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INTEGRATING EXPLAINABLE AI (XAI) INTO CHATBOTS FOR AUTOMATED DECISION-MAKING IN HOSPITALITY

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Abstract: This paper presents the design and implementation of a hybrid generative AI chatbot for the hospitality domain, integrating Explainable Artificial Intelligence (XAI) techniques to enhance transparency, build trust, and support decision-making. The system processes guest data to generate responses with suggestions and determine appropriate actions, including the necessity in offering upgrades, providing additional details or delivering appreciation messages to improve guest experience. The system combines multiple technologies starting with Pandas for structured data handling, model RandomForestClassifier for user classification, SHapley Additive exPlanation (SHAP) as an interpreter of forecasting model, NumPy for numerical operations and OpenAI GPT-3.5 API for natural language generation based on the request. To identify most influential features in the decision-making process was used SHAP. Prompt engineering was used to ensure accuracy and professionalism in responses. The evaluation of the model includes classification reports with accuracy, recall, and F1-score metrics. The system demonstrates the alignment between AI-driven predictions with real world operations and personalized responses based on contextual and probabilistic factors. By integrating XAI with generative models the aim is to improve both operational efficiency and customer feedback. This integration results in a combination of automated context-aware responses and transparent decision explanations. Results were interesting after evaluating each class of the dataset. Finally, this study serves as an aid to increase trust and confidence in guests, mainly in explaining the answer provided by the chatbot as well as future research directions involving alternative algorithms, larger datasets and optimization strategies.

Keywords: hospitality, chatbot, GPT-3.5, explainable AI, SHAP, RandomForestClassifier, prompt engineering, decision-making automation, hybrid chatbot, imbalanced data

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INTRODUCTION

AI is part of different fields of our life. Hospitality is a well-known domain that sometimes needs support by adopting and integrating AI such as chatbots, recommendation engines, predictive analyses, improving decision-making etc. For (Batra & Chatterji, 2024) AI can enhance customer service efficiency and satisfaction in the hospitality industry through personalized recommendations, automated customer service, and data-driven insights (Prentice et al., 2020) stated that AI and employee service quality both impact on customer satisfaction and loyalty in the hotel industry, but AI alone is not sufficient to drive these outcomes. In an empirical study of luxury hotels (Al-Hyari & Al-Smadi, 2023) it was found that AI has the potential to increase customer satisfaction in luxury hotels, but human interaction is also essential for a balance.

Another perspective presented by Rawat et al., 2024 was a successful implementation of AI depends on workforce integration and employee satisfaction. In the hospitality and service sector, customer reviews and rating play a crucial role in shaping perceptions of service quality and overall reputation. These comments are usually done on online platforms such as Google, where customers, based on their experience, can leave comments that have a direct and essential impact on the formation of the reputation of hotels (Kosta et al., 2025). Online guest reviews often published on platforms like Google, Booking.com, and TripAdvisor—have a significant impact on a hotel's reputation, revenue, and customer retention strategies (Huseynov & Güler, 2021). But processing and responding to these reviews manually is time-consuming and a huge effort, especially in high-traffic environments. The achievement of this study is to use generative artificial intelligence by automating the process of responding to customer reviews, maintaining a professional and resemble human response.

Specifically, we present a chatbot system built on the GPT-3.5 model, integrated with multilingual support and explainability features tailored for hospitality applications. Chatbots have now become indispensable tools in the hospitality sector to enhance customer service and streamline mundane operations. Traditional generative models of artificial intelligence, like those based on the transformer architecture, enable dynamic and personal interaction. Counterintuitively, more advances in transformer-based language models, like the GPT series implemented by OpenAI, enabled chatbots to

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handle sophisticated linguistic structures, enable natural conversation flow, and respond contextually. Even though endowed with excellent capabilities, one of the main disadvantages of large language models (LLMs) is their ambiguity - their users and administrators typically do not know how and why specific responses are created, and sometimes ill-trained models generate wrong responses. For Amann (Amann et al., 2020) this behavior is called "black box" which faces challenges to trust, accountability, and compliance in customer service scenarios. To overcome this, Explainable AI (XAI) frameworks have been developed to improve and make more explainable the decision of AI systems, making them more transparent and auditable to end users and decision makers (Ali et al., 2023) . While powerful AI models (like GPT, BERT, or deep neural networks) can make very accurate predictions, they often function like a “black box” — we get a result, but we don’t know how or why the AI came to that conclusion. XAI helps open that box. Explainable AI (XAI) is important for building trust and understanding AI in decision-making (Tiwari, 2023). If performance should be included for (Singh et al., 2024) interpretable AI models can enhance explainability in complex decision-making without compromising it.

Related Work

The field of artificial intelligence within hospitality has seen significant growth, particularly the application of chatbots for greater customer engagement and automating routine services. Many research studies in the past have been focused on applying chatbots to routine daily processes such as assisting reservations, automated check-in, complaint resolution, or providing general information related to hotel operations. Automatic decision-making technologies encompassing artificial intelligence, machine learning, automation, and business intelligence, produce measurable benefits in hospitality operations.

