Applying a Decision-making Technique to Evaluate the Key Factors Affecting Customer Churn Using a Text-mining Approach: A Case Study in the Hotel Industry

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Abstract–Customer churn is a critical challenge faced by the hotel industry, impacting revenue and profitability. Identifying and prioritizing the factors that contribute to customer churn is essential for hotel managers to devise effective retention strategies. The prioritization of these factors enables hotel managers to allocate resources efficiently towards implementing targeted retention initiatives. By understanding the factors that influence customer churn, hotels can proactively tailor their services and improve customer experiences to enhance loyalty and reduce churn rates. This study aims to determine and prioritize the key factors influencing customer churn in the hotel industry. The data is analyzed using advanced text mining techniques, including tokenizing, stemming, and eliminating stop words, to identify the significant factors affecting customer churn. The findings highlight factors such as room conditions, the beauty of the hotel, food quality, staff interactions, hotel hygiene, restrooms, and proximity to important centers. To prioritize these factors, we utilized the AHP technique in Expert Choice software. According to the findings, among these factors, staff interaction with 32%, room conditions with 22%, restrooms with 19%, food quality with 12%, proximity to important centers with 8%, hotel hygiene with 4%, and beauty of the hotel with 3%are respectively the most important factors affecting customer churn.

Keywords: Customer Churn, Hotel Industry, Text Mining, Analytic Hierarchical Processing

1. Introduction

Customer churn, which refers to customers ending their business relationships or canceling subscriptions, presents major obstacles for companies in different sectors [1]. The hotel industry is particularly affected by customer churn, as it impacts revenue, profitability, and customer satisfaction. It is essential for organizations to understand and recognize the main factors that influence customer churn in order to create effective strategies for customer retention and loyalty. Hotels face a significant challenge in dealing with customer churn, where customers decide to end their affiliation with a specific hotel. It is crucial for hotels to identify and prioritize the key factors that contribute to customer churn in order to develop effective retention strategies and improve customer satisfaction.

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Received: 2023.08.02; Accepted: 2023.09.18

Traditional methods often involve manually analyzing customer feedback and surveys, which can be time-consuming and subject to human biases. It is crucial for the hotel industry to identify and prioritize the key factors that contribute to customer churn. To effectively understand and address customer churn, hotels need to gain insights into the underlying factors. In the past, surveys and manual analysis were relied upon to identify these factors. However, advancements in technology, particularly in natural language processing and text mining, have introduced new approaches. To tackle this issue, it is necessary to employ a text-mining approach to extract valuable insights from large amounts of unstructured customer feedback data. This approach aims to identify and prioritize the significant factors that impact customer churn in the hotel industry. By utilizing techniques such as natural language processing and sentiment analysis, patterns and trends can be discovered in customer comments, reviews, and feedback. Text mining, a subset of data mining, involves extracting useful information and patterns from extensive sets of unstructured text data. This approach has proven highly effective in analyzing customer feedback, online reviews, and various forms of textual data found on the internet,

enabling businesses to uncover hidden insights about customer churn. This study aims to employ a text mining approach to identify and prioritize the key factors that influence customer churn in the hotel industry. By analyzing a large volume of textual data, including customer reviews, feedback forms, social media posts, and other sources, we can reveal patterns, sentiments, and themes related to customer churn.

While there has been extensive research on customer churn, there is no consensus on the specific factors that have the greatest impact on churn rates. Previous studies have examined factors such as demographics, service quality, pricing, competitor influence, and customer engagement individually [2–5]. However, there is a need to consolidate and prioritize these factors to provide businesses with actionable insights for effective churn management. Moreover, existing research lacks a standardized methodology for identifying and prioritizing the key factors that affect customer churn. Although some studies have explored factors influencing customer satisfaction in the hotel industry [6–9], there is a lack of research on identifying and prioritizing the key factors that contribute to customer churn in this industry. Additionally, there is a need for research that utilizes Persian text mining approaches to analyze customer feedback and reviews in order to identify the most critical factors that lead to customer churn in the hotel industry. Therefore, this study aims to address this research gap by using Persian text mining approaches to identify the factors and the AHP method to prioritize them, which affect customer churn in the hotel industry. The study will offer insights into the factors that contribute to customer churn in hotels and assist hotel managers in developing effective strategies to reduce churn and enhance customer retention. This gap in the literature highlights the necessity for a structured approach that combines qualitative and quantitative techniques to systematically identify and rank the factors based on their relative importance and impact on customer churn.

