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Original Article

Information Attraction Using Multi-Agent Conversational System For Online Booking

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ABSTRACT

Elevated urbanization and the influx of student population and other working adults have greatly led to the high housing demand of economical units like rent rooms and Paying Guest (PG) rooms. Despite all these existing online booking websites, the majority of them are based on traditional form-based interfaces and command-based search options, which could not meet the intricate user preferences written in natural language. More natural language interaction is made possible by Conversational Artificial Intelligence and Large Language Mod- els (LLM) but standalone LLM-based chatbots typically produce hallucinated or untrustworthy responses on transactional needs like booking an accommodation use.

To overcome this constraint, the proposed paper will present a multi-agent Retrieval-Augmented Generation (RAG) enhanced conversational system in booking unified room and PG accom- modation with the assistance of a facility-conscious decision- support system. The system combines both Natural Language Understanding approaches, such as intent recognition, entity extraction, and a RAG pipeline which retrives confirmed ac- commodation information in structured databases and semantic vector stores. The specialized conversational agents deal with search, facility filtering, comparison and booking confirmation. The experimental assessment illustrates both the accuracy of 92 and the precision of 89, making recommendations relevant and prompting booking time, and user satisfaction greater than using the old-fashioned web-based booking systems.

Keywords: Conversational AI, Retrieval-Augmented Gener- ation, Multi-Agent Systems, Chatbot, Accommodation Booking, Paying Guest Housing.

INTRODUCTION

The urbanization is taking modernizing strides, institutions
of higher learning are on the rise and employment is available to the students and other laboring classes in the cities hence they migrate to the urban areas in large numbers. Due to this migration, there has been a high demand of low-cost accom- modation plans such as rented rooms and Paying Guest (PG) reside. These categories of accommodation are highly digital because they are rather cheap to utilize, can be approached with ease close to the work stations and academic institutions and they tend to provide some of the requirements needed such as food, internet, electricity and security.

Even though online accommodation systems are present in abundant numbers, searching, comparing and reserving suitable rooms or PG locations to stay are inefficient and time- consuming. Most of the systems that are in place operate on the strict form interface in which the search engines demand the users to complete filters which consist of location, price range, room type and available facilities in the search engines. Although these platforms are searchable, not all of them can at times decipher end user preferences that exist in form of complex natural language. An example of this is a query such as a single PG near college with food and Wi-Fi under a strict budget, and a few implicit limits cannot be known well using the typical systems of key-word searches.

As a result, clients often have to re-search, browse the listings manually and review facilities descriptions step by step and analyze them properly before making

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a decision. Through this process the overhead of thinking, the space consumed in decision-making is transferred and might lead to less-than-optimal accommodation decisions. It is particularly challenging to newcomers, students and migrants who may not have a clue on the available accommodation market in the area.

Conversational Artificial Intelligence (AI), is also an at- tractive model of improving the human-computer interaction by enabling systems to understand and respond to queries of its users in the natural language. Chatbots which are developed based on Natural Language Processing (NLP) empower users to interact with online applications with conversational interface as opposed to traditional graphical interfaces [4]. These systems have already been successfully implemented in such areas like health sector, education, customer support, e-commerce and people perform tasks there through talks of interaction.

The recent development of conversational systems is en- abled by the Large Language Models (LLM) development [9]. These models understand language very well, can always generate responses and can also handle multi-turn dialogue. However, autonomous LLM based chatbots will often present hallucinatory responses [6], which may be false, out of date,

or not supported by authoritative sources of information. Such kinds of inaccuracies could severely undermine the user trust and confidence in the system that is particularly related to transaction and decision based programs such as accommoda- tion booking.

The Retrieval-Augmented Generation (RAG) is an approach that overcomes these drawbacks through the integration of language models along with external knowledge retrieval [2]. Rather than using the model internal parameters only, relevant information is first accessed via external data bases and then acted as a context on which response generation can be done.In the RAG based model, the related information would first be acquired as structured or unstructured data ware and supplied as contextual input to the generative model. Such is done to promote factual accuracy, topicality, and transparency of reporting generated. Recent studies demonstrate that con- versational systems built with RAG perform better than the independent generative models in solving knowledge-intensive tasks (question answering, document retrieval, and decision support).

