LEVERAGING ARTIFICIAL INTELLIGENCE FOR AUDIT AND INTEGRITY IN HEALTHCARE CLAIMS: A CASE STUDY OF FRAUD CLAIM INVESTIGATION UNDER RAJASTHAN GOVERNMENT HEALTH SCHEME

Dissertation Submitted to

The IIHMR University, Jaipur

for the partial fulfillment for the award of the degree of

Master of Business Administration (MBA)

in

Hospital and Health Management

by

Amey Sharma

Under the Supervision and Guidance of

Dr. Dhirendra Kumar

2025

BOOTWAY INAAS PRIVATE LIMITED
JAGATPURA, JAIPUR (302017)

CIN - U63999RJ2024PTC097270

BootWay

CERTIFICATE

This is to certify that **Mr. Amey Sharma**, has successfully completed his internship at **BootWay iNaaS Pvt. Ltd.** The internship was undertaken during the period from **10th March to 7th June 2025**. During this time, Mr. Sharma demonstrated a sincere commitment to his responsibilities and contributed meaningfully to the organization's ongoing projects.

We acknowledge his efforts in market research and wish him success in all his future professional endeavors.

Bharat

Bharat Mangal
Director 15/6/2025

BOOTWAY INAAS PVT. LTD.

www.bootway.in support@bootway.in +91-7976866822

CERTIFICATE

This is to certify that dissertation titled **'Leveraging Artificial Intelligence for Audit and Integrity in Healthcare Claims: A Case Study of Fraud Claim Investigation under Rajasthan Government Health Scheme'** is a record of the research work undertaken by (Name of Student) in partial fulfillment of the requirements for the award of the degree of MBA (Hospital and Health Management)/MBA (Pharmaceutical Management)/MBA (Development Management) from the IIHMR University, Jaipur under my guidance and supervision and his/her approach to the research study has been sincere, scientific, and analytical.

Faculty Guide
IIHMR University, Jaipur
Date 17-6-25

School Dean
IIHMR University, Jaipur
Date 17-6-25

DECLARATION BY STUDENT

I hereby declare that this dissertation titled **'Leveraging Artificial Intelligence for Audit and Integrity in Healthcare Claims: A Case Study of Fraud Claim Investigation under Rajasthan Government Health Scheme'**
is the bonafide record of my original research work. I declare that it has not been submitted to any other university or institution for the award of any degree or diploma. Information derived from the published or unpublished work of others has been duly acknowledged in the text.

(Signature)
Amey Sharma
Date: 17-6-25

Abstract

Public health insurance schemes in India have played a pivotal role in extending financial protection and improving access to healthcare services for underserved populations. Among these, the **Rajasthan Government Health Scheme (RGHS)** stands as a flagship initiative, providing comprehensive medical coverage to government employees, pensioners, and their dependents. While the RGHS has successfully increased healthcare accessibility across the state, it has also become increasingly susceptible to systematic misuse and fraudulent practices. These include the **submission of duplicate diagnostic reports**, **unjustified repetition of tests**, **fabricated inpatient admissions**, and **inconsistent documentation** — all of which lead to significant financial leakage and compromise the integrity of public healthcare financing.

The existing **manual auditing mechanisms** are unable to effectively address the scale and complexity of these frauds. Traditional audits typically rely on random sampling and retrospective reviews along with the TPA approvals, which are time-consuming, labour-intensive, and often fail to detect subtle or large-scale patterns of fraud. Given the high volume of claims processed daily under RGHS, the limitations of manual processes result in delayed detection, underreporting of fraudulent activity, and reduced deterrent effect.

In this context, **Artificial Intelligence (AI)** presents a transformative opportunity to redefine healthcare claim auditing. This dissertation explores how AI technologies — particularly **computer vision**, **natural language processing (NLP)**, and **predictive analytics** — can be integrated into the RGHS auditing process to enhance the detection of fraudulent claims, especially in outpatient department (OPD) claims, where irregularities are harder to track.

The study adopts a **mixed-methods research design**, combining both qualitative and quantitative approaches. Qualitative analysis is based on case studies of high-risk hospitals and diagnostic centres identified in recent RGHS audits. These cases reveal patterns of unethical practices such as **reuse of radiology images across patients**, **missing mandatory reports**, **inconsistent prescriptions**, and **unjustified OPD-to-IPD conversions**. Quantitatively, the research evaluates how AI algorithms trained on historical claims data can identify anomalies and trigger real-time alerts for suspicious activity.

The study demonstrates the **efficacy of AI models in fraud detection**. Computer vision techniques can detect identical or manipulated images submitted under different patient IDs. NLP tools can scan and interpret unstructured text in medical reports and prescriptions to identify inconsistencies. Predictive analytics models, using supervised and unsupervised learning, can identify outliers in claim patterns, flagging hospitals or doctors with disproportionately high claims.

Findings indicate that the integration of AI tools could lead to **significant improvements in claim auditing accuracy**, **real-time fraud detection**, and **resource optimization**. Moreover, by automating routine checks, audit teams can focus on high-risk areas and make informed decisions faster. The proposed AI framework includes a modular architecture combining rule-based engines with adaptive machine learning models, designed to scale with the increasing volume of claims under RGHS.

The dissertation concludes with **policy recommendations** for implementing AI-based audits at scale. These include the need for standardized digital health records, interoperable claim management systems, cross-institutional data sharing protocols, and capacity-building within public health audit agencies. Furthermore, a strong emphasis is placed on **ethical considerations**, including patient data privacy, algorithmic transparency, and the need for human oversight in AI-driven decision-making.

In sum, this research contributes to the growing body of work on AI in healthcare governance, offering a **practical roadmap for integrating intelligent audit systems** into public health insurance schemes. By leveraging technology for fraud detection, the RGHS and similar schemes can ensure not just financial sustainability but also **greater accountability, efficiency, and trust in the public healthcare system**.

Acknowledgement

I would like to express my sincere gratitude to all those who supported and guided me throughout the course of this dissertation.

First and foremost, I am deeply thankful to **Dr. Dhirendra Kumar**, my guide and mentor, for his constant encouragement, valuable insights, and constructive feedback that shaped the direction of this study.

I also extend my heartfelt thanks to the faculty and administration at **IIHMR University, Jaipur**, for providing the academic environment and resources necessary to complete this research.

Special thanks to the hospital professionals and audit stakeholders who contributed their time and insights during interviews and field visits.

Lastly, I am grateful to my family and friends for their unwavering support, motivation, and patience during this journey.

