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Examining the Influence of Trust in AI on Patient Satisfaction: Insights from AI-Driven Healthcare

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Abstract

Artificial Intelligence (AI) is transforming the healthcare sector by improving treatment planning, diagnostics, and patient care. As AI become more widely used in healthcare, building and maintaining patient trust in these technologies has never been more important. Patient trust is increasingly recognised as a foundational element that determines whether AI tools are embraced or rejected in clinical environments. This study examines AI's role by evaluating AI Diagnosis Confidence (ADC) scores, quantifying patient trust in AI, along with biomedical parameters such as heart rate, blood pressure, and recovery time. Built on the Technology Acceptance Model (TAM) and the Health Belief Model (HBM), this study examines how AI affects patient satisfaction and health outcomes, with a specific focus on the role of pharmaceutical companies in advancing AI-driven healthcare solutions. This study uses a mixed-method approach to provide a comprehensive understanding of AI adoption in healthcare. A dataset of 5,000 patient records was collected and analyzed from Kaggle using machine learning techniques such as Gradient Boosting and Random Forests. Additionally, the K-Means clustering algorithm was adopted to group patients based on ADC scores and biomedical data. A thematic analysis of interviews with doctors, AI experts and pharmaceutical professionals was also conducted to identify qualitative insights. Findings of the study reveal that in quantitative analysis, the Gradient Boosting algorithm achieved the highest accuracy of 0.6369, indicating that trust in AI and optimal biomedical parameters have a significant impact on patient satisfaction. Cluster analysis identified three different patient satisfaction groups, showcasing how different patients respond to AI-assisted care. Through qualitative thematic analysis, four important themes were discovered: (1) Transparency - Patients and physicians emphasised the importance of understanding AI's decision-making process to build trust. (2) Human-AI Cooperation - AI should complement human care, not replace. (3) Cultural Acceptance - Institutional validation boosts confidence in AI, while regional variations affect trust. (4) Pharmaceutical Role - To boost patient confidence in AI systems, clinical validation must be conducted by pharmaceutical companies. This study provides valuable insights into building trust in AI by integrating both qualitative and quantitative findings. It highlights the importance of collaboration across technology, healthcare, and pharmaceutical sectors in improving patient outcomes. This research offers a practical framework for healthcare organisations, contributing to the development of more patient-centred and trustworthy healthcare systems.

Keywords: Artificial Intelligence, Patient Satisfaction, Machine Learning, Healthcare, Diagnostics

1. Introduction

In modern healthcare, artificial intelligence (AI) has evolved from a theoretical concept to a transformative agent. Its application spans a wide range of applications including enhanced diagnostic accuracy, disease progression prediction, optimized treatment protocols, personalized medicine and improved patient engagement and operational efficiencies (Rajkomar et al., 2018; Sendak et al., 2023; Cascella et al., 2023; Esteva et al., 2019). In particular, the integration of AI with biomedical data has enabled significant advances in predictive analytics and clinical decision support systems (Topol, 2019; Heaven, 2020). These advancements are not only technical but strategic as pharmaceutical companies and healthcare providers are rapidly embedding AI into their ecosystems to expedite drug development, enhance clinical trial outcomes and deliver tailored interventions at scale (Ahrens et al., 2025; Shaban-Nejad et al., 2018).

Ahrens et al. (2025) forecast that AI could add up to $254 billion in operating profits annually for pharmaceutical firms by 2030 through accelerated R&D, automated workflow and redefined patient engagement. Companies like Amgen and Bristol Myers Squibb have already demonstrated faster trial recruitment and more precise protein targeting using AI, proving its real-world business and clinical impact (KPMG, 2024).

However, one critical factor – patient trust, remains central to AI's long term success. While many physicians view AI as a valuable cognitive extension for diagnostic precision (Yu et al., 2018; He et al., 2019), patients often emphasize on human empathy, transparency and ethical clarity in their interactions with AI (Moy et al., 2022; Cummins, 2025). Furthermore, trust becomes crucial in contexts where AI influences life altering decisions.

To quantify trust in AI, this study introduces and analyses the AI Diagnosis Confidence (ADC) score, a patient-centric metric ranging from 0 to 1, reflecting confidence in AI-generated medical decisions (Johnson et al., 2020; Embed, 2021). Trust is not isolated, it is often tied to measurable biomedical outcomes, such as blood pressure, heart rate, blood glucose, and recovery time. Patients use these tangible results to validate the accuracy and reliability of AI-supported care (Bautista et al., 2023; Yin et al., 2021; George et al., 2023). However, limited empirical research has investigated the relationship between ADC scores, clinical parameters, and patient satisfaction in real-world settings.

To bridge this gap, the present study adopts a mixed-methods approach, analysing 5,000 anonymized patient records sourced from Kaggle. Using machine learning models including gradient boosting, decision trees, logistic regression, random forests, and support vector classifiers. This study identifies which variables most strongly predict patient satisfaction. To uncover hidden patterns, K-means clustering segments patients based on ADC scores and biomedical parameters, categorizing them into satisfaction levels.

To enrich the quantitative insights, the study also incorporates a qualitative thematic analysis of interviews with doctors, AI researchers, and pharmaceutical experts from India and the USA. The comprehensive thematic analysis reveal that patient trust is affected not only by accuracy of the outcome, but also by explainability, cultural perceptions, algorithmic bias concerns and organizational credibility (Doshi-Velez & Kim, 2017; Dilsizian & Siegel, 2014; Greenhalgh et al., 2022). These insights are grounded into two well established behavioural theories:

- The Technology Acceptance Model (TAM) explains how perceived usefulness and ease of use shape acceptance of AI systems (Davis, 1989; Holden & Karsh, 2010).

- The Health Belief Model (HBM) provides a framework for understanding how patients' beliefs about risk and benefits influence engagement with AI in medical contexts (Rosenstock, 1974; Janz & Becker, 1984).

Building on this conceptual foundation, the study proposes the following hypotheses:

- H_0 (Null Hypothesis): There is no association between the ADC score, biomedical parameters (e.g., heart rate, blood pressure, and recovery time), and patient satisfaction.

- H_1 (Alternative Hypothesis): There is a significant association between the ADC score and biomedical indicators, with higher trust and better clinical outcomes linked to higher patient satisfaction.

By synthesizing statistical modelling, machine learning classification, clustering and expert-led thematic analysis, this research presents a robust, multidimensional view of how AI trust is built and how it shapes healthcare outcomes. These findings aim to guide the ethical, transparent, and human-centred deployment of AI in medical practice, ensuring that innovation is balanced with empathy and patient empowerment.

2. Literature Review

The integration of AI into healthcare systems has redefined the way medical services are delivered, with potential to enhance diagnostic precision, personalized treatment plans and optimized recovery pathways (Sendak et al., 2023; Rajkomar et al., 2018). As AI's successful adoption relies heavily on trust, understanding how patients perceive and respond to AI powered healthcare systems is pivotal. Therefore, this literature review explores patient trust and satisfaction within the framework of AI in healthcare, with particular emphasis on AI Diagnosis Confidence (ADC) scores, biomedical indicators and theoretical underpinnings like the Technology Acceptance Model (TAM) and Health Belief Model (HBM).

2.1 AI in Diagnostics and Patient Monitoring

Numerous studies have highlighted AI's ability to deliver faster and more accurate diagnoses. For instance, AI-powered tools like IBM Watson and DeepMind Health have successfully demonstrated superior performance in identifying patterns for imaging data, supporting decision-making and reducing diagnostic errors (Lee et al., 2023; Topol, 2019). Moreover, AI-enabled wearables and monitoring systems can capture real time biomedical parameters such as blood pressure, glucose levels, heart rate and oxygen saturation, which are critical indicators in managing chronic and acute conditions (Mehta, 2023; Cascella et al., 2023). AI-enabled CRM capabilities also support service innovation by fostering continuous care and responsive patient management (Kumar, Sharma & Dutot, 2023).

2.2 Trust as a Determinant of AI Adoption

While technological capabilities are well documented, the patient's trust in AI remains a complex and often under researched area. Studies by Cummins (2025) and Hancock et al. (2022) have shown that demographics, transparency of algorithms and ethical design significantly impact how much trust patients put in AI systems. Keragon (2024) reported that despite widespread AI deployment across 18 leading healthcare organizations, trust is identified as a critical barrier, emphasizing the need for explainable AI to foster user confidence. Furthermore, Kumar, Sharma, and Dutot (2024) highlight the importance of information processing among healthcare stakeholders, noting that trust is enhanced when AI systems provide transparent and context-aware support to users.