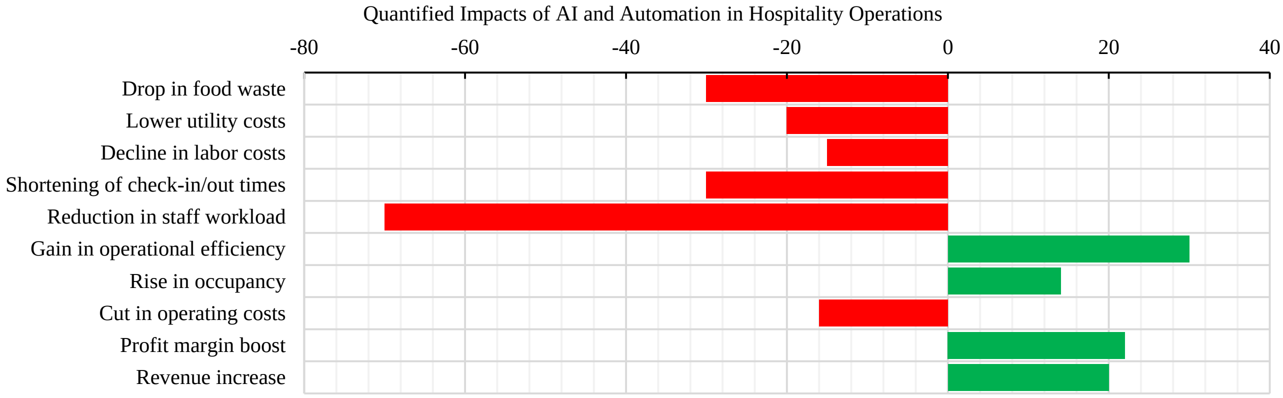

Figure 1. Operational metrics -percentage change

Figure 1 also presents the operational metrics with percentage variations according to several scientific articles. Kumar and Ranjan (Reddy & Kumar, 2023) report shorter processing times and fewer errors in guest registration and billing, while (Bhuiyan et al., 2023) observe a 20% revenue increase, a 22% profit margin boost, a 16% cut in operating costs, and a 14% rise in occupancy across diverse hotel formats. In five-star hotel settings (Anwar et al., 2024) note a 30% gain in operational efficiency, a 70% reduction in staff workload, and a 30% shortening of check-in/out times; (Ridzky, 2024) records a 15% decline in labor costs, 20% lower utility costs, and a 30% drop in food waste. Castelli et al., 2022 further document improvements in prediction accuracy up to 93% that contribute to higher productivity. Studies describe qualitative gains in service delivery, enhanced decision-making, and improved guest experiences through technologies such as contactless interfaces and robotic process automation but not neglecting implementation challenges, including high initial capital, system integration complexities, and the need for staff training.

Overall, the evidence supports that automatic decision-making technologies yield tangible improvements in operational efficiency within the hospitality industry. Explainable Artificial Intelligence (XAI) has emerged for addressing and clarifying the complexity of AI models, particularly deep neural networks (Das & Rad, 2020). XAI aims to develop interpretable and transparent AI systems, enhancing trust and decision-making processes across various domains. There are techniques employed to create interpretable models, and explainability (Reddy & Kumar, 2023) like SHAP (SHapley Additive exPlanations), Lime (Local Interpretable Model-Agnostic Explanation) etc. As intelligent software becomes more common, it’s important to use tools that help people understand clearly how decisions are made. A comparison is performed between SHAP and LIME for Roshinta & Gábor, 2024 highlighting the fact that SHAP provides more robust and global insights than LIME for explainable AI, despite higher computational overhead.

Chatbots in Hospitality

Chatbot is a software system that performs conversation in an interactive mode, though it cannot yet convincingly pass the Turing test (Prakash et al., 2021). They use natural language understanding and processing to assist users with various tasks (Gupta, 2020). They interact with users using natural language or text, utilizing AI algorithms to generate responses (Hussain et al., 2019). Chatbots have evolved significantly since their inception, from early rule-based systems like ELIZA in the 1960s to today's advanced AI-powered conversational agents like ChatGPT (Madhi & Mustafa, 2024; Wang, 2024). The development of chatbots has been driven by advancements in natural language processing, machine learning, and artificial intelligence (Al-Amin et al., 2024). Key milestones include the introduction of Turing tests and influential projects like CALO 9 (Cognitive Assistant that Learns and Organizes), leading to the creation of transformer-based models. Chatbots have found applications across various sectors, including healthcare, education, entertainment, and commerce (Madhi & Mustafa, 2024). As chatbots become more prevalent in everyday situations, such as e-commerce interactions, their development raises ethical concerns regarding bias, transparency, and privacy. Future developments in chatbot technology are expected to focus on personalized interactions to enhance user engagement and satisfaction (Wang, 2024). The process begins with a user question, for example "Are there any rooms available next weekend?" which is defined as an interaction between the client and the system. The next step is the Hybrid Chatbot. It is called Hybrid Chatbot because it is a combination of a Rule-Based component, which searches the database to retrieve the information requested by the user and the AI component, which generates natural language so that the user receives a response that is as understandable as possible. The next step is the process of integrating the XAI component, specifically SHAP (SHapley Additive exPlanations). The component explains why a certain answer was given by the chatbot. This results in an increasement of credibility in the eyes of the user as well as clarity of the response in applications where the client makes important decisions. Finally, there is the last step defined as Response, which provides a personalized answer, "We have rooms available on Friday and Saturday. Do you want a standard or deluxe room?"

Many sectors are exploring ways to discover and leverage the power of ChatGPT and similar tools in their businesses, one of which is hospitality. Recent studies indicate that while the hospitality and tourism industry has always been lagging in terms of adopting new technologies due to the service-oriented character of its operations, there is a growing trend towards digitalization (Buhalis et al., 2023). Unique tools such as ChatGPT, has stunned with its capacity to enhance customer experience and employee productivity through swift, accurate responses to general queries (Mich & Garigliano, 2023). These systems help visitors make more informed decisions, such as travel arrangements, travel plans, and prices, thus enhancing a visitor's experience. Companies are integrating these chatbots now into front-desk and concierge services, reservations, guest queries, and feedback systems. An example is the use of ChatGPT, which is able to answer frequently asked customers' queries at a high degree of accuracy and fluency, thereby improving user experience and freeing up human staff for more complex problems (Mich & Garigliano, 2023). The tools help visitors to make informed decisions for travel planning, hotel selection, and cost by generating personalized recommendations on demand.