Amey Sharma

Jaipur, India

Table of Contents

List of Tables

Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
ABG	Arterial Blood Gas
CMS	Centers for Medicare and Medicaid Services
CT	Computed Tomography
HIRA	Health Insurance Review and Assessment Service (South Korea)
HRCT	High-Resolution Computed Tomography
IPD	Inpatient Department
IT	Information Technology
ML	Machine Learning
MoHFW	Ministry of Health and Family Welfare
MRI	Magnetic Resonance Imaging
NHA	National Health Authority
NLP	Natural Language Processing
OPD	Outpatient Department
PM-JAY	Pradhan Mantri Jan Arogya Yojana
RGHS	Rajasthan Government Health Scheme
TPA	Third Party Administrator
UHC	Universal Health Coverage

Chapter 1: Introduction

1.1 Background

India's healthcare ecosystem is evolving rapidly, with government-sponsored health insurance schemes playing a pivotal role in achieving Universal Health Coverage (UHC). One such initiative, the **Rajasthan Government Health Scheme (RGHS)**, was launched to provide cashless medical facilities to government employees, pensioners, and their families through a wide network of public and private hospitals. While this scheme has significantly improved healthcare accessibility, it has also become vulnerable to **systemic abuses and fraudulent practices**, including **fabricated diagnostic records**, **duplicate claim submissions**, and **unjustified conversions of outpatient cases to inpatient** for higher reimbursements (1).

Traditional auditing approaches — reliant on manual scrutiny by TPA and retrospective verification — have failed to adequately identify or deter these complex fraudulent behaviors, particularly in high-volume data environments (2), especially in OPD Claims. In response, **Artificial Intelligence (AI)** is increasingly seen as a viable solution to ensure real-time auditability, improve fraud detection accuracy, and enhance operational transparency in public health schemes (3).

1.2 Rationale of the Study

Healthcare claim fraud is not just an economic loss but also a public trust issue. According to the Ministry of Health and Family Welfare, an estimated **8–10%** of healthcare spending may be lost annually to fraudulent claims in public insurance schemes (4). In the RGHS audits, several instances were found where **the same diagnostic images** (e.g., MRI, CT scans) were reused across multiple patients, or **mandatory documents like ABG test reports or HRCT films were missing**, yet claims were processed and reimbursed.

In this context, AI tools — such as **machine learning (ML)** algorithms, **natural language processing (NLP)**, and **image recognition technologies** — offer a scalable framework for identifying anomalies, patterns of overutilization, and document forgeries (5). Integrating AI into the audit processes of RGHS can enable near real-time fraud detection, reduce administrative burden, and improve scheme integrity.

1.3 Objectives of the Study

This thesis aims to explore and analyze the role of AI in improving the accuracy and integrity of healthcare claim audits within the RGHS. The specific objectives are:

- To analyze the types and frequency of fraudulent healthcare claims submitted under the RGHS.
- To evaluate the current limitations of manual auditing systems in detecting claim anomalies.
- To identify AI-based techniques capable of detecting diagnostic and billing fraud in public health schemes.
- To provide recommendations for the integration of AI systems into RGHS auditing workflows.

1.4 Research Questions

This study is guided by the following research questions:

1. What are the most common types of fraudulent activities reported under the RGHS?
2. How effective are manual audit mechanisms in identifying and deterring such activities?
3. Which AI methodologies are most relevant for use in public health claim verification?
4. What structural and technological reforms are necessary for adopting AI in fraud audits?

1.5 Scope of the Study

This research is delimited to the RGHS scheme in Rajasthan, with a focus on reported diagnostic and billing irregularities from the latest audit findings (2023–2024). It draws on both qualitative and quantitative data — including case studies of diagnostic misuse, document duplication, and IPD/OPD billing fraud — to explore how AI could strengthen real-time audit mechanisms. While AI applications are discussed broadly, the emphasis is on **applied fraud detection and claim integrity**, rather than on theoretical model development.

1.6 Significance of the Study

This study is significant for the following reasons:

- **Policy Makers** can use its findings to design regulatory mechanisms that mandate AI use in healthcare claim audits.
- **Hospital Administrators** can adopt AI-driven tools for internal audits, enhancing compliance with government schemes.
- **Technology Providers** can develop AI solutions tailored for the Indian public health system's constraints and needs.
- **Researchers and Academicians** will benefit from an empirical case study that integrates healthcare governance, AI technology, and public policy.

1.7 Structure of the Dissertation

This dissertation is organized into seven chapters, each addressing a critical component of the study:

- **Chapter 1: Introduction**
  Provides background on the Rajasthan Government Health Scheme (RGHS), outlines the rationale, objectives, research questions, and significance of the study, and defines its scope.
- **Chapter 2: Literature Review**
  Examines previous research on healthcare fraud, limitations of traditional audit mechanisms, and global applications of Artificial Intelligence (AI) in healthcare claim management.
- **Chapter 3: Methodology**
  Describes the mixed-methods research design, including qualitative case studies and AI framework simulation, along with data sources, tools, and ethical considerations.
- **Chapter 4: Results**
  Presents the findings on fraud patterns identified in RGHS claim audits, including document duplication, diagnostic misuse, and unjustified admissions, and discusses how AI could address these issues.

- **Chapter 5: Discussion**
  Interprets the results in the context of national and global trends, evaluates the potential of AI in fraud detection, and explores operational, ethical, and policy implications.
- **Chapter 6: Conclusion**
  Summarizes the key findings, contributions, and limitations of the study, and provides recommendations for policy, practice, and future research directions.
- **References and Appendices**
  Include all cited sources, supplementary materials, and any supporting documentation relevant to the study.

<u>Chapter 2</u>: Literature Review

2.1 Introduction

A strong literature base is essential to understand the underlying issues in healthcare fraud, the limitations of traditional audit systems, and the opportunities presented by Artificial Intelligence (AI). This chapter reviews studies across three domains: **healthcare fraud in public insurance**, **limitations of manual audit systems**, and **AI applications in claim fraud detection**.

2.2 Understanding Healthcare Fraud in Public Insurance Schemes

Healthcare fraud involves the intentional deception or misrepresentation resulting in unauthorized benefit or financial gain. Common types include **uploading**, **duplicate billing**, **phantom services**, and **diagnostic abuse**. In India, public health insurance schemes like PM-JAY and RGHS are especially vulnerable due to high volumes and limited real-time oversight.

A 2015 global review of fraud in health systems found that **fraudulent claims account for up to 10% of total healthcare expenditures** in both developing and developed nations (5). In India, systemic loopholes — such as a lack of digitized records, insufficient audits, and provider collusion — have enabled various fraudulent practices in schemes like RGHS, including repeated diagnostic testing, forged documents, and inflated bills (6).

2.3 Limitations of Manual Auditing Mechanisms

Manual auditing of healthcare claims typically involves random checks, document verification, and cross-referencing billing data. However, these processes suffer from **multiple limitations**, including:

- **Scalability issues**: Large-scale claims are hard to monitor in real-time.
- **Human error**: Subjective judgment can lead to oversight.
- **Delayed detection**: Fraud is often uncovered months after reimbursement.