More approaches to conversational AI, other than the retrieval-based form of grounding, have also found an ar- chitecture based on multi-agent systems. Multi-agent systems decompose the functionality of a conversational platform into specialised agents [1], and each agent has specialised tasks, which could encompass intent recognition, information re- trieval, reasoning, comparison or recommendation. To a great extent, this kind of modular system increases the scaling, easy interpretability, and strength of a system, particularly when the system contains numerous sources of the data, as well as when it contains complicated interactions between the users. Although conversational booking systems have been created in the hotel industry [5], most of the existing applications are applied in hotel reservations and frame-based dialogue management has been applied to execute short term booking processes. It is a research that is not quite made in conver- sational system, long-term accommodation that would require facility aware decision support and conversational interfaces especially on rented rooms and on-PG accommodation.

Relying on this gap, the current paper is based on the hypothesis of a multi-agent Retrieval-Augmented conversa- tion AI system to integrate room and PG accommodation booking in a room. The proposed system makes it possible to specify the accommodation requests with the help of the natural language and the controlled activities of the specialized conversational agents to organize the search, sort out the facil- ities, compare them, and check out the booking. The system reduces hallucinations and also improves the consistency of the responses by grounding responses to known accommodation data on a RAG pipeline.

The key contributions of this work are: (i) the allocation of a conversational platform where one booking system and the other reserve the rooms and the institutions of the necessary facility respectively, (ii) the integration of multi-agent architec- ture and Retrieval-Augmented Generation, which helps users to spend a lesser amount of energy and less time to search, and (iii) an experimental study which proves that this work is more efficient than the current booking systems are.

The remaining part of the paper has the following structure. Part II is the literature review on the related topics in con- versational AI, Retrieval-Augmented Generation, and booking systems. Part III is a discussion on the proposed multi-agent system architecture. Methodology, as well as implementation details, is contained in the section IV. Section V includes the discussion of the experimental results and analysis, and section VI is the final part of the paper and provides the potential lines of research in the future.

RELATED WORK

Conversational Artificial Intelligence has also been improv- ing over time with less complex rule-based chatbots giving place to more sophisticated data-driven and generative conver- sational systems. In this section, the literature review will be conducted with regards to conversational AI, which is primar- ily divided into the discussed areas: Large Language Models (LLM), Retrieval-Augmented Generation (RAG), multi-agent chatbot architecture, and conversational booking systems.

A. Rule-Based and Early Machine Learning Chatbots

Early chatbot systems were based on rule-based systems and pattern-matching based systems as an attempt to simulate conversation [12]. These systems were not flexible, contextual and scaled though they were effective in predefined inter- actions. With the introduction of machine learning methods, intent classification and response selection was possible based on training data, but the systems were limited by a small contextual awareness and domain specificity.

B. Large Language Models in Conversational Systems

Larger Language Models have made great strides in im- proving a conversational AI because the models can process context and promptly generate a response in natural language that will sustain multiple dialogue turns. Transformer-based architectures make text transformers capable of extracting semantic relationships over very long text sequences [7], [8], which makes them suitable to open-ended dialogues. However, several researchers have revealed that LLMs tend to hallucinate when operated without knowledge foundations and are not very reliable when it comes to areas that require decisions to be taken.

C. Retrieval-Augmented Generation

The Retrieval-Augmented Generation (RAG) has been sug- gested to reduce the hallucination in the LLM-based systems by combining the information retrieval with response gener- ation [6].In a RAG pipeline, documents or database records that are semantically related to the user query are retrieved by the system. Such retrieved records are then fed to the language model as contextual input, and the generation of the final response is made. Studies prove that the RAG-based systems are more accurate in factual and contextually relevant in knowledge intensive tasks than the standalone generative models.

D. Multi-Agent RAG-Based Chatbot Architectures

Recent research indicates the usefulness of integrating RAG and multi-agent system architectures [1]. Multi-agent systems have separate roles of specialized agents, including obser- vation, retrieval, reasoning and visualization. Gamage et al. showed that, multi-agent RAG chatbots are very effective in the enhancement of decision support in complex and data- intensive settings. Their contribution makes it quite inspira- tional to make use of a modular and agent-based design in conversational decision-support systems.