2.3 The Role of AI Diagnosis Confidence (ADC) Scores

The AI Diagnosis Confidence (ADC) score is a novel metrics to measure how much patients trust AI recommendations. It has become an important tool for measuring user experience and satisfaction. According to research, people with higher ADC scores are more likely to accept decisions made with the help of AI and stick to their treatment (Bautista et al., 2023; Johnson et al., 2020). Also, connecting ADC scores to biomedical parameters gives a comprehensive assessment of AI's effectiveness.

2.4 Influence of Biomedical Indicators on Patient Satisfaction

Heart rate, blood pressure, blood sugar, and recovery time are all physiological indicators that directly reflect the efficacy of treatment and patient well-being. When integrated with AI tools, these factors can be used as benchmarks to measure performance and patient satisfaction (Yin et al., 2021; George et al., 2023). According to research, AI's ability to manage and optimize these indicators can have significant impact on patient's perception of quality care. Kumar, Sharma, and Dutot (2020) stress that the inclusion of contextual data also makes the patient experience more personalized and acceptable.

2.5 Theoretical Foundation: TAM and HBM

The Technology Acceptance Model (TAM) provides insight into why patients choose to accept or reject AI in healthcare, focusing on perceived usefulness and ease of use (Davis, 1989). On the other hand, the Health Belief Model (HBM), shows how patients' perception about disease severity and treatment effectiveness, impact their attitude towards AI (Rosenstock, 1974). Recent studies (Asan et al., 2023; D'Amiano et al., 2022) have used these models to look at digital health interventions. They found that believing in the system's effectiveness and personal relevance are strong indicators of trust and satisfaction. Marvi et al. (2025) further suggest that users are more likely to be engaged in AI-human collaboration when they adopt a mastery-oriented mindset that focuses on flexibility and mutual learning.

2.6 Pharmaceutical Sector's Role in AI Integration

AI-driven transformation in the pharmaceutical industry is a key role of building patient trust. Amgen and Bristol Myers Squibb are two companies that use AI to personalize drug development and accelerate clinical trials, leading to enhanced treatment outcomes and patient engagement (Ahrens et al., 2025). As pharmaceutical companies continue to use AI in drug discovery and delivery, their commitment to safety, transparency and personalization directly helps strengthen patient trust in AI-driven interventions.

2.7 Thematic Analysis to Deepen Patient-Centred Understanding

While quantitative methods such as machine learning and cluster analysis are essential for modelling patient satisfaction and identifying predictors of trust, recent literature also emphasize on the role of qualitative approaches in unpacking patient experiences with AI in healthcare. Specifically, thematic analysis enables researchers to methodically interpret recurrent patterns in patient's narrative, particularly those concerning trust, diagnosis confidence and perception of huma-AI collaboration (Braun & Clarke, 2006; Nowell et al., 2017).

Digital health studies (Greenhalgh et al., 2022; Lupton, 2018) have demonstrated how thematic analysis can enhance structured data by highlighting subjective issues like apprehension about algorithmic decision-making, fear of automation or preference for human empathy. Despite being overlooked in models like TAM and HBM, these aspects are essential to understand the psychological and emotional aspects of AI acceptance (Topaz & Pruinelli, 2023). By anchoring concepts like "perceived usefulness" or "perceived threat" in actual patient experiences, thematic analysis enhances theory-informed evaluation in healthcare AI research (Asan et al., 2023; D'Amiano et al., 2022). This is especially crucial when evaluating trust that is mediated by diagnostic confidence, as overall satisfaction with AI-powered tools which is shaped by sociocultural interpretations and individual expectations. Thus, the inclusion of thematic analysis in AI-healthcare studies enhances methodological rigor, provides richer insight into user attitudes, and supports the development of more empathetic and ethically aligned AI interventions.

2.8 Gaps in Existing Literature

Despite growing enthusiasm for AI in healthcare, technical performance and patient experience are frequently treated as distinct fields in the existing literature. There are very few studies that look at patient satisfaction, biomedical indicators, and trust in AI (ADC scores) in a holistic fashion (Gao et al., 2023; Hoffman & Podgurski, 2020). Additionally, demographic variables such as age, gender and prior health conditions are also underexplored as potential moderators of trust and engagement. On the other hand, the pharmaceutical sector has emerged as a major hub for AI-driven innovation. For example, leading companies like Amgen and Bristol Myers Squibb are integrating AI into personalized drug discovery, treatment monitoring and clinical trial optimization, therefore, creating more responsive and targeted healthcare solutions (Ahrens et al., 2025).

Yet, literature still lacks insights about how these innovations driven by pharmaceutical companies result in patient-centred outcomes, particularly in real-world clinical settings. Furthermore, thematic analysis remains underutilized in AI-healthcare research, although it is proved to be a valuable tool for unpacking patients' lived experiences, emotional responses and nuanced trust dynamics (Braun & Clarke, 2006; Greenhalgh et al., 2022).

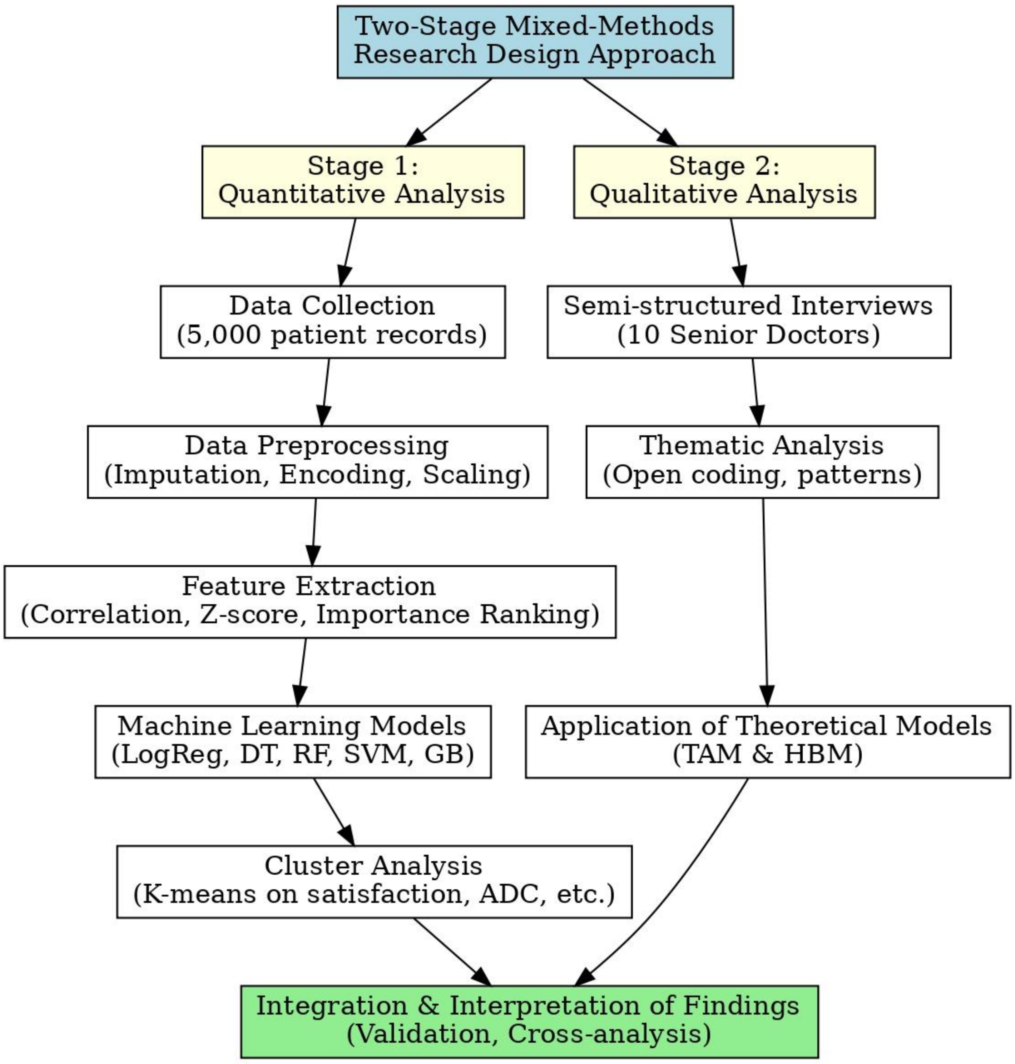
Based on the TAM and HBM frameworks, this study uses a mixed-methods approach that combines machine learning, cluster analysis, and thematic analysis to address these gaps. The goal of this design is to provide a thorough understanding of how diverse patient populations perceive, trust and accept AI-powered healthcare systems.