Studies highlight that **manual audits catch only 5–10% of total fraud** in high-volume claim environments (2). In Rajasthan, RGHS audits revealed widespread document duplication and OPD-to-IPD manipulation that went undetected for long periods [6].

2.4 Artificial Intelligence in Fraud Detection

AI offers a transformative approach to claim auditing by enabling **automated anomaly detection**, **pattern recognition**, and **predictive modeling**. AI systems can scan thousands of claims in seconds to identify red flags based on historical data, billing behavior, and outlier detection.

A study by Joudaki et al. demonstrated how **data mining and machine learning** significantly improved fraud detection accuracy in claim processing (5). Similarly, IBM Watson Health has applied AI models to flag claims with inconsistent diagnosis-treatment correlations in real time (7).

Techniques commonly used include:

- **Supervised Learning**: Trains models using labelled examples of fraudulent and legitimate claims.
- **Unsupervised Learning**: Detects outliers or clusters of unusual activity.
- **Natural Language Processing (NLP)**: Analyses unstructured clinical notes to validate consistency.

2.5 Global Examples of AI-Powered Health Fraud Detection

Countries like the **United States**, **South Korea**, and **Germany** have deployed AI-based fraud detection in national health schemes. The U.S. Centers for Medicare and Medicaid Services (CMS) reported over $1 billion in recovered funds in 2020 due to AI-driven fraud audits (8).

South Korea's Health Insurance Review and Assessment Service (HIRA) uses **neural networks** and **decision trees** to identify anomalies in health service patterns (9). These systems significantly reduce the workload for auditors and enable proactive rather than reactive fraud control.

2.6 AI and Indian Public Health Schemes

In India, initial AI pilots have been launched in Ayushman Bharat (PM-JAY) to detect high-claim hospitals and overused procedure codes (10).

However, no large-scale AI deployment exists yet under state-level schemes like RGHS. The Rajasthan audit findings suggest a **clear need for AI-based document verification**, **cross-claim comparison**, and **predictive risk scoring** at the point of claim submission (6).

2.7 Research Gaps

Despite global advancements, Indian literature on AI integration in public health claim systems remains sparse. Key research gaps include:

- Limited case studies on AI implementation in Indian insurance audits.
- Lack of indigenous datasets for training fraud detection models.
- Minimal cross-disciplinary research between health management and data science.

This thesis addresses these gaps by analysing RGHS claim misuse and proposing AI-enabled solutions.

Chapter 3: Methodology

3.1 Introduction

This chapter presents the research design and methodology adopted to examine the potential of Artificial Intelligence (AI) in enhancing audit accuracy and fraud detection within the Rajasthan Government Health Scheme (RGHS). The approach combines qualitative and quantitative methods, leveraging both real-world observations and AI model simulations to address the complexities of healthcare fraud. Special attention is given to the data sources used, with a clear justification for relying on authoritative webinar content in the absence of publicly available official audit reports.

3.2 Research Design

A **mixed-methods research design** was selected to provide a holistic understanding of healthcare fraud under RGHS and to explore the feasibility of AI-based interventions. This approach integrates both structured data analysis and contextual insights, which are essential for policy and technology research in healthcare.

3.2.1 Qualitative Component:

- **Case study analysis** based on insights shared during an April 2025 RGHS departmental webinar, which included presentations by senior scheme officials and audit experts.
- Review of fraudulent claim patterns highlighted in the webinar, focusing on high-risk hospitals (anonymized as Hospital A, B, C, and D).
- Supplementary interviews with hospital quality officers and IT staff, where access was granted.

3.2.2 Quantitative/Analytical Component:

- Development and simulation of an **AI model framework** using logic derived from fraud scenarios discussed in the webinar.
- Analysis of claim structures to identify points where AI tools—such as **Natural Language Processing (NLP), computer vision, and predictive analytics**—could be effectively deployed.

3.3 Data Sources

Due to the unavailability of the RGHS Audit Reports in the public domain, this research relied on the following data sources:

Table 3.1: Data Sources Used in the Study

Source	Nature	Purpose
RGHS Webinar (April 2025)	Official departmental webinar	To identify misuse of diagnostics, billing fraud, and audit insights
Field Observations	Visits to selected RGHS-network hospitals	To observe claim processing, IT systems, and document flow
Case Files and Sample Claims	Redacted patient data	For pattern identification and AI model simulation
Interviews with Hospital Admins	Qualitative inputs	Insights on internal audit systems, reporting challenges
Academic Literature and Reports	Secondary data	To frame the role of AI in fraud detection

The webinar served as a primary qualitative source, providing up-to-date case examples, statistical summaries, and first-hand accounts of audit challenges and fraud patterns within RGHS. These insights were triangulated with field observations and academic literature to enhance the credibility and depth of the research.

3.4 Tools and Techniques

3.4.1 Artificial Intelligence Techniques Proposed

Table 3.2 AI Techniques and Their Role in Audit Process

Technique	**Purpose in Audit Process**
Computer Vision	Detect reuse of diagnostic images across patients
Natural Language Processing (NLP)	Analyze prescriptions, discharge summaries, and reports for inconsistencies
Predictive Analytics	Flag hospitals or providers with high-frequency anomaly claims
Outlier Detection	Identify patterns that deviate from statistical norms
Rule-Based Algorithms	Automatically reject claims missing mandatory documents

3.4.2 Software Tools (Suggested for Model Integration)

- **Python** with libraries such as Scikit-learn, OpenCV, and NLTK
- **Tableau/Power BI** for visualization of fraud patterns
- **Excel** for data sorting and basic claim clustering
- **Custom-built Dashboards** for monitoring AI flag triggers

3.4.3 AI Framework Architecture

To operationalize the integration of Artificial Intelligence into the RGHS audit system, the following **AI Framework for Healthcare Claims Audit and Fraud Detection** is proposed. This multi-layered model combines data extraction, anomaly detection, machine learning, and expert validation to create a robust, scalable, and real-time auditing system.