The aim of this study is to use text mining techniques to analyze customer feedback data and identify the key factors that contribute to customer churn in the hotel industry. The results will help hotel management to understand the underlying causes of churn and prioritize actions to reduce churn rates. The ultimate goal of this research is to provide a data-driven approach for stakeholders in the hotel industry to improve customer retention and overall business performance. This study contributes to the existing knowledge by comprehensively analyzing customer churn in the hotel industry through a text-mining approach. The findings will offer valuable insights to hotel managers, enabling them to make data-driven decisions and implement effective retention strategies. Ultimately, this research aims to assist the hotel industry in reducing customer churn rates and strengthening its competitive position in the market.

The structure of this research is such that in the second and third parts, a review of the previous literature, the gap, and the importance of the research will be done. In the fourth part, the research method will be described. In the fifth part, the findings of the research will be presented, and finally, in the last part, they will be discussed and concluded.

2. Literature review

Customer churn is a significant concern for businesses, particularly in the telecom sector, where it has a significant impact on companies' profitability and competitiveness. Researchers have conducted numerous studies to identify the factors that contribute to customer churn. A review of 75 recent journal articles on telecom churn literature identified various churn factors and their complex relationships [10]. The push-pull-mooring framework of migration was used to understand and determine the switching barriers and variables affecting a customer's decision to remain with a service provider [11]. The article [12] presents a comprehensive review of the literature on customer satisfaction, providing insights into the factors that affect customer satisfaction and how they can be measured and utilized to improve business performance. A systematic literature review of churn prediction identified popular machine-learning techniques used in churn prediction and provided directions for future research [13]. Another study used machine learning to analyze the factors affecting customer churn in the telecommunications industry [14]. Technical factors, such as usefulness, ease of use, data-related, monetary factors, technical issues, and user experience, were found to affect patients' adoption of Health tools [15]. Finally, a study on delivery applications found that factors affecting customer satisfaction could be classified into five items of the Honeycomb Model [16]. A study in Indonesia used the Theory of Planned Behavior, a framework including key elements like customer experience and satisfaction, price and promotions, service quality, social influence, brand image, ease of use, and features of the service. Key findings from the analysis indicate that while there is moderate satisfaction with the online bill payment service, there are areas that require improvement, including recurring payment failures, limited availability of certain payment

methods, and insufficient awareness of certain features. To address these issues and enhance customer retention, recommendations were made [17]. [18] evaluated switching cost, customer dissatisfaction, customer dissatisfaction, and customer status as effective factors in customer churn based on the Hanvali model. They showed that customer dissatisfaction, service utilization, and demographic characteristics of customers have the most impacts on customer churn or customer retention. In addition, customer status affects customer churn indirectly. For predicting customer churn, [19] presented a prediction model using the Decision Tree algorithm and a neural network. [20] determined the reasons for customer churn by evaluating one of the insurance company databases. The results indicated that the customer attraction method is the major factor in predicting customer churn or retention. While the shopping experience is the next factor, [21] evaluated Iran's banks' current accounts to recognize factors affecting customer churn. They demonstrated that employee attitudes affect customer churn directly. Moreover, [22] applied clustering techniques to evaluate factors affecting customer churn in insurance companies. The results indicated that educated people leave the company mostly because of employees' attitudes, while merchants leave it because of the company's reputation. [23] explored the possible factors affecting churn in the Danish telecommunications industry and how those factors connect with retention strategies. They used five machine learning algorithms on four datasets to extract the key factors reflecting the preferences of customers in two regions. Table 1 shows other studies and methods in the literature that are closer to our research topic.