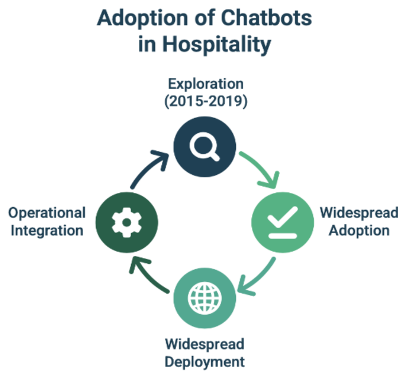

Figure 2. Chatbots lifecycle

Figure 2 shows the adoption of chatbots in the Hospitality industry. The development of chatbots in the hospitality industry can be divided into three main phases. During the first phase (2015–2019), chatbots were used in a limited way, mainly for frequently asked questions (FAQs) and simple reservations. The technologies used included rule-based systems and keyword triggers, but the lack of flexibility and natural interaction made the experience less appealing to users.

The second phase (2020–2022) saw a digital acceleration due to the COVID-19 pandemic, driving demand for contactless services. Chatbots were used to automate processes such as check-in/out, as well as provide information on safety measures. Technologies evolved to include natural language processing (NLP) and machine learning for more accurate query analysis. Well-known brands such as Marriott, Hilton, and Accor began using chatbots in their mobile apps (Fouad et al., 2024). The third phase (2023–present) is characterized by the integration of generative artificial intelligence, especially the use of large language models (LLMs) such as GPT-3.5 and ChatGPT. These models enable natural, multilingual, and personalized responses. An important aspect is the inclusion of eXplainable Artificial Intelligence (XAI), which justifies the decisions made by chatbots, increasing transparency and trust. Companies such as Holiday Inn (with the Bebot chatbot), Booking.com, and Airbnb have already integrated these systems (Fouad et al., 2024).

Generative Chatbots and Large Language Models (LLMs)

Over the years, generative chatbots have evolved from early chatbots that relied on pre-defined responses and rule-based keyword triggers. Newer chatbots have begun to use deep learning techniques to produce dynamic, human-like responses that are context-aware and linguistically coherent. These models are trained on a massive corpus of text and use probability distributions to predict the next word in a sequence, enabling them to construct new responses in real time. Chatbots process data to provide answers to requests of all kinds using artificial intelligence, automated rules, natural language processing (NLP), and machine learning (ML). AI chatbots and multimodal AI models can help travel and tourism companies improve customer service and engagement by accelerating and automating their services, such as customer support, content creation, analyzing current trends, designing competitive strategies, designing promotional packages and offers, and training employees. AI chatbots can make all travel and tourism companies' services efficient with fast responses, in no or minimal waiting time, enabling multilingual support and minimizing operational costs. According to (Naik et al., 2024) Large Multimodal Models (LMMs) are a big step for AI to become more precise, more creative, more contextual, and better able to mimic human interaction. Generative AI is a broad term that covers all AI technologies used to create content, where LMMs can accept and generate textual data, and LMMs can accept and generate more than one data modality type, which are also known as multimodal AI models. AI chatbots and multimodal AI models have many benefits, such as speed, accuracy, creativity, efficiency, and agility; therefore, they can be applied in any field, such as content creators, proactive assistants, trusted companions, customer assistants, and business operations facilitators.

Several state-of-the-art generative chatbots today are built upon large language models (LLMs) that enable highly contextual and human-like interactions. Notable examples include ChatGPT by OpenAI, powered by GPT-3.5 and GPT-4, widely adopted across domains such as education, healthcare, and hospitality. Google Bard, based on the PaLM 2 (Pathways Language Model) model, excels in information retrieval and reasoning tasks. Claude, developed by Anthropic, employs constitutional AI to generate aligned, safe, and coherent responses. Open-source LlaMA (Large Language Model Meta AI) models have been made available by Meta that serve as the foundation for multilingual and trainable chatbot systems (Touvron et al., 2023). In addition, generative AI is applied in enterprise support and productivity software through Amazon Q and Microsoft Copilot, showcasing how LLMs will drive business decision-making and streamline interaction-intensive tasks. These innovations in generative AI are particularly relevant to hospitality, where guest expectations for real-time, personalized, and trustworthy digital service are continuously rising.

Explainable AI (XAI) and Conversational Systems

In the areas of hospitality and customer service, trust in AI systems depends not only on the fluency of responses, but also on the ability of users to understand why a certain decision or recommendation was made. Thus, the need for transparency and interpretability in their decision-making processes becomes increasingly critical. To enable this, Explainable Artificial Intelligence (XAI) comes to our aid. One major goal of Explainable Artificial Intelligence (XAI), with the reason to enhance trust in technology, is to enable the user to enquire information and explanation directly from an intelligent agent. XAI refers to methods and techniques that make the behavior of complex AI systems interpretable and understandable to humans (Ali et al., 2023). Traditional AI technologies, such as deep learning (e.g., GPT), are typically "black boxes" in the sense that what happens inside the company is not understandable. The challenge of not being able to understand them is a problem for firms such as hospitality, whose customer satisfaction and operational choices must be transparent, auditable, and consistent with firm's policies (Amann et al., 2020). XAI chatbots will be able to justify results, e.g., why a customer could not be moved to a room or why a certain service was suggested.

In fields that require high accuracy and transparency, such as hospitality, healthcare, or finance, the explainability of conversational systems is a primary element, whether for debugging and auditing model behavior, or building trust with the user. Specifically, a generative chatbot that assists hotel customers should cover a range of functionalities, ranging from informing the user whether a room upgrade is available, to explaining the reason behind each response, such as loyalty level status or room availability. Such a level of transparency helps users perceive the system as fairer and more knowledgeable. According to Zhang et al., 2025 the effectiveness of explainable artificial intelligence in conversational systems depends on the accuracy of the explanation and the compatibility that the explanation has with the user's mental model, especially in cases where the user is not familiar with artificial intelligence.