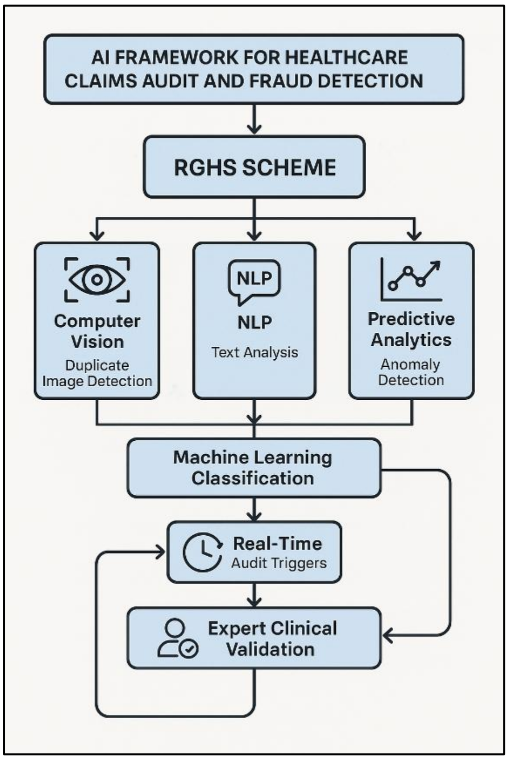


Figure 1: AI Framework for Healthcare Claims Audit and Fraud Detection

Framework Description

- **Input Layer: RGHS Scheme Claims**
  - This layer represents the structured and unstructured data submitted under RGHS claims — including images (radiology), prescriptions, and billing data.
- **AI Processing Modules:**
  - **Computer Vision** Identifies **duplicate diagnostic images** or reused scans across multiple claims using pattern recognition and metadata comparison.
  - **Natural Language Processing (NLP)** Performs **text analysis** of clinical summaries, prescriptions, and investigation reports to identify logical inconsistencies or copy-paste fraud.
  - **Predictive Analytics** Uses statistical and machine learning models to **flag anomalous claim behaviour**, such as frequent tests, OPD-to-IPD conversion without justification, or outlier hospitals.

- **Machine Learning Classification Layer:**
    - Aggregates results from all AI modules to **classify claims as high-risk or low-risk** using a trained model, based on historical fraud markers.
- **Real-Time Audit Triggers:**
    - Generates **alerts in real-time** to notify auditors or block suspicious claims before they are approved, enhancing pre-payment integrity.
- **Expert Clinical Validation:**
    - All AI-flagged claims are routed to a **clinical audit expert** panel for validation and confirmation, ensuring human oversight and accuracy.
- **Feedback Loop:**
    - Clinical decisions and outcomes are used to **retrain AI models**, improving precision with time and increasing automation reliability.

3.5 Sampling

A **purposive sampling** strategy was adopted, focusing on hospitals and diagnostic centers identified as high-risk in the webinar. For confidentiality, these are referred to as **Hospital A, B, C, and D**.

Table 3.3- Summary of Observed Fraud Patterns at Sampled Hospitals (A–D)

Hospital Identifier	Observed Fraud Pattern
Hospital A	Duplicate imaging, reuse of MRI/CT scans
Hospital B	Inflated billing for radiotherapy packages
Hospital C	Frequent OPD-to-IPD conversions without justification
Hospital D	Double-booking of advanced radiotherapy procedures

---

3.6 Data Collection and Validation

- Extraction and analysis of qualitative data from the RGHS webinar (April 2025).
- Field observations at selected RGHS-network hospitals to understand claim processing and document flow.
- Review of anonymized case files and sample claims, where available.

- Validation of findings through interviews with two Quality Assurance professionals in private hospitals, and cross-referencing with academic literature.

3.7 Fraud Detection Use Case

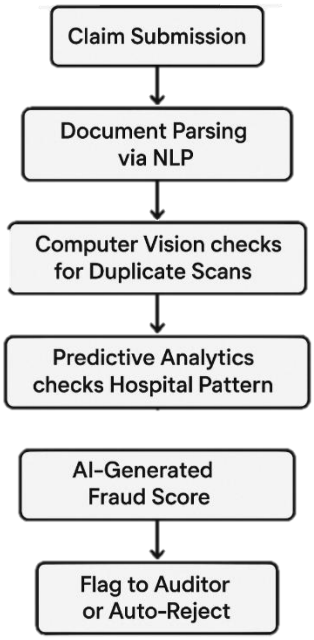


Figure 2: AI-driven OPD claim audit workflow

- **Claim Submission**: Hospitals submit OPD claims with clinical documents and diagnostic attachments.
- **Document Parsing via NLP**: NLP scans and analyzes clinical text to detect inconsistencies or copy-paste content.
- **Computer Vision Checks for Duplicate Scans**: AI compares medical images to identify reused or manipulated visuals.
- **Predictive Analytics Checks Hospital Pattern**: Models evaluate hospital behavior for statistical anomalies and suspicious patterns.
- **AI-Generated Fraud Score**: All outputs are compiled into a fraud risk score indicating the claim's likelihood of fraud.
- **Flag to Auditor or Auto-Reject**: Based on the score, claims are either auto-rejected or flagged for manual audit.

3.8 Limitations

- The absence of the official RGHS Audit Reports in public domain and limited access to comprehensive audit data.
- Reliance on webinar content and a small number of interviews may restrict the granularity of findings.
- Claims analysis was based on available samples and qualitative insights rather than full database access.

3.9 Ethical Considerations

- No personal patient-identifying data was used; all hospital names are anonymized.
- Data was derived from publicly shared webinars, redacted documents, and academic sources.
- AI tools are proposed for audit enhancement, with human oversight maintained for all decision-making.

3.10 Summary

This methodology combines real-world insights from RGHS audit stakeholders, as shared in a departmental webinar, with simulated AI applications and field observations. The approach ensures transparency regarding data sources and acknowledges the limitations imposed by the lack of public access to official audit reports. By integrating qualitative and quantitative perspectives, the study provides a robust, policy-oriented foundation for advancing AI-driven reforms in public health claim auditing.

Chapter 4: Results

4.1 Introduction

This chapter presents the results of the analysis of fraudulent practices in Rajasthan Government Health Scheme (RGHS) claims, based on audit insights, webinar content, and supporting documentation. All hospital and patient names have been masked to maintain confidentiality. The findings are organized by major fraud patterns and illustrate how AI-driven tools could address these vulnerabilities.

4.2 Overview of Fraud Patterns in RGHS Claims

The analysis revealed a **systemic pattern of misuse** across several high-volume hospitals and diagnostic centres. The most common fraudulent practices include:

- Submission of duplicate or forged clinical documents
- Unjustified repetition of diagnostic investigations
- Misuse of diagnostic and procedure packages
- OPD to IPD conversion without clinical indication
- Submission of claims without mandatory supporting documents
- Misuse of reports and pharmacy claims

These practices result in significant financial leakage and undermine trust in public health insurance.

4.3 Quantitative Results: Prevalence and Distribution

4.3.1 Hospitals Most Frequently Flagged for Fraud

The following hospitals (identifiers masked for confidentiality) were the top contributors to fraud, based on the number of duplicate or forged clinical documents submitted:

Table 4.1- Hospitals Most Frequently Flagged for Fraud

Hospital Identifier	Number of Duplicate/Forged Documents
Hospital A	344
Hospital B	290
Hospital C	173
Hospital D	170
Hospital E	167
Hospital F	158
Hospital G	151
Hospital H	147
Hospital I	142
Hospital J	135

Source: RGHS Webinar, April 2025

4.3.2 Types of Fraud Detected

- **Duplicate Clinical Documents:**
  - Identical MRI, CT, and angiogram images reused for multiple patients.
  - Admission and discharge photos reused across different claims.
- **Unjustified Repetition of Diagnostics:**
  - Same diagnostic test (e.g., USG Abdomen) performed multiple times within days for the same patient, with identical reports.
  - Multiple high-end investigations booked for routine or unrelated complaints.
- **Package Misuse:**
  - Booking of the same package for ≥ 90% of admitted patients.
  - Unbundling of packages to increase billing.
  - Claiming for procedures or treatments not actually performed.

