access management. The interface facilitates integration without technical knowledge, allowing SMEs with low digital maturity to activate multiple channels progressively in a visual and guided manner

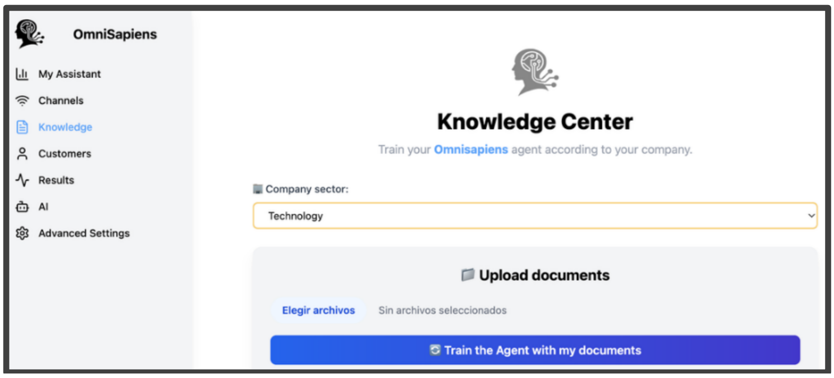

Fig. 4. The SME trains its intelligent agent by uploading business documents.

Figure 4 shows how the SME trains its intelligent agent through business documents, applying recommendation R7. From the "Knowledge Center", it selects its industry sector and uploads manuals, protocols, or key files, allowing the system to process content in a structured manner. By activating "Train the Agent with my documents", it initiates automated learning that improves precision and coherence in customer service based on real company knowledge. This functionality allows SMEs without technical knowledge to adapt their agent to the specific context, ensuring relevant and useful responses.

Early validation

This This section describes an initial validation performed to verify the applicability of the proposed recommendations. The web application (see Section 4) integrates the ten proposed recommendations (R1–R10) for designing a multimodal and omnichannel intelligent agent oriented toward customer service in small and medium-sized enterprises (SMEs). The validation involved 25 participants who interacted with the application: 18 employees from Peruvian SMEs in technology, retail, and service sectors, and 7 university students with prior experience in customer support tasks. Their average age was 28.4 years (SD = 4.2), ensuring diverse but relevant user perspectives for evaluating usability and satisfaction. All participants provided informed consent. The researchers offered a brief demonstration and assigned tasks in each section of the application. Participants interacted with the system by selecting predefined alternatives; correct answers increased their score, while incorrect ones triggered instant feedback explaining the right solution. After completing the case study, participants answered an online satisfaction survey based on the Moody model [47], derived from Lindland et al. [48], which evaluates Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Intention to Use (ITU) using a 5-point Likert scale (1 = Totally disagree, 5 = Totally agree). Figure 5 summarizes the satisfaction results.

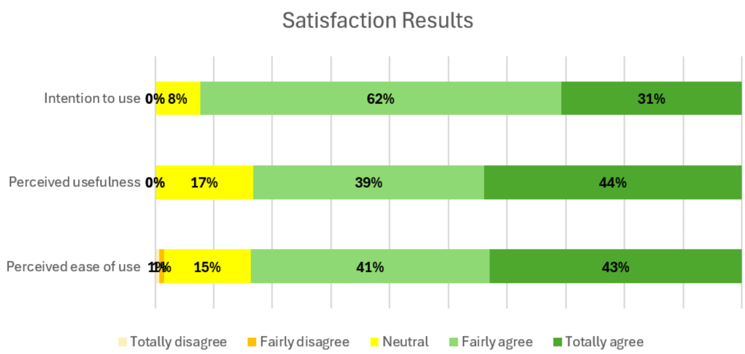

Fig. 5. Satisfaction results

Figure 5 shows a divergent stacked bar of the responses provided by subjects to the questionnaire for this property: For Perceived Ease of Use (PEOU), approximately 43% totally agreed and 41% fairly agreed (over 80% total), suggesting that the majority of subjects considered the web application to be easy and potentially useful to use. For Perceived Usefulness (PU), approximately 44% totally agreed and 39% fairly agreed (over 80% total), suggesting that the majority of subjects considered the application to be useful. For Intention to Use (ITU), approximately 31% totally agreed and 62% fairly agreed (over 90% total), suggesting that the majority of subjects intend to use the web application. A minority of subjects are undecided and do not perceive the application as useful.

5 Conclusions and Future Research Directions

This article presents a set of ten technical recommendations for designing a customer service application for SMEs, based on a multimodal and omnichannel intelligent agent with Deep Learning and Natural Language Processing technologies. From the analysis of 37 scientific studies and 18 applications, good practices, common challenges, and technical patterns applicable to the SME business context were identified. The recommendations were structured into three categories: (i) Technical architecture of the web application: recommends a structure based on decoupled microservices, autonomous monitoring, and operational continuity (R1 and R2), (ii) Interface, configuration, and SME experience: improvements in landing page, federated authentication, simple dashboards, channel integration, knowledge center, and multichannel tracking are proposed (R3 to R8), and (iii) Conversational AI and end-customer experience: personalization with RAG (Retrieval-Augmented Generation) and generative AI, intention and emotion understanding, and generation of adaptive and coherent responses are recommended (R9 to R10). Additionally, an experiment was conducted with 25 subjects to measure satisfaction with the web application designed according to the proposed recommendations, yielding positive results. As future work, the following is considered: (i) implement web applications with recommendations such as Omnisapiens in real SMEs to evaluate their operational impact, (ii) conduct scientific experiments to validate metrics such as satisfaction, effort, and usability, (iii) improve multimodal processing with intention and emotion detection in voice, image, and text, (iv) train generative models by industry sector using real company data, and (v) measure customer experience with proactive agents in real service scenarios.

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