The study of these elements emphasizes that the presentation of explanations should be conversational and context-sensitive to achieve a level of trust for user satisfaction. In hospitality applications, a high number of users may not be familiar with the technical side, and consequently conversational explanations help clarify why a chatbot recommends or rejects services, such as room upgrades or personalized offers. Zhang et al., 2025highlight that interactive explanations foster greater understanding, allowing users to ask questions or seek further clarification, making artificial intelligence systems perceived as more transparent and responsive. This conversational form of AI is particularly critical in-service areas such as hospitality, where user experience and perceived fairness are paramount to a satisfying user experience.

Building on this He et al., 2025 contrasted the impact of conversational XAI interfaces with that of the traditional XAI dashboards. Based on their report, while conversational interfaces enhance the understanding and confidence of users mildly, they also induce over-reliance, especially when powered by LLM-based agents.

The study highlights that these types of interfaces make people think they have a wrong impression of the AI capability, which the authors refer to as the "illusion of explanatory depth." These findings highlight the importance of designing conversational XAI systems carefully so that interaction and critical thinking are well-balanced so that the users do not forget AI limitations even when they are interacting with seemingly natural dialogue-like interfaces.

SYSTEM ARCHITECTURE / PROPOSED MODEL

1. Overview of the System

The proposed system, as described by Figure 3, is a hybrid chatbot meaning that is not based only on rules or information provided by the database but also includes an explainable chatbot for automated review replies in hospitality and simple guest service decisions including the "Why" behind each answer. In the frontend is used React and backend Node.js. For prediction and explanation is considered a lightweight ML decision engine (RandomForest+SHAP) orchestrated with a generative NLG layer (GPT-3.5).

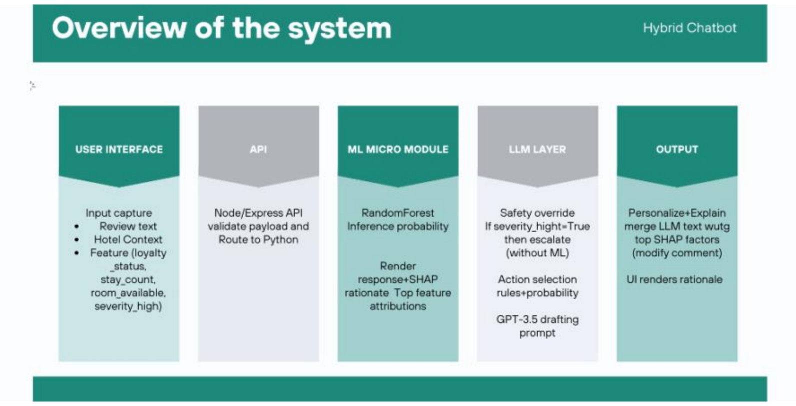

Figure 3. Overview of Hybrid Chatbot System

2. System layers

The architecture of the proposed system is divided into three layers:

1. The presentation layer includes the front-end, or the graphical interface, as an important part that supports communication between the client and the chatbot. The software system runs in the browser. Inside the presentation layer was included React as a JavaScript library, that increases the speed of the graphical interface components. For creating a modern and fast front-end, Vite was used, which includes native ES modules and hot-module replacement (HMR). In every change of the graphical interface, Vite refreshes the browser instantly. The last one is Tailwind, which makes styling faster and consistent and is a utility-first CSS (Cascading Style Sheets) framework. In the graphical interface the information collected is the review text, the selected hotel and the informative data about the user (e.g. loyalty status, stay count, room available and severity high).

2. Logic layer means Back-end. It is the brain of the software system where requests received from the front-end are processed. Here business rules and communication with the database or AI model are also applied. Node.js is used for building server-side applications. Unlike the front-end that runs in the browser, Node.js runs on the server. To simplify the creation of REST APIs (Representational State Transfer Application Programming Interface), is used express.js as a web framework for Node.js and it is sufficient just to define routes(endpoints) instead of writing raw server code. Node.js and Express act as an intermediate layer between the frontend(client) and the ML script. Rest API specifies the route and accepts requests (from client) and sends back responses. Through orchestration, various services of this software system are coordinated.

3.ML micromodule (Python) is perceived as an extension of the backend. It includes the predictive model and the explanatory model. This is a small but very specialized module used by the server to make fast local predictions. The main parts of this module include Random Forest Model, a powerful ensemble algorithm that combines many decision trees. The output of this model in our case is the probability or classification of the client. Meanwhile, within this module, the explanatory method of prediction made, SHAP (Shapley Additive exPlanations), is also defined. The explanation includes the presentation of the weight or contribution of each feature in the decision-making. For example, it can say: "Loyalty status contributed 40% to the upgrade decision", "Review text contributed 30 %" and "Room availability contributed 20 %". The Node.js server calls this module through an internal API. This module is lightweight and serves only for inference (not model training). This approach is called micro-module because it is a small and independent service that performs prediction and explanation. The file ml_respomse_generator.py is the local brain of the chatbot. Through it, prediction, decision and explanation are performed with the help of SHAP (SHapley Additive exPlanation).