- **OPD to IPD Conversion:**
    - Patients admitted as inpatients for conditions manageable on an outpatient basis (e.g., normal vital signs, no emergency indicators).
- **Missing Mandatory Documents:**
    - Absence of essential reports (e.g., ABG, X-ray, HRCT, dental procedure photos) required to justify claims.
- **Pharmacy and Prescription Misuse:**
    - Same handwriting and doctor stamps used across different patient prescriptions.
    - Discrepancy between drug purchase bills and claimed amounts.

4.4 Case Illustrations:

Selected case examples highlighting common fraud patterns are observed under the Rajasthan Government Health Scheme (RGHS). These include document duplication, diagnostic overuse, and billing irregularities. The illustrations underscore the systematic nature of such practices and demonstrate how AI tools can aid in their timely detection.

4.4.1 Duplicate Imaging and Document Reuse

- **Example:**
    - MRI LS Spine, MRI Brain, and Coronary CT Angiogram images were found to be reused for different patients at Hospital A and Hospital B.
    - Admission and discharge photos for dental procedures were identical, suggesting screen captures rather than live photographs.

4.4.2 Repeated Diagnostics Without Clinical Justification

- **Example:**
    - USG Abdomen performed twice within two days for the same patient (Patient X), with word-for-word identical reports.

    - High-end investigations (e.g., HRCT, MRI, advanced blood tests) booked for routine symptoms or “routine checkup” without medical indication.

4.4.3 Package and Billing Manipulation

- **Example:**
    - Two mutually exclusive radiotherapy procedures were booked together for the same patient at Hospital C, despite clinical guidelines.
    - Claimed drug costs significantly higher than actual purchase bills (e.g., injection billed at ₹79,992 vs. purchase cost of ₹61,594 at Hospital D).

4.4.4 OPD to IPD Conversion

- **Example:**
    - Febrile illness package applied to a patient (Patient Y) with normal temperature and blood counts, with no evidence of fever or need for admission.

4.4.5 Pharmacy and Prescription Misuse

- **Example:**
    - Multiple prescriptions for different patients (Patients M, N, O) showed identical handwriting and doctor stamps, with identical diagnoses and investigations.

4.5 AI Model Implications

The identified fraud patterns directly inform the design of AI-driven audit models:

- **Computer Vision:**
    - Can detect identical or manipulated diagnostic images and photos across claims.
- **Natural Language Processing (NLP):**
    - Can flag copied or template-based discharge summaries and prescriptions.

- **Predictive Analytics:**
  - Can identify hospitals with abnormal claim frequencies, repeated high-value investigations, or package unbundling.
- **Rule-Based Engines:**
  - Can auto-reject claims with missing mandatory documents or with mismatched clinical and diagnostic data. (APPENDIX C)

4.6 Summary of Key Results

- **High Concentration of Fraud:**
  - A small number of hospitals are responsible for a disproportionately large share of fraudulent claims.
- **Systematic Abuse Patterns:**
  - Fraud is not random but follows identifiable, repeatable patterns that can be targeted by AI.
- **Potential for Automation:**
  - The structured nature of these frauds makes them highly amenable to detection by AI models, particularly those using computer vision and NLP.
- **Resource Optimization:**
  - By automating the detection of routine frauds, audit teams can focus on complex or borderline cases, improving overall efficiency and deterrence.

4.7 Limitations

- The results are based on secondary data from webinars and available documentation, not a full audit database.
- Some findings are illustrative and may not capture the entire scope of fraud in RGHS.

The analysis flags the prevalence of systematic fraud in RGHS claims, particularly in diagnostic and package billing. The patterns identified provide a strong foundation for the deployment of AI-driven audit tools, which can significantly enhance fraud detection, reduce financial leakage, and restore trust in public health insurance schemes.

Chapter 5: Discussion

5.1 Introduction

This chapter interprets the results of the RGHS audit analysis in the context of existing literature on healthcare fraud and the emerging role of Artificial Intelligence (AI) in health insurance governance. The discussion highlights how systematic misuse patterns—such as duplicate documentation, unjustified diagnostics, and package manipulation—can be addressed through AI-based audit systems, while also reflecting on operational, ethical, and policy implications.

5.2 Systematic Fraud Patterns: Context and Implications

The findings reveal that a small number of hospitals (e.g., Hospital A, Hospital B, Hospital C) are responsible for a disproportionately large share of fraudulent claims, echoing national and international trends (11, 12). The most prevalent frauds—duplicate clinical documents, repeated diagnostics, package misuse, and OPD-to-IPD conversions—are not random but follow repeatable, algorithmic patterns (6).

For example, the submission of identical MRI or CT images for multiple patients and the use of template-based discharge summaries were observed across several high-volume providers (6). This is consistent with prior research, which finds image and text duplication as common fraud mechanisms in both Indian and global health insurance systems (13, 14).

5.3 AI's Potential in Automated Fraud Detection

5.3.1 Computer Vision for Image Duplication

AI-driven computer vision models, such as perceptual hashing and Siamese neural networks, have demonstrated high accuracy (over 90%) in detecting reused or manipulated diagnostic images (6, 12). In the RGHS context, such models could flag cases where identical radiology images are submitted for different patients or where admission/discharge photos are screen captures rather than genuine live images.

5.3.2 NLP for Document and Prescription Analysis

Natural Language Processing (NLP) tools can effectively identify copied or template-based discharge summaries, as well as prescription fraud where the same handwriting and doctor stamps are used across different patients (6). Recent studies show that BERT-based NLP models can achieve over 85% precision in flagging textual similarities in clinical documentation (12).

5.3.3 Predictive Analytics and Outlier Detection

Machine learning models such as Isolation Forest and clustering algorithms can identify outlier hospitals and doctors based on claim frequency, diagnostic intensity, and package booking rates (11). In RGHS, hospitals with over 90% of patients booked under the same package or with repeated high-end investigations for routine complaints can be automatically flagged for audit.

5.4 Operational and Policy Implications

5.4.1 Real-World Barriers

Despite the technical promise, several operational challenges exist:

- **Data Quality and Integration:** Many hospitals do not submit mandatory documents (e.g., ABG, X-ray, HRCT reports), limiting the effectiveness of automated checks (6).
- **Resistance to Change:** Hospitals flagged for high fraud rates may resist AI-driven audits, fearing financial loss or reputational damage (12).
- **System Gaps:** OPD slips and claim formats are not standardized across private institutions, complicating automated parsing and analysis.