3. Methodology

3.1 Research Design: Two-Stage Mixed-Methods Approach

This study utilizes a two staged mixed methods design (see Figure 1), combining qualitative insights with quantitative data analysis, to obtain a robust and contextually rich understanding of the phenomenon being studied.

Figure 1. Flowchart of Research Methodology



Source: Created by Authors

This design is supported by the existing literature for drawing strong inferences and understanding complex socio-technical phenomena (Venkatesh et al., 2013; Fox & James, 2020). According to Hou et al. (2022), a staged mixed-methods approach enables the incorporation of multiple perspectives, thus enriching the overall interpretation of the results.

3.1.1 Stage 1: Quantitative Analysis

In the first stage, a dataset of 5,000 patient records sourced from Kaggle was used to conduct a large scale quantitative analysis. The dataset included information on AI-assisted diagnostic outputs, patient satisfaction scores, biomedical parameters and demographic details like age, gender, diagnosis and recovery time.

Key analytical techniques included:

- Descriptive and inferential statistics.
- Machine learning classification models.
- Cluster analysis to predict satisfaction and recovery outcomes.

This stage helped identify statistical relationships and performance trends in AI-assisted healthcare, offering a broad, data-driven foundation for further exploration.

3.1.2 Stage 2: Qualitative Analysis

Following the quantitative stage, a qualitative approach was employed in Stage 2 to deepen the understanding of patterns observed in the data and explore underlying factors which might not be captured by the numerical dataset. For the purpose of qualitative analysis, we conducted in depth, semi structured interviews of 10 senior, remunerated medical professionals from both the United States and India who have hands on experience with AI tools in healthcare.

Key qualitative objectives included:

- Exploring physicians' perspectives on the integration of AI in clinical settings.
- Understanding ethical, contextual, and operational challenges.
- Gaining insights into trust, decision-making, and AI-human collaboration in diagnosis and treatment.

The interviews were thematically analysed to identify recurrent patterns, divergences in views, and context-specific insights, which were then interpreted in light of the Stage 1 findings.

3.1.3 Justification for the Two-Stage Design

The two staged structure enabled sequential exploration by first establishing empirical trends through quantitative data and then contextualizing and explaining those trends via qualitative interviews. This approach ensured both depth and breadth to our study thus, enhancing the validity and richness of the findings.

For studying emergent technologies like AI, where both numerical performance and human experience are critical to understand the real world impact, staged mixed methods frameworks are particularly effective (Hou et al., 2022; Venkatesh et al., 2013).

3.2 Quantitative Analysis

3.2.1 Data Collection

The medical dataset obtained from Kaggle includes 5,000 patients. The dataset has essential human biomedical parameters, AI's diagnosis confidence, and patient satisfaction (see Table 1).

3.2.1.1 Descriptive Statistics

Table 1. Descriptive Statistics of ADC scores and Biomedical Parameters

Variable	**Mean**	**Standard Deviation**
Age (years)	53.43	20.93
Blood Pressure (mmHg)	119.86	15.06

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Variable	Mean	Standard Deviation
Heart Rate (bpm)	74.76	9.97
Temperature (°F)	98.60	1.00
Treatment Duration (days)	14.97	8.40
Lab Test Results of blood sugar/glucose (mg/dL)	100.20	19.81
Recovery Time (days)	4.94	2.57
Patient Satisfaction of AI-assisted medical procedure (score from 1-5)	2.99	1.42
AI Diagnosis Confidence (ADC) (score from 0-1)	0.80	0.08

3.2.2 Data Preprocessing

Prior to modelling, the dataset was cleaned and pre-processed by handling missing values using imputation techniques and encoding categorical variables using one-hot encoding. Next, standardisation was applied to the continuous variables to bring them into a common scale, which ensured that the models would not be biased by any one feature. The data were then analysed using Python and various data science libraries. As suggested by Ghassemi et al. (2019), the dataset was pre-processed using Pandas for data manipulation and cleaning, whereas NumPy facilitated the numerical computations.

3.2.3 Feature Extraction

In machine learning models, feature extraction plays a major role as it determine the most relevant characteristics to predict patient satisfaction (Choudhury and Asan, 2020; Zhang *et al.,*2023; Habouch and Mane, 2021; Winn *et al.,* 2023; Straw, 2020; Panahiazar *et al.,* 2021). The Skit-learn Standard Scaler was used to standardize continuous features, which ensured that all variables contributed equally during the analysis. Moreover, Z-score normalization from SciPy was helpful is detecting and addressing the outliers. Next, Matplotlib and Seaborn were utilized for Exploratory Data Analysis (EDA) by visualizing data distributions, corelations and feature importance (Choudhury and Asan, 2020).

In this study, we used the following feature extraction techniques:

- Correlation Analysis: To determine the relationship between different features, a correlation matrix was analysed, where features with no or less correlation (positive or negative) were identified as key contributors to the model (Straw and Callison-Burch, 2020).

- Statistical Significance Testing: To focus on variables which are most likely to influence patient satisfaction, features that were statistically significant in relation to patient satisfaction were selected for modelling (Hirsh *et al.*, 2019).

- Feature Importance Ranking: We ranked features based on their contribution to predicting the patient satisfaction using machine learning algorithms, then the top – ranked features were used to train and test models (Frownfelter *et al.*, 2019).

3.2.4 Machine learning Models

We employed several machine learning models which predicted patient satisfaction based on ADC score and biomedical parameters for hypothesis testing:

- Logistic Regression
- Decision Tree
- Support Vector Classifier
- Random Forest
- Gradient Boosting

Cross-validation and performance metrics (precision, recall, f1-score, accuracy) were used to assess model efficacy (Xie *et al.*, 2023).

3.2.5 Cluster Analysis

K-means clustering was implemented in this study to classify patients into distinct groups based on their satisfaction with AI-assisted treatments. For the clustering process, input variables were key features, including biomedical parameters (e.g., blood pressure, blood sugar and heart rate) and treatment-related metrics (e.g., ADC score, recovery time and treatment duration) (Pham *et al.*, 2020). Homogeneous subgroups were identified by the algorithm by iteratively portioning the dataset, while ensuring minimal intra-cluster variance and maximal inter-cluster distinction. In accordance with accepted best practices in unsupervised machine learning, the clustering process was performed to ensure robust group formation and accurate characterization of patient satisfaction levels (Giordano *et al.*, 2021). This clustering methodology provided a structured approach which uncovered patterns and insights into a relationship between patient satisfaction and health outcomes with AI-assisted healthcare (Behura, 2021).

3.3 Qualitative Analysis

As part of qualitative analysis methodology, thematic analysis was employed in this study, which explored the experiences and perceptions of doctors in India and the USA regarding AI-supported diagnosis. A sample of various key quotes from healthcare professionals was collected, which focused on major aspects such as transparency, cultural differences, human AI-collaboration and the emotional impact of AI on patient care. This data was then analysed through a process of open coding, where recurring themes and patterns were identified. Next, each identified theme was examined in relation to the Technology Acceptance Model (TAM) and health Belief Model (HBM), which guided the understanding of how perceived usefulness, self-efficacy and cultural factors influenced trust in AI and its impact on patient outcomes. This approach provided a rich, context-sensitive understanding of the factors which shapes the integration of AI in healthcare settings. Key references that inform this analysis include Davis (1989) on the Technology Acceptance Model (TAM), Rosenstock et al. (1988) on the Health Belief Model (HBM), and Patel et al. (2019) on the adoption of AI technologies in healthcare.