3. Explainability Module (XAI Integration)

Explainable AI is all about making artificial intelligence less of a "mystery box". Sometimes an answer is not enough, but we want to know why this answer was given, what factors influenced it and how reliable it is. This is why artificial intelligence works best by incorporating explainability, especially to highlight hidden biases or errors. DARPA (Defense Advanced Research Projects Agency) summarizes the concept well: XAI should let AI explain its reasoning, show its strengths and weaknesses, and help people understand and trust it (Ridley, 2022). Which are the reasons for using XAI:

- Increase trust between humanity and AI
- Ensure that AI follows laws and rules
- Identify and reduce bias or unfair results
- Justify decision-making
- Control and evaluate the functioning of the model

According to Ridley, 2022 XAI was categorized By Purpose, By Scope and By Access (Figure 4). Considering By Purpose category, the interest is to answer the question "why" we want an explanation from AI, therefore its results are proof, so that everything is clear, testable, and traceable. Then there is Validations, a subcategory of By Purpose, which verifies whether the decision made by AI makes sense, and finally, there are Authorizations who include explanations that are based on rules, standards related to the safe and responsible use of AI. In the second category, "By Access," the focus is on how much we can see inside the AI model. The cases are grouped into the agnostic model, where the decision is explained without the need to understand the functionality of the model, and by being satisfied with the inputs and outputs.

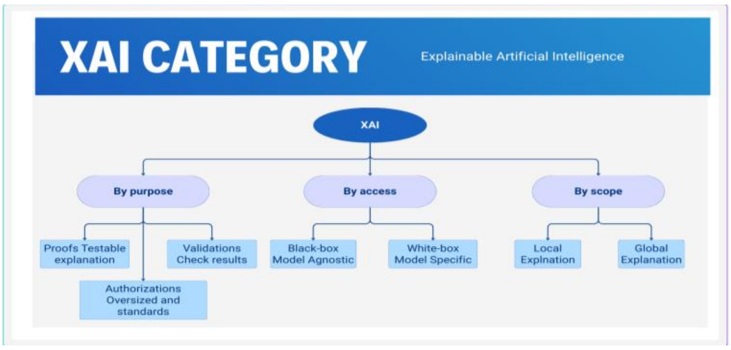

Figure 4. Explainable Artificial Intelligence categorization

Meanwhile, the specific model, also known as the "White-Box," includes cases where access to the inside of the model, the parameters, and logical decisions is required. In the third category, "By Scope," the focus is on how broad the explanation is. The division of this category includes local explanation, which describes why the AI made a particular decision for one case, and the global explanation, which describes the general logic or behavior of the AI model for all cases.

The integration of Explainable AI (XAI) is realized by adding a post-hoc module to the existing chatbot. This module runs in parallel with the core or main chatbot dialogue engine. The dialogue engine understands what the user is asking for and provides the answer or decision. Instead, the XAI (post-hoc) module analyzes the decision and generates an explanation. The explanations provided are categorized as global and local. As mentioned by LIME (Local Interpretable Model-agnostic Explanation), local explanations provide interpretation on each individual response by modeling the local behavior of the model. Global explanations are attempted by SHAP (Shapley Additive exPlanation) and help identify how different features affect the overall situation (Kohli, 2024). This approach makes the chatbot more transparent and helps build user trust, as they can understand “why” a certain answer was presented, e.g. “The suggestion was based on previous choices of similar users” (Nguyen et al., 2023). Furthermore, the XAI dialogic method, described in the literature as a “multi-turn” approach, enables interactive exploration where users can ask additional questions and deepen explanations in a conversational style (Mindlin et al., 2025).

4. Practical Implementation and Interface

The proposed system will integrate an Explainable Artificial Intelligence (XAI) module to enhance explainability, interpretability, and trust among users in the automatic review response process. In its current deployment, the explainability layer uses a rule-based rationale strategy to insert explanations into every response generated. For instance, if the system detects a negative sentiment in a review such as *"Unfriendly and unprofessional at the checking desk,"* the system automatically generates an apology response with a description of why the apology was made because there was a negative sentiment. Similarly, if the system detects positive sentiment in a comment such as *"An amazing hotel, the suites and views are exceptional"* the system generates *”Thank you so much for your kind words! We are thrilled to hear that you enjoyed your stay with us and that our suites, views, and spa area met your expectations.”* with the reason being that the positive comment prompted the generated acknowledgment. These rule-based just-in-time explanations allow end-users and hotel managers to understand why a specific response was produced, and this is crucial in hotel environments where confidence and customer satisfaction are critical. The practical system was developed to collect and process hotel reviews.

Figure 5 demonstrates the first interface after user login. As you have noticed there is a list of the registered hotels. It is important that the user select the hotel and go to the option review and write the opinion for the stay at that hotel.

