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Integrating LLM Chatbot in HR Business Process of Small it Enterprise

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ABSTRACT

The purpose of this study is to design an LLM-powered chatbot that can assist small businesses in their HR business process, specifically to document knowledge. Employing the Design Science Research (DSR) methodology, the research progresses through problem identification, solution design, artifact development, demonstration, and evaluation phases. The proposed chatbot artifact is evaluated using the Retrieval Augmented Generation Assessment (RAGA) framework for technical performance and the Unified Theory of Acceptance and Use of Technology (UTAUT) for user acceptance. RAGA evaluation demonstrates strong performance, with average scores of 0.95 for context recall, 0.98 for response relevancy, and 1.00 for faithfulness, indicating the chatbot successfully maintains conversational focus and adheres to design specifications. UTAUT results reveal positive user acceptance, particularly in effort expectancy (average 3.30) and facilitating conditions (average 4.08), though employees continue preferring human interaction for complex knowledge-sharing tasks. This study uniquely contributes by developing the first LLM-based chatbot specifically designed for knowledge documentation in small IT enterprise HR contexts, combining technical rigor with practical implementation insights. The artifact design can be replicated and enhanced by future researchers exploring LLM applications in organizational knowledge management, with implications for democratizing advanced knowledge management capabilities in resource-constrained environments.

KEYWORDS *Large Language Model, Knowledge Management, Chatbot, Knowledge documentation, Knowledge transfer, Design Science Research, Small Businesses*

INTRODUCTION

The widespread adoption of generative artificial intelligence has experienced remarkable growth in recent years, with platforms like ChatGPT achieving record-breaking numbers of daily users (Hidayat-ur-Rehman & Ibrahim, 2023). This surge represents a paradigm shift in how organizations approach business process automation and knowledge management. However, this growth was followed by a notable decline in ChatGPT usage in March 2023, as reported in Hindustan Times (Jha, 2023). While news sources attribute the decline to the emergence of new players in Generative AI (GAI), such as Google Bard and Microsoft Bing (now known as Copilot), underlying concerns about privacy, ethical implications, and limitations in reasoning, factual accuracy, mathematics, coding, and bias continue to persist (Borji, 2023; Shahriar & Hayawi, 2023).

The integration of artificial intelligence, particularly in the form of large language models (LLM), into business processes has become increasingly prevalent across various industries (Linkon et al., 2024). Recent studies have explored the potential applications of LLMs in diverse contexts, including generating process knowledge from enterprise content (Franzoi et al., 2024), leveraging medical knowledge graphs (Park, Lee, and Jeong, 2024), reviewing technical specification documents (Lee, Jung, and Baek, 2024), and even plant disease detection (Zhao et al., 2024). These applications demonstrate the versatility and potential of LLM technology in addressing complex organizational challenges across multiple domains.

Knowledge management remains a critical challenge for organizations, particularly small and medium enterprises (SMEs) that often lack the resources and infrastructure necessary for comprehensive knowledge documentation and transfer systems. Small businesses face significant challenges in managing knowledge effectively due to limited resources, expertise, and infrastructure (Desouza & Awazu, 2006). These constraints result in difficulties organizing, retrieving, and utilizing critical information, ultimately hindering operational efficiency and growth potential. The challenge becomes particularly pronounced when attempting to convert tacit knowledge into explicit knowledge (Ajibade, 2016), a process that requires structured approaches and dedicated resources often unavailable to smaller organizations.

The human resource management function in small IT enterprises presents unique challenges related to knowledge documentation and transfer. Traditional knowledge management approaches designed for larger organizations often prove inadequate for SMEs due to their complexity, cost, and resource requirements. When employees leave organizations, valuable knowledge often departs with them, creating operational gaps and increasing recruitment and training costs (König et al., 2021). This knowledge loss can be particularly devastating for small organizations where individual employees often possess unique insights and specialized knowledge critical to business operations. According to Teece (2000), knowledge assets represent the most strategically important resources in knowledge-intensive industries, yet Wong and Aspinwall (2004) found that small businesses typically lack formal knowledge management systems, relying instead on informal, person-dependent approaches that create vulnerability to knowledge loss.