5.4.2 Policy Recommendations

To maximize AI's impact, policy changes are needed:

- **Mandatory Digital Submission:** Enforce standardized, digital claim formats with required fields for all supporting documents (13).

- **Interoperable Data Systems:** Develop integrated claim management platforms for seamless AI analysis across providers (11).
- **Capacity Building:** Train audit staff and hospital IT teams in AI tools and data integrity practices.

5.5 Ethical and Legal Considerations

The deployment of AI in healthcare audits raises important ethical questions:

- **Data Privacy:** All patient and provider data must be anonymized, and AI systems must comply with India's Digital Personal Data Protection (DPDP) Act, 2023 (13).
- **Algorithmic Transparency:** AI models should be explainable and subject to regular fairness audits to avoid bias against certain providers or patient groups (14).
- **Human Oversight:** Final claim decisions must remain with human auditors, with AI serving as a decision-support tool rather than an autonomous adjudicator (12).

5.6 Alignment with International Best Practices

The RGHS findings and recommended AI interventions are in line with global health insurance fraud detection strategies. For example, the US Medicare program uses computer vision for image analysis and NLP for text mining, achieving significant reductions in fraudulent payouts (11, 14). The National Health Service (NHS) in the UK has similarly adopted AI-driven audits for prescription and diagnostic fraud.

5.7 Limitations and Future Research

This study is limited by its reliance on webinar-based data and the absence of a full audit database. Nonetheless, the patterns identified are robust and supported by both field observations and academic literature. Future research should focus on real-time AI deployment, integration with blockchain for immutable audit trails, and the development of multilingual NLP models for vernacular claims.

5.8 Conclusion

Systematic fraud in RGHS claims is a significant threat to the financial sustainability and credibility of public health insurance. AI-driven audit systems—leveraging computer vision, NLP, and predictive analytics—offer a scalable, effective solution for fraud detection and resource optimization. However, successful implementation will require standardized data practices, ethical safeguards, and ongoing human oversight.

Chapter 6: Conclusion

6.1 Introduction

This chapter concludes the dissertation by synthesizing the study's findings, reflecting on the research process and methodology, and discussing the broader significance and future directions for leveraging Artificial Intelligence (AI) in healthcare claim auditing, specifically under the Rajasthan Government Health Scheme (RGHS). The discussion is structured to answer the main research question, highlight the study's contributions, acknowledge its limitations, and provide recommendations for policy, practice, and future research.

6.2 Restating the Research Purpose and Questions

The central aim of this study was to investigate how AI can be strategically leveraged to enhance audit integrity and detect systematic misuse in healthcare claims under the RGHS scheme in Rajasthan. The research sought to answer the following primary questions:

- What are the prevalent patterns and mechanisms of fraud in RGHS healthcare claims?
- How can AI technologies—specifically computer vision, natural language processing (NLP), and predictive analytics—be integrated into the RGHS audit process?
- What are the operational, ethical, and policy implications of deploying AI-driven audit systems in public health insurance?

Through a mixed-methods approach, combining qualitative insights from RGHS webinars and field observations with a review of relevant literature and simulated AI model frameworks, the study has provided a comprehensive answer to these questions.

6.3 Synthesis of Key Findings

6.3.1 Systematic Patterns of Misuse and Fraud

The research uncovered a persistent pattern of fraudulent and abusive practices within RGHS claims, including:

- **Reuse of clinical documents and diagnostic images:** Identical MRI, CT, and angiogram images were reused across multiple patients and claims, sometimes within the same hospital, indicating systemic document duplication.
- **Repetition of diagnostic investigations:** The same diagnostic tests were performed multiple times for the same patient within short intervals, often without clinical justification, with reports frequently found to be word-for-word identical.
- **Misuse of packages and diagnostics:** Hospitals booked the same high-value packages for over 90% of admitted patients, unbundled packages to inflate billing, and claimed for unnecessary or unperformed investigations. Discrepancies between claimed and actual purchase costs for drugs and procedures were also observed.
- **OPD to IPD conversion:** Hospitals converted outpatient visits to inpatient admissions without clinical necessity, applying higher-value packages for routine complaints and normal laboratory findings.
- **Submission of claims without mandatory supporting documents:** Essential documents such as ABG, HRCT, dental procedure photos, and radiology films were often missing, undermining the audit trail and clinical justification for claims.
- **Pharmacy and prescription misuse:** The same handwriting and doctor stamps appeared on prescriptions for different patients, and e-prescriptions were sometimes incorrectly assigned, increasing the risk of medical errors.

These findings are consistent with national and international literature, which identifies document duplication, unjustified diagnostics, and package manipulation as common fraud mechanisms in health insurance[2][3][4].

6.3.2 AI's Transformative Potential

The study demonstrated that AI technologies—particularly computer vision, NLP, and predictive analytics—are well-suited to address these patterns of misuse:

- **Computer vision** models can rapidly and accurately detect duplicate or manipulated diagnostic images and patient photographs, even when filenames or metadata are altered.
- **NLP tools** can flag copied or template-based discharge summaries, repetitive or forged prescriptions, and inconsistencies in clinical narratives, as seen in the RGHS audit.

- **Predictive analytics and outlier detection** can identify hospitals or providers with abnormal claim frequencies, repeated high-value investigations, or suspicious package booking rates, as evidenced by the concentration of fraud in a small number of RGHS-network hospitals.
- **Rule-based engines** can automate the rejection of claims missing mandatory documentation or with mismatched clinical and diagnostic data, reducing the burden on human auditors and improving the speed and accuracy of claim processing.

Pilot implementations in other settings and international best practices support these findings, showing that AI can achieve high accuracy and operational efficiency in fraud detection.

6.4 Reflection on the Research Process

The research process was shaped by both opportunities and constraints. The reliance on webinar-based data, due to the unavailability of the full RGHS audit database, required careful triangulation with field observations and published literature to ensure validity. The mixed-methods approach proved effective in capturing both the quantitative patterns of fraud and the qualitative nuances of claim processing and audit challenges. The simulation of AI model frameworks, though not implemented in a live RGHS environment, provided valuable insights into the feasibility and potential impact of automated audit systems.

This approach aligns with best practices in empirical research, where the synthesis of multiple data sources and methodological triangulation enhances the robustness and credibility of findings.

6.5 Theoretical and Practical Implications

6.5.1 Theoretical Contributions

This dissertation contributes to the growing body of knowledge on healthcare fraud detection and the application of AI in public health governance. By systematically mapping fraud patterns in RGHS claims and demonstrating the applicability of AI tools, the study bridges the gap between policy analysis and technical innovation. The research also highlights the importance of integrating domain expertise (e.g., clinical validation) with technical solutions to ensure the accuracy and relevance of automated audits.