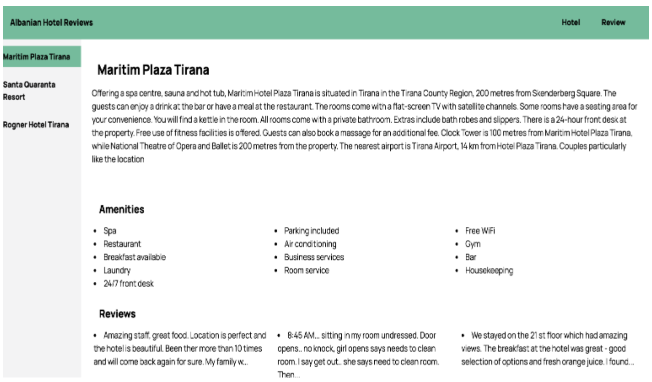

Figure 5. The User interface

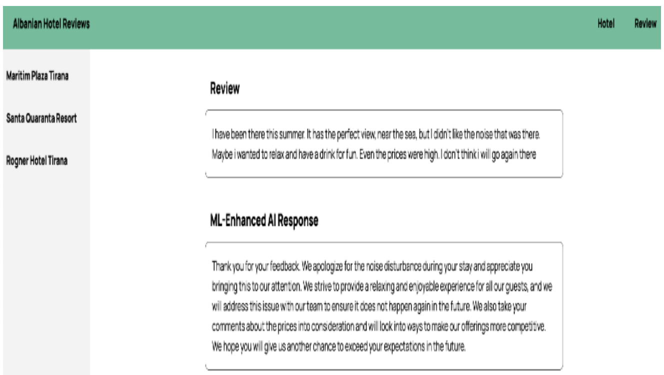

Figure 6. The AI response generated by AI

Automatically after the client writes the review our chatbot prepares a response based on the defined rule, database information and response simulated from GPT3.5 (Figure 6). It takes only 3 seconds, but it is also a notification for the hotel. Through the integrated XAI module, the system also provides a basic explanation for its response, making it credible that a human and not a robot is responding. This combination of explainable reasoning and human-like dialogue increases guest confidence and operational transparency for hotel operators. The answers produced are not only contextually relevant and compassionate but also reduce the need for human staff to manually handle repetitive responses, saving time and ensuring consistency in brand voice, feedback, saving time and ensuring consistency in brand voice.

MATERIALS AND METHODS

The materials needed during this research include several libraries with necessary functionality. Starting with Pandas where the guest features will be stored in a Data Frame, then the Random Forest Classifier algorithm of the Supervised Learning type, which is mainly used for classification (even also has a regression version - RandomForestRegressor) but in the current case, the user's classification is sufficient. To explain how a Machine Learning model decides, SHAP (SHapley Additive exPlanations) is used as a method of Explainable AI (XAI). During the construction of several functionalities, it was necessary to handle numeric arrays and SHAP output, which was achieved by importing the NumPy (Numerical Python) library. NumPy is widely used for numerical calculations and in cases of working with data in the form of matrices and vectors. Finally, the OpenAI library is imported, which serves to create a direct connection from our code with OpenAI API so that its models can be used, as specified GPT 3.5. In this article, it was attempted to generate text from the GPT 3.5 model by sending a slightly more formal question than the text written as a review by the client.

```python
FEATURES = ["loyalty_status", "stay_count", "room_available","severity_high"]
def evaluate_user(user_dict):
    df = pd.DataFrame([user_dict])[FEATURES]
    prob = float(model.predict_proba(df)[:, 1][0])
    try:
        exp = explainer(df)
        shap_vals = np.array(exp.values)[0]
    except TypeError:

        vals = explainer.shap_values(df)
        if isinstance(vals, list):
            arr = vals[-1]
        else:
            arr = vals
        shap_vals = arr[0]
    explanation = dict(zip(FEATURES, shap_vals))
    return prob, explanation
```

Figure 7. Code used for function evaluate_user

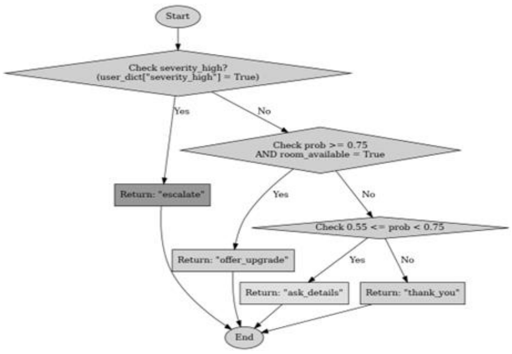

Figure 8. Schematic view for function decide_action

The evaluate_user function, Figure 7, takes as input the previous user data and returns the probability value calculated by the predictive model and explains the prediction using SHAP values and highlights the characteristics that have influenced the prediction. The old version of SHAP is also considered where a list or an array is returned. The last element of the list is taken vals[-1] which is often the positive class otherwise arrivals. To store the information for the first user arr[0] is specified. The function returns the probability and explanation. The decide_action function takes as input parameters; the probability calculated in the evaluate_user function and the user information. The schematic workflow and decisions of this function are described by Figure 8. In this function, importance has parameter severity_high when it is True which ignores the probability and immediately escalates the case to higher support, meaning emergencies have higher priority than forecasts. If there are rooms available and the probability is >=75%, the system offers the client a room upgrade, and this case is a true combination of model confidence with real-world constraint. If the probability is >=55% and <75%, the client is asked for more details to take action to avoid wrong decisions because it is assessed that the model is not safe. In cases of a probability <55%, the system thanks the client and closes the case. Effective prompts can improve accuracy, consistency and relevance about the information requested from GPT 3.5, so for this reason prompt phrasing matters-a lot. There is growing scientific work to guide systematic prompt design, especially for specialized uses like clinical reasoning or education. The construction of the request was carried out based on some of the strategies specified in the article (White et al., 2023), where initially the context and domain, that the question includes, were determined.

The decomposition of the request was carried out by breaking it down into two main sub-points, the type of action and the customer review. Normally, these two pieces of information were set as variables that could be changed by the customer. Creativity was also included as a strategic element, where the response method was requested through prompt engineering as a combination of professionalism and friendliness. Schematically, the description of the generate_base_ comment function is given at Figure 9, where the three strategies used in formulating the request are distinguished.

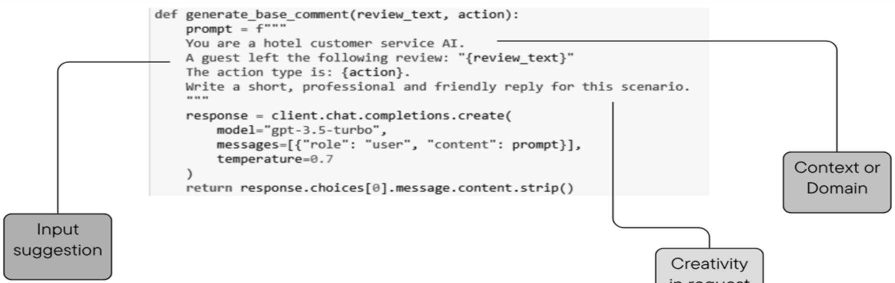

Figure 9. Code grouped for function generate_base_comment

Based on the action type and explanation, it was decided to modify the AI-generated text by adding personalized messages. To ensure that values are handled consistently when calculated was necessary a helpful function like _scalar(x) for converting x into a NumPy array. This function was used inside the modify_comment). Input elements are specified base_comment, which is the AI-generated text, action as a string representing action type and explanation which specified the importance values or factors. Within the function, the two most important factors are searched, where explanation dictionary items are ranked by absolute importance, meaning highest first and usage of _scalar to ensure each important value is handled consistently. We are interested in preserving the name of the factors that are the key to the dictionary. Finally, through conditions depending on the value of action, customization is achieved, where reason is associated with the formal text according to the conditions. By weighing the most important factors from the AI model's explanation, this feature generates an improved and personalized response. Actions are categorized as below:

