

Exploring Patient Decision-Making In Hospital Choice: A Statistical Evaluation Using Exploratory Factor Analysis And Logistic Regression

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Abstract

This study investigates the determinants influencing patients' hospital selection for healthcare services, aiming to identify the most pertinent factors and categorize the decision-makers involved in choosing between private and public hospitals. A pre-designed questionnaire was employed to obtain data from patients utilizing multispecialty hospitals in Bengaluru, India. The study developed a logistic regression model by using Exploratory Factor Analysis. The environment, convenience and economic feasibility, personal experiences, care efficiency, referrals and suggestions, and professional healthcare services significantly affect patients' decisions. The results established five factors such as Hospital Service Quality Dimensions, Hospital Quality and Service Indicators, Patient Care Experience and Amenities, Healthcare Service Assessment Criteria, and Patients' facility and Service Criteria. Although the model is moderate it is not suitable for prediction since the overall accuracy level is only 53%. Findings from this study could support predicting, as well as enhancing the understanding of criteria influencing hospital selection.

Keywords: Healthcare; Hospital Selection; Logistic Regression; Quantitative method; Patient satisfaction; Verbal communication; Social media; Service quality.

1. Introduction

Choosing the right hospital is a critical decision that can significantly impact a patient's health and well-being. Patients consider various parameters before making a choice, including the hospital's reputation, availability of specialized doctors, quality of care, and accessibility. Some prioritize advanced medical technology and facilities, while others focus on affordability and insurance coverage. In line with previous research on decision-making in healthcare, (Kumpunen et al., 2014) suggest that public reporting not only enhances consumer trust but also incentivizes providers to improve service quality. Public reporting refers to the practice of making information about the performance of organizations, services, or institutions available to the public. In the context of healthcare, it often involves publishing data on the quality, outcomes, and patient satisfaction of hospitals, clinics, or other providers. The objective is to empower patients or their relatives to make informed choices.

In developed countries, notably the UK, patients are generally given the freedom to select the hospital where they will get consultant-led care under the UK NHS. Patients may choose a hospital based on a variety of factors, and the NHS is one of the organizations that offers information about hospitals (Nam et al., 2023). While, in India, the onus of selecting hospitals meeting their specific healthcare needs, lie with patients or their relatives/friends.

This is due to a lack of structured information/framework/dedicated organizations to guide patients in making informed decisions. Consequently, patients often rely on

physician referrals, online searches, and word-of-mouth recommendations when choosing a hospital (Ghosh, 2015).

In India, the Best Hospital Survey 2024 was released by Healthcare Outlook magazine with the goal of identifying India's best hospitals and offering consumers useful advice. A number of factors, such as infrastructure, medical knowledge, patient satisfaction, and technology innovations, were taken into consideration when evaluating hospitals. Every piece of information gathered from the chosen hospitals were based on the criteria such as number of beds, number of specialized doctors, trained nurses, modern technology like use of AI, robotics, etc. While these metrics provide valuable insights into hospital capabilities, the study may not fully address certain patient-centered factors that influence hospital choice, including patients often prioritize the effectiveness and outcomes of medical care when selecting a hospital (Adhikari et al., 2024). The standard of cleanliness within a hospital significantly impacts patient comfort and trust. Facilities such as payment options and food services contribute to the overall patient experience. Affordability and transparency in pricing are significant factors in hospital selection. A hospital's standing and credibility in the community can heavily influence patient decisions. Incorporating these patient-centric factors into future evaluations enables a thorough assessment of hospital performance metrics based on patient-reported experiences. There are multi-specialty hospitals which provide advanced treatment, modern technology, and customised services to the patients (Chauhan et al., 2019). Therefore, patient feedback is very important to consider for selecting or not selecting a hospital. This study aims to identify the key factors influencing patients' decisions to select a hospital (Kamakura et al., 2000).

The present study employed Exploratory Factor Analysis (EFA) and Logistic Regression to understand the factors influencing patients' hospital selection decisions. EFA is a widely utilized statistical method in marketing research, particularly due to the discipline's dependence on measurement scales (Sürücü et al., 2024). The choice of restaurant is greatly influenced by social media, with elements like family income and educational background being important considerations. Additionally, the study indicates that as technology advances, social media's impact on dining choices is anticipated to increase (Vasumathi et al., 2024).