The urgency of this research is amplified by the rapid evolution of LLM technology and its increasing accessibility to small businesses. As these technologies become more affordable and user-friendly, organizations need evidence-based guidance on their implementation and effectiveness. The potential for LLM-powered chatbots to democratize advanced knowledge management capabilities could level the playing field between large corporations and SMEs, providing smaller organizations with sophisticated tools previously available only to enterprises with substantial IT budgets and technical expertise.

Despite the potential benefits of LLM technology, a significant research gap exists regarding how LLMs can assist knowledge management in organizational contexts, particularly for small businesses. While previous research has explored the use of chatbots to facilitate knowledge transfer within organizations (Ong et al., 2021; Adnyana, Octavia, and Ariasih, 2021), these implementations typically relied on knowledge graphs rather than LLM technology (Ait-Mlouk & Jiang, 2020). Recent advances in LLM capabilities, including improved natural language understanding and generation (Radford et al., 2018), suggest that LLM-powered chatbots could offer superior performance in conversational knowledge extraction compared to rule-based or knowledge graph-dependent systems. However, empirical evidence demonstrating this potential specifically within small business HR contexts remains absent from current literature.

Previous research has established that chatbots can facilitate knowledge transfer within organizations, and that integrating knowledge graphs can improve chatbot performance (Pan et al., 2024). Building on these foundations, this study hypothesizes that an LLM-powered chatbot would demonstrate superior performance in facilitating knowledge documentation within organizational contexts due to its ability to: (1) generate contextually appropriate follow-up questions without predefined decision trees, (2) adapt conversational flow based on user responses, and (3) synthesize collected information into structured documentation formats. The combination of LLM capabilities with traditional chatbot functionality presents an opportunity to create more sophisticated, adaptive, and effective knowledge management tools specifically tailored to resource-constrained environments.

The novelty of this research lies in being the first study to develop and evaluate an LLM-based chatbot specifically designed for knowledge documentation within small IT enterprise HR processes, addressing the unique constraints of resource-limited environments while providing both technical performance assessment and user acceptance evaluation. Unlike previous studies that examined general chatbot applications or LLM implementations in larger organizations, this research addresses the unique constraints and requirements of SMEs. The study advances existing literature by: (1) demonstrating practical LLM implementation for knowledge documentation in resource-constrained settings, (2) providing empirical evidence of chatbot effectiveness using both technical (RAGAs) and behavioral (UTAUT) evaluation frameworks, (3) offering replicable artifact design that balances sophistication with accessibility for small businesses, and (4) identifying specific challenges and success factors relevant to SME contexts that differ from enterprise implementations.

The primary objective of this research is to 14622evelopp an LLM-powered chatbot that can effectively assist in knowledge documentation processes within small IT enterprises. Secondary objectives include measuring the chatbot's performance using established evaluation frameworks and assessing user acceptance among employees. The study aims to answer two fundamental research questions: whether LLM chatbots can perform effectively in knowledge documentation processes, and whether employees perceive the benefits of such systems positively.

The practical implications of this research extend beyond the immediate study context. The artifact design presented in this study can be replicated and improved by future researchers exploring the potential of LLMs in organizational knowledge management. The findings will benefit business owners, human resource practitioners, and researchers interested in the intersection of artificial intelligence and knowledge management. Furthermore, the study addresses the suggestion from Pasca & Arcese (2024) that encourages managers to support employees using LLMs such as ChatGPT by providing information and continuous support, while ensuring data is processed and handled securely (Baber et al., 2023).

The significance of this study lies in addressing a notable void in research on LLM utilization within workplace contexts, particularly in knowledge management systems. While numerous studies have explored LLM applications within educational environments (Elbanna & Armstrong, 2024; Hidayat-ur-Rehman & Ibrahim, 2023; Qasem, 2023), discussion regarding workplace applications remains limited. This research aims to fill this gap by providing valuable, context-specific insights regarding LLM usage in knowledge documentation, offering findings that can inform business owners, human resource practitioners, and future studies concerning LLM and knowledge management applications in small business environments.

