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). 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. 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 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; (ii) configuration and usage experience by SMEs in the web application; and (iii) intelligent interaction with end-user customers, such as. To illustrate their applicability, an illustrative example of a web application design called Omnisapientes. This application is based on 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 democratize access to advanced conversational technologies and bridge the digital gap that limits the competitiveness of small businesses. This article is structured as follows: Section 2 reviews related work. 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 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 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. The exclusion criteria are: topics unrelated to customer service, studies without the use of multiple interaction channels or multimodal inputs. The initial Scopus search yielded 60 articles. After applying inclusion/ exclusion criteria, 8 core articles were selected. The research works were divided into two groups:

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. 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. 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. 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. 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. 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.

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. 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. 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. 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. 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: (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.* This recommendation is derived from the following works: (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. 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*. This recommendation is derived from the following works: (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 [44] 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.* This recommendation is derived from the following works: (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.

R4: *Generate trust through simplified authentication mechanisms.* This recommendation is derived from the following works: (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.* This recommendation is derived from the following works: (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. (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) This recommendation is derived from the following works and applications: (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*. This recommendation is derived from the following works: (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. 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*. This recommendation is derived from the following works and applications (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*. This recommendation is derived from the following works: (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.* This recommendation is derived from the following works: (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.

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). 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.

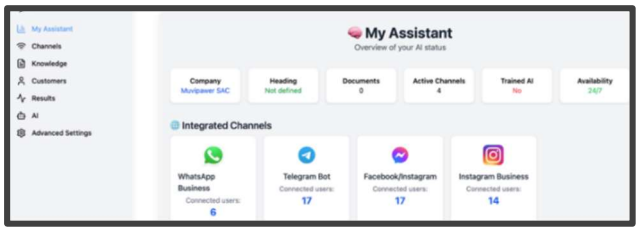

Fig. 1. Main agent dashboard with access to configuration and general status.

Figure 1 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.

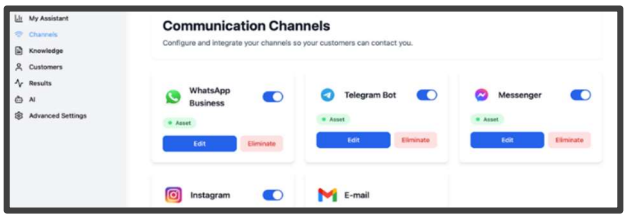

Fig. 2. The SME integrates its communication channels with the intelligent agent

Figure 2 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.

5 Early Validation

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 of the 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 application by selecting predefined alternatives, correct answers increased their score. After completing the case study, participants answered an online satisfaction [45] survey based on the Moody model [46], derived from Lindland et al. [47], 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).

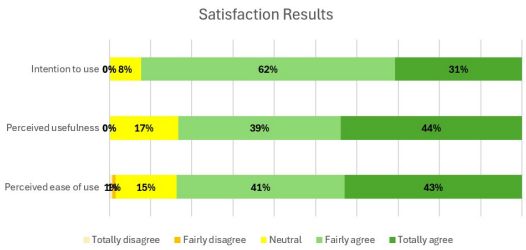

Fig. 5. Satisfaction results

Figure 5 shows a divergent stacked bar of the responses provided by subjects to the questionnaire for this property: For (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 (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 (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.

6 Conclusions and Future Research Directions

This article presents a set of 10 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) train generative models by industry sector using real company data.

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