Examining Influential Factors in the selection of private higher education institutions in Malaysia using Binary logistic regression analysis was utilized. Logistic Regression is a supervised machine learning algorithm used in different research areas (Buya et al., 2020).

In most research papers, either factor analysis or logistic regression has been used to analyze patient satisfaction (Liu et al., 2021) as consumers and to choose healthcare providers based on the services received, limited to a small number of parameters. The authors employed the Multinomial Logit (MNL) model to analyze the factors influencing patient hospital selection, using patient choice estimates to understand decision-making patterns in healthcare utilization (Smith et al., 2018). In this paper, parameters such as digital payment methods, rules for visiting patients, sustainability measures used by hospitals, the use of modern technology for treatment, telemedicine, and language translators have been included as recent criteria.

In different studies, the authors explore Indonesian consumers' decision-making process regarding the use of a Shariah-based e-wallet or the analysis of factors related to consumer behaviour in China for purchasing online. The findings reveal that perceived trust and intention act as a critical component in influencing consumers' decisions to adopt the digital payment method (Aisyah et al., 2023, Ma, Y. 2025).

Telemedicine has emerged as a transformative approach in healthcare delivery, offering environmental benefits through reduced travel, improved social equity by enhancing access to care, and economic advantages for both patients and providers. In the current scenario, especially post-pandemic, assessing these multidimensional impacts using standardized quantitative methodologies is essential to inform data-driven policy decisions and support sustainable healthcare systems (Savoldelli et al., 2024).

This paper intends to examine the complicated restraints among the parameters that influence to choose a hospital, aiming to comprehend how these parameters outline patients' opinions. We have utilized Python to develop the hospital selection logistic regression framework.. To evaluate the model's effectiveness, we conducted a comprehensive evaluation of the model's performance by analyzing key classification metrics: precision, recall, and accuracy.

The paper is structured as follows: Section 2 outlines the mathematical models, with details of the methodology. Section 3 provides an analysis of the results, followed by a discussion of the study's limitations in Section 4, and Section 5 represents the conclusion.

2. Methodology

Many research has been conducted on selecting a particular service provider using different statistical methods. After going through various research papers based on selection of hospital from patient's point of view a set of parameters were considered for this study. Patients consider various criteria when choosing a hospital, and several organizations provide information to assist in this decision-making process. A few possible parameters like infrastructure, accessibility, reviews either through Word-of-Mouth or through social media, payment process, out of pocket expenditure, etc.

For instance, it is found that shorter travel times to hospitals increased the likelihood of hospital utilization. It highlighted that proximity and ease of access are crucial determinants in patients' decisions to seek hospital care (Mseke et al., 2024). In this paper we have considered this parameter as location and accessibility. The specific healthcare needs of the local population have not been clearly identified. This study presents a strong, practical, and trustworthy method to address the critical issue of choosing the most suitable site for establishing new hospitals, taking into account the unique healthcare demands of the area to enhance service delivery (Okengwu et al. 2022).

If we consider infrastructure, larger hospitals may benefit from economies of scale, allowing them to offer a broader range of services and specialized care, which can attract more patients (McFarland et al., 2017). In this study we consider this as basic physical facilities.

In recent years, patients have become increasingly concerned about hospital cleanliness, recognizing its critical role in their overall healthcare experience and safety (Kumpunen et al., 2014). In this study we have considered this as Cleanliness and hygiene.

Quality of care and services is another very crucial parameter. Whereas hassle free payment facility, educating patient about the disease and line of treatment, etc are also few deciding parameters. Providing accessible, user-friendly, quality information enables patients to make informed choices about healthcare providers (Singh, 2024).