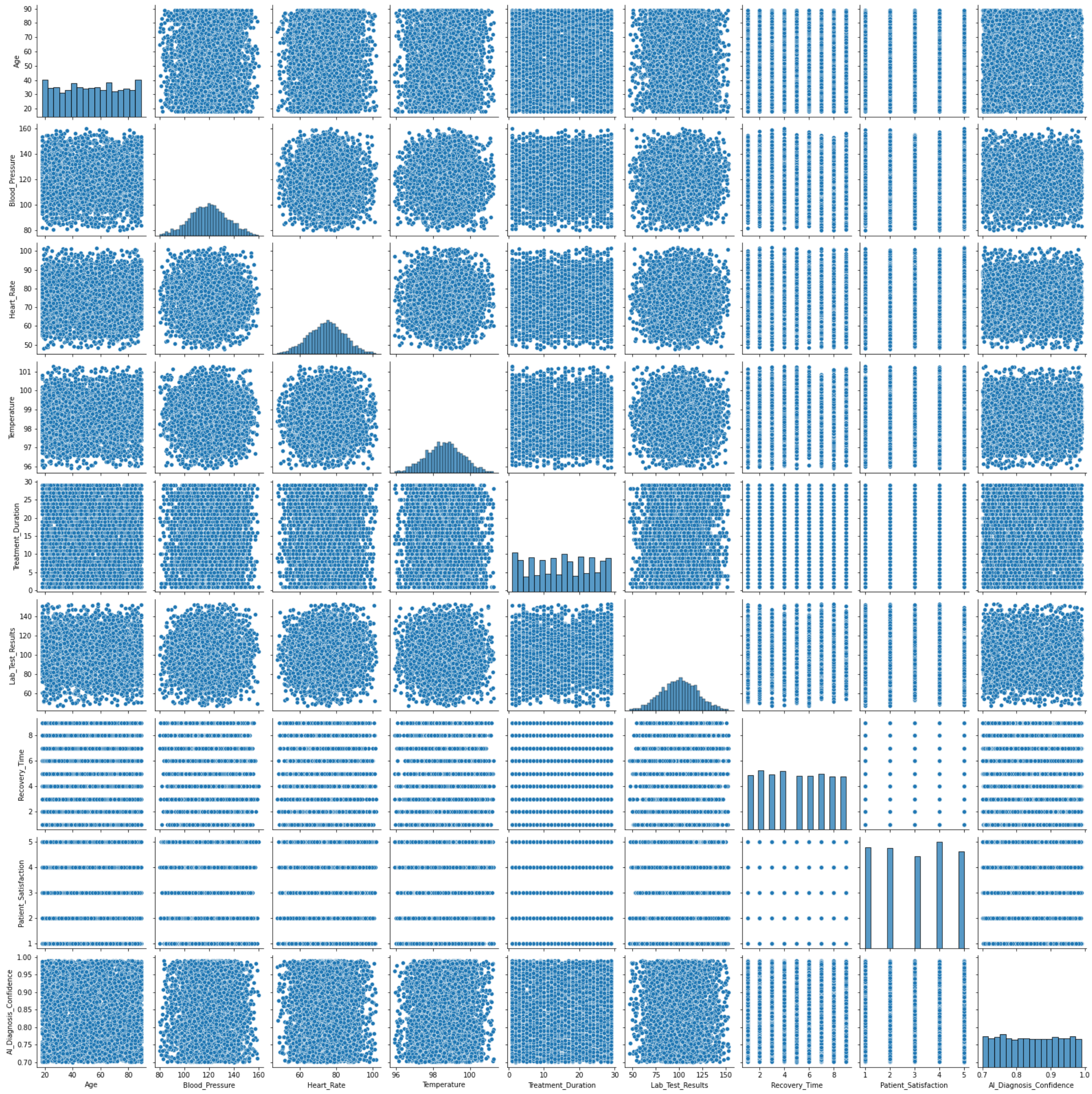
4. Results

4.1 Quantiitative Analysis

4.1.1 Descriptive Analysis

The dataset analysed in this study comprised 5000 patient records from Kaggle, containing detailed biomedical data and satisfaction scores for each patient (see Figure 2).

Figure 2. Scattered plots of Data Distribution



Source: Authors' self-computation using Python

The descriptive statistics provided a general overview of the data distribution and variability of the key features in the dataset.

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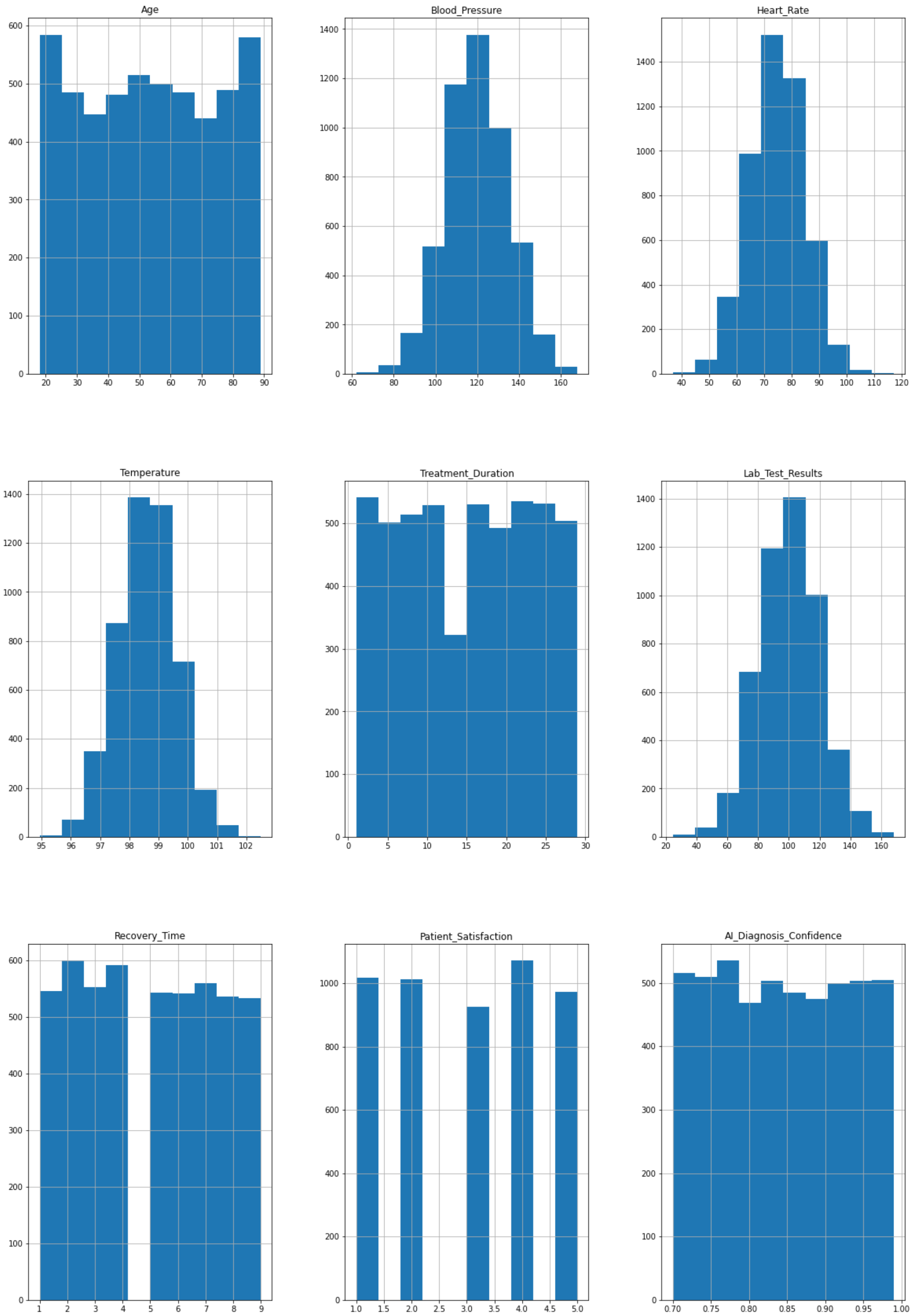
Figure 3. Histogram plots for biomedical features



Source: Authors' self-computation using Python

The analysis of patient data revealed the following trends across the key variables. The mean age of the patients was $M = 53.43$ years ($SD = 20.93$), indicating a broad age range spanning from younger to older individuals (see

Figure 3). Blood pressure levels averaged *M* = 119.86 mmHg (*SD* = 15.06), suggesting that most patients maintained readings within a healthy range, albeit with some variability (Tang *et al.*, 2021). Similarly, heart rates had a mean of **M** = 74.76 bpm (*SD* = 9.97), which aligns with the normal range for adults (60–100 bpm). Body temperatures were highly consistent across the sample, with a mean of *M* = 98.60 °F (*SD* = 1.00) (see Figure 3).