In summary, these studies emphasize the significance of understanding the factors that influence customer churn and implementing strategies to mitigate it. Based on the literature, the following strategies have been found effective in reducing customer churn:

- Enhancing customer service: Improving customer service by promptly addressing complaints, providing personalized service, and offering incentives to loyal customers [10].
- Offering competitive pricing: Providing competitive pricing and promotions to retain customers who may be enticed by better deals from competitors [10].
- Improving product or service quality: Focusing on enhancing the quality of offerings to increase customer satisfaction and reduce churn [10].
- Utilizing data analytics: Employing data analytics and machine learning techniques to identify at-risk customers and take proactive measures to retain them [24, 13-14].
- Increasing customer engagement: Engaging with customers through various channels such as social media and email marketing to establish a relationship and foster loyalty [10].
- Minimizing switching barriers: Simplifying the process for customers to switch to the company's services and providing incentives to encourage them to stay [24].

In order to decrease customer churn, companies need to implement a comprehensive strategy that tackles the different factors that lead to it. This includes enhancing customer service, providing competitive prices, improving the quality of products or services, utilizing data analytics, increasing customer engagement, and removing obstacles that might make customers switch to other brands. By doing so, companies can lower churn rates and enhance customer loyalty.

Table 1. List of related literature and techniques about customer churn

Authors	*Description*
[25]	using the Focal Loss hard example mining technique to add the class weight Y and the focus parameter to the cross-entropy loss function of LightGBM.
[26]	(i) proposing a ready-to-use framework to extract customer churn determinants from VOC (Voice of Customer)interactions; (ii) proposing a text mining process to automate the extraction of customer churn determinants from VOC interactions; (iii) proposing a text-mining model, applicable in a specific domain
[27]	estimating churn probabilities directly from text data, by adopting classical text mining methods and combining them with state-of-the-art statistical prediction modelling and Comparing the churn prediction based on text data to classical churn prediction based on structured CRM data.
[28]	proposing a customer churn prediction model utilizing the unstructured data, which is the spoken contents in phone communication with machine learning.
[29]	this paper explores the combination of two operations research models (analytic hierarchy process and Markov chain) for solving subscribers' churn and retention problem peculiar to most service firms. A conceptual model for unraveling the problem customer churn and retention decision management was proposed and tested with data on third level analysis of AHP for determining appropriate strategies for customer churn and retention in the Nigeria telecommunication industries.
[30]	This paper develops a methodological framework to address strategic decision-making processes from a multi-criteria perspective, assisted by text analytics and

	interviews.
[31]	This study aims at ranking the switching barriers to identify critical success factors of telecom service providers to retain customers and attain a competitive advantage in the market. The analytical hierarchy process (AHP) is used as a tool to rank the identified switching barriers.

3. Research Gap

While the importance of identifying and prioritizing factors that contribute to customer churn in the hotel industry is acknowledged in the existing literature, there is still a significant research gap in the use of advanced text-mining and decision-making techniques, particularly the Analytic Hierarchy Process (AHP), for thorough factor assessment and prioritization. In order to provide a more precise and data-driven approach to understanding the dynamics of customer churn in the hotel sector, existing research have mostly used qualitative or survey-based methods without the use of cutting-edge data analysis techniques.

Furthermore, the bulk of earlier studies frequently focused on a small number of variables or employed conventional statistical techniques that might have missed the subtle interactions between different variables that affect churn. The opportunity to give hotel managers a more nuanced and practical understanding of where to focus their resources and efforts for the most efficient customer retention strategies remains unexplored in the absence of a comprehensive and systematic examination of these factors through text mining and the subsequent prioritization through AHP.

In order to close this gap, the current study uses text-mining techniques to comprehensively identify and analyze a wide range of factors that influence customer churn. Next, it applies AHP to prioritize these factors according to how important they are in the context of the hotel industry. This research gap highlights the need for a more data-centric and methodologically advanced approach to address the complex challenge of customer churn in the hotel industry and provide actionable insights for industry practitioners and scholars alike.