E. Conversational Search and Document Retrieval Systems

Conversational retrieval systems like DocBot Connect use semantic embeddings, and vector databases [4], and conver- sational memory to allow interactions in natural language with large collections of documents. These systems show that the integration of LLMs and vector-based retrieval as well as conversational context tracking can be very effective and present insights into how to design conversational systems in the domain.

F. Conversational AI in Booking Systems

One area where conversational AI has been implemented successfully is in the hospitality business to help people with hotel search and hotel booking [5]. Chatbots based on intent recognition, slot filling, and dialogue management have proven to be more interactive and efficient in regards to user engagement and booking. Nevertheless, these systems are mainly configured to hotels reservation and do not consider the special needs of long-term stay like rooms and PGs.

G. Chatbots for Decision Support in Education

Educational chatbot systems are information retrieval/generative models to aid in decision-making and access to information. Research on this area has highlighted the significance of domain grounding, hybrid retrieval-generation strategies, and situation understanding to guarantee the correct and pertinent answers. These systems have found good use in learning institutions to help users in administrative questions, learning facilitation, and information search. The concepts embraced in educational decision- support chatbots, specifically, the application of knowledge grounding and context-sensitive response generation, can be directly transferred to conversational accommodation booking systems.

Even though the field of conversational artificial intelligence has been improved greatly, Retrieval-Augmented Generation (RAG) and task-oriented booking chatbots, there are still a number of limitations in the current research. The majority of conversational booking systems are mostly hotel-centric and use the frame-based dialogue management models best suited to the short-term and well-focused booking contexts. Likewise, recent conversational systems based on RAG and multi-agent chatbot systems have been largely implemented to solve problems in areas like document retrieval, educational support systems, and energy decision-support systems as opposed to accommodation booking.

Moreover, the current room and Paying Guest (PG) booking websites remain based on the static and the form-based search services and do not support the conversational interface, un- derstanding the context and the decision service aware of the facilities. Little research is available that combines multi-agent architecture and Retrieval-Augmented conversational AI to facilitate the process of unified room and PG accommodation booking, as well as provide the accuracy of response by grounding it in verified data. Specifically, the lack of facility- conscious conversational decision support and modular agent-based design is an impaired research gap.

To address this gap, the present work proposes IntelliHost, a multi-agent Retrieval-Augmented conversational AI system designed to work with unified room and PG accommodation booking. With the combination of Natural Language Under-standing, semantic retrieval, and specialized conversational agents, the proposed system will be efficient in booking, user effort reduction, and trustworthiness improvement over the current offerings.

SYSTEM ARCHITECTURE

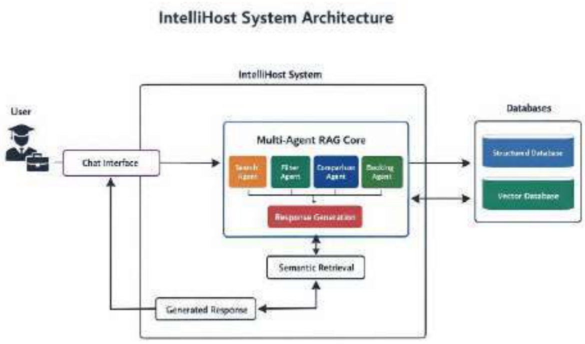

Fig. 1. Proposed System Architecture

Fig.1. shows the general layout of the proposed Intelli- Host system. The system is guided by multi-agent Retrieval- Augmented Generation (RAG) guided conversational design that aims at supporting unified room and Paying Guest (PG) accommodation booking.

The system is used by the user in the form of a chat-based user interface, where accommodation requirements are formulated in natural language. The Natural Language Un- derstanding (NLU) module takes input of the user query to process it by doing intent classification and entity extraction which determines or identifies the parameters like location, budget, facilities and accommodation type.

The processed query is sent to the multi-agent conversational core which is composed of specialized agents that perform search, filtering of facility, comparison, booking man- agement and knowledge retrieval. These agents combine their efforts to process user requests depending on the intent that is detected.

The Retrieval-Augmented Knowledge Layer retrieves rele- vant accommodation information and is the union of structured databases and semantic vector stores. The context retrieved is fed to the response generation module in which a RAG- based language model produces correct and context relevant responses. To facilitate multi-turn communications, the state of a conversational manager preserves conversationality. The last response is then sent back to the user using the chat interface.