In this study, a structured methodology was employed to identify significant factors influencing hospital selection. A comprehensive questionnaire was administered to patients and their attendants to gather relevant data. The collected data underwent preprocessing, which included: identifying and eliminating data points that deviated significantly from the norm to enhance data quality, and addressing incomplete responses through appropriate techniques to ensure a robust dataset. The statistical

method EFA was applied to reveal latent structure. The factors identified through EFA were utilized as predictors in a logistic regression model to determine their significance in hospital selection decisions (Hosmer et al., 2000). Fig. 1 shown below, depicts the overall structure of the model.

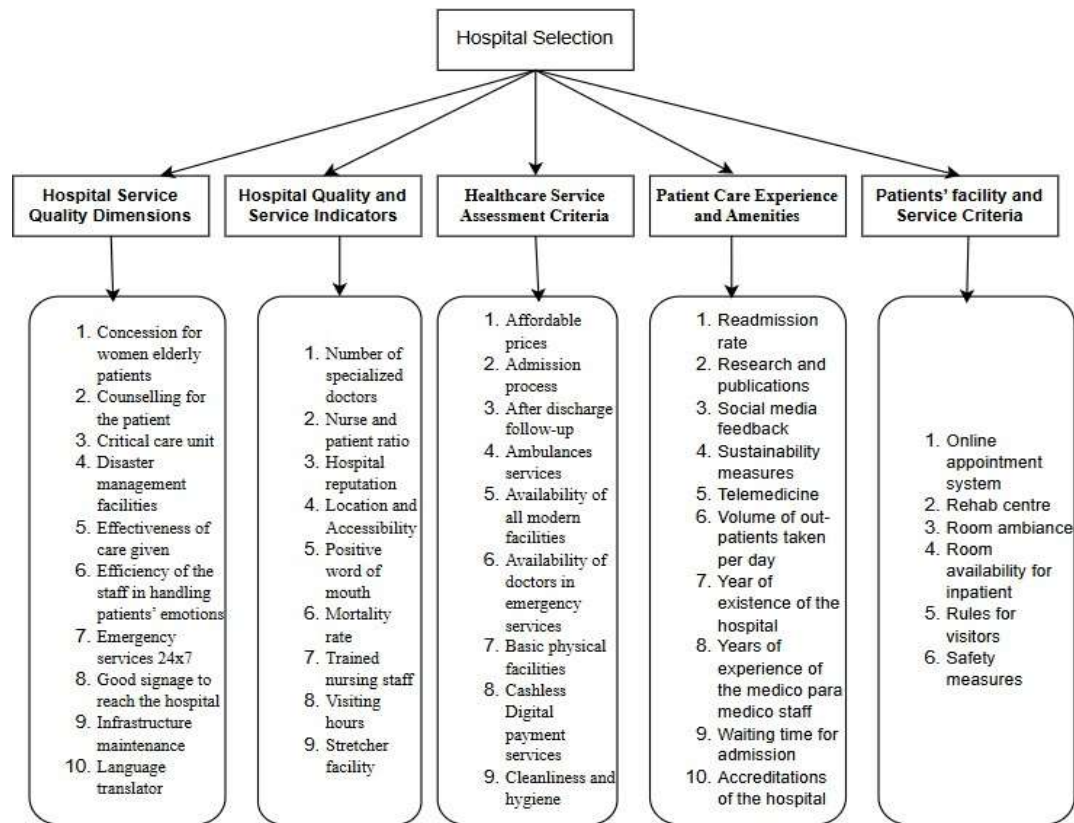


Fig1 The Research Model

2.1 Data Collection

This study was conducted using a questionnaire to collect data from individual patients and/or their relatives. The Ethics Committee waived the requirement for formal ethics approval and informed consent, as the study was non-interventional. All procedures were carried out in accordance with relevant guidelines and regulations, ensuring the privacy and confidentiality of all participants.

A well-designed research study depends fundamentally on the careful selection of the target population and the appropriate choice of sampling methods. It is a useful tool for improving the reliability and generalizability of study findings in a variety of fields by giving researchers a thorough grasp of demographic factors and sampling techniques. Considering participants' availability, researchers decide on the population of interest, sampling framework, sample techniques, unit of analysis, and unit of observation. In accordance with the population and sampling methods debate, researchers employ non-probability sampling, more especially convenience sampling approaches, depending on the participants' availability and accessibility within the city (Hossan et al., 2023).