METHOD

This study employed the Design Science Research (DSR) methodology, which was particularly well-suited for developing and evaluating technological artifacts in organizational contexts. DSR provided a systematic approach to creating innovative solutions while generating design knowledge through creative problem-solving approaches (Hevner et al., 2004). The methodology emphasized both the development of functional artifacts and the generation of theoretical insights that contributed to academic knowledge.

The research process followed the six-step DSR methodology process model as outlined by Hevner et al. (2004): problem identification and motivation, definition of solution objectives, design and development, demonstration, evaluation, and communication. This systematic approach ensured rigorous development and assessment of the proposed LLM-powered chatbot while maintaining scientific validity.

The study involved collaboration with an IT service company located in Tangerang, Indonesia, employing fewer than 20 people. This partnership provided access to a realistic testing environment that reflected the constraints and characteristics typical of small IT enterprises. The company provided hardware solutions including self-service kiosks and payment terminals, representing a knowledge-intensive business where effective knowledge management was crucial for operational success. All 14 employees participated in the study, providing complete data for both chatbot interaction and survey evaluation phases.

Data collection employed both quantitative and qualitative approaches. Quantitative assessment utilized RAGAs metrics to evaluate chatbot performance objectively, while the UTAUT framework measured user acceptance across multiple dimensions including performance expectancy, effort expectancy, social influence, and facilitating conditions. Qualitative insights were gathered through focus group discussions and open-ended survey responses, providing contextual understanding of user experiences and organizational impacts.

Table 1. Research Instruments and Sample Questions

Framework	Dimension	Sample Question
RAGAs	Context Recall	Does the chatbot question align with predefined information needs?
	Response Relevancy	Is the chatbot response relevant to user input?
	Faithfulness	Does the chatbot maintain consistency with design instructions?
UTAUT	Effort Expectancy	“I feel that using the chatbot is very easy”
	Performance Expectancy	“I found no issue when interacting with the chatbot”
	Social Influence	“I think others should use the chatbot”

Framework	Dimension	Sample Question
	Facilitating Conditions	"My work device allows me to use the chatbot effortlessly"
	Behavioral Intention	"I think the company should continue to use the chatbot"

The UTAUT questionnaire was adapted from Hidayat-ur-Rehman & Ibrahim (2023) with modifications for organizational context. Content validity was established through expert review by two HR practitioners and one information systems researcher. Reliability analysis conducted on pilot data (n=5) showed Cronbach's alpha values ranging from 0.72 to 0.89 across dimensions, indicating acceptable internal consistency. RAGAs metrics were automatically calculated using the RAGAs Python library (version 0.1.0), with scores interpreted as: 0.00-0.50 (poor), 0.51-0.70 (fair), 0.71-0.85 (good), 0.86-1.00 (excellent). For practical interpretation, a context recall score of 0.80 means the chatbot successfully addressed 80% of predefined information requirements during conversation.

The chatbot development follows an iterative approach with three distinct iterations. The first iteration uses publicly available ChatGPT 4o to demonstrate proof of concept. The second iteration employs character.ai platform to refine chatbot behavior and consistency. The third iteration involves custom development using TypeScript with Next.js framework, hosted on Netlify.com with PostgreSQL database management via Supabase.com and Amazon Web Services. Each iteration incorporated feedback from technical evaluation and user testing, with design refinements addressing identified limitations before progressing to the next development phase.

This research adhered to ethical guidelines for human subjects research. All participants provided informed consent before data collection, with clear explanation of study purposes, data usage, and voluntary participation rights. Employee anonymity was maintained throughout data analysis and reporting. Company management approved the research protocol and data collection procedures. All personal and organizational information was stored securely with access limited to research team members. The study protocol received approval from the institutional review board prior to data collection commencement.

RESULTS AND DISCUSSION

Partner Company Analysis and Problem Identification

The collaborating IT service company demonstrates typical characteristics of small enterprises facing knowledge management challenges. Through interviews with management team, three primary issues were identified that align with literature findings on SME knowledge management challenges. First, inadequate knowledge documentation occurs because employees lack sufficient time to document knowledge following completion of daily work routines. This finding supports previous research indicating that SMEs often struggle with formal documentation processes due to resource constraints.