METHODOLOGY

The suggested system will have a systematic approach that incorporates conversational Artificial Intelligence (AI), multi-agent coordination, semantic information retrieval, and Retrieval-Augmented Generation (RAG). This approach will make sure that user intent is interpreted correctly, that ac- commodation information is retrieved reliably, and responses are context-sensitive across the entire conversation booking procedure.

The process of developing the website starts with the gathering of room and Paying Guest (PG) accommodation in- formation obtained on publicly available rental sites. The data is structured including accommodation type, price, location, availability status, and facility information, and unstructured textual descriptions. The preprocess techniques are used to as- sure data consistency and data quality through missing values processing, processing the facility names so that they become standard, processing the pricing format so that data formatting remains consistent; and cleaning textual descriptions to ensure they are to the point. This preprocessing step is critical towards achieving successful semantic retrieving and credible response generation.

The queries logged in by users in the chat interface are first handled by the Natural Language Processing (NLP) techniques [12]. The system conducts intent recognition where the intent of the user query is ascertained whether the user query aims at searching accommodation, asking further information about the facilities, seeking a comparison, or to make a booking. Language models are also transformer based which is why the intent of the user is classified in order to provide the opportunity to address the variety and informal expressions of the natural language used by users [7], [8].

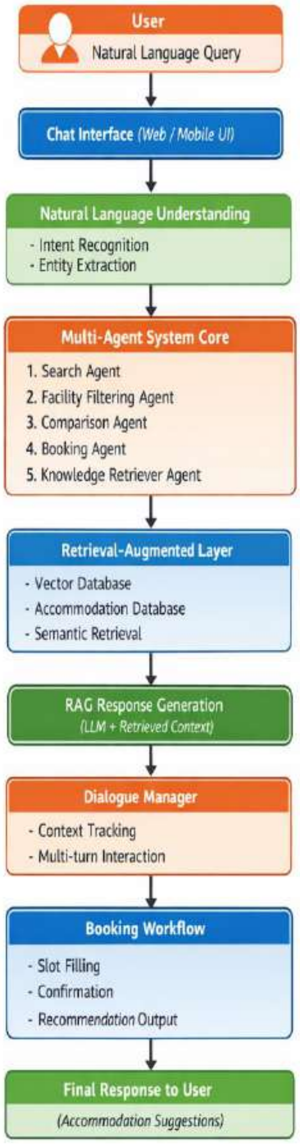

Fig. 1. Flow diagram of the multi-agent Retrieval-Augmented conversational booking system.

At the same time, entity extraction is performed in order to determine significant parameters in user queries. Such parameters are name of the place, minimum budget cost, accommodation (room or pg), facilities (preferred like food services or internet connection), and time (day that you can move in or period of stay). Extracted entities are transformed into organizations by Named Entity Recognition (NER) methods to allow downstream components of systems to process them.

Description of accommodation is turned into vectors through per trained models [10]. Those embeddings are used to capture semantic relationships between listings and user searches, which can be used to search the vector database with similarity. These embeddings store context and semantic relations between properties of accommodation listing and search queries by the user. The similarity-based retrieval is made possible through storing the generated embeddings in a vector database. Including query processing, the user query embedding is compared with the available embeddings through a search with cosine similarity to achieve the most relevant records of accommodations.

The system is developed based on a multi-agent conver- sational framework to execute the core functionality of the system. Depending on the purpose of the user, the query is redirected to the right agent in the conversational core. Search Agent retrieves the listing of candidates on the basis of such basic constraints as location and budget. Facility Agent does amenity-based filtering to make sure that suggestions are in line with the preferences of the user. The Comparison Agent creates brief summaries in cases where users are doing comparisons between accommodation. The Booking Agent is the one that handles the workflow of conversational slot filling and confirmation of booking. Knowledge Retriever Agent assists these agents with the help of credible knowledge based on the Retrieval-Augmented Generation pipeline.

Generation of responses is accomplished with the help of Retrieval-Augmented Generation strategy wherein the re- trieved accommodation information serves as the contextual grounding by introducing it to the prompt of the language model. The mechanism behind the grounding is to make sure that the responses generated are correct, within contextual scope and are grounded on tested data instead of relying purely on the language model generative ability. This would go a long way in curbing hallucination and instilling confidence on the system by the users.