4. Significance of the Work:

- Relevance, to the Hotel Industry; The hotel industry heavily relies on keeping customers coming for its success. If customer churn rates are high it can greatly impact revenue and profitability. This research focuses on a challenge faced by this industry making it extremely valuable and pertinent to hotel managers and stakeholders.
- Effective Allocation of Resources; It is crucial for hotel managers to identify and prioritize the factors that contribute to customer churn. This work assists them in allocating resources by pinpointing the influential factors. This allows hotels to invest in targeted initiatives that enhance customer experiences and loyalty ultimately reducing churn rates.
- Proactive Strategy Development; This research empowers hotels to adopt an approach towards preventing customer churn. By comprehending the factors that influence churn hotels can tailor their services. Make necessary improvements. This proactive strategy has the potential to foster increased customer loyalty and long term business growth.
- Utilization of Cutting Edge Techniques; The application of text mining techniques in this research, such, as tokenizing, stemming and eliminating stop words showcases the adoption of methods to tackle real world business challenges.

This demonstrates how data driven methods have the ability to address issues successfully.

4.1. The case study's significance:

Applied Relevance: The hotel industry, a significant player in the worldwide hospitality sector, is the subject of your case study. Your findings are immediately applicable to a wide range of venues because churn rates are a real worry for hotels around the world.

Practical Insights: By offering practical insights into the particular elements that matter most in the context of the hotel sector, your research goes beyond theoretical principles. Hotel management can follow this practicality to make wise decisions.

4.2. Significance of the results:

Prioritization of factors the research gains rigor by using the Analytic Hierarchy Process (AHP) to rank the important elements impacting customer attrition. The relative relevance of each aspect may be understood clearly and quantitatively using this strategy, which can help with decision-making.

Relevant Learning's: The findings show that the most

important elements influencing consumer churn are staff interactions, room conditions, and restroom quality. Hotel managers may take action with this information because it identifies the precise areas where adjustments will have the biggest impact on retaining customers.

In conclusion, this research is very important because it targets a serious issue in the hotel business, provides useful insights, and employs cutting-edge methods to provide results that can be put into practice. This paper provides hotel management with the knowledge they need to improve customer experiences, foster loyalty, and ultimately improve the bottom line by identifying and prioritizing the reasons causing customer turnover.

5. Methodology

The necessary data for conducting this study was collected from the customer databases of social networks and hotel websites, specifically focusing on the hotels located on Kish Island ranging from three to five-star ratings. The data obtained consisted of textual content provided by customers, in the Persian language, and totaled over 6,000 records. In order to gather user opinions, which is the initial stage of this research, customer feedback from Persian websites was extracted using Python programming language.

In the initial stage of preprocessing in this study, the texts are divided into tokens and any stopwords are eliminated from the tokens. In the following step, any irrelevant words are removed from the tokens. In the case-folding step, all words are standardized to either lowercase or uppercase form. This is done to ensure that if a word appears multiple times with different capitalization, they are treated as a single word.

In the subsequent stage, we employ stemming to standardize the extracted words. Stemming methods help group together words that have similar meanings and only vary in their appearance, treating them as features.

The IDF-TF weighting method is utilized to determine the suitable weight for each word. This method, commonly employed in text mining research, assigns appropriate weights to words in documents based on the frequency of each word's occurrence in each document and across all documents.

This study focuses on text mining and involves collecting a data set consisting of customer opinions and a label indicating whether they have churned or not. After preprocessing and applying TF-IDF operations, the texts are transformed into numerical features for data mining.

The research data, consisting of comments from both satisfied and dissatisfied customers, underwent a text mining operation to identify the key factors that impact customer satisfaction or churn. As the factors varied, they were grouped into general categories to facilitate their review.

After identifying the factors affecting customer churn, we will use the analytic hierarchical processing (AHP) technique to prioritize them, and we utilized Expert Choice Software for that. AHP is a technique used in quantitative research to prioritize indicators or factors based on their relative importance. The AHP technique involves breaking down a complex problem into smaller, more manageable parts and then comparing the importance of each part to the overall problem. The proposed system is shown in Figure 1.