Second, employee resignation creates cascading effects including increased workload for remaining team members, additional strain on HR division for recruitment activities, and rushed recruitment processes that may result in suboptimal candidate selection. These impacts reflect the vulnerability of small organizations to knowledge loss, as identified by Desouza & Awazu (2006). Third, insufficient knowledge transfer occurs when new employees have limited interaction time with predecessors, resulting in incomplete knowledge transfer and loss of tacit knowledge.

The company's previous attempts to implement knowledge management tools were unsuccessful due to three primary factors: cost considerations where enterprise-focused tools priced in USD were deemed unjustifiable for a small company earning in Indonesian Rupiah; difficulty of use given the absence of dedicated IT support and minimal HR staffing; and time constraints where project-based work patterns left insufficient time for tool training and knowledge documentation activities.

Chatbot Development and Iteration Process

The iterative development process revealed important insights about LLM-powered chatbot design and functionality. The first iteration using ChatGPT 4o demonstrated basic capability to perform role-playing functions for knowledge extraction. The chatbot successfully asked predetermined questions while also generating additional relevant questions not explicitly instructed in the initial prompt. This emergent behavior suggests that LLM-powered chatbots can provide more comprehensive knowledge extraction than traditional structured approaches.

However, the first iteration suffered from session management limitations where chatbot behavior reset with each new conversation, requiring users to re-enter initial prompts. This limitation highlighted the need for persistent behavior definition across multiple sessions. The second iteration using character.ai platform addressed this concern through the definition feature, which maintains chatbot behavior consistency across sessions.

The second iteration demonstrated improved conversational flow and more refined questioning patterns despite using an older GPT 3.5 engine. However, significant issues emerged including failure to ask about key performance indicators (KPIs), inability to automatically generate summary outputs, poor quality summaries when manually requested, and susceptibility to distraction when users provided unexpected responses. These limitations informed the design requirements for the third iteration.

Table 2. Evaluation of First and Second Iteration Advantages and Disadvantages

Iteration	Advantages	Disadvantages
1	Very easy to use, publicly accessible, requires single prompt for functionality	No behavior persistence between sessions, requires monthly subscription fee
2	Consistent behavior across sessions, refined conversational patterns	Fails to summarize conversations, poor output quality, easily distracted by irrelevant responses

The third iteration addressed identified limitations through custom development incorporating specific design requirements: persistent behavior definition across sessions, ability to reject invalid responses, capability to detect insufficient information provision, and automatic conversation summarization when adequate information is collected. The final implementation uses TypeScript with Next.js framework, hosted on Netlify.com with PostgreSQL database management and OpenAI Assistant backend.

Chatbot Performance Evaluation Using RAGAs

The evaluation of chatbot performance using RAGAs metrics provides objective assessment of the system's effectiveness in knowledge documentation tasks. Three relevant metrics were selected based on the chatbot's primary function as a question-asking rather than answer-providing system: context recall, response relevancy, and faithfulness. Other RAGAs metrics were deemed irrelevant due to the chatbot's specific role in knowledge extraction rather than information retrieval or factual response generation.

Table 3. RAGAs Evaluation Results for All Interactions

Interaction	Context Recall	Response Relevancy	Faithfulness
1	0.95	1.00	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
4	1.00	1.00	1.00
5	1.00	1.00	1.00
6	1.00	1.00	1.00
7	1.00	1.00	1.00
8	0.90	1.00	1.00
9	0.95	1.00	1.00
10	1.00	1.00	1.00
11	0.80	1.00	1.00
12	0.85	1.00	1.00
13	1.00	0.80	1.00
14	0.90	1.00	1.00
Average	0.95	0.98	1.00

The results demonstrate strong overall performance across all three dimensions. Perfect faithfulness scores indicate that the chatbot consistently asked relevant questions aligned with its design instructions without generating inappropriate or off-topic inquiries. High response relevancy scores show that the chatbot generally maintained appropriate conversational flow, with only one instance of system malfunction requiring user intervention to continue the session.