- Offer upgrade
- Ask details
- Escalate
- Appreciation

The final function is process_review which takes user information and review_text as input and calls all the above functions inside it. The return is a data structure which includes probability, action, final_comment and explanation. The code for this function is shown in Figure 10.

```python
def process_review(user_dict, review_text):
    prob, explanation = evaluate_user(user_dict)
    action = decide_action(prob, user_dict)
    base_comment = generate_base_comment(review_text, action)
    final_comment = modify_comment(base_comment, action, explanation)

    return {
        "probability": prob,
        "action": action,
        "final_comment": final_comment,
        "explanation": explanation
    }
```

Figure 10. Code used for function process_review

```
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred))

              precision    recall  f1-score   support

           0       0.83      0.99      0.90        83
           1       0.00      0.00      0.00        17

    accuracy                           0.82       100
   macro avg       0.41      0.49      0.45       100
weighted avg       0.69      0.82      0.75       100
```

Figura 11. Classification report for the two classes

Evaluation of the model and dataset

At first glance, the outcome appeared to be highly consistent, based on the response received. However, the evaluation of accuracy and F1 score for the dataset brought to light new findings**.** The dataset consists of 500 records in xlsx format, and the data were split, 80% for training and 20% for testing. There are no missing values and the format is readable. The target (in this case severity_high) is in binary form (0/1) and is suitable for classification. The train set has 400 rows where class 0 has 314 cases and class 1 has 86 cases. Meanwhile, the test set has 100 rows where class 0 has 78 cases and class 1 has 22 cases. In this way, the data balance of the dataset has been achieved and the accuracy in this case is 0.82. Meanwhile, to calculate the F1-Score, it is enough to import this function from sklearn.metrics where the parameters are the real labels, the model predictions and the weighted average which varies according to the size of the class (i.e. the class with more examples has a greater weight). This is truer when the dataset is unbalanced. Since F1-score is the harmonic mean of precision and recall, and in this case evaluated as 74 %, it means that the model has a good balance between these two although there is still room for improvement. The same evaluation was performed for each class; and were achieved different and unexpected results. Classification_report was used to highlight each class

precision-Indicates how many of the cases predicted as a class are of that class

recall-Indicates how many of the real cases of a class were found by the model

F1-score- Is the harmonized average of precision and recall

Support- Is the actual number of samples for each class in the data. According to the classification report in Figure 11, it is noted that the model works very well for the dominant class 0 (with 83 samples) where 83% of the cases resulted 0 were actually 0. The model caught 99% of the real cases. Meanwhile, the situation is different for class 1 (with 17 samples) where the conclusion implies that the model has not managed to identify any case from this class and this is because of the unbalanced dataset, i.e. more 0 samples than 1. The model has learned to favor the dominant class 0 because it is easier to achieve high accuracy. To slightly improve the situation, several balancing techniques were used such as Smote (Synthetic Minority Oversampling Technique), undersampling and balanced class_weight.

```
SMOTE
              precision    recall  f1-score   support

           0      0.800     0.564     0.662        78
           1      0.244     0.500     0.328        22

    accuracy                          0.550       100
   macro avg      0.522     0.532     0.495       100
weighted avg      0.678     0.550     0.588       100

AUC: 0.49067599067599077
UnderSampler
              precision    recall  f1-score   support

           0      0.717     0.423     0.532        78
           1      0.167     0.409     0.237        22

    accuracy                          0.420       100
   macro avg      0.442     0.416     0.385       100
weighted avg      0.596     0.420     0.467       100

AUC: 0.4463869463869464
Class_weight='balanced'
              precision    recall  f1-score   support

           0      0.757     0.679     0.716        78
           1      0.167     0.227     0.192        22

    accuracy                          0.580       100
   macro avg      0.462     0.453     0.454       100
weighted avg      0.627     0.580     0.601       100

AUC: 0.486013986013986
```

Figure 12. Classification results report after balancing technique

Each technique was applied to each class, and the results are shown on Figure 12. The SMOTE technique has a decrease in accuracy of 55%. It creates synthetic samples for the minor class (class 1). Class 0 has high precision for low recall, so the model finds some cases but leaves many cases uncaught. While again for class 1 the precision is very low 0.24 and recall 0.50 which means half the time it manages to find cases of class 1 but often makes mistakes. This technique has better performance in recall but is very low precision. The undersampling technique has a decrease in accuracy of 42% and during this procedure many samples are removed from class 0 to balance the dataset. For class 0 precision is 0.71 and recall is 0.42 (very low), while for class 1 precision is 0.17 and recall 0.41 (it manages to find cases, but very inaccurate). The accuracy has resulted very low because we have lost a lot of information from class 0. As a result, this technique is not working well because a lot of data is lost from the large class. This technique lost information and decreased performance. The Class Weight (balanced) technique results in an accuracy of 48%. The model gives more weight to errors in class 1. As for class 0, the precision is estimated at 0.76 and the recall is 0.68, which seems to be a slightly better situation than the above techniques. For class 1, the precision is 0.17 and the recall is 0.23, which is again very weak but slightly better than undersampling. Since the F1-score of this technique is approximately 60%, we can say that the model has a little more balance, however, class 1 is still not learning well. This technique is a compromise, but it did not improve results for class 1.