While non-probability sampling methods, when applied carefully, can allow researchers to generalize results, probability sampling is generally preferred for obtaining representative samples. However, in many situations, employing probability sampling techniques may not be feasible. Therefore, it is often recommended that the choice of

sampling method be guided by the study's objectives, research scope, and the availability of a sampling frame (Adhikari et al., 2024).

In this study, the interviewees were nominated using the snowball sampling technique from the patient population of public and private hospitals in Bengaluru city. The respondents who had opted for the healthcare service at different hospitals in this survey were provided with the survey questionnaire during June to August in 2024. The survey question comprised of three parts A to C. Part A is the demographic study of the patient. While part B attempted to find the satisfaction level of the patients for the various services provided by the healthcare providers, part C was aimed at understanding a few other ancillary parameters. Parts B and C of the questionnaire consist of a five-point Likert scale.

Identification of variables, questionnaire distribution, and result analysis were carried out. The variables included in the questionnaire were derived from the authors' previous research. In this study, nine factors influencing the selection of Higher Education Institutions (HEIs) were identified and incorporated (Othman et al. 2024). Similar pattern was followed in our study. Parameters considered are mostly taken from different research papers, and a few are added to the list to make it more comprehensive (Pande et al. 2023, Singh et al. 2022, Malik et al. 2017). Since the number of parameters is seventy-one, Exploratory factor Analysis has been implemented to reduce the dimensionality. We found that there were 48 missing data which is 15.9 percentage. All missing data were treated by using the mean of each column to replace the missing value.

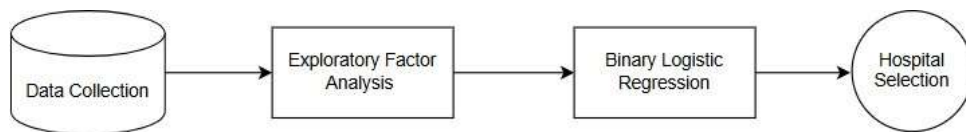


Fig. 2. Steps to follow

2.2 Exploratory Factor Analysis (EFA)

EFA efficiently reduces many variables into a smaller number of more interpretable components by examining correlation patterns to find unobserved factors that explain these relationships (Howard et al., 2023).

In determining the appropriate sample size for exploratory factor analysis (EFA), researchers often consider the sample-to-item ratio, which relates the number of participants (N) to the number of items or variables (p) in the study. A commonly cited guideline recommends a minimum ratio of 5:1, meaning at least five participants per item. For instance, in this study, 71 items, this guideline would suggest a minimum of 350 respondents. This recommendation is supported by theory (Memon et al. 2020).

The model in EFA hypothesizes that each observed variable X can be expressed as a combination of underlying latent factors F and unique variances or errors

$$X = \Lambda F + e \quad (1)$$

Where in Eq. (1),

X – Vectors of measured variables

Λ: Factor loading matrix that shows how each factor affects the variables that are observed

F: Vector of latent factors.

e: Vector of unique variances (errors).

In factor analysis, each factor is associated with an eigenvalue indicating the amount of variance it explains. According to Kaiser's criterion (1960), factors with eigenvalues

greater than 1 should be retained. However, this rule has been criticized for potentially leading to over-extraction. As a result, alternative methods—such as parallel analysis and inspection of the scree plot—are often recommended to more accurately determine the number of factors to retain (Chemkomnerd et al., 2024).

The KMO Measure: 0.879, and Bartlett's Test p-value: 0.00000 suggest data sufficiency. The Scree plot (Fig 3.) displays eigenvalues against factor numbers, where the 'elbow' point indicates the cutoff beyond which factors are considered less significant and typically discarded.