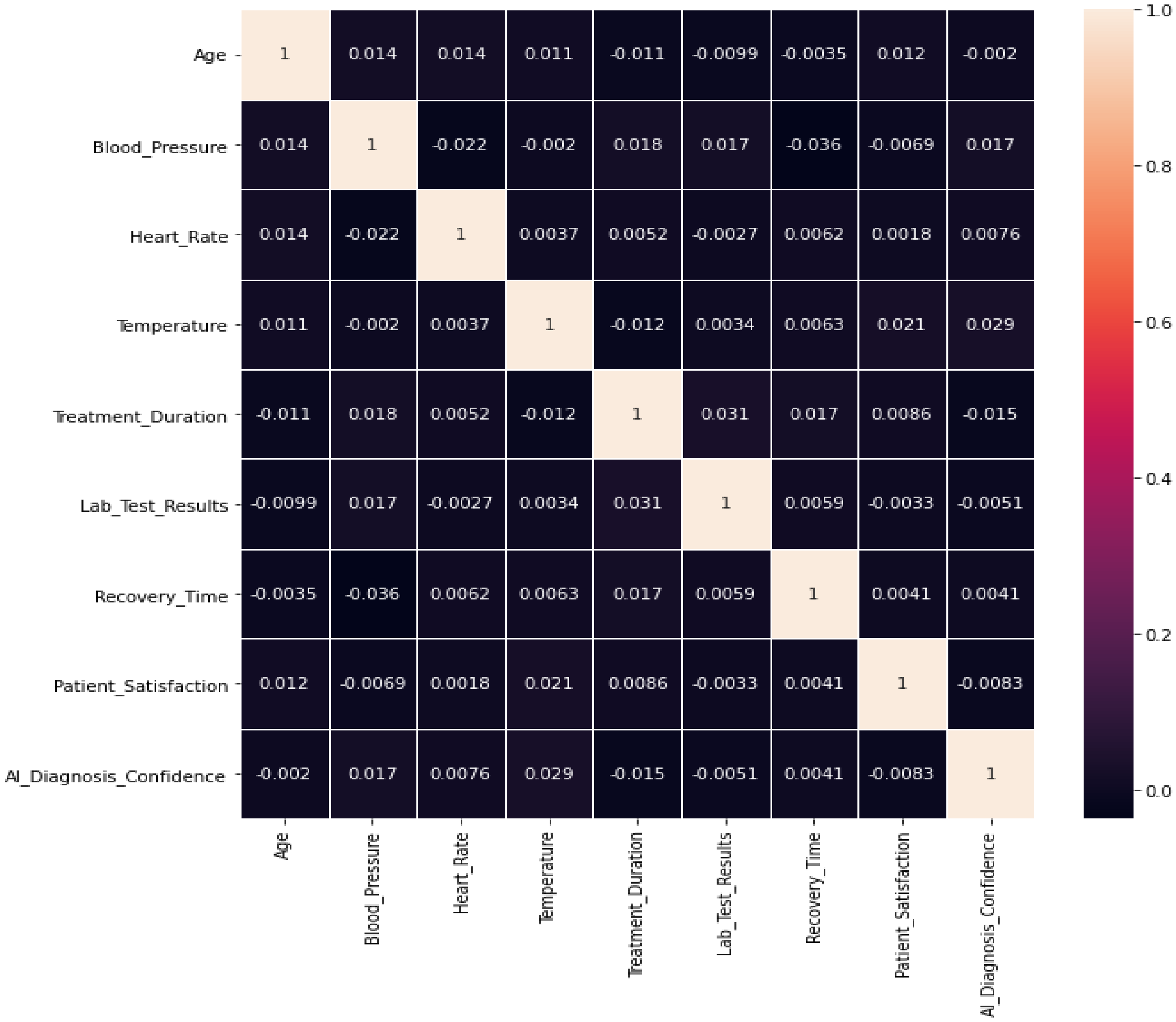
The treatment duration varied significantly, with an average of *M* = 14.97 days (*SD* = 8.40), reflecting differences in illness severity and treatment requirements (Istasy *et al.*, 2021). Laboratory blood glucose levels showed a mean of *M* = 100.20 mg/dL (*SD* = 19.81), indicating a generally normal range, but with notable variability due to individual health conditions. The recovery time averaged *M* = 4.94 days (*SD* = 2.57), suggesting variability in recovery periods linked to patient-specific factors (see Figure 3).

With considerable individual variations, patient satisfaction scores for AI-assisted medical procedures had a mean of *M* = 2.99 (*SD* = 1.42), which reflects moderately positive experiences. Lastly, the average AI Diagnostic Confidence (ADC) score *M* = 0.80 (*SD* = 0.08), indicates a high overall trust in AI-driven diagnoses, although slight fluctuations were observed due to case complexities (Frownfelter *et al.*, 2019). These findings provide valuable insights into the interplay between biomedical parameters and patient satisfaction in AI-assisted healthcare (see Figure 3).

4.1.2 Correlation Analysis

A correlation analysis was conducted to explore the relationships between the key features in the dataset.

Figure 4. Correlation plot and matrix



Source: Authors' self-computation

Notably, no significant correlations were found between most features, indicating that these variables are largely independent of each other (Choudhury and Asan, 2020). This finding supports the idea that these features—such as blood pressure, heart rate, treatment duration, and recovery time—can be analysed separately in terms of their effects on patient satisfaction (see Figure 4).

4.1.3 Feature Extraction and Model Performance

The feature extraction process was critical in identifying the most influential features for predicting patient satisfaction.

Table 2. Feature extraction

	Features Extracted	Feature Weight
1	Lab_Test_Results of sugar	0.14498
2	Heart_Rate	0.14122
3	Blood_Pressure	0.13693
4	AI_Diagnosis_Confidence	0.13608
5	Temperature	0.12726
6	Age	0.0491
7	Recovery_Time	0.04065
8	Treatment_Duration	0.03374

Among these features, blood sugar/glucose emerged as the most important, with a feature weight of 0.14498. This suggests that abnormal sugar levels, as indicated by laboratory tests, play a crucial role in determining patient satisfaction, likely because patients with more severe conditions, such as diabetes, experience greater satisfaction if treated properly or higher dissatisfaction if not treated accurately. The heart rate, with a feature weight of 0.14122, was also an important predictor of satisfaction. Abnormal heart rates, especially those that are too high or too low, may contribute to discomfort and influence overall patient satisfaction (Hirsh *et al.*, 2019; Frownfelter *et al.*, 2019) (see Table 2).

Blood pressure also emerged as a key feature, with a feature weight of 0.13693, supporting the common understanding that hypertension can significantly impact both health outcomes and patient experiences. ADC score, with a feature weight of 0.13608, was another important predictor, underscoring the role of AI in determining patients' trust in their diagnoses and, consequently, their satisfaction with the care they receive (Table 2).

Temperature, with a feature weight of 0.12726 and age (0.0491), while being less influential than some of the biomedical parameters, still played a role in predicting satisfaction. Recovery time (0.04065) and treatment duration (0.03374) were the least important factors, suggesting that the duration of treatment or recovery may be secondary to other factors, such as the severity of the diagnosis and the patient's biomedical status (see Table 2).

4.1.4 Model Performance and Analysis

Several machine learning models were applied to predict patient satisfaction, and their performance was evaluated using cross-validation scores. These models include Logistic Regression, Decision Tree, Support Vector Classifier

(SVC), Random Forest, and Gradient Boosting. The following summarises the performance of each model. In this section, we present the performance of different machine learning classifiers used to predict patient satisfaction, with and without hyperparameter tuning through grid search.

Table 3. Machine learning Modelling and Hypertuning of model

Classifiers	**Base Model Cross Val Mean Score**	**Hypertuning of Model using Grid Search**
Logistic Regression	0.339212	0.357364073
Decision Tree	0.363848	0.407710514
Support Vector Classifier	0.342827	0.411428639
Random Forest	0.367991	0.407717864
Gradient Boosting	0.350593	0.636857143

The base model scores were compared to the performance after hyperparameter optimization (see Table 3).

4.1.4.1 Logistic Regression

- Base Model Cross-Validation Mean Score: 0.339212
- Hypertuned Model (using Grid Search): 0.357364073

This study found that logistic regression provided a good fit for predicting patient satisfaction in its basic formulation. By applying hyperparameter-tuning searching with a grid search, the accuracy of the model improved slightly. This increase indicates that additional fine-tuning of other hyperparameters, including the regularisation term, may be possible and yield even better generalization results, as well as improve the main output of the model—the level of patient satisfaction (George *et al.*, 2023).

4.1.4.2 Decision Tree

- Base Model Cross-Validation Mean Score: 0.363848
- Hypertuned Model (using Grid Search): 0.407710514

The decision tree classifier demonstrated significant improvement after the hyperparameters of the classifier set were optimised. When measuring the cross-validation score of the base model, the result obtained was 0.363848, whereas for the tuned model, there was a much higher value of 0.407710514 (Jeyaraj and Avsm, 2023).