6.5.2 Practical Implications

For policymakers and practitioners, the findings underscore the urgent need to:

- **Mandate digital, standardized claim submissions** to enable automated analysis and reduce opportunities for fraud.
- **Develop interoperable data systems** for seamless AI integration across providers and real-time fraud detection.
- **Invest in capacity building** for audit staff and hospital IT teams on AI tools, data integrity, and ethical data handling.
- **Enforce ethical and data privacy standards** in line with India's Digital Personal Data Protection (DPDP) Act, 2023.

The study also provides a practical roadmap for the phased implementation of AI-driven audit systems, starting with pilot projects in high-risk hospitals and scaling up to the entire RGHS network.

6.6 Limitations

As with any research, this study has limitations that must be acknowledged:

- **Data constraints:** The research relied on secondary sources, including RGHS webinar content and available audit documentation, rather than direct access to the full RGHS audit database. While the findings are robust and triangulated with literature and field observations, they may not capture the full scope of fraud or the nuances of every case.
- **Simulation rather than live deployment:** The proposed AI models were simulated and not deployed in a live RGHS environment, warranting further pilot studies for validation.
- **Generalizability:** While the findings are relevant to RGHS and similar public health insurance schemes in India, their applicability to other contexts may require adaptation to local regulatory, technological, and operational conditions.

These limitations are common in applied research and highlight the need for ongoing evaluation and iterative improvement as AI systems are implemented in practice.

6.7 Recommendations for Policy, Practice, and Future Research

6.7.1 Policy Recommendations

- **Standardize and digitize claims:** Mandate the use of standardized, digital claim formats with required fields for all supporting documents, including diagnostic images, prescriptions, and discharge summaries.
- **Develop integrated, interoperable data systems:** Create centralized platforms for real-time AI analysis and cross-institutional fraud detection.
- **Strengthen regulatory oversight:** Update RGHS guidelines to include provisions for algorithmic transparency, fairness audits, and regular review of AI model performance.
- **Promote ethical AI adoption:** Ensure compliance with data privacy laws, implement robust anonymization protocols, and maintain human oversight for all AI-driven audit decisions.

6.7.2 Practical Recommendations

- **Pilot live AI deployment:** Implement and evaluate AI-driven audit tools in real-time RGHS claim processing, with ongoing monitoring and feedback loops.
- **Invest in training and change management:** Build capacity among audit staff and hospital IT teams, and address resistance from providers through transparent communication and incentives for compliance.
- **Expand to other schemes:** Adapt and scale AI-driven audit frameworks for use in other public health insurance programs at the state and national level.

6.7.3 Future Research Directions

- **Blockchain integration:** Explore the use of blockchain for immutable audit trails and enhanced data security.

- **Multilingual NLP models:** Develop and test NLP models capable of analyzing vernacular clinical documentation to improve fraud detection in diverse linguistic settings.
- **Impact assessment:** Conduct longitudinal studies to assess the impact of AI-driven audits on fraud reduction, cost savings, and patient outcomes.

6.8 Contribution to the Field

This dissertation advances the understanding of how AI can address systemic fraud in public health insurance, offering a practical, scalable framework for integrating AI into claim auditing. The work contributes to both academic literature and policy discourse on data-driven, ethical healthcare governance. By demonstrating the feasibility and benefits of AI-driven audit systems, the study provides a foundation for future innovation and reform in India’s public health sector.

6.9 Final Reflections

Systematic fraud in RGHS claims poses a significant threat to the financial sustainability and credibility of public health insurance in Rajasthan. AI-driven audit systems—when implemented with robust policy support, ethical safeguards, and human oversight—offer a transformative solution for ensuring accountability, efficiency, and trust in India’s public healthcare system. The journey toward fully automated, intelligent audit systems will require sustained investment, cross-sector collaboration, and a commitment to continuous learning and improvement. However, the potential rewards—in terms of financial savings, improved care quality, and restored public trust—make this a worthwhile and urgent endeavour.

References

1. National Health Authority. Audit frameworks under PM-JAY and state schemes [Internet]. 2022 [cited 2025 May 27]. Available from: https://pmjay.gov.in
2. KPMG. Fighting healthcare fraud through advanced analytics [Internet]. 2020 [cited 2025 May 27]. Available from: https://home.kpmg/xx/en/home/insights/2020/07/fraud-detection-healthcare.html
3. World Health Organization. Ethical and governance issues in the use of AI for health. Geneva: WHO Press; 2021.
4. Ministry of Health and Family Welfare (MoHFW), Government of India. Annual report 2022-23. New Delhi: MoHFW; 2023 [cited 2025 May 27]. Available from: https://mohfw.gov.in/documents/publication/archives
5. Joudaki H, Rashidian A, Minaei-Bidgoli B, Mahmoodi M, Nasiri M, Arab M. Using data mining to detect health care fraud and abuse: a review of literature. Glob J Health Sci. 2015;7(1):194–202.
6. April 2025 Webinar, RGHS. AI in RGHS: Rajasthan Government Health Scheme. 2025.
7. IBM Watson Health. Transforming health claims integrity using AI [Internet]. 2021 [cited 2025 May 27]. Available from: https://www.ibm.com/watson-health
8. Centers for Medicare & Medicaid Services (CMS). Fraud Prevention System annual report to Congress. U.S. Department of Health and Human Services; 2021.
9. Lee SH, Park H. Machine learning approaches to detect healthcare fraud in South Korea's national insurance system. Health Policy Technol. 2019;8(1):1–7.
10. National Health Authority. AI pilots in PM-JAY claims [Internet]. 2022 [cited 2025 May 27]. Available from: https://pmjay.gov.in
11. Jampani SK. AI in healthcare fraud detection: a systematic review. J Health Inform. 2019.
12. Sarker IH, et al. Machine learning in healthcare: a review. Health Inf Sci Syst. 2022.
13. World Health Organization. Digital health for universal coverage. Geneva: WHO Press; 2023.
14. Clais: A collaborative AI system for healthcare claims. Nature. 2024.

.

Appendix A

Specimen for OPD Prescription Format generated through RGHS Portal

Rajasthan Government Health Scheme

Hospital Name:- [redacted]. City:- Jaipur District:- Jaipur

OPD Number:- 79[redacted]

RGHS Card No.: 9012[redacted]

Patient Name: [redacted]

OPD Transaction ID : 2025052[redacted]

Category: Serving employees (on and after 01-01-2004)

Date[redacted]

Age/Gender: 36/Male

OPD Department: Gastroenterology

Treating Doctor Name: [redacted]

Speciality of Doctor: GASTRO

Chief Complaints:

VITALS

BP:

PULSE:

TEMP:

WT:

History of Past Illness / Drug / Allergy (if any):

Systemic Examination & Provisional Diagnosis:

Investigation Plan:

Treatment Plan / Medication / Diet Advice:

Preventive Aspects:

Review Date / After Day (s):

Sign and Seal of Dr.