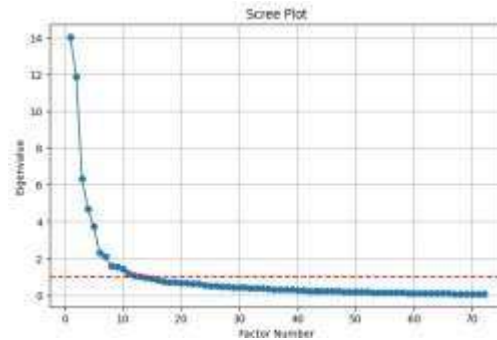


Fig.3. Scree plot to identify the optimum number of components

Table 1 Parameters considered prior to hospital selection (Pattern Matrix)

	Parameters	Score		Parameters	Score
	Factor 1: Hospital Service Quality Dimensions		37	Hospital reputation	0.814
1	Concession for women elderly patients	0.666	38	Location and Accessibility	0.796
2	Counselling for the patient	0.665	39	Mortality rate	0.652
3	Courteous and friendly support staff	0.714	40	Number of specialized doctors	0.745
4	Critical care unit	0.554	41	Nurse and patient ratio	0.663
5	Disaster management facilities	0.494	42	Positive word of mouth	0.564
6	Discharge Procedure	0.554		Factor 3: Patient Care Experience and Amenities	
7	Effectiveness of care given	0.677	43	Affordable prices	0.342
8	Efficiency of the staff in handling patients' emotions	0.746	44	Admission process	0.712
9	Efficient use of imaging	0.775	45	After discharge follow-up	0.637
10	Emergency services 24x7	0.727	46	Ambulances services	0.797
11	Experience with the hospital	0.743	47	Availability of all modern facilities	0.801
12	Facility for patient's relatives	0.776	48	Availability of doctors in emergency services	0.721

13	Fast and hassle-free billing	0.664	49	Basic physical facilities	0.778
14	Food quality given to the inpatient	0.620	50	Blood bank	0.721
15	Food quantity given to the inpatient	0.540	51	Cafeteria.	0.341
16	Good signage to reach the hospital	0.595	52	Cashless Digital payment services	0.652
17	Hospital website	0.556	53	Cleanliness and hygiene	0.696
18	Infrastructure maintenance	0.719	54	Comfort of waiting area lobby	0.658
19	In house pharmacy facility	0.743		Factor 4: Healthcare Service Assessment Criteria	
20	Insurance coverage	0.669	55	Prayer room	0.602
21	Language translator	0.529	56	Readmission rate	0.675
22	May I help counter	0.639	57	Research and publications	0.676
23	Modern laboratory and equipment	0.638	58	Social media feedback	0.773
24	Protection against infectious diseases	0.502	59	Sustainability measures	0.752
24	Patient education and explanation of treatment	0.541	60	Telemedicine.	0.736
	Factor2: Hospital Quality and Service Indicators		61	Videos put on the You Tube	0.768
26	Stretcher facility	0.592	62	Volume of out-patients taken per day	0.758
27	Trained nursing staff	0.654	63	Year of existence of the hospital	0.807
28	Visiting hours	0.602	64	Years of experience of the medico para medico staff	0.751
29	Voluntary assistance for patients	0.690	65	Grievance handling	0.699
30	Waiting time for admission	0.653		Factor 5: Patients' facility and Service Criteria	
31	Well-equipped private rooms	0.499	66	Online appointment system	0.567
32	Wheelchair accessibility	0.561	67	Rehab centre	0.474
33	Accreditations of the hospital	0.793	68	Room ambiance	0.578
34	Brand name of the hospital	0.860	69	Room availability for in patient	0.615
35	Calling doctors from outside for critical cases	0.831	70	Rules for visitors	0.578
36	Foreign doctors visiting the hospital for short duration	0.619	71	Safety measures	0.425

Table 1 presents the Pattern Matrix generated by Python using varimax rotation, showing standardized regression coefficients that indicate how strongly each observed variable loads onto the extracted factors while accounting for inter-factor correlations. The Pattern Matrix identified five factors with meaningful variable loadings (≥ 0.3). It is always recommended to use EFA before Logistic Regression if more features are there, because it reduces the number of predictors to avoid multicollinearity, identifies meaningful latent constructs instead of individual variables, helps to make the regression model simpler, interpretable, and stable.