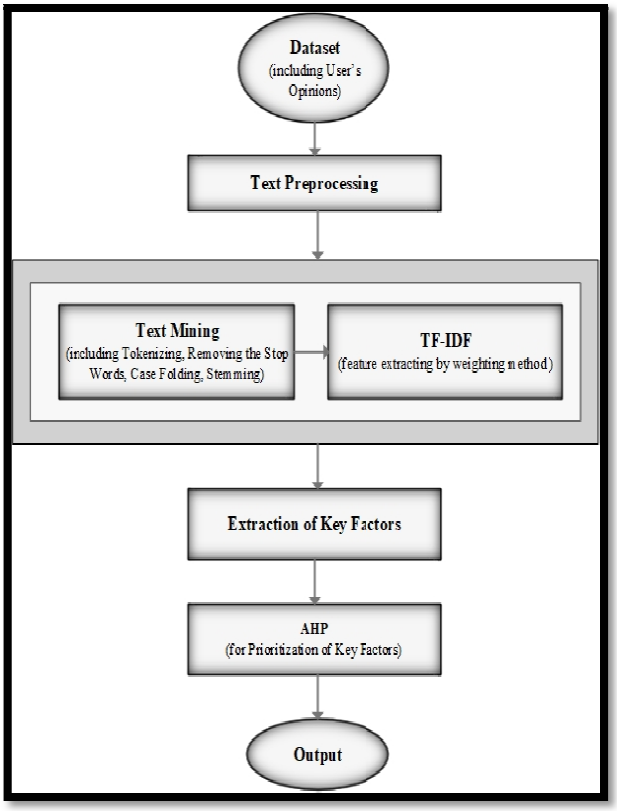


Fig.1 Proposed System

6. Results

Following the text mining analysis of customer comments, a compilation of key factors impacting customer satisfaction or churn was generated. As these factors varied in opinion, they were organized into general categories to facilitate review. These categories include "staff interaction," "hotel hygiene," "food quality," "room conditions," "proximity to important centers," "beauty of the hotel," and "restroom quality." Figures 2 and 3 display

the prevalence of each factor in positive comments regarding customer satisfaction (non-churn) and negative comments regarding customer churn, respectively.

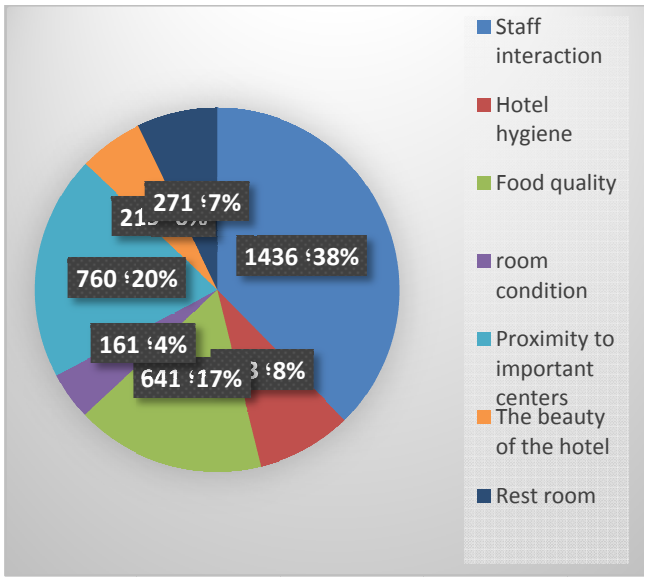


Fig. 2 The abundance of each of the effective factors in customer satisfaction in positive comments (non-churn)