RESULTS AND DISCUSSION

In this study is proposed an explainable AI-driven chatbot framework in the domain of hospitality. It included a combination of the ensemble model Random Forest, by using many decision trees, mathematical explanation method SHAP, focusing and highlighting mostly some feature attribution, and a large language model like GPT-3.5 to provide responses based on client reviews. The system is mainly based on transparency, context-aware for decision-making, balancing automation based on rules so critical cases can be prioritized. By integrating interpretability into the model and at the response of the customer, the approach enhances trust, auditability and personalization. Future research will focus on larger-scale evaluations, comparison with alternative XAI techniques, and user-centered validation to strengthen adoption in real-world hospitality environments. An important issue consists in highlighting the importance of addressing data imbalance in predictive models for the hospitality sector. The analysis is shown in Table 1 and clarifies that the existing techniques to solve the imbalance problem in machine learning, such as SMOTE, undersampling and class weights, significantly affect the performance of the minority class, but none provided consistent results. SMOTE usage achieved a better balance between classes compared with other methods. Accuracy was 55 % and F1-Score of the minority class was 0.328, even those with an AUC (Area Under the Curve) relatively low (0.49). This indicates that artificial increase of data can improve accuracy but fails to provide clear differentiation between classes. The Undersampling method proved less effective, with an accuracy of 42% and a low F1-score (0.237) for the positive class, suggesting loss of information during sample reduction.

Table 1. Empirical Evaluation of Balancing Techniques on Chatbot Classification Model

Balancing Technique	Accuracy (%)	F1-Score (Minority Class)	F1-Score (Majority Class)	AUC (Area Under Curve)	Interpretation
SMOTE (Synthetic Minority Oversampling Technique)	**55**	**0.328**	—	**0.49**	Improved balance between classes but limited separability; synthetic oversampling increases accuracy but still causes misclassification.
Random Undersampling	**42**	**0.237**	—	—	Least effective method: performance drop due to data loss from majority class reduction.
Class Weight = ‘balanced’	**58**	**0.192**	**0.716**	—	More consistent overall results, but weak minority-class performance, show potential of cost-sensitive adjustment.

Meanwhile, using Class_weight= ‘balanced’ yielded somewhat more consistent results, achieving an accuracy of 58% and a higher F1-score for the main class (0.716), but with noticeable weakness in the minority class (F1-score 0.192). This suggests that more advanced approaches such as ensemble learning, cost-sensitive algorithms or hybrid combinations of existing methods are required for significant improvement. The study confirms that data imbalance is a critical factor for achieving reliable results in artificial intelligence applications in hospitality and tourism. Overall, these outcomes demonstrate that data imbalance remains a critical challenge in developing AI systems that are reliable for the hospitality sector. To achieve more robust predictive performance further research should be focused on addressing this imbalance through advanced resampling techniques (SMOTE with TOMEK Links or ADASYN) and by collecting additional data (i.e. increasing the dataset) for the minority class. Furthermore, experimenting with more robust algorithms such as XGBoost, LightGBM, or neural networks with focal loss could enhance predictive performance. Finally, A broader evaluation using domain-specific validation metrics including precision-recall curves and customer satisfaction indice will be essential to confirm the real-world applicability and scalability of the proposed framework.

CONCLUSION

This paper proposes an explainable AI–driven chatbot framework in the domain of hospitality. It included a combination of RandomForest model, the explanation of SHAP based on some feature attributions, and the responses generated by GPT-3.5. The system focus is transparency, context-aware for decision-making, balancing automation based on rules so critical cases can be prioritized. By integrating interpretability into the model and at the response of the customer, the approach enhances trust, auditability and personalization. Future research will focus on larger-scale evaluations, comparison with alternative XAI techniques, and user-centered validation to strengthen adoption in real-world hospitality environments. An important issue is that this study highlighted the importance of addressing data imbalance in predictive models for the hospitality sector. The analyses showed that existing techniques such as SMOTE, undersampling and class weights significantly affect the performance of the minority class, but none provided consistent results. This suggests that more advanced approaches such as ensemble learning, cost-sensitive algorithms or hybrid combinations of existing methods are required for significant improvement. The study confirms that data imbalance is a critical factor for achieving reliable results in artificial intelligence applications in hospitality and tourism.

Limitations and Future Work

One of the problems encountered during this work is the imbalanced data, where the minority class is underrepresented compared to the majority class. This imbalance results in a low performance for the minority class, and this is best reflected in the recall and F1 results. Although balancing techniques were applied, a partial adjustment of the problem occurred again, and the AUC (Area under the curve) values remain close to the random prediction. A promising direction for future exploration is addressing this imbalance through advanced resampling techniques (SMOTE with TOMEK Links or ADASYN) and by collecting additional data (i.e. increasing the dataset) for the minority class. Furthermore, experimenting with more robust algorithms such as XGBoost, LightGBM, or neural networks with focal loss could enhance predictive performance. Finally, a broader evaluation with domain-specific validation metrics will be necessary to ensure that the system is both reliable and applicable in real-world scenarios.

Recommendation

This paper is recommended to all businesses operating in the tourism sector. The integration of Explainable AI (XAI) in hospitality chatbots will be focused mostly on enhancing transparency, customer trust, and managerial decision-making. Hotel managers will be encouraged to adopt hybrid systems where AI-driven recommendations are complemented by human interaction, ensuring both efficiency and personalized service quality. For the training staff it will be necessary to understand and utilize XAI explanations, such as SHAP, by improving collaboration between employees and intelligent systems.

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