A dialogue management element ensures context of con- versation throughout a series of interactions in multi-turn communication [11]. The conversational memory will contain previously extracted entities and user preferences that will be used to dynamically refine recommendations even though the system does not need users to restate constraints. It is a context-rich interaction, which makes the conversation easier to understand and the user experience more pleasant.

The kind of booking is conversational slot filling. In case of any missing essential information in booking, the system will prompt user to give the necessary information. After collecting and having all required information, the system provides a booking summary and asks the person to confirm the information to achieve transparency and accuracy prior to making the reservation final.

The success of the offered methodology is measured by the following metrics: accuracy of responses offered, time spent to complete the booking process, and satisfaction of users. These metrics will be compared to the standard filter- based accommodation platforms to determine the efficiency, reliability, and usability improvements. It has been shown in the methodology that the systematic combination of conversa- tional AI, multi-agent coordination, and Retrieval-Augmented Generation provide an intelligent and convenient system of booking an accommodation.

ALGORITHM USED

Algorithm 1: Multi-Agent Retrieval-Augmented Conversa- tional Booking

1. Receive user query Q through chat interface
2. Perform Natural Language Understanding (NLU) on Q
3. Identify user intent using intent classification
4. Extract entities such as location, budget, facilities, and accommodation type
5. Convert query Q into semantic embedding vector
6. Retrieve relevant accommodation listings using vector similarity search
7. Route the query to the appropriate conversational agent
8. Search Agent: Retrieve candidate accommodation results

9. Facility Agent: Filter listings based on user-required amenities
10. Comparison Agent: Generate comparison summaries if requested
11. Retrieve verified information using Retrieval-Augmented Generation (RAG)
12. Inject retrieved context into the language model
13. Generate context-aware response
14. Update dialogue manager and conversational memory
15. if booking intent detected then
16. Perform slot filling for required booking details
17. Generate booking confirmation summary
18. end if
19. Return final recommendation or booking confirmation to the user

RESULTS AND DISCUSSION

A. Evaluation Metrics

In order to measure the performance of the proposed con- versational system of booking, popular information retrieval measures such as accuracy and precision were employed. These measures are useful to measure the accuracy of system reaction, and the applicability of retrieved accommodation suggestions.

Accuracy reflects the number of correct responses entries that are made by the system in comparison with the number

of queries that are processed. It shows the effectiveness of the system to recognize the right results of accommodation according to the query in the system.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives.

Precision is the ratio of relevant accommodation outcomes to the total outcome of the results that are presented by the system. High precision means that the system retrieves more recommendations that are relevant and less irrelevant listings.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

Such assessment measures can be used to determine the success of the conversational booking system in retrieving accurate and relevant accommodation recommendations to user queries.

The performance results suggest that the suggested conver- sational booking system has an accuracy of 92 percent when used to locate the relevant accommodation results according to user queries. The quality of precision 89% indicates that the listings of the accommodation that the user has retrieved are mostly the ones that are required by the user. Retrieval-Augmented Generation and multi-agent coordination may be highly beneficial because it leads to the relevance of the recommendations being more useful than when the traditional software based on the keywords available helps to find a proper booking system.

TABLE I

Performance Evaluation Of The Proposed System

Metric	Value
Accuracy	92%
Precision	89%
Average Booking Time Reduction	35%
User Satisfaction Score	4.5/5

This part shows the experimental assessment of the developed conversational accommodation reservation system and evaluates its functionality in terms of performance relative to traditional accommodation search services. The analysis dwells on the accuracy of the response, precision of the retrieved listings of accommodation facilities, efficiency in booking, the quality of facility-sensitive recommendations, and the overall experience of user interaction.

The representative dataset that was used to test the system comprised of room and Paying Guest (PG) accommodation listings. Attributes: structured (price, location, availability, facilities) and unstructured textual description of accommoda- tions were covered in the dataset. Various user requests were to be used to approximate the real world booking contexts such as low level accommodation search, facility based search, comparison search and full booking processes.