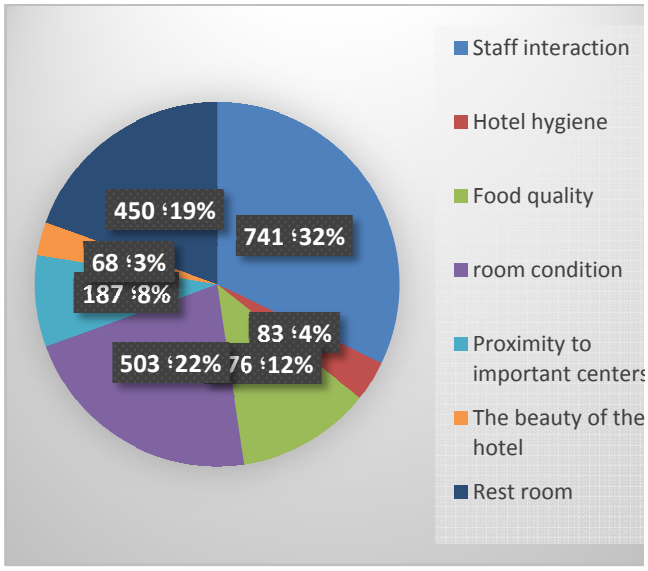


Fig. 3 The abundance of each of the effective factors in customer churn in negative comments (churn)

To prioritize the factors, we used the AHP technique in the following steps [32-33]:

• Define the decision problem: Clearly define the research problem and identify the factors or criteria that need prioritization.

• Create a hierarchy: Develop a hierarchical structure by decomposing the problem into a series of levels. The top level represents the decision objective, followed by intermediate levels representing the criteria, and the lowest level representing the alternative factors.

• Pairwise comparisons: Conduct pairwise comparisons of the criteria or factors to determine their relative importance. These comparisons are done using a scale (e.g., numerical scale or verbal descriptors) where factors are ranked in terms of their importance.

• Construct a preference matrix: Based on the pairwise comparisons, construct a matrix that represents the preferences and relative importance of the factors.

• Calculate weights and priorities: Using mathematical calculations, derive the weights and priorities of each factor based on the preference matrix. These weights represent the relative importance of each factor concerning others.

• Sensitivity analysis and interpretation: Perform sensitivity analysis to ensure the robustness of the results. Interpret the prioritized factors based on their weights and priorities to inform decision-making.

In this method, we compared and weighted seven factors identified by text mining and two alternatives (churn or non-churn) so that the results of the model implemented in Figures 5 to 10 show the degree of preference of each of the factors in the two alternatives. According to the opinions of customers in our dataset, Figure 4 shows that 45.4% of customers are churners and 54.6% are non-churners.