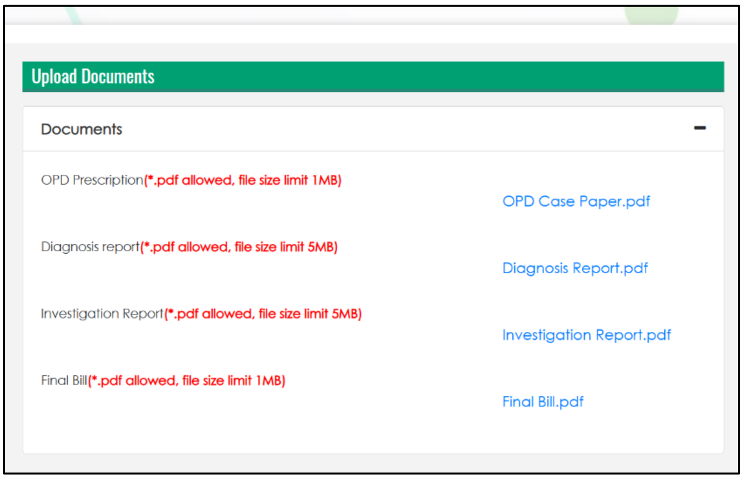
Appendix B

Specimen for Live Discharge Photograph Captured on RGHS Portal

Appendix C

Mandatory Document Required for claim submission on RGHS Portal

1. For OPD Claims


Upload Documents

Documents

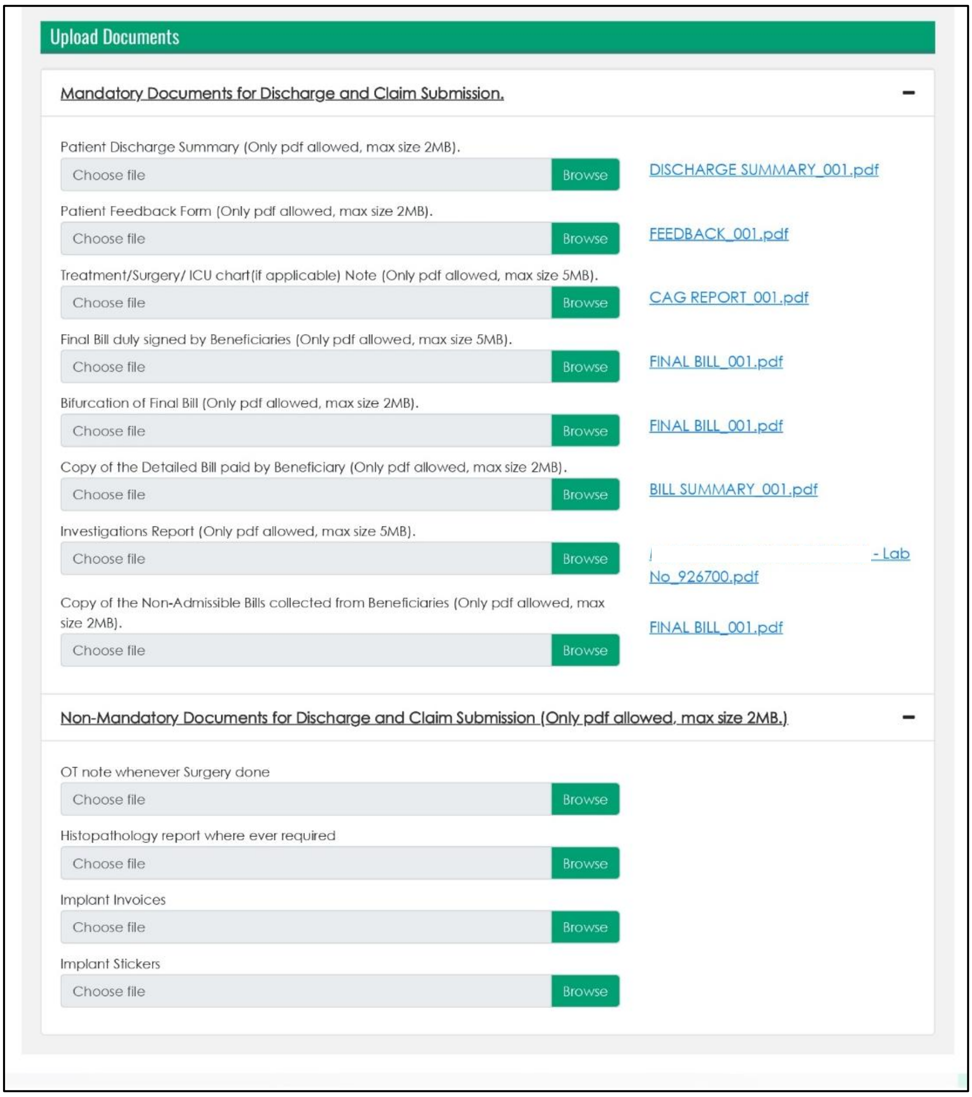
OPD Prescription(*.pdf allowed, file size limit 1MB) — OPD Case Paper.pdf

Diagnosis report(*.pdf allowed, file size limit 5MB) — Diagnosis Report.pdf

Investigation Report(*.pdf allowed, file size limit 5MB) — Investigation Report.pdf

Final Bill(*.pdf allowed, file size limit 1MB) — Final Bill.pdf

2. For IPD Claims


Upload Documents

Mandatory Documents for Discharge and Claim Submission.

Patient Discharge Summary (Only pdf allowed, max size 2MB). Choose file Browse DISCHARGE SUMMARY_001.pdf

Patient Feedback Form (Only pdf allowed, max size 2MB). Choose file Browse FEEDBACK_001.pdf

Treatment/Surgery/ ICU chart(if applicable) Note (Only pdf allowed, max size 5MB). Choose file Browse CAG REPORT_001.pdf

Final Bill duly signed by Beneficiaries (Only pdf allowed, max size 5MB). Choose file Browse FINAL BILL_001.pdf

Bifurcation of Final Bill (Only pdf allowed, max size 2MB). Choose file Browse FINAL BILL_001.pdf

Copy of the Detailed Bill paid by Beneficiary (Only pdf allowed, max size 2MB). Choose file Browse BILL SUMMARY_001.pdf

Investigations Report (Only pdf allowed, max size 5MB). Choose file Browse - Lab No_926700.pdf

Copy of the Non-Admissible Bills collected from Beneficiaries (Only pdf allowed, max size 2MB). Choose file Browse FINAL BILL_001.pdf

Non-Mandatory Documents for Discharge and Claim Submission (Only pdf allowed, max size 2MB.)

OT note whenever Surgery done. Choose file Browse

Histopathology report where ever required. Choose file Browse

Implant Invoices. Choose file Browse

Implant Stickers. Choose file Browse