4.1.4.3 Support Vector Classifier

- Base Model Cross-Validation Mean Score: 0.342827
- Hypertuned Model (using Grid Search): 0.411428639

The SVC also significantly improved its performance after hyperparameter optimisation. Based on cross-validation, the model with the base had a score of 0.342827, whereas after the grid search, the score improved to 0.411428639. This improvement indicates that in future work to enhance the model, it is essential to determine how to further tune the kernel and other hyperparameters, such as regularisation (Yin *et al.*, 2021).

4.1.4.4 Random Forest

- Base Model Cross-Validation Mean Score: 0.367991
- Hypertuned Model (using Grid Search): 0.407717864

In the random forest classifier, hyperparameter optimisation improves classification accuracy. For the base model, the mean score was 0.367991, whereas, after applying the grid search, the score improved slightly to 0.407717864.

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This leads us to the conclusion that, if necessary, finer tuning of the number of trees, maximum depth, and other parameters will produce even better performance (Zeng-Treitler and Nelson, 2019).

4.1.4.5 Gradient Boosting

• Base Model Cross-Validation Mean Score: 0.350593

• Hypertuned Model (using Grid Search): 0.636857143

Gradient Boosting demonstrated the most significant increment, with the initial score in the base model set to 0.350593. After hyperparameter tuning, the score rose to 0.636857143. Hence, it can be concluded that after applying hyperparameter tuning, Gradient Boosting is the best model, followed by the Support Vector Classifier and then the Decision Tree. From these findings, it can be summarised that while base models seem to perform fairly well, it is critical to obtain the right grid search as the foundation to achieve even higher accuracy and better prediction of patient satisfaction levels (Bautista *et al.*, 2023).

4.1.5 Cluster Analysis: Low, Medium, and High Satisfaction Groups

Cluster analysis was conducted using K-means clustering, which categorised patients into three distinct satisfaction groups based on their responses to AI-assisted treatment. The K-Means algorithm partitioned the data into three clusters: Low Satisfaction (n=2031), Medium Satisfaction (n=925), and High Satisfaction (n=2044) (see Table 4).

Table 4. K-Means Cluster Analysis

FEATURES	CLUSTERS		
	Low Satisfaction	Medium Satisfaction	High Satisfaction
	N=2031	N=925	N=2044
Blood Pressure	120.0672	119.4340	119.8558
Blood Sugar	100.2168	99.7716	100.3808
Heart Rate	74.7394	74.8146	74.7444
AI Diagnosis Confidence	0.7348	0.8006	0.8416
Temperature	98.5858	98.5759	98.6341
Age	53.1285	53.9719	53.4922
Recovery Time	4.9089	4.9351	4.9834
Treatment Duration	15.0675	14.1189	15.2471
Group Centroid	**51.9508**	**58.3090**	**58.5224**

The group centroids representing the average values for each feature within each group were as follows: Low Satisfaction (51.95), Medium Satisfaction (58.31), and High Satisfaction (58.52). These centroids provide insights into the central tendencies of health characteristics and satisfaction levels within each group, shedding light on how AI-assisted treatments impact patient outcomes and satisfaction.

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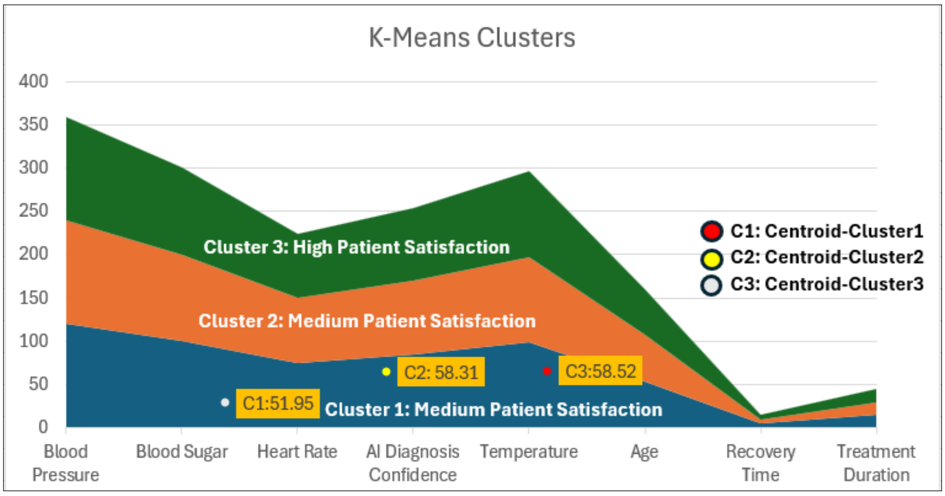
Figure 5. Cluster Analysis Plot with Centroid



Source: Authors' self-computation

4.1.5.1 Low Satisfaction Group (n=2031, Centroid: 51.95)

The Low Satisfaction group was characterised by higher average Blood Pressure (*M* = 120.07) and Blood Sugar (*M* = 100.22) values, both of which exceeded normal medical standards. According to Chorney (2023), normal adult blood pressure is generally 120/80 mmHg and normal fasting blood glucose levels should be between 70-99 mg/dL (American Diabetes Association [ADA], 2020). The elevated BP and BS values in this group suggest that health control may be insufficient even with AI-assisted diagnosis and treatment, which likely contributes to the lower satisfaction reported by these patients. Additionally, the Heart Rate (*M* = 74.74) falls within the typical range of 60-100 bpm (Catai *et al.*, 2022), but is at the higher end, indicating possible stress or unresolved health issues. ADC score (*M* = 0.73) in this group was lower than that in the other groups, suggesting a lack of trust in the AI system's capabilities. Although the Recovery Time (*M* = 4.91) was moderate, the Treatment Duration (*M* = 15.07) was relatively long, reflecting the possibility that AI interventions may not be sufficiently tailored or effective in addressing the specific needs of these patients, which likely contributes to their dissatisfaction (see Figure 5).

4.1.5.2 Medium Satisfaction Group (n=925, Centroid: 58.31)

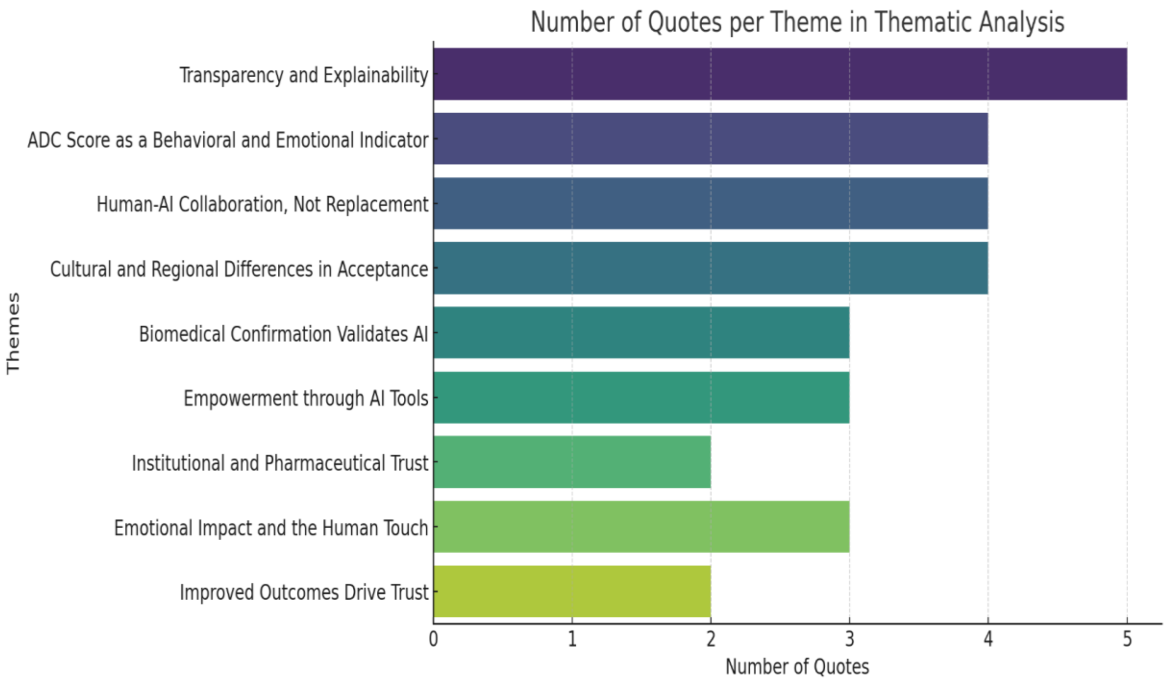
The Medium Satisfaction group showed some improvement in health outcomes compared to the Low Satisfaction group. Blood Pressure (*M* = 119.43) and Blood Sugar (*M* = 99.77) were lower than those in the Low Satisfaction group, but remained above normal levels. According to AHA (2020) and ADA (2020), ideal BP is 120/80 mmHg, and normal fasting blood glucose is 70-99 mg/dL. These values suggest some degree of better health management, although they are not within the optimal range for healthy individuals. The Heart Rate (*M* = 74.81) was similar to that of the low-satisfaction group, indicating that while improvements in health have been made, challenges remain. ADC score (*M* = 0.80) was higher than that in the low-satisfaction group, indicating a modest increase in trust toward AI-assisted treatments. However, the Recovery Time (*M* = 4.94) was marginally longer and the Treatment Duration (*M* = 14.12) was shorter, suggesting that while AI treatments in this group may have improved effectiveness, there are still perceived shortcomings in their comprehensiveness, contributing to moderate satisfaction levels (see Figure 5).