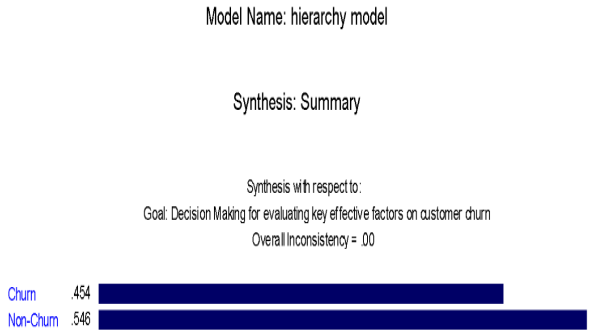


Fig. 4 Summary of the model

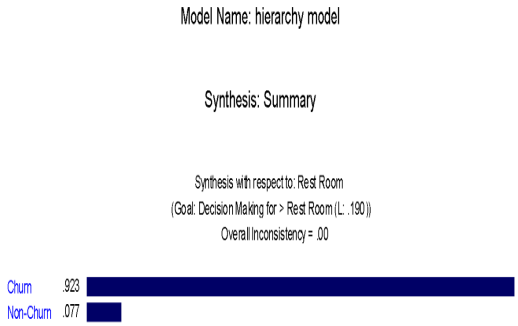


Fig. 5 Synthesis of "restroom" factor

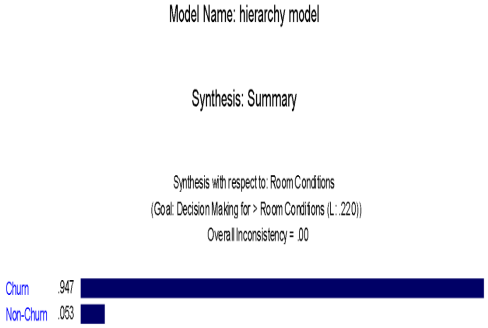


Fig. 6 Synthesis of "room conditions" factor

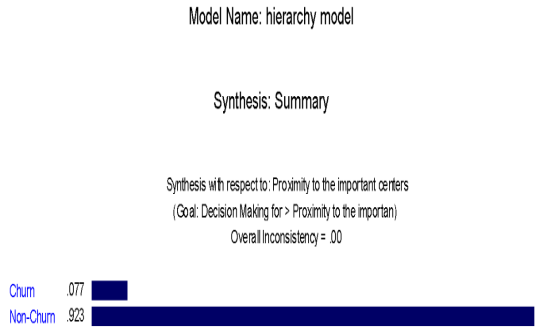


Fig.7 Synthesis of "proximity to the important centers" factor

Fig.8 Synthesis of the "food quality" factor

Fig. 9 Synthesis of the "staff interactions" factor

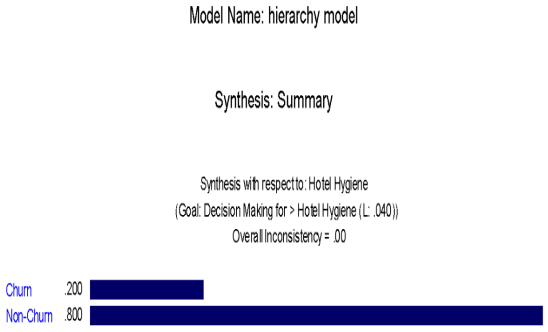


Fig. 10 Synthesis of the "hotel hygiene" factor

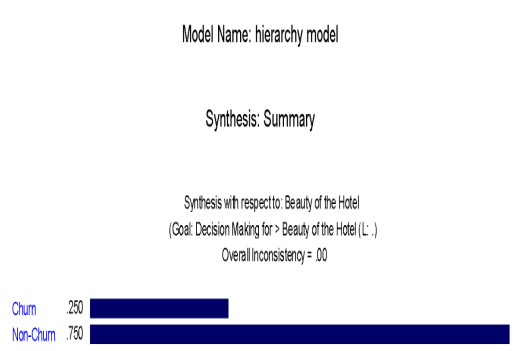
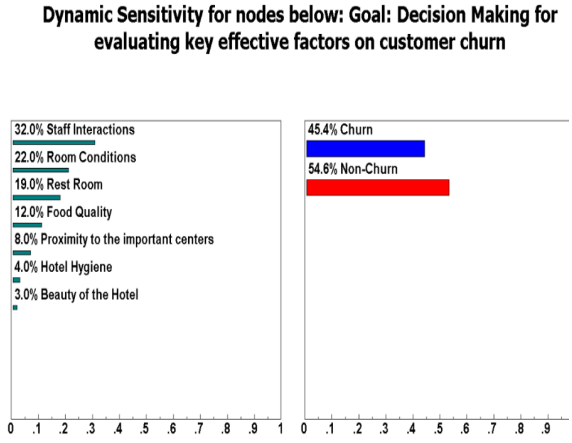


Fig. 11 Synthesis of the "beauty of the hotel" factor

In the final step, the consistency of the pairwise comparison matrix was checked to ensure that the results are reliable and valid. The result has been shown in Figures 12 to 14.



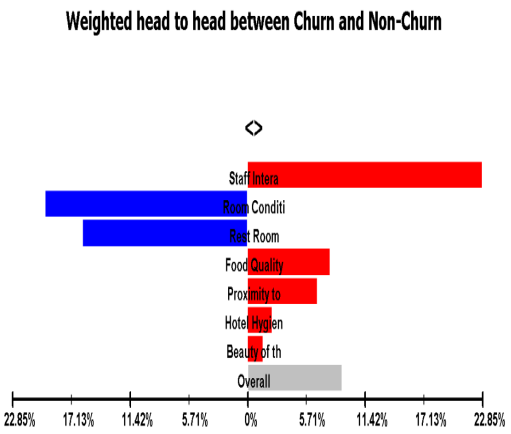
Objectives Names

Staff Intera	Staff Interactions
Room Conditi	Room Conditions
Rest Room	Rest Room
Food Quality	Food Quality
Proximity to	Proximity to the important centers
Hotel Hygien	Hotel Hygiene
Beauty of th	Beauty of the Hotel