2.3 Logistic Regression

In the next step, through logistic regression, the relationship between predictor variables and a binary outcome variable is quantified. The model predicts the probability of the dependent variable being 1 (indicating success) based on the values of the independent factors. This relationship is modelled using the logistic function:

$$\pi = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p)}} \quad (2)$$

Eq. (2) has e as the base of the natural logarithm, β_0 as the intercept, $\beta_1, \beta_2, \dots, \beta_k$ are the coefficients of the independent variables $X_1, X_2, \dots, X_k$, and the symbol π representing the predicted probability of the outcome of interest in logistic regression.

The application of logistic regression in a paper about HR analytics to analyze employee attrition, categorizes crucial aspects conducive for employee turnover, and demonstrates how predictive modelling can support data-driven decision-making in human resource management (Setiawan et al., 2020).

A logistic regression model generates odds ratios, which specify the forte and path of the associations. However, these estimated odds ratios are influenced by the underlying data and the specific configuration of the model. (Purwanto et al., 2024).

The logit function represents the natural logarithm of the odds ratio, where the odds are defined as the ratio of the probability of success, is expressed as:

$$\begin{aligned} \log_e \left[\frac{P(Y = 1 | X_1, \dots, X_p)}{1 - P(Y = 1 | X_1, \dots, X_p)} \right] &= \log_e \left[\frac{\pi}{1 - \pi} \right] \\ &= \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p \end{aligned} \quad (3)$$

To evaluate these assumptions, logistic regression estimates the effect sizes (coefficients) given in Eq. (3) as $\beta_0, \beta_1, \beta_2, \dots$ etc, their statistical significance, mostly with the aid of tests such as the likelihood ratio test or the Wald test. In this study, the factors derived from EFA were employed as predictor variables in a binary logistic regression model. This statistical method provides a quantitative assessment of the relationship between each predictor variable and the probability of the result by estimating the odds ratios for each one. An odds ratio larger than one suggests a good correlation, meaning that as the predictor variable rises, so do the probability of the outcome happening. On the other hand, an adverse link is implied by an odds ratio smaller than 1, where greater predictor values translate into lower likelihood of the result. These odds ratios offer a useful and comprehensible statistic for figuring out how each predictor affects the outcome variable (Zabor et al., 2022).

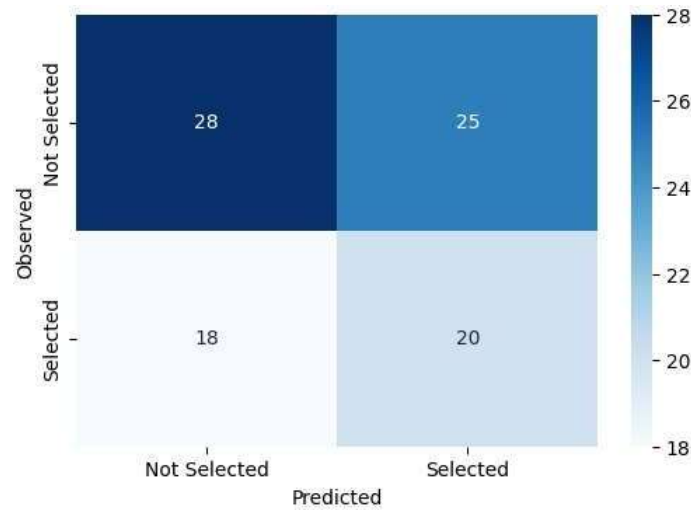


Fig.4. Confusion Matrix

The accuracy of a model can be measured using a confusion matrix from Fig. 4 to validate its overall performance in correctly predicting both positive and negative instances. Accuracy: 53% of the predictions were correct overall, which is only slightly better than random guessing for a balanced dataset. The model has moderate recall for both classes but relatively low precision, especially for positive class.