4.1.5.3 High Satisfaction Group (n=2044, Centroid: 58.52)

The High Satisfaction group demonstrated the most favourable health outcomes. Blood Pressure (*M* = 119.86) is closer to the ideal range of 120/80 mmHg (AHA, 2020), and Blood Sugar (*M* = 100.38) is near the upper end of the normal range of 70-99 mg/dL (ADA, 2020). These values suggest that AI-assisted treatments are more effective in managing health conditions in this group, particularly blood sugar levels. The Heart Rate (*M* = 74.74) was also within the normal range of 60-100 bpm (Mayo Clinic, 2020), indicating less stress compared with the other groups. While the ADC score ($M = 0.84$) was slightly lower than in the Medium Satisfaction group, it still reflected a relatively high level of trust in AI-assisted diagnoses. The Temperature ($M = 98.63$) is stable and falls within the normal range of 97 °F-99 °F (Kuht and Farmery, 2021). The Recovery Time ($M = 4.98$) was slightly longer, indicating that patients in this group may have received more thorough treatment regimens. The Treatment Duration ($M = 15.25$) was the longest, reflecting the more comprehensive and personalised AI-assisted treatments provided to these patients, which likely contributed to their higher satisfaction. Additionally, the larger number of patients in this cluster compared to the others indicates a growing trust in AI-assisted healthcare despite the presence of higher biomedical parameters such as blood sugar. This suggests that AI-assisted treatment could emerge as a key solution for managing chronic diseases and abnormal health parameters in the future (see Figure 5).

4.2 Qualitative Analysis

Figure 6. Thematic Analysis



Source: Authors' self-computation

The thematic analysis from expert interviews with ten healthcare professionals and AI researchers revealed nine dominant themes as evaluated in Figure 6, which reflects critical aspects that influence trust in AI- supported healthcare systems. The analysis revealed the most prominent theme as "Transparency and Explainability" which was cited in 5 interviews, showcasing respondents' emphasize on the necessity for interpretable AI systems which would enable both clinicians and patients to understand the decision-making process. This transparency was viewed to be essential in building confidence, especially when AI decisions diverged from medical judgement.

Further following were three themes with four quotes each viz – "ADC scores as a Behavioral and Emotional Indicator", "Human AI Collaboration, not Replacement" and "Cultural and Regional Differences in Acceptance". Experts state that ADC scores reflect not only diagnostic precision but also the emotional reassurance which AI systems offer patients. Simultaneously, they also expressed hat AI should serve as more of a cognitive partner by augmenting human judgement, rather than supplanting it. Additionally, cultural acceptance was another influential factor as attitudes towards AI varied significantly between regions, shaped by local healthcare norms, technological familiarity and institutional reputation.

Next in line were themes with three quotes each, namely – "Biomedical confirmation validates AI", "Empowerment through AI tools" and "Emotional Impact and Human Touch". These themes suggested that the patients are more likely to trust AI when its predictions align with traditional diagnostics d clinical outcomes. Moreover, AI tools that offer greater control over their journeys such as through personalized monitoring, were perceived positively. Furthermore, these findings also suggest that down the line, emotional factors such as the perception that AI lacks empathy, remains a raised concern which highlights the needs for human interaction in healthcare delivery.

Lastly, the final two themes – "Institutional and Pharmaceutical Trust" and "Improved outcomes drive trust", received two quotes each. These themes laid emphasis on institutional credibility, including endorsement by respected pharmaceutical or hospital systems, plays a role in trust development. Finally, improved clinical outcomes, while important, were viewed as reinforcing trust only when paired with transparent communication and personalized engagement.

5. Discussion

Patient satisfaction levels were tested with the calibration of the ADC score and five specific biomedical parameters, all in a sample of 5000 patients, and hypothesis testing was conducted using machine learning models (Jackson *et al.*, 2019). According to the results, AI diagnostic confidence allied with the main biomedical parameters such as heart rate, blood pressure, time-to-recovery, and laboratory investigations affected patient satisfaction ((Embed, 2021; Mehta, 2023).

Our results show a partially yet important relationship between ADC score, biomedical parameters, and patient satisfaction through the feature extraction process (Clark *et al.*, 2021; Gao *et al.*, 2023).

In this research, we developed a high-performance model for patient satisfaction levels using the Gradient Boosting method (accuracy = 0.636857143) (Leung *et al.*, 2022). Although this implies a strong predictive probabilistic responsiveness, it is crucial to consider overfitting. Future studies should replicate these findings using different datasets to avoid bias associated with the current study.

Finally, the results were compared with the findings of previous research, revealing similarities and differences. For instance, study findings (Zhang *et al.*, 2023; Bailey *et al.*, 2021; Jones and Kerber, 2022) reveal a positive link between AI-based diagnosis and patient confidence. However, our study advances this by including biomedical parameters in the model, presenting a more comprehensive analysis of the determinants of patient satisfaction.

On the other hand, our results partially negate the studies of Tang *et al.* (2021), who observed an interaction between the level of confidence in AI and the satisfaction of patients in emergency care facilities. The results of the ROAD map might be due to variations in healthcare systems and the context within which they are brought forward for patients and client expectations in another setting or with other specialties, and further studies are needed across different specialties.

4.1 Feature Extraction and its Role in Supporting the Hypothesis

Feature selection was significant in determining which study features significantly affected patient satisfaction (Panahiazar *et al.*, 2021). While identifying the feature's importance, further using models such as Gradient Boosting and Random Forest, it came to the forefront that biomedical parameters such as blood glucose, heartbeat, and blood pressure are the most important predictors of patient satisfaction. ADC score, similar to the previous predictor, also contributed to the final model, once again underlining the importance of AI in the construction of patient experience (Habouch and Mane, 2021).

Based on the feature importance scores, it was found that among all the laboratory abnormalities, the variable 'elevated blood sugar levels 'was most important, mainly because most patients with chronic illness complained of dissatisfaction (Straw, 2020). This finding aligns with the HBM to the extent that the nature of health conditions shapes people's health behaviours and perceptions. Therefore, patients who benefit from proper diagnoses backed by AI and favourable biomedical markers should be more assured of their health journeys, thus resulting in high satisfaction levels (Winn *et al.*, 2023).

ADC score is among the most important factors affecting patient satisfaction, which supports TAM. It posits that there is an increased propensity for technology acceptance due to perceived usefulness and ease of use. Our outcomes support this theory, since ADC score at higher levels are related to patient satisfaction. This implies that when patients accept the expanded role of AI-based diagnostic systems, their perception of their healthcare experiences are likely to be positive.

4.2 Machine learning Models and Accuracy

To confirm that increased ADC score and positive biomedical outcomes directly lead to increased patient satisfaction, Logistic Regression, Decision Trees, SVC, Random Forest, and Gradient Boosting were employed. All models were assessed by comparing the extent to which each could predict the level of patient satisfaction (Gebran *et al.*, 2023).

The first results revealed that Gradient Boosting achieved the best performance of all models, with a cross-validation mean score of 0.636857143, after hyperparameter tuning (Battaglia *et al.*, 2020). This means that more complex learners, such as gradient-boosting learners who learn strong learners sequentially, are fit to capture the details of the data and better predict the level of patient satisfaction. The decision tree model also increased after the hyperparameter tuning reached 0.407710514 (Bigman *et al.*, 2021). This proved that simpler models could capture many patterns in data but may not optimise the interacting relationships of the features. The results of the Random Forest and SVC models were slightly better, with scores of 0.407717864 and 0.411428639, respectively, suggesting that given proper optimisation, AI models can be viable prognostic instruments for patient satisfaction (Glauser, 2020).