Alternatives Names

Churn	Churn
Non-Churn	Non-Churn

Fig. 12 Dynamic Sensitivity Diagram



Objectives Names

Staff Intera	Staff Interactions
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Beauty of th	Beauty of the Hotel

Alternatives Names

Churn	Churn
Non-Churn	Non-Churn

Fig. 13 Weighted Head-to-Head Diagram

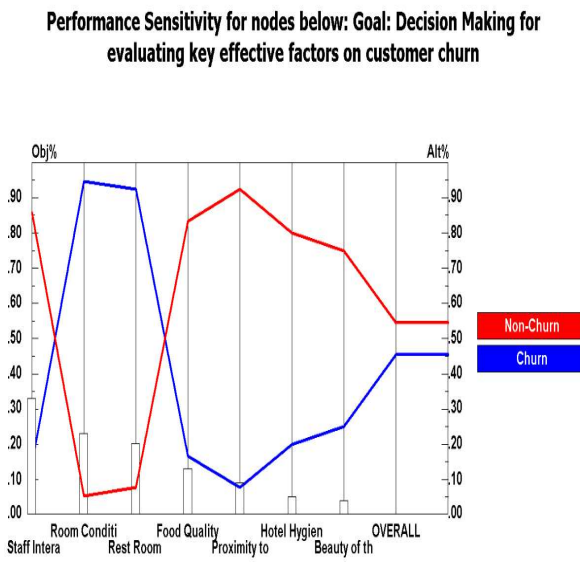

Fig. 14 Performance Sensitivity Diagram

7. Discussion and Conclusion

In conclusion, this study aimed to investigate and determine the key factors influencing customer churn in the hotel industry. By conducting a comprehensive literature review and analyzing data from user-generated content and hotel performance metrics, the study employed advanced text-mining techniques to identify significant factors affecting customer churn. The findings of the study revealed several important factors that contribute to customer churn in hotels. Among these factors, staff interaction with 32%was identified as the most influential factor in customer churn, followed by room conditions at 22%,restroom at 19%,food quality at 12%,proximity to the important centers at 8%, hotel hygiene with 4%, and beauty of the hotel with 3%.In general, the findings of the research show that 45.4% of the customers of the hotels related to our dataset are churners and 54.6% of the customers of these hotels are non-churners and loyal. The prioritization of these factors provides valuable insights for hotel managers to allocate their resources efficiently and develop targeted retention initiatives. By addressing these key factors, hotels can proactively tailor their services and enhance customer experiences, ultimately reducing churn rates and improving customer loyalty. Overall, this study underscores the importance of understanding the factors that drive customer churn in the hotel industry. By leveraging this knowledge, hotel managers can make informed decisions and implement effective strategies to mitigate churn, thereby positively impacting revenue and profitability.

However, it's critical to recognize a few limitations on our study. First off, our analysis excluded direct feedback from hotel guests through surveys or interviews and instead relied on information from user-generated content and hotel performance measures. Due to the possibility that some churn-related characteristics were implicit in the data, this constraint might have limited the thoroughness of our findings. The generalizability of our findings to the larger hotel sector, particularly in diverse geographic regions and situations, was constrained by the fact that our dataset was restricted to a subset of hotels on Kish Island.

We suggest directions for future research in order to solve these restrictions and advance the study of this topic. First, academics should think about enlarging their data sources to include a wider variety of hotels in different settings and places. This would improve the findings' representativeness and give a more comprehensive picture of the causes of customer attrition. Future research can also profit from the use of sophisticated analytical methods like machine learning or deep neural networks. These techniques can make complex data patterns visible that conventional methodologies might miss, providing a more detailed knowledge of the variables affecting customer churn.

Additionally, we suggest performing cross-industry comparison research to investigate customer attrition drivers in sectors beyond the hotel industry. Researchers can contribute to a deeper knowledge of customer retention dynamics by highlighting similarities and differences in the factors influencing

churn across various areas. This multifaceted strategy could provide significant insights for both academia and business, fostering better customer retention tactics and favorably affecting revenue and profitability.

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