The results of the performance indicate that the suggested system will be characterized with high response accuracy to interpret the queries and retrieve the information about the accommodation that is relevant to the users. The system sup- ports generated responses on the base of Retrieval-Augmented Generation (RAG); thus, the generated responses are based on reviewed accommodation information stored in structured databases and semantic vectors. This system will go a long way to enhance the reliability of the system responses over the traditional search platform in a keyword set, where a user is required to go through a series of listings manually to find information s/he needed.

The precision metric also reveals that most of the accom- modation recommendation retrieved can be related to user requirements. The integrated semantic search and facility con- scious filtering can help the system identify the user preference well such as, the budget limit, the distance between the facility and the location as well as the amenities catered to such as the food facilities, the internet access and security. Consequently, the user gets a better recommendation and results that are not irrelevant.

Booking efficiency was scored on perception of time taken by the user to find an appropriate accommodation and the booking process to be done. The dialogue aspect of the conversation greatly shortened the time of booking completion through facilitation of users through search, and confirmation process through a natural language dialogue. Users could bypass the repetitive process of refining search filters instead of stating what they want in a more straightforward way like by location, budget, and facilities in the conversation itself. This focused contact saved mental work and made the process of decision making less complex.

Effectiveness of facility-sensitive recommendations also was another significant component of evaluation. The multi-agent system allow other agents, which are specialized, handle various parts of the booking process. The Search Agent is used to find the candidate accommodations by basic constraints whereas the Facility Agent is used to filter the listings depend- ing on amenities preference of the user. Comparison Agent will produce brief summaries of alternative accommodations when the user order comparisons. The modular method en- ables the system to handle complex queries that have several constraints with high efficiency.

Qualitative feedback was also used to measure user experi- ence and satisfaction when it came to testing the system. The users indicated that it was conversational interface that was easier to use as compared to the filter-based booking systems. The possibility of expressing needs using natural language and the system to recall user preferences during the multiple conversational turns were observed to be key benefits. The dialogue manager kept the context of conversation at a high level, and the system was able to narrow down suggestions as the conversation went on.

Conversational architecture with multi-agents enhanced scalability and modularity as seen in system design. Through the allocation of duties among the specialized agents, the system was capable of managing the various types of queries and did not overload a particular component. The system is also more maintainable (because of this design) since the individual agents can be updated/extended at the same time and do not impact the overall architecture.

Although these are strong points, some weaknesses were noted in the process of evaluation. The implemented version was experimented on the small fixed dataset and controlled experimental conditions, which may not truly mirror the reality of the accommodation marketplace. Moreover, the current system only has text-based interaction, which might be lim- iting to users who would wish to use voice-based systems. Although the Retrieval-Augmented Generation model removes hallucination in the responses generated, the quality of output of the system is still subject to the completeness and accuracy of the underlying accommodation data.

On the whole, the findings of the experiment prove that the suggested conversational booking system shows much more accuracy, relevance, and efficiency of accom- modation search in relation to conventional booking ser- vice. Contextually-coordinated multi-agent interactions with Retrieval-Augmented Generation make conversational deci- sion support consistent and reliable enough to point out the future of conversational AI systems in smart accommodation management software.

CONCLUSION

In this paper, we are using the Retrieval-Augmented Gen- eration (RAG)-based smart room and Paying Guest (PG) ac- commodation bookings system on a multi-agent conversational artificial intelligence system. Unlike the outdated characteristic of earlier style filter-based systems, it enables users to present complex preferences to include in their selections; such as budget, location, amenities and duration of stay, using natural words.

The system fuses Natural Language Understanding (NLU) system with the modular multi-agent system in which spe- cialised agents process search, filtering, comparison and book- ing functions. This architecture is increased to have a better scalability, robust and maintainability. RAG basing answers based on established structured and semantic information reduces hallucinations and provides dependable and valid information.

The results of the experiment prove relevance to recommen- dations, efficiency in booking, and overall user experience is enhanced, and dialogue management will maintain the con- text of conversations with customers to remain personalized. Nevertheless, performance is based on quality of data and the existing system can only interact by text. The directions that will be gained in the future are the growing datasets, voice interfaces and field testing.

On the whole, the paper proves that there is a multi-agent system with RAG that allows achieving a scalable and trusted solution to accommodation booking.

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