Eq. (4) represents the logistic regression equation obtained

$$\log_e \left[\frac{\pi}{1-\pi} \right] = 0.0603 + (-0.1302) * X_1 + (-0.2901) * X_2 + (-0.0651) * X_3 + 0.0728 * X_4 + 0.0782 * X_5 \quad (4)$$

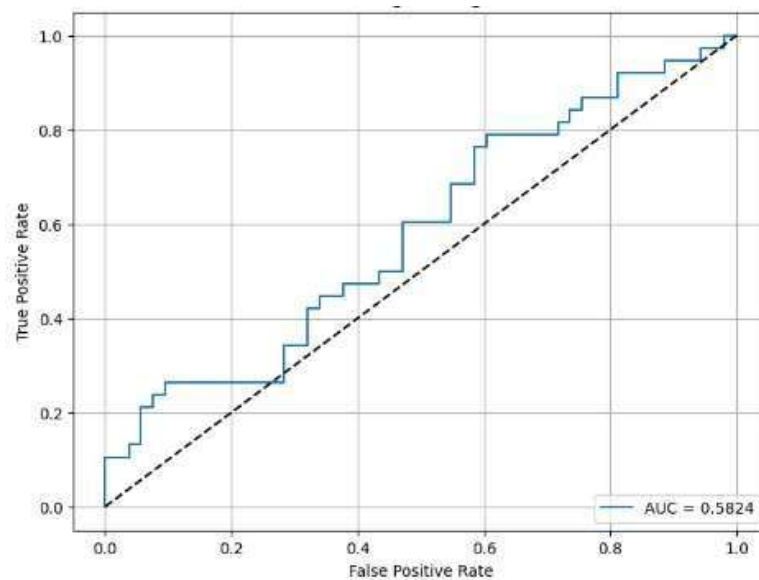


Fig.5. ROC curve for the Logistic Regression Model

Receiver Operating Characteristic (ROC) graphs are valuable tools for evaluating and comparing the performance of classification models. Widely applied in medical decision-making, these graphs have also gained popularity in recent years within the fields of machine learning and data mining for assessing classifier effectiveness (Fawcett 2006). Fig.5 shows the model's ROC curve obtained for this study, which is slightly above the diagonal, with an AUC of 0.5824. This suggests that the model's predictive performance is modest.

3. Result Analysis and Discussion

To make a wise hospital selection decision, it is essential for patients to comprehend the elements that affect the quality of hospital care. Recognizing both aspects that positively and negatively impact the patient experience is crucial for improving overall satisfaction.

3.1 The areas of concern are as follows

Hospital Service Quality Dimensions encompasses the competence of healthcare providers, effectiveness of treatments, and efficiency of care, ensuring timely and appropriate attention for improved health outcomes.

Hospital quality and service indicators reflect readiness through modern equipment, clean facilities, and sufficient staff, ensuring timely and comfortable patient care.

Patient Care Experience and Amenities where patients can obtain necessary treatments more easily and can concentrate on their recuperation rather than worries when hospitals provide cost-effective care solutions, hassle free payment such as digital payment method.

3.2 Following are the positive factors:

Healthcare Service Assessment Criteria: Patient comfort and trust must not be impacted by issues with a hospital's physical infrastructure and reputation. Issues with the provided facilities may lead to concerns.

Patients' facility and Service Criteria: Positive outcomes may result in quick recovery during hospital stays, such as good infection control or enhanced patient monitoring. Maintaining strong safety procedures is essential to safeguarding patients' health while they are in the hospital.

4. Limitations

A key limitation of this study is the use of snowball sampling, which, while effective for reaching hard-to-access populations, may reduce the precision and generalizability of the results compared to probabilistic sampling methods. Additionally, the limited dataset may affect the robustness of the model, and the modest performance suggests that alternative modeling techniques, such as Bayesian approaches or Random Forests, could better address uncertainty and improve predictive accuracy across multiple criteria.

5. Conclusions

This analysis reveals that enhancing service quality, facility availability, and awareness significantly boosts hospital preference. Key factors influencing hospital choice include quality, reputation, and accessibility. While proximity matters in emergencies, patients prioritize research for planned treatments to ensure optimal care. City-specific focus offers insights into local healthcare dynamics, informing targeted improvements. Snowball sampling effectively reached hard-to-access populations. Future research should involve more multispecialty hospitals to better reflect community needs. Ultimately, effective hospital selection balances trust, convenience, and clinical standards to ensure appropriate and compassionate care.

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