Context recall scores, while generally high, revealed specific areas for improvement. Lower scores occurred when the chatbot failed to follow up on incomplete responses to multi-part questions. Analysis showed that when the chatbot asked multiple questions in a single message, users often answered only partially, and the system failed to request missing information. This behavior suggests that while the chatbot can distinguish between relevant and irrelevant responses, it struggles to identify incomplete information provision.

Interestingly, one interaction demonstrated the chatbot's resilience to user distraction attempts. When an employee attempted to divert the conversation by discussing lunch preferences, the chatbot briefly engaged with the topic before redirecting to the original question. This behavior indicates that the system can maintain focus on its primary objectives while managing minor conversational diversions.

Employee Acceptance Analysis Using UTAUT Framework

The UTAUT survey results provide comprehensive insights into employee acceptance of the LLM-powered chatbot across five key dimensions. All 14 employees participated in the survey, achieving 100% response rate likely due to management encouragement and the small organization size facilitating peer reminders for task completion.

Table 4. UTAUT Survey Results Summary

Dimension	Question	Average Score
Effort Expectancy	I feel comfortable interacting with the chatbot	3.84
	I feel that using the chatbot is very easy	4.15
	It took me awhile to learn how to use the chatbot (reverse scored)	1.92
Performance Expectancy	I found no issue when interacting with the chatbot	3.60
Social Influence	I think others should use the chatbot	3.70
	I feel driven by my peers to use the chatbot	3.00
	I feel driven by my manager to use the chatbot	3.90
Facilitating Conditions	My work device allows me to use the chatbot effortlessly	4.15
	Using the chatbot doesn't take much of my work time	4.00
Behavioral Intention	I think the company should continue to use the chatbot	4.00
	I prefer using the chatbot over interacting with my HR	2.80
	I prefer using the chatbot over interacting with my leader	2.30
	I prefer using the chatbot over filling online forms	3.46

The results indicate strong performance in effort expectancy and facilitating conditions dimensions. Employees found the chatbot easy to use, required minimal learning time, and experienced no device compatibility issues. These findings suggest successful design implementation regarding user interface and technical requirements. Performance expectancy scores indicate generally positive experiences, though some technical issues were noted in qualitative feedback.

Social influence results reveal interesting patterns where employees felt stronger pressure from management than from peers to use the chatbot. This pattern likely reflects the study context where participation was required within set deadlines rather than organic adoption patterns. Future implementation would require developing policies or standard operating procedures to encourage voluntary, regular usage.

Behavioral intention results present nuanced findings. While employees support continued company use of the chatbot and prefer it to online forms, they still prefer human interaction for knowledge documentation tasks. This preference suggests that the chatbot serves as a useful complement to rather than replacement for human-mediated knowledge transfer processes.

Qualitative analysis of open-ended responses provides additional insights into user experiences. Technical difficulties included language comprehension challenges, interface sizing issues on large screens, connectivity dependencies, and occasional system responsiveness problems. These findings suggest areas for future technical improvements while highlighting the importance of user training and support.

Regarding behavioral intentions, employees expressed concerns about the chatbot's ability to understand complex questions and uncertainty about employees' own job description clarity. Several respondents emphasized the importance of emotional aspects and empathy in communication, suggesting that human interaction remains valued for its relational qualities beyond mere information exchange.

Time investment analysis revealed that employees spent an average of 12 minutes completing chatbot interactions, with most accessing the system via laptop browsers. This duration appears reasonable for comprehensive knowledge documentation, though variation across users suggests different levels of detail in responses or varying complexity of individual roles.

Focus Group Discussion Findings

The focus group discussion involving company HR, division managers, and the researcher provided valuable insights into the practical effectiveness of the chatbot-generated documentation. Unlike the RAGAs evaluation which assessed individual messages, this evaluation focused on the overall quality and utility of the final handbook outputs produced by the chatbot interactions.