This high accuracy further supports the major argument of this study that using an AI model for diagnosis along with biomedical data can predict patient satisfaction with high accuracy. This has provided evidence for the research hypothesis, assuming that consumer confidence in artificial intelligence, when accompanied by positive biomedical results, enhances satisfaction with healthcare services.

4.3 K-Means Cluster Analysis and Group Centroids

K-means clustering has, therefore, performed a good job of segmenting the data into three separate groups based on satisfaction levels, health status, and attitude towards AI-supported therapies. The group centroids encourage the values of each feature within each cluster, which states the health status and treatment response of the patients. The distance between centroids depicts the differentiation between satisfaction groups (Behura, 2021). As can be seen, the Low Satisfaction (centroid: 95) group was farther from the Medium Satisfaction (centroid: 58.31) and High Satisfaction (centroid: 58.52) groups; hence, this group of clients experienced most of the health and treatment challenges. In contrast, the medium- and high-satisfaction groups demonstrated similar health parameters; however, a higher percentage of high satisfaction indicated better treatment efficacy (Lee, 2020).

Hence, K-means cluster analysis offers a clear background of how different health parameters affect patient satisfaction with AI-provided treatment (Jiao *et al.*, 2023). The Low Satisfaction group had significantly higher Blood Pressure and Blood Sugar yet lower ADC scores, indicating worse Health Management and less satisfactory treatment results, leading to dissatisfaction Stypińska and Franke, 2023; Matheny *et al.*, 2019). The Medium Satisfaction group might have enhanced their health indicators, but they still experienced difficulties, which increased their moderate satisfaction. In contrast, the subjects in the High Satisfaction group demonstrated improved health indicators, higher efficacy of treatments with the help of AI tools, and longer time spent on such treatments, which led to the desired level of satisfaction (Kelly *et al.*, 2019). The centroids and distances between the groups reveal the significance of AI in its effects on health and the perspectives of patients, ensuring that overall satisfaction contributes to more difficulties in managing health despite the utilisation of AI-supported treatment plans (Ski *et al.*, 2020).

4.4 Supporting Theories: Technology Acceptance Model and Health Belief Model

This study competently supports TAM and HBM because of the conclusions drawn from the research. According to the TAM, patients' acceptance is characterised by their perceived usefulness of AI technology and their perceived ease of using AI systems. The findings of our study unequivocally reflect this reason, as higher ADC score significantly predicts the level of patient satisfaction, explicitly indicating that the usefulness of AI systems is directly related to the degree of patient trust and satisfaction (Esmaeilzadeh *et al.*, 2020; Xie *et al.*, 2023; Correa *et al.*, 2022; Biswas *et al.*, 2023).

Second, the HBM holds that health behaviours and their consequences are determined by people's beliefs concerning their susceptibility to disease and its risks. In this study, the biomedical outcomes, which included regulating the patient's heart rate, blood pressure, and typical laboratory values, were confirmed to have helped boost satisfaction in the patient population. If patients feel that their health condition is improving or managed primarily through diagnosis by artificial intelligence, their overall satisfaction with healthcare service vendors will be relatively high. This indicates that expectations from AI-assisted healthcare firms and biomedical factors influence healthcare satisfaction (George *et al.*, 2023; Khan, 2023; Jeyakumar *et al.*, 2023; Pearce *et al.*, 2021; Lee, 2020; Ski *et al.*, 2020).

4.5 Thematic Analysis

The qualitative findings of thematic analysis align closely with the Technology Acceptance Model (TAM) and Health belief Model (HBM), providing deep insights into socio-psychological dimensions of AI trust in Healthcare (Esmaeilzadeh et al., 2021; Chen et al., 2019). The prominence of Transparency and Explainability as the most cited theme resonates with TAM’s focus on perceived ease of use and usefulness (Chen et al., 2023). When stakeholders understand how an AI system operates, they are more likely to view it as trustworthy and integrate into clinical practice.

The recurring emphasis on *Human AI-Collaboration, Not Replacement* indicates towards a broader sentiment that AI’s role should remain assistive, thus, preserving the relational and ethical dimensions of human healthcare. This mirrors with HBM’s concern with perceived severity and susceptibility that patients are more receptive to AI when it augments, rather than replaces, the relationship between physician and patient (Jeyakumar et al., 2023).

Furthermore, cultural and regional differences emphasize the need of localized AI implementation, as acceptance varies based on trust dynamics, language and tech exposure which is specifically visible in diverse settings like India and the USA (Barwise et al., 2024; Clark et al., 2021). The ADC score emerged as a key emotional and behavioural indicator, reflecting patient comfort and trust beyond technical accuracy (Chen et al., 2019; Sendak et al., 2023). Overall, the thematic analysis demonstrated that the trust in AI in shaped by explainability , culture, emotion and institutional credibility. Therefore, there is a need for deploying ethical, human-centred and context aware AI systems in healthcare.

a. Ethical Considerations

While promising, the integration of AI into healthcare raises important ethical considerations that must be addressed. Our study demonstrated the benefits of AI in healthcare. However, it is essential to note that AI should complement, not supplement, expert medical care (Chase, 2020). We need clear protocols for the human oversight of AI systems. The impact on the psychology of people diagnosed by AI systems instead of human doctors should be studied further. As AI becomes increasingly involved in the healthcare decision-making process, liability questions arise in case of misdiagnosis or mistakes in treatment. These situations require the development of clear guidelines and legal frameworks (Chen *et al.*, 2023).

This, in turn, will help us achieve an AI-enabled implementation of healthcare that is not only good for patients in terms of satisfaction and outcomes, but also ensures the patient's rights, reasonably serves those of society, and does not exchange human touch in medicine (Flores *et al.*, 2023).

b. Practical Implications

The main implications of our findings are for healthcare providers and policymakers. Second, the evidence of association between ADC score and patient satisfaction was very strong. This means that healthcare organisations should invest in best-quality AI systems and ensure that these systems can best communicate their level of confidence to patients (Straw and Callison-Burch, 2020; Sethi *et al.*, 2018).

Third, the importance of biomedical parameters in our model emphasises the need for comprehensive patient monitoring. Thus, it is important to consider integrated systems wherein, for instance, AI diagnostics are combined with the information tracking of real-time biomedical data streams (Sethi *et al.*, 2018).

Our results indicate that AI can benefit healthcare and policies should be created to promote the responsible adoption of AI concerning patient privacy and data security. This could entail constructing rules for implementing AI in healthcare settings or laying out lines to represent AI-resulting insights to patients (George *et al.*, 2023).

Education regarding AI in healthcare may also benefit patients. Therefore, healthcare providers and policymakers should consider developing programs to increase patients' understanding of AI's role of AI in diagnosis and treatment, thus enhancing trust and satisfaction Rajkomar *et al.*, 2018.

Finally, the importance of each biomedical parameter also varies, indicating that personalised medicine based on AI insights can significantly improve patient satisfaction. This means that we need flexible, AI-powered healthcare delivery models that can be adapted to specific patient needs and preferences (George *et al.*, 2023.

c. Limitation Future Research Directions

One limitation of this study is the potential confounding variables that were yet to be captured in this model. For example, other variables that may affect satisfaction include the educational level of patients and their past experiences with healthcare institutions. These variables can also affect satisfaction levels, disregarding their confidence in AI or biomedical results.

Future research should examine the evolving relationship between AI confidence and patient satisfaction over time, across various healthcare settings, and through mixed-method studies to better understand patient perceptions (West *et al.*, 2022). It should also explore the impact of AI decision explainability on trust, conduct cross-cultural studies, and investigate the interactions between AI systems and healthcare providers. Additionally, ethical considerations related to data privacy and decision-making autonomy as well as the economic effects of AI on patient satisfaction should be explored to gain a comprehensive understanding of AI's impact of AI on healthcare outcomes (Temsah *et al.*, 2023).

6. Conclusion

The results of this study showed that ADC score and favourable biomedical outcomes lead to significantly better patient satisfaction. Given the high accuracy of machine learning models, especially Gradient Boosting, in predicting patient satisfaction, the hypothesis that AI technologies can increase patient experience is supported. AI-assisted treatments have the potential to improve patient outcomes and satisfaction, particularly when health parameters are effectively managed, underscoring the need for tailored and comprehensive healthcare solutions. These results reaffirm the value of using the Technology Acceptance Model and Health Belief Model to characterise the extent to which AI and biomedical parameters affect patient satisfaction in healthcare. By utilising ADC score and monitoring key biomedical parameters, healthcare providers can offer better patient care and greater patient satisfaction with health treatment.

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