Participants agreed that chatbot effectiveness remained heavily dependent on user input quality. Shallow documentation resulted from employees providing minimal detail, and the chatbot failed to probe for additional information. This limitation suggests that future versions should incorporate reference documents or benchmarks to guide appropriate information depth expectations. The system should be trained to recognize insufficient detail and request elaboration accordingly.

Suspicions arose regarding potential use of other LLMs by some employees to generate responses to chatbot questions. Writing style variations within individual conversations suggested possible AI-generated content, though factual accuracy remained intact. While managers could not definitively confirm LLM usage, they noted unnaturally general responses and inorganic writing styles. This finding raises interesting questions about training chatbots to detect and appropriately handle AI-generated user inputs.

A significant gap emerged regarding key performance indicator (KPI) documentation. No employees provided specific KPI information because the chatbot asked general evaluation questions without specifically requesting KPI details. This limitation reflects insufficient specificity in the chatbot's instruction design rather than system technical limitations. Future implementations should include more explicit prompts for critical organizational information.

Despite limitations, the chatbot demonstrated valuable capabilities including resilience to user distraction attempts and ability to elicit previously unexpressed employee feedback.

The conversational nature of interactions appeared to make some employees more comfortable sharing concerns and suggestions that had not been raised through traditional channels. This finding suggests potential applications beyond knowledge documentation for employee engagement and feedback collection.

Company representatives concluded that while the chatbot successfully automated aspects of knowledge documentation and was preferred over traditional online forms, results remained below expectations compared to personal interviews. However, they identified potential value in using chatbot-generated documents as interview guides, providing structured foundations for more detailed follow-up discussions with employees.

The evaluation revealed that chatbot performance remained relatively consistent regardless of user cooperation levels, but the system could not distinguish between users withholding information versus those providing complete responses. Future development should incorporate training data regarding information depth standards and implement mechanisms to identify and address insufficient information provision.

Implications for Small Business Knowledge Management

The study findings have significant implications for small business knowledge management practices. The successful development and deployment of an LLM-powered chatbot demonstrates the feasibility of implementing advanced AI technologies in resource-constrained environments. The relatively low development costs and technical requirements suggest that similar solutions could be accessible to other small enterprises seeking to improve their knowledge management capabilities.

The high user acceptance rates, particularly regarding ease of use and technical compatibility, indicate that employee resistance to AI-powered tools may be less significant than anticipated. However, the preference for human interaction in knowledge-sharing activities suggests that AI tools should complement rather than replace human-mediated processes. This finding supports a hybrid approach where chatbots handle initial knowledge capture while human resources focus on verification, elaboration, and relationship-building activities.

The chatbot's ability to elicit previously unexpressed employee feedback represents an unexpected benefit beyond knowledge documentation. This capability suggests potential applications in employee engagement, performance feedback, and organizational culture assessment. Small businesses could leverage similar tools to improve communication channels and gather insights that might not emerge through traditional management approaches.

Technical limitations identified in the study, particularly regarding information depth assessment and response completeness, highlight areas where current LLM technology requires augmentation with additional systems or training data. Future implementations should consider integrating multiple evaluation mechanisms to ensure comprehensive knowledge capture while maintaining user-friendly interaction patterns.

CONCLUSIONS

This study developed and evaluated an LLM-powered chatbot to support knowledge documentation in small IT enterprises, filling a notable research gap in AI applications for SME knowledge management. The chatbot performed well technically, with strong RAGAs scores, and users expressed positive acceptance based on the UTAUT framework, especially regarding ease of use and compatibility. Despite these successes, employees still valued human interaction, indicating that AI tools should enhance rather than replace traditional knowledge-sharing methods. The effectiveness of the chatbot relied heavily on the quality of user input and precise system design. While promising for standardizing documentation and gathering feedback, the technology requires careful implementation to overcome challenges in assessing information depth and response completeness. Future research should develop advanced information quality evaluation techniques, compare different LLM models, integrate verification mechanisms to detect incomplete or AI-generated responses, and explore modular system designs adaptable to technological advances. Longitudinal studies examining sustained use and organizational impact would also deepen understanding of long-term adoption and effectiveness